CHAPTER TWO

Common Biases

Please read the following list of large companies:

Boeing
American Express
China Petroleum & Chemical (Sinopec)
Intel
Home Depot
China Construction Bank
Microsoft
Petrobras-Petróleo Brasil
AT&T
Crédit Agricole
Mizuho Financial
Société Générale Group
E.ON
ENI
AXA Group
Verizon Communications
HBOS
IBM
Procter & Gamble
Barclays
Banco Santander
BNP Paribas
Royal Bank of Scotland
Wal-Mart Stores
ExxonMobil
Bank of America
General Electric

Without looking back at the list, please estimate whether there are:

a. more companies on the list that are based in the United States, or

b. more companies on the list that are based outside the United States.

If you guessed that there are more American firms on the list, you are in the majority. Most people (at least, most Americans polled) estimate that there are more American companies than foreign companies on the list. Most people also guess that the American firms are larger than the foreign companies listed.

However, this majority response is incorrect. In fact, there are thirteen American firms on the list and fourteen based outside of the United States. What's more, the non-U.S. firms were ranked higher than the American firms on *Fortune* magazine's 2006 list of the largest global corporations.

Why do most people overestimate the frequency of American firms on the list? Because the American company names are more familiar, more recognizable, and more memorable to Americans than the foreign company names.

This problem illustrates the availability heuristic, which we introduced in Chapter 1. For Americans, the names of American firms are more available in our memories than the names of foreign firms after reading the list. We err in assuming that the prevalence of American firms in our minds mirrors the real world. Awareness of the bias resulting from the availability heuristic should inspire us to question our judgments and adjust them accordingly.

As we noted in Chapter 1, individuals develop rules of thumb, or heuristics, to reduce the information-processing demands of making decisions. By providing managers with efficient ways of dealing with complex problems, heuristics produce good decisions a significant proportion of the time. However, heuristics also can lead managers to make systematically biased judgments. Biases result when an individual inappropriately applies a heuristic when making a decision.

This chapter is comprised of three sections that correspond to three of the general heuristics we introduced in Chapter 1: the availability heuristic, the representativeness heuristic, and the confirmation heuristic. (We will discuss a fourth general heuristic, the affect heuristic, in Chapter 5.) The three heuristics covered in this chapter encompass twelve specific biases that we will illustrate using your responses to a series of problems. The goal of the chapter is to help you "unfreeze" your decision-making patterns by showing you how easily heuristics become biases when improperly applied. Once you are able to spot these biases, you will be able to improve the quality of your decisions.

Before reading further, please take a few minutes to respond to the problems presented in Table 2.1.

Table 2-1 Chapter Problems

Respond to the following problems before reading the rest of the chapter.

Problem 1. Please rank order the following causes of death in the United States between 1990 and 2000, placing a 1 next to the most common cause, 2 next to the second most common, etc.

___ Tobacco
___ Poor diet and physical inactivity
___ Motor vehicle accidents
___ Firearms (guns)
___ Illicit drug use

Now estimate the number of deaths caused by each of these five causes between 1990 and 2000.

Problem 2. Estimate the percentage of words in the English language that begin with the letter "a."

Problem 3. Estimate the percentage of words in the English language that have the letter "a" as their third letter.

Problem 4. Lisa is thirty-three and is pregnant for the first time. She is worried about birth defects such as Down syndrome. Her doctor tells her that she need not worry too much because there is only a 1 in 1,000 chance that a woman of her age will have a baby with Down syndrome. Nevertheless, Lisa remains anxious about this possibility and decides to obtain a test, known as the Triple Screen, that can detect Down syndrome. The test is moderately accurate: When a baby has Down syndrome, the test delivers a positive result 86 percent of the time. There is, however, a small "false positive" rate: 5 percent of babies produce a positive result despite not having Down syndrome. Lisa takes the Triple Screen and obtains a positive result for Down syndrome. Given this test result, what are the chances that her baby has Down syndrome?

a. 0–20 percent chance
b. 21–40 percent chance
c. 41–60 percent chance
d. 61–80 percent chance
e. 81–100 percent chance

Problem 5. (from Tversky & Kahneman, 1974). A certain town is served by two hospitals. In the larger hospital, about forty-five babies are born each day. In the smaller hospital, about fifteen babies are born each day. As you know, about 50 percent of all babies are boys. However, the exact percentage of boys born varies from day to day. Sometimes it may be higher than 50 percent, sometimes lower.

