By James Guszcza

Analyzing Analytics: The Debate

MOST READERS WHO GREW UP IN A CERTAIN COUNTRY IN A CERTAIN DECADE FONDLY REMEMBER (well, let's just say, remember) the television game show *Let's Make a Deal*, hosted by Monty Hall. The premise of the show was to have a contestant guess behind which of three doors—A, B, or C—lurked a valuable prize (often a mustard-colored station wagon). To build suspense, Monty would always open one of the two doors that the contestant did not choose. Pointing out that the door he just opened had not concealed the prize, Monty would offer the contestant the option to change his or her guess. So, suppose you are a contestant and you have guessed that the car is behind door A. Monty opens door C, revealing not the car but a goat. Monty then gives you a choice: you can either stay with your original guess or change your guess to door B. What should you do—switch to door B or stick with door A?

If your answer is that it doesn't matter, you are not alone. Most people intuit that after Monty revealed the goat behind door C, the probability of the car's being behind doors A, B, and C goes from $\{\frac{1}{3}, \frac{1}{3}, \frac{1}{3}\}$ to $\{\frac{1}{2}, \frac{1}{2}, 0\}$. Therefore, Monty's opening door C should have no bearing on your subsequent decision about whether to switch from door A to door B.

But this common answer turns out to be wrong. If you switch from door A to door B, you double your chance of winning. Few people are able to figure this out in real time, without the benefit of pencil, paper, and either Venn diagrams or Bayes' Theorem. Indeed, many are not able to figure it out even with unlimited time and resources. In fact, when this problem was popularized by Marilyn vos Savant in *Parade* magazine in 1990 (it was she who named it the "Monty Hall Problem"), approximately 10,000 readers, hundreds of whom were mathematicians, wrote back to *Parade*, chiding vos Savant for publishing the wrong answer.

Demonstrating that vos Savant, true to her name, was right and that her critics were wrong makes a nice probabilistic parlor trick (see Page 44). But the moral of the story goes much deeper. Construed in broader terms, the Monty Hall Problem is a parable about our ability to effectively process information when making decisions about contingent events. Alas, it seems that we're often not very good at it.

Baseball, Underwriting, and Cognitive Biases

This is the theme—either implicit or explicit—underlying a spate of recent books about the growing ubiquity of analytic and predictive modeling applications in fields such as business, law, medicine, education, and even professional sports. The celebrated journalist Michael Lewis initiated the genre in 2003 with his sensational book *Moneyball*. Lewis vividly tells the story of how the Oakland A's gen-

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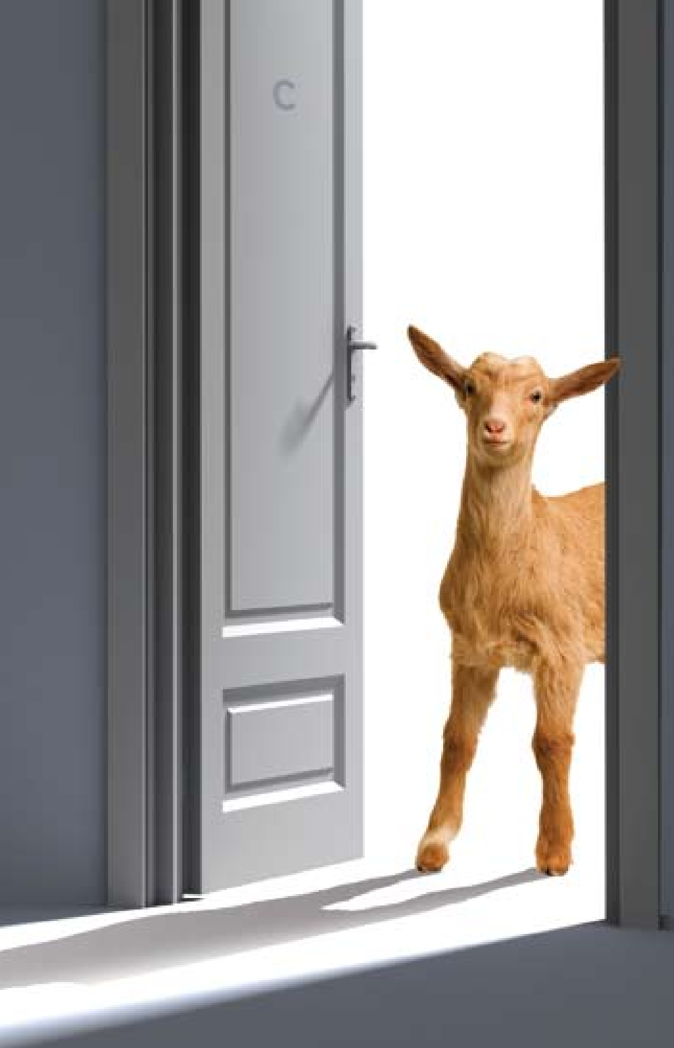