For a period of one year, each hospital recorded the days on which more than 60 percent of the babies born were boys. Which hospital do you think recorded more such days?

a. The larger hospital
b. The smaller hospital
c. About the same (that is, within 5 percent of each other)

Problem 6. You and your spouse have had three children together, all of them girls. Now that you are expecting your fourth child, you wonder whether the odds favor having a boy this time. What is the best estimate of your probability of having another girl?

a. 6.25 percent (1 in 16), because the odds of getting four girls in a row is 1 out of 16
b. 50 percent (1 in 2), because there is roughly an equal chance of getting each gender
c. A percentage that falls somewhere between these two estimates (6.25–50 percent)

Problem 7. You are the manager of a Major League Baseball team, and the 2005 season has just ended. One of your most important jobs is to predict players' future performance. Currently, your primary interest lies in predicting batting averages for nine particular players. A measure of a player's performance, batting averages range from 0 to 1. Larger numbers reflect better batting performance. You know the nine players' 2005 batting averages, and must estimate each one's 2006 batting average. Please fill in your guesses in the right-hand column.

Player	2005	Estimated 2006 Batting Average
1	.215	
2	.242	
3	.244	
4	.258	
5	.261	
6	.274	
7	.276	
8	.283	
9	.305	

Problem 8. Linda is thirty-one years old, single, outspoken, and very smart. She majored in philosophy. As a student, she was deeply concerned with issues of discrimination and social justice, and she participated in antinuclear demonstrations.

Rank the following eight descriptions in order of the probability (likelihood) that they describe Linda:

___ a. Linda is a teacher in an elementary school.
___ b. Linda works in a bookstore and takes yoga classes.
___ c. Linda is active in the feminist movement.
___ d. Linda is a psychiatric social worker.
___ e. Linda is a member of the League of Women Voters.
___ f. Linda is a bank teller.
___ g. Linda is an insurance salesperson.
___ h. Linda is a bank teller who is active in the feminist movement.

Problem 9. Take the last three digits of your phone number. Add the number one to the front of the string, so that now you have four digits. Think of that number as a year. Now try to estimate the year that the Taj Mahal was completed. Was it before or after the date made by your phone number?

____________ Before ____________ After

On the line below, please make your best estimate of the actual year in which the Taj Mahal was completed:

____

Problem 10. Which of the following instances appears most likely? Which appears second most likely?

a. Drawing a red marble from a bag containing 50 percent red marbles and 50 percent white marbles.

b. Drawing a red marble seven times in succession, with replacement (i.e., a selected marble is put back into the bag before the next marble is selected), from a bag containing 90 percent red marbles and 10 percent white marbles.

c. Drawing at least one red marble in seven tries, with replacement, from a bag containing 10 percent red marbles and 90 percent white marbles.

Problem 11. Ten uncertain quantities are listed below. Do not look up any information about these items. For each, write down your best estimate of the quantity. Next, put a lower and upper bound around your estimate, so that you are confident that your 98 percent range surrounds the actual quantity.

Estimate	Lower	Upper	
___	___	___	a. Wal-Mart's 2006 revenue
___	___	___	b. Microsoft's 2006 revenue
___	___	___	c. World population as of July 2007
___	___	___	d. Market capitalization (price per share times number of shares outstanding) of Best Buy as of July 6, 2007
___	___	___	e. Market capitalization of Heinz as of July 6, 2007
___	___	___	f. Rank of McDonald's in the 2006 *Fortune* 500
___	___	___	g. Rank of Nike in the 2006 *Fortune* 500
___	___	___	h. Number of fatalities due to motor vehicle accidents in the United States in 2005
___	___	___	i. The national debt of the U.S. federal government as of July 2007
___	___	___	j. The U.S. federal government budget for the 2008 fiscal year

Problem 12. If you had to describe the relationship between baseball players' batting averages in one season and their batting averages in the subsequent season, which of the following four descriptions would you pick?

1. **Zero correlation:** Performance is entirely unpredictable, in the sense that knowing how well a player hits one year does not help you predict how well he is going to hit the next year.
2. **Weak correlation of about .4:** Performance from one season to the next is moderately predictable, but there are also a lot of random, unpredictable influences on how well a particular player hits in a particular season.
3. **Strong correlation of about .7:** Performance is quite predictable from one season to the next, but there is a small random component in how well a player hits.
4. **Perfect correlation of 1.0:** Performance is stable from one year to the next. The player with the highest batting average in one season always has the highest batting average the next season.