Many people, even experts, go with their gut when making important decisions. Can actuaries help?

Between Intuition and Statistical Thinking

eral manager Billy Beane was able to take his cash-strapped team to the top of the American League through the use of statistical analysis. (See also "Stat of the Art," May/June 2004 *Contingencies*, www.contingencies.org/mayjun04/stat.pdf.)

Beane's problem was that richer teams such as the New York Yankees, with two or three times the budget of the A's, could easily outbid them when scouting for new talent. But Beane had a crucial insight: Baseball scouts often use flawed reasoning and fallible "gut feelings" (or "professional judgment") when selecting baseball players. Beane realized that by using a more objective approach, he could identify excellent players ignored by the richer teams and lure them at bargain salaries.

As recounted by Lewis, Beane's insight was born of personal experience. As a high school player, Beane was singled out by the scouts as a future baseball star. The scouts' judgments were based mostly on appearances and intuitions and hardly at all on baseball statistics. When the scouts evaluated him, they saw a fit athlete, a fast runner, and a strong batter—someone who looked the part of a good baseball player. They didn't have to think hard about the statistics; it was obvious to them that Beane had the makings of a top baseball player.

But the scouts turned out to be wrong. Billy Beane flopped as a player and ultimately quit to become a scout for the A's. By the time he made general manager, he was determined not to repeat the mistakes of the scouts who had singled him out in high school. Beane turned to the writings of baseball statistician Bill James in order to take a more scientific approach to evaluating baseball players.

For example, James had constructed a formula that could predict the number of runs a hitter is expected to create as a function of his on-base percentage. Taking his cue from James, Beane hired Paul DePodesta to statistically analyze players' performances. One of Beane's and DePodesta's findings was that college baseball players went on to perform better than high school recruits. Based on this finding, Beane decided to let the richer teams waste their time recruiting players out of high school while he and DePodesta used their statistical analyses to select the excellent college players that were being ignored by the scouts.

In short, Beane realized that the market for baseball players was inefficient because it was dominated by scouts making decisions based on intuitions rather than objective, data-driven analyses. Borrowing a phrase from the medical profession, you might say he took an "evidence-based" approach to player selection. Because of this, as Lewis put it, Beane was able to "run circles around taller piles of cash."

Even when the stakes are high, rational behavior does not always It takes time and effort to switch from simple intuitions to careful

Lewis' story is fascinating and has important implications well beyond baseball. I can vouch for this based on my own experience as an actuary. In recent years, I have participated in teams that built multivariate scoring models to help underwriters better select and price insurance risks. The goal was never to replace human decision-makers but rather to give them a tool that would enable them to make better decisions. Just as analytical methods outperform traditional methods of scouting baseball players, we have seen that underwriters consistently do a better job of selecting risks with a predictive model in hand. The implications have proven quite valuable to those insurance companies that have adopted analytical methods.

But how can this possibly be? Why do Bill James' simple formulas predict things that baseball scouts can't predict even after years of experience? Analogously, why do predictive model-based scoring engines enable underwriting pros to do a better job selecting and pricing risks? In a very insightful review of *Moneyball*, University of Chicago law professor Cass Sunstein and behavioral economist Richard Thaler discuss the clues that Lewis offers. Sunstein and Thaler write:

> Why do professional baseball executives, many of whom have spent their lives in the game, make so many colossal mistakes? They are paid well, and they are specialists. They have every incentive to evaluate talent correctly. So why do they blunder? In an intriguing passage, Lewis offers three clues. First, those who played the game seem to overgeneralize from personal experience: "People always thought their own experience was typical when it wasn't." Second, the professionals were unduly affected by how a player had performed most recently, even though recent performance is not always a good guide. Third, people were biased by what they saw, or thought they saw, with their own eyes. This is a real problem, because the human mind plays tricks, and because there is "a lot you couldn't see when you watched a baseball game."

Sunstein and Thaler then make a fascinating connection. They point out that Lewis is describing a central finding in cognitive psychology: People tend to use what is known as the "availability heuristic" when making judgments.

> As Daniel Kahneman and Amos Tversy have shown, people often assess the probability of an event by asking whether relevant examples are cognitively available. Thus, people are likely to think that more words on a random page end with the letters "ing" than have "n" as their next-to-last letter—even though a moment's reflection will show that this couldn't possibly be the case.

Perhaps this is also why so many people get the Monty Hall Problem wrong. It is easy to think of cases where "near ignorance" means "equally probable": tossing a coin, rolling a die, or spinning a roulette wheel. Many of Monty Hall's contestants—and Marilyn vos Savant's readers—were probably led astray by a false analogy between tossing a coin and the door A versus door B decision.

Sunstein and Thaler continue:

> The problem is not that baseball professionals are stupid; it is that they are human. Like most people, including experts, they tend to rely on simple rules of thumb, on traditions, on habits, on what other experts seem to believe. Even when the stakes are high, rational behavior does not always emerge. It takes time and effort to switch from simple intuitions to careful assessments of evidence.

As Sunstein and Thaler point out, this is true even though a lot of money is at stake in professional baseball and accurate statistics comparing players' performances are widely available. Similar points can be made about many aspects of insurance.

Underwriting is a classic example. The insurance industry is awash in data, yet my own modeling experience has convinced me that, until recently, much of this information was not being effectively used to guide decisions. Similar points could be made about claims management, premium auditing, marketing, customer service, policyholder retention efforts, fraud detection, and cultivating a household-level view of one's policyholders.

The emerging field of insurance price optimization is a further example: Rather than rely primarily on the instincts and tacit knowledge of pricing managers, U.S. insurers are beginning to consider analytic approaches to better understanding the tradeoff between price and volume of sales. These are all areas of insurance where experts—who are smart and talented but, after all, only human—make better and more profitable decisions when aided by predictive analytics. An even more direct analogy with *Moneyball* is agency management. If statistics can be used to select better teams of baseball players, why not use them to select better teams of agents?

Enter the Super Crunchers

Ian Ayres, in his entertaining new book *Super Crunchers*, expands on this theme and picks up where Lewis, Sunstein, and Thaler leave off. Ayres is a law and economics professor at Yale and seems to share the behavioral economics, anti-rational expectations perspective of Sunstein and Thaler.

Carrying Lewis' theme beyond baseball, Ayres discusses applications of predictive analytics in a number of disparate domains. "Super crunching" is Ayres' playful umbrella term for the various types of data mining, predictive modeling, and econometric, statistical, and actuarial analyses that can be used to guide human decisions. One should approach *Super Crunchers* not as a rigorous discussion of statistics but as an attempt to popularize the subject and explain to the layperson the reasons that super crunching is becoming ever more common. Certainly, few of the analytical concepts Ayres discusses will surprise actuarial readers; but the sheer breadth of his examples is compelling.

Ayres' opening example is nearly as striking as Lewis': the use of predictive models to judge wine quality. He tells the story of

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assessments of evidence.

how his economist colleague Orly Ashenfelter built regression models that have proven surprisingly effective at assessing the quality of Bordeaux wines. Ayres reproduces a regression equation that seems absurdly simple:

$$E[\text{Price}] = 12.145 + 0.00117 \text{ winter rainfall} + 0.0614 \text{ average growing season temperature} - 0.00386 \text{ harvest rainfall}$$

An elegant bouquet. Playing up the man-versus-machine drama of the story, Ayres quotes the acidulous reactions of eminent, yet ultimately misguided, wine critics from magazines such as *Wine Spectator*. "The formula's self-evident silliness invite[s] disrespect," wrote one. "An absolute and total sham… so absurd as to be laughable," wrote another. And yet, Ashenfelter's newsletter Liquid Assets accurately predicted that the 1989 and 1990 Bordeaux would be two "vintages of the century." Furthermore, Ashenfelter made his predictions while the wine was still in casks, before the critics could even sample it.