BIASES EMANATING FROM THE AVAILABILITY HEURISTIC

Bias 1: Ease of Recall (based on vividness and recency)

Problem 1. Please rank order the following causes of death in the United States between 1990 and 2000, placing a 1 next to the most common cause, 2 next to the second most common, etc.

___ Tobacco

___ Poor diet and physical inactivity

___ Motor vehicle accidents

___ Firearms (guns)

___ Illicit drug use

Now estimate the number of deaths caused by each of these five causes between 1990 and 2000.

It may surprise you to learn that, according to the *Journal of the American Medical Association* (Mokdad, Marks, Stroup, & Gerberding, 2004, p. 1240), the causes of death above are listed in the order of frequency, with tobacco consumption causing the most deaths and illicit drug use causing the fewest. Even if you got the order right or came close, you probably underestimated the magnitude of difference between the first two causes and the last three causes. The first two causes, tobacco and poor diet/physical inactivity, resulted in 435,000 and 400,000 annual deaths, respectively, while the latter three causes resulted in far fewer deaths—43,000, 29,000, and 17,000 deaths, respectively. Vivid deaths caused by cars, guns, and drugs tend to get a lot of press coverage. The availability of vivid stories in the media biases our perception of the frequency of events toward the last three causes over the first two. As a result, we may underestimate the likelihood of death due to tobacco and poor diet, while overestimating the hazards of cars, guns, and drugs.

Many life decisions are affected by the vividness of information. Although most people recognize that AIDS is a devastating disease, many individuals ignore clear data about how to avoid contracting AIDS. In the fall of 1991, however, sexual behavior in Dallas was dramatically affected by one vivid piece of data that may or may not have been true. In a chilling interview, a Dallas woman calling herself C.J. claimed she had AIDS and was trying to spread the disease out of revenge against the man who had infected her. After this vivid interview made the local news, attendance at Dallas AIDS seminars increased dramatically, AIDS became the main topic of Dallas talk shows, and requests for HIV tests surged citywide. Although C.J.'s possible actions were a legitimate cause for concern, it is clear that most of the health risks related to AIDS are not a result of one woman's actions. There are many more important reasons to be concerned about AIDS. However, C.J.'s vivid report had a more substantial effect on many people's behavior than the mountains of data available.

The availability heuristic describes the inferences we make about event commonness based on the ease with which we can remember instances of that event. Tversky and Kahneman (1974) cite evidence of this bias in a lab study in which individuals were read lists of names of well-known personalities of both genders. Different lists were presented to two groups. One group was read a list in which the women listed were relatively more famous than the listed men, but the list included more men's names overall. The other group was read a list in which the men listed were relatively more famous than the listed women, but the list included more women's names overall. After hearing their group's list, participants in both groups were asked if the list contained the names of more women or men. In both groups, participants incorrectly guessed that the gender that included the relatively more famous personalities was the more numerous. Participants apparently paid more attention to vivid household names than to less well-known figures, leading to inaccurate judgments.

While this example of vividness may seem fairly benign, it is not difficult to see how the availability bias could lead managers to make potentially destructive workplace decisions. The following came from the experience of one of our MBA students: As a purchasing agent, he had to select one of several possible suppliers. He chose the firm whose name was the most familiar to him. He later found out that the salience of the name resulted from recent adverse publicity concerning the firm's extortion of funds from client companies!

Managers conducting performance appraisals often fall victim to the availability heuristic. Working from memory, vivid instances of an employee's behavior (either positive or negative) will be most easily recalled from memory, will appear more numerous than commonplace incidents, and will therefore be weighted more heavily in the performance appraisal. The recency of events is also a factor: Managers give more weight to performance during the three months prior to the evaluation than to the previous nine months of the evaluation period because it is more available in memory.

In one clever experiment that illustrates the potential biasing effect of availability, Schwarz and his colleagues (1991) asked their participants to assess their own assertiveness. Some participants were instructed to think of six examples that demonstrated their assertiveness—a fairly easy assignment. Other participants were instructed to come up with twelve instances of their own assertiveness—a tougher task. Those who were supposed to come up with twelve instances had more trouble filling out the list. Consistent with the predictions of the availability heuristic, those who were asked to generate *more* examples actually wound up seeing themselves as *less* assertive, despite the fact that they actually listed more instances of their own assertiveness. Because it was more difficult for them to come up with examples demonstrating their assertiveness, they inferred that they must not be particularly assertive.

Along these lines, research shows that people are more likely to purchase insurance to protect themselves from a natural disaster that they have just experienced than they are to purchase such insurance before this type of disaster occurs (Kunreuther, 1978; Simonsohn, Karlsson, Loewenstein, & Ariely, 2008). This pattern may be sensible for some types of risks. After all, the experience of surviving a hurricane may offer solid evidence that your property is more vulnerable to hurricanes than you had thought or that climate change is increasing your vulnerability to hurricanes. This explanation cannot account for trends in the purchase of earthquake insurance, however. Geologists tell us that the risk of future earthquakes subsides immediately after an earthquake occurs. Nevertheless, those who lived through an earthquake are more likely to purchase earthquake insurance immediately afterward (Lindell & Perry, 2000; Palm, 1995). The risk of experiencing an earthquake becomes more vivid and salient after one has experienced an earthquake, even if the risk of another earthquake in the same location diminishes.

Perhaps it ought not to be surprising that our memories and recent experiences have such a strong impact on our decisions. Nevertheless, it can be fascinating to discover just how unaware we are of our own mental processes and of the powerful influence of availability on our recollections, predictions, and judgments.

Bias 2: Retrievability (based on memory structures)

Problem 2. Estimate the percentage of words in the English language that begin with the letter "a."

Problem 3. Estimate the percentage of words in the English language that have the letter "a" as their third letter.

Most people estimate that there are more words beginning with "a" than words in which "a" is the third letter. In fact, the latter are more numerous than the former. Words beginning with "a" constitute roughly 6 percent of English words, whereas words with "a" as the third letter make up more than 9 percent of English words. Why do most people believe the opposite to be true? Because we are better at retrieving words from memory using the word's initial letter than the word's third letter (see Tversky & Kahneman, 1973), something you'll see for yourself if you attempt both tasks. Due to the relative ease of recalling words starting with "a," we overestimate their frequency relative to words that have "a" as a third letter.

Tversky and Kahneman (1983) demonstrated this retrievability bias when they asked participants in their study to estimate the frequency of seven-letter words that had the letter "n" in the sixth position. Their participants estimated such words to be less common than seven-letter words ending in the more memorable three-letter "ing" sequence. However, this response pattern must be incorrect. Since all words with seven letters that end in "ing" also have an "n" as their sixth letter, the frequency of words that end in "ing" cannot be larger than the number of words with "n" as the sixth letter. Tversky and Kahneman (1983) argue that "ing" words are more retrievable from memory because of the commonality of the "ing" suffix, whereas the search for words that have an "n" as the sixth letter does not easily generate this group of words.

Sometimes the world structures itself according to our search strategies. Retail store location is influenced by the way in which consumers search their minds when seeking a particular commodity. Why are multiple gas stations at the same intersection? Why do "upscale" retailers want to be in the same mall? Why are the biggest bookstores in a city often located within a couple blocks of each other? An important reason for this pattern is that consumers learn the location of a particular type of product or store and organize their minds accordingly. To maximize traffic, the retailer needs to be in the location that consumers associate with this type of product or store.

Other times, the most natural search strategies do not serve us as well. For instance, managers routinely rely on their social networks to identify potential employees.

While this approach has the distinct benefit of eliminating the need to review the hundreds of resumes that may arrive in response to a broader search, it results in a highly selective search. The recommendations that come from people in a manager's network are more likely to be of a similar background, culture, and education as the manager who is performing the search. One consequence is that, without intending to discriminate, an organization led by white, college-educated males winds up hiring more of the same (Petersen, Saporta, & Seidel, 2000).

As these first two biases (ease of recall and retrievability) indicate, the misuse of the availability heuristic can lead to systematic errors in managerial judgment. We too easily assume that our available recollections are truly representative of the larger pool of events that exists outside of our range of experience. As decision makers, we need to understand when intuition will lead us astray so that we can avoid the pitfall of selecting the most mentally available option.