Steeped in their traditional professional methodology, the wine critics considered Ashenfelter's predictions ludicrous. But it was Ashenfelter who prevailed in the end. Wine buyers are increasingly putting their money with Ashenfelter's regression models.

One of Ayres' chapter titles succinctly captures the theme of his book: "Experts versus Equations." Ayres reviews a litany of examples in which statistical formulas outperform what intuition-based decision-making could hope to achieve.

- Matchmaking websites such as eHarmony take a data-driven approach to human matchmaking, using combinations of personality traits of which even the clients themselves may be only dimly aware.
- Companies such as Lowe's, Circuit City, and Wal-Mart have found that personality traits such as conscientiousness, agreeableness, and extroversion are better predictors of worker productivity and turnover than IQ.
- Harrah's casinos use data collected about repeat customers to predict the maximum a particular player can lose and still be willing to come back for more. When a customer approaches his or her estimated "pain point," he or she might be visited by a "luck ambassador" offering a free meal at the Harrah's restaurant.
- When one of its credit card customers calls Capital One, scoring engines use data about previous calls to predict the nature of the call and modify the menu options accordingly. The call

center representative is also given a list of other products or services that the customer is likely to buy.

- In 2006, a physician studied the effect of implementing six simple reforms—such as elevating the heads of patients on ventilators and better hand-washing for medical personnel who handle central line catheters—on the way hospital patients are treated. The reforms were chosen based on the results of statistical, evidence-based medicine studies. An 18-month trial of the reforms was estimated to have saved over 120,000 lives. The physician is now launching a "5 Million Lives Campaign" to protect patients from harm due to preventable medical errors.
- A company has built a neural net model that estimates a movie's box-office receipts using predictive variables derived from characteristics of its script. Interestingly, the neural net model makes accurate predictions even though it doesn't account for the movie's stars. Despite the model's promise, movie studio executives have been reluctant to adopt its predictions for fear of alienating powerful vested interests. Meanwhile, hedge fund managers are eager to use it to exploit inefficiencies in a market dominated by a culture of intuition-based decision-making. The situation is much the same as the one Lewis describes in *Moneyball*.

These are but a few recent examples, but as Ayres points out, the widespread supremacy of equations over experts has been the subject of psychological research for over 50 years. The subject originated in 1954 with the publication of psychologist Paul Meehl's *Clinical Versus Statistical Prediction*. Meehl's "disturbing little book," as he called it, documented over 20 empirical studies comparing the predictions of human experts with those of simple actuarial models. The types of predictions ranged from how well schizophrenic patients would respond to electroshock to how well prisoners would respond to parole. Meehl concluded that in none of the 20 cases could human experts outperform the actuarial models.

Near the end of his life, surveying the field he initiated in the 1950s, Meehl wrote:

> There is no controversy in social science which shows such a large body of quantitatively diverse studies coming out so uniformly in the same direction as this one. When you are pushing over 100 investigations, predicting everything from the outcome of football games to the diagnosis of liver disease, and when you can hardly come up with half a dozen studies showing even a weak tendency in favor of the clinician, it is time to draw a practical conclusion.

Ayres quotes two other cognitive psychologists who put the matter even more starkly: "Human judges are not merely worse than optimal regression equations; they are worse than almost any regression equation." Like Sunstein and Thaler in their review of *Moneyball,* Ayres considers the problem of cognitive biases intrinsic to human nature. For example, people have a documented tendency to be overconfident in the accuracy of their own predictions, let emotions and philosophical biases cloud their judgment, and tend to over-generalize from their personal experience.

A recurring theme in Ayres' book is that the super-crunching revolution threatens to subvert traditional professions and drain the status away from various vocations. He gives the job of bank loan officer as an example. A job that was once a well-paid position of responsibility now requires one to merely follow the indications of a statistical algorithm. Ayres writes: "We see the struggle of intuition, personal experience, and philosophical inclination waging war against the brute force of numbers."

With this, Ayres overstates his case. Indeed, Ayres himself says that the rise of super crunching doesn't mean the obsolescence of intuition. Rather, it implies that intuition is best steered away from case-by-case, instinctive decision-making and instead systematically harnessed to provide the heuristics and hypothesis needed to build effective predictive models.

Take the movie returns neural net model as an example. Rather than resist the super crunchers, studio executives could collaborate with them and actually help them build better models. Specifically, they could call on their experience to suggest new predictive variables that might elude a non-Hollywood insider. Furthermore, once the model has been built, it is hard to imagine movie scripts being selected and modified entirely on predictive model autopilot. Movie studio executives will undoubtedly remain central to the process, but in the future they will perhaps employ powerful statistical tools to harness their insights, thereby enabling them to make more accurate, objective, and consistent decisions.

Analogous points can be made about insurance underwriting. It would be perverse to view the process of building underwriting models as one of experts versus equations. Super crunchers (aka actuaries) always build better underwriting models when they collaborate with the underwriters for whom the models are intended. Also, far from eliminating the need for underwriters, predictive models will enhance the professional status of underwriters by enabling them to strategically rely on more automated decision-making for smaller, more uniform risks and focus their attention on larger, more complex risks. Models enable underwriters to take a broader view of managing a portfolio of risks.

Toward the end of his book, Ayres nicely encapsulates the situation thus:

> The rise of statistical thinking does not mean the end of intuition or expertise. Rather, [it] underscores how intuition will be reinvented to coexist with statistical thinking. Increasingly, decision makers will switch back and forth between their intuitions and data-based decision making. Their intuitions will guide them to ask new questions of the data that non-intuitive number crunchers would miss. And databases will increasingly allow decision makers to test their intuitions—not just once, but on an ongoing basis… while there is now great conflict between dyed-in-the-wool intuitivists and the new breed of number crunchers, the future is likely to show that these tools are complements rather than substitutes. Each form of decision making can pragmatically counterbalance the greatest weaknesses of the other.

Ayres' pluralist view of the intuition versus statistical thinking debate is judicious and convincing. When implementing a solution based on predictive analytics, it is necessary to craft decision rules that manage the dialectic between qualitative insights of the experts (to say nothing of the innumerable rare exceptions of which they are aware) and statistical regularities quantified by super-crunching actuaries or statisticians. How best to manage this dialectic is a matter of business strategy. Building better models is of course crucial, but not the whole story. Ultimately, the greatest benefits will go to those companies best able to seamlessly integrate their predictive models' indications with the tacit knowledge of their business experts. "Man versus machine" makes for engaging storytelling, but not effective business strategy.

Don't Blink

Another recent entry in the debate is *Blink: The Power of Thinking Without Thinking,* by the *New Yorker* staff writer Malcolm Gladwell. In his books and articles, Gladwell has long displayed an impressive talent for identifying interesting issues at the intersections of decision and statistical sciences, business, and public policy. These skills make Gladwell an engaging, but not always reliable, writer. The very subtitle of Gladwell's book suggests a somewhat muddled thesis. This is indeed what the reader finds after getting past the title page.

Gladwell claims that "decisions made very quickly can be every bit as good as decisions made cautiously and deliberately." And "there can be as much value in the blink of an eye as in months of rational analysis." His opening example is a counterpoint to Ayers' opening story of the regression equations that prevailed over the snippy wine critics.

Gladwell tells the story of how the Getty Museum bought a statue after an exhaustive scientific analysis to determine its authenticity. The statue passed the scientific tests but nevertheless turned out to be a fake. To add insult to injury, art experts who were later brought in were immediately able to tell that the statue was a fake, merely by looking at it. Gladwell writes, "In the first two seconds of looking—in a single glance—they were able to understand more about the essence of the statue than the team at the Getty was able to understand after fourteen months." Gladwell's story seems to point in the opposite direction from Lewis' and Ayres' accounts. Might thinking without thinking be superior to data-driven analytics after all?

This is unlikely. "Thinking without thinking" is an inapt and misleading way to describe the story's significance. After all, the critics were able to make their "snap decision" only after years of training and professional experience. This training and experience is loosely analogous to the process of "training" a regression or neural net model on a data set, before turning it loose on fresh data. It is therefore unfair to say that the laborious scientific approach failed where unaided intuition succeeded in the blink of an eye.

Furthermore, one could easily imagine the story having turned out differently: For example, a mineral analysis could have pro-

Solving the Monty Hall Problem

Before Monty opens door C, there is no reason to believe that any of the doors A, B, or C is more or less likely to conceal the prize. Therefore, at the time the contestant chooses door A, his or her initial or "prior" probability distribution of the car being behind door {A,B,C} is uniform:

$$\mathbf{Pr}(A) = \mathbf{Pr}(B) = \mathbf{PR}(C) = \mathbf{1/3}$$

Let MC denote the event that Monty opens door C, revealing that door C had not concealed the prize. To solve the Monty Hall Problem, we must compute the posterior probability distribution resulting from evidence MC: {Pr(A|MC), Pr(B|MC), Pr(C|MC)}.