BIASES EMANATING FROM THE REPRESENTATIVENESS HEURISTIC

Bias 3: Insensitivity to Base Rates

> **Problem 4.** Lisa is thirty-three and is pregnant for the first time. She is worried about birth defects such as Down syndrome. Her doctor tells her that she need not worry too much because there is only a 1 in 1,000 chance that a woman of her age will have a baby with Down syndrome. Nevertheless, Lisa remains anxious about this possibility and decides to obtain a test, known as the Triple Screen, that can detect Down syndrome. The test is moderately accurate: When a baby has Down syndrome, the test delivers a positive result 86 percent of the time. There is, however, a small "false positive" rate: 5 percent of babies produce a positive result despite not having Down syndrome. Lisa takes the Triple Screen and obtains a positive result for Down syndrome. Given this test result, what are the chances that her baby has Down syndrome?

How did you reach your answer? If you are like most people, you decided that Lisa has a substantial chance of having a baby with Down syndrome. The test gets it right 86 percent of the time, right?

The problem with this logic is that it ignores the "base rate"—the overall prevalence of Down syndrome. For a thousand women Lisa's age who take the test, an average of only one will have a baby with Down syndrome, and there is only an 86 percent chance that this woman will get a positive test result. The other 999 women who take the test will have babies who do not have Down syndrome; however, due to the test's 5 percent false positive rate, just under 50 (49.95) of them will receive positive test results. Therefore, the correct answer to this problem is that Lisa's baby has only a 1.7 percent (.86/[.86 + 49.95]) chance of having Down syndrome, given a positive test result. Due to the simplifying guidance of the representativeness heuristic, specific information about Lisa's case and her test results causes people to ignore background information relevant to the problem, such as the base rate of Down syndrome.

This tendency is even stronger when the specific information is vivid and compelling, as Kahneman and Tversky illustrated in one study from 1972. Participants were given a brief description of a person who enjoyed puzzles and was both mathematically inclined and introverted. Some participants were told that this description was selected from a set of seventy engineers and thirty lawyers. Others were told that the description came from a list of thirty engineers and seventy lawyers. Next, participants were asked to estimate the probability that the person described was an engineer. Even though people admitted that the brief description did not offer a foolproof means of distinguishing lawyers from engineers, most tended to believe that the description was of an engineer. Their assessments were relatively impervious to differences in base rates of engineers (70 percent versus 30 percent of the sample group).

Participants do use base-rate data correctly when no other information is provided (Kahneman & Tversky, 1972). In the absence of a personal description, people use the base rates sensibly and believe that a person picked at random from a group made up mostly of lawyers is most likely to be a lawyer. Thus, people understand the relevance of base-rate information, but tend to disregard such data when individuating data are also available.

Ignoring base rates has many unfortunate implications. Prospective entrepreneurs typically spend far too much time imagining their success and far too little time considering the base rate for business failures (Moore, Oesch, & Zietsma, 2007). Entrepreneurs think that the base rate for failure is not relevant to their situations; many of them lose their life savings as a result. Similarly, unnecessary emotional distress is caused in the divorce process because of the failure of couples to create prenuptial agreements that facilitate the peaceful resolution of a marriage. The suggestion of a prenuptial agreement is often viewed as a sign of bad faith. However, in far too many cases, the failure to create prenuptial agreements occurs when individuals approach marriage with the false belief that the high base rate for divorce does not apply to them.

Bias 4: Insensitivity to Sample Size

Problem 5 (from Tversky & Kahneman, 1974). A certain town is served by two hospitals. In the larger hospital, about forty-five babies are born each day. In the smaller hospital, about fifteen babies are born each day. As you know, about 50 percent of all babies are boys. However, the exact percentage of boys born varies from day to day. Sometimes it may be higher than 50 percent, sometimes lower.

For a period of one year, each hospital recorded the days on which more than 60 percent of the babies born were boys. Which hospital do you think recorded more such days?

- **a.** The larger hospital
- **b.** The smaller hospital
- **c.** About the same (that is, within 5 percent of each other)

Most individuals choose C, expecting the two hospitals to record a similar number of days on which 60 percent or more of the babies born are boys. People seem to have some basic idea of how unusual it is to have 60 percent of a random event occurring in a specific direction. However, statistics tells us that we are much more likely to observe 60 percent of male babies in a smaller sample than in a larger sample. This effect is easy to understand. Think about which is more likely: getting more than 60 percent heads in three flips of a coin or getting more than 60 percent heads in 3,000 flips of a coin. Half of the time, three flips will produce more than 60 percent heads. However, ten flips will only produce more than 60 percent heads about 17 percent of the time. Three thousand flips will produce more than 60 percent heads only .000001 percent of the time (odds of one in a million). However, most people judge the probability to be the same in each hospital, effectively ignoring sample size.