It is obvious that Pr(C|MC)=0: after Monty opens door C, the contestant is certain that door C does not conceal the car. From here, most people jump to the conclusion that Pr(A|MC)= Pr(B|MC)=1/2. But this is demonstrably false. To see this, we can appeal to Bayes' rule for updating subjective probabilities. In this case, Bayes' rule states that:

$$\Pr(A|MC) = \frac{\Pr(MC|A)\Pr(A)}{\Pr(MC)} = \frac{\Pr(MC|A)\Pr(A)}{\Pr(MC|A)\Pr(A) + \Pr(MC|B)\Pr(B) + \Pr(MC|C)\Pr(C)}$$

From the above expression, it is clear that we need to specify the likelihood function: {Pr(MC|A), Pr(MC|B), Pr(MC|C)}. The likelihood function is often referred to as a "statistical model." The art of statistical modeling is to specify a likelihood function that reflects the salient aspects of the process being modeled. Let's pursue this systematically for the "Monty Hall Process":

Pr(MC|A)=1/2. If door A (the door the contestant chose) does in fact conceal the prize, then Monty could equally well have decided to open either door B or C. Therefore Pr(MC|A)=Pr(MB|A)=1/2. Clearly Monty couldn't open the same door the contestant chose: Pr(MA|A)=0.

Pr(MC|B)=1. If door B in fact conceals the prize, then Monty has no choice: He must open door C.

Pr(MC|C)=0. This is symmetric to the previous case: If door C had in fact concealed the prize, Monty couldn't have opened it. He would have been forced to open door B.

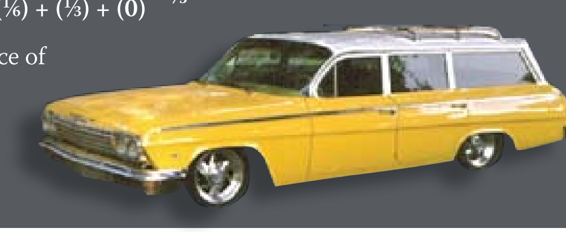
Now we have all of the ingredients needed to calculate Pr(A|MC):

$$\Pr(A|MC) = \frac{(\tfrac{1}{2})(\tfrac{1}{3})}{(\tfrac{1}{2})(\tfrac{1}{3}) + (1)(\tfrac{1}{3}) + (0)(\tfrac{1}{3})} = \frac{(\tfrac{1}{6})}{(\tfrac{1}{6}) + (\tfrac{1}{3}) + (0)} = \tfrac{1}{3}$$

The calculation for Pr(B|MC) is equally straightforward:

$$\Pr(B|MC) = \frac{(1)(\tfrac{1}{3})}{(\tfrac{1}{2})(\tfrac{1}{3}) + (1)(\tfrac{1}{3}) + (0)(\tfrac{1}{3})} = \frac{(\tfrac{1}{3})}{(\tfrac{1}{6}) + (\tfrac{1}{3}) + (0)} = \tfrac{2}{3}$$

Therefore Pr(B|MC)=2*Pr(A|MC). The contestant doubles his or her chance of winning if he or she switches from door A to door B. The logic is sound, but few correctly intuit the answer.



vided decisive evidence that the statue was a fake, while at the same time the trained experts could have been fooled by appearances. The Getty Museum would be unwise to dispense with further scientific analyses of its potential acquisitions on the basis of Gladwell's analysis.

At times, it is hard to know how Gladwell intends his stories—many of which are quite interesting—to buttress his overall claims about the power of snap judgments. Gladwell relates a fascinating story about a physician at Chicago's Cook County Hospital (the hospital that inspired the TV show *ER*) who adopted a simple classification tree model to predict which emergency room patients complaining of chest pains were most likely to suffer heart attacks. To Gladwell, the decision tree enables physicians to make snap judgments that are more reliable than lengthy analyses.