Although the importance of sample size is fundamental in statistics, Tversky and Kahneman (1974) argue that sample size is rarely a part of our intuition. Why not? When responding to problems dealing with sampling, people often use the representativeness heuristic. For instance, they think about how representative it would be for 60 percent of babies born to be boys in a random event. As a result, people ignore the issue of sample size—which is critical to an accurate assessment of the problem.

Consider the implications of this bias for advertising strategies. Market research experts understand that a sizable sample will be more accurate than a small one, but use consumers' bias to the advantage of their clients: "Four out of five dentists surveyed recommend sugarless gum for their patients who chew gum." Without mention of the exact number of dentists involved in the survey, the results of the survey are meaningless. If only five or ten dentists were surveyed, the size of the sample would not be generalizable to the overall population of dentists.

Bias 5: Misconceptions of Chance

Problem 6. You and your spouse have had three children together, all of them girls. Now that you are expecting your fourth child, you wonder whether the odds favor having a boy this time. What is the best estimate of your probability of having another girl?

a. 6.25 percent (1 in 16), because the odds of getting four girls in a row is 1 out of 16

b. 50 percent (1 in 2), because there is roughly an equal chance of getting each gender

c. A percentage that falls somewhere between these two estimates (6.25–50 percent)

Relying on the representativeness heuristic, most individuals have a strong intuitive sense that the probability of having four girls in a row is unlikely; thus, they assume that the probability of having another girl in this instance ought to be lower than 50 percent. The problem with this reasoning is that the gender determination of each new baby is a chance event; the sperm that determines the baby's gender does not know how many other girls the couple has.

This question parallels research by Kahneman and Tversky (1972) showing that people expect a sequence of random events to "look" random. Specifically, participants routinely judged the sequence of coin flips H–T–H–T–T–H to be more likely than H–H–H–T–T–T, which does not "appear" random, and more likely than the sequence H–H–H–H–T–H, which does not represent the equal likelihood of heads and tails. Simple statistics, of course, tell us that each of these sequences is equally likely because of the independence of multiple random events.

Problem 6 triggers our inappropriate tendency to assume that random and nonrandom events will balance out. Will the fourth baby be a boy? Maybe. But your earlier success producing girls is irrelevant to its probability.

The logic concerning misconceptions of chance provides a process explanation of the "gambler's fallacy." After holding bad cards on ten hands of poker, the poker player believes he is "due" for a good hand. After winning $1,000 in the Pennsylvania State Lottery, a woman changes her regular number—after all, how likely is it that the same number will come up twice? Tversky and Kahneman (1974) note: "Chance is commonly viewed as a self-correcting process in which a deviation in one direction induces a deviation in the opposite direction to restore the equilibrium. In fact, deviations are not corrected as a chance process unfolds, they are merely diluted."

In the preceding examples, individuals expected probabilities to even out. In some situations, our minds misconstrue chance in exactly the opposite way. In sports such as basketball, we often think of a particular player as having a "hot hand" or being "on fire." If your favorite player has made his last four shots, is the probability of his making his next shot higher, lower, or the same as the probability of his making a shot without the preceding four hits? Most sports fans, sports commentators, and players believe that the answer is "higher."

There are many biological, emotional, and physical reasons that this answer could be correct. However, it is wrong! In an extensive analysis of the shooting of the Philadelphia 76ers and the Boston Celtics, Gilovich, Vallone, and Tversky (1985) found that immediately prior shot performance did not change the likelihood of success on the upcoming shot.

Out of all of the findings in this book, this is the effect that our managerial students often have the hardest time accepting. We can all remember sequences of five hits in a row; streaks are part of our conception of chance in athletic competition. However, our minds do not think of a string of "four in a row" shots as a situation in which "he missed his fifth shot." As a result, we have a misconception of connectedness when, in fact, chance (or the player's normal probability of success) is actually in effect.

The belief in the hot hand arises from the human mind's powerful ability to detect patterns. We can recognize a face, read distorted writing, or understand garbled language far better than even the most sophisticated and powerful computer. But this ability often leads us to see patterns where there are none. Despite many sports fans' fervent beliefs, thousands of analyses on innumerable sports data sets have shown again and again that there is no such thing as a hot hand, only chance patterns and random streaks in performances that are partially influenced by skill and partially by luck (see Reifman, 2007).

The belief in the hot hand has interesting implications for how players compete. Passing the ball to the player who is "hot" is commonly endorsed as a good strategy. Similarly, the opposing team often will concentrate on guarding the "hot" player. Another player, who is less hot but equally skilled, may have a better chance of scoring. Thus, the belief in the "hot hand" is not just erroneous, but also can be costly if people allow it to influence their decisions.

Misconceptions of chance are not limited to gamblers, sports fans, or laypersons. Research psychologists Tversky and Kahneman (1971) found that research psychologists themselves fall victim to the "law of small numbers": They believe that sample events should be far more representative of the population from which they were drawn than simple statistics would dictate. By putting too much faith in the results of initial samples, scientists often grossly overestimate the degree to which empirical findings can be generalized to the general population. The representativeness heuristic may be so well institutionalized in our decision processes that even scientific training and its emphasis on the proper use of statistics may not eliminate the heuristic's biasing influence.

Bias 6: Regression to the Mean

Problem 7. You are the manager of a Major League Baseball team, and the 2005 season has just ended. One of your most important jobs is to predict players' future performance. Currently, your primary interest lies in predicting batting averages for nine particular players. A measure of a player's performance, batting averages range from 0 to 1. Larger numbers reflect better batting performance. You know the nine players' 2005 batting averages and must estimate each one's 2006 batting average. Please fill in your guesses in the right-hand column.

Player	2005	Estimated 2006 Batting Average
1	.215	
2	.242	
3	.244	
4	.258	
5	.261	
6	.274	
7	.276	
8	.283	
9	.305	

How do you think a prediction like this should be made, absent more specific information about each player? Your answer will depend on how predictable you think batting averages are, which is the question that you answered in Problem 12. If you think that batting averages hold constant from year to year, then you probably would predict that players will repeat their previous year's performance exactly. If you think that last year's performance is worthless for predicting this year's, then you might predict that each player would do about as well as the team's average (about .262).

Most people understand that there is an imperfect relationship between the performance of a baseball player—or a corporation, for that matter—from one year to the next. Specifically, the basic principles of statistics tell us that any extreme performance is likely to regress to the mean over time. A player or a business that is lucky one year cannot expect to be lucky in just the same way the following year. When it comes time to apply this knowledge to performance expectations, however, most people do not do so systematically. Most people who respond to Problem 7 predict that a player's 2006 performance will be almost identical to his 2005 performance.

In fact, statistics show that the correlation between Major League Baseball players' batting averages from one year to the next is only .4. The nine players listed in Problem

7 actually played for the Chicago Cubs in 2005 and 2006. Here are the players' names and actual batting averages for the 2005 and 2006 seasons:

Player	2005	2006
Corey Patterson	.215	.276
Henry Blanco	.242	.266
Todd Hollandsworth	.244	.246
Jeremy Burnitz	.258	.230
Jerry Hairston	.261	.207
Neifi Perez	.274	.254
Michael Barrett	.276	.307
Nomar Garciaparra	.283	.303
Todd Walker	.305	.277

The correlation from 2005 to 2006 among these nine players is roughly the same as in the league overall (.39). You will note that exceptional performances tend to regress to the mean—the worst performances improve and the best performances decline from one year to the next.

Accordingly, your estimates in Problem 7 would have been pretty good if you had simply predicted that each player's 2006 batting average would have been equal to the team's 2005 average. Your 2006 predictions would have been even better for each player if you had equally weighted the team's average with that player's 2005 average.

Such instances of regression to the mean occur whenever there is an element of chance in an outcome. Gifted children frequently have less successful siblings. Short parents tend to have taller children. Great rookies have less impressive second years (the "sophomore jinx"). Firms that achieve outstanding profits one year tend to perform less well the next year. In each case, individuals are often surprised when made aware of these predictable patterns of regression to the mean.

Why is the regression-to-the-mean concept, a fundamental principle of statistics, counterintuitive? Kahneman and Tversky (1973) suggest that the representativeness heuristic accounts for this systematic bias in judgment. They argue