Fair enough, but this misses a crucial point. The decision tree wasn't researched, built, and validated in the blink of an eye. Rather, a statistically trained physician employed an iterative scientific process to produce an algorithm that dramatically outperforms traditional emergency room triage procedures. Gladwell's fascinating story belongs on Ian Ayres' long list of examples in which

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equations outperform unaided intuition, not in an argument about the uncanny power of snap decisions.

As Ayres discusses at the end of *Super Crunchers*, the indications of data analyses will typically need to be complemented with the intuitions, hypotheses, and tacit knowledge of human experts. Gladwell is therefore clearly on to something important. But examples such as the Getty statue and Cook County Hospital's heart attack decision tree might lead the reader to make the snap judgment that Gladwell is an entertaining but ultimately unreliable guide to this important subject.

Synthesizing Analytics

By telling compelling stories and making tantalizing connections to the findings of cognitive science, Lewis, Sunstein and Thaler, and Ayres do an effective job of convincing the reader that predictive analytics-driven decision-making will continue to grow in ubiquity in many areas of human endeavor. Thomas H. Davenport and Jeanne G. Harris, in their recent book, *Competing on Analytics*, provide a useful survey of how predictive analytical methods are currently enabling certain farsighted companies to rise to the tops of their respective industries.

Competing on Analytics is an expanded version of Davenport's influential *Harvard Business Review* article of the same title. What Harris and Davenport lack in Ayres' econometric and legal depth, they make up for in comprehensiveness. They are the ornithologists, and the diverse set of companies and business applications they discuss are the birds. Their book is divided into two parts. In the first part, they describe the nature of analytical competition; in the second part, they outline what they consider to be the steps necessary for a company to become an analytical competitor.

Davenport and Harris define analytics as "the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions." They go on to define an analytic competitor as "an organization that uses analytics extensively and systematically to outthink and outexecute the competition." They helpfully list several hallmarks of the companies they identified as analytic competitors:

> (1) Analytics supported a strategic, distinctive capability; (2) the approach to and management of analytics was enterprise-wide; (3) senior management was committed to the use of analytics; and (4) the company made a significant strategic bet on analytics-based competition.

Appealing to these hallmarks, Davenport and Harris identify analytical competitors in a number of industries and make the plausible case that these companies' cultures of analytical decision-making are in large measure responsible for their success. Many of their examples of analytic competitors will be familiar to the reader: Capital One and Progressive Insurance in financial services, Google and Netflix in e-commerce, Tesco and Wal-Mart in retail, and Harrah's, the Oakland A's, and the Boston Red Sox in entertainment.

Davenport's and Harris' primary thesis is simple but valuable and worth emphasizing. The companies that truly compete on analytics are the ones that have been able to establish what they call a "fact-based culture." The impetus for this cultural change typically comes from the top, as exemplified by Billy Beane undertaking the difficult process of transforming the Oakland A's into an analytically oriented team. As Michael Lewis described, instilling culture change was a major—and difficult—part of Beane's job.

Davenport and Harris list the CEOs of Harrah's Casino, Amazon, Capital One, and Sara Lee as other examples of executives who have been able to instill fact-based cultures at their respective firms. The Sara Lee CEO reportedly kept a sign on his desk quoting W. Edwards Deming's famous aphorism "In God we trust; all others must bring data."

This has an important implication for the actuarial profession. Many actuaries will rightfully feel that Ian Ayres is describing them in his portrait of the new breed of super crunchers. They should naturally play a central role in their companies' strategies for competing on analytics. But while most large insurance companies employ teams of actuaries engaged in analytic work, Davenport and Harris wouldn't consider all of these companies analytic competitors. For them, an analytic competitor is not one that restricts its analytical activities to specific departments (such as the loss reserving or state pricing departments). Rather, they are companies that take an executive-sponsored, strategic, and enterprisewide approach to predictive analytics.

Fittingly, Harris and Davenport give Progressive as their example of an insurance analytic competitor par excellence. They also describe the case of an insurance company CFO who simultaneously took responsibility for analytics related to cost control as well as analytical initiatives in the company's actuarial, claims, and marketing areas. These are all areas where actuaries can apply their statistical and analytic skills to make contributions beyond the traditional conceptions of their roles.

Actuaries have been super crunching for decades; but the increasing executive-level appreciation of the power of analytics—as evidenced by Davenport's and Harris' book—means that technically minded actuaries will increasingly be called on to do innovative work and function as key partners in their companies' core strategies. ●

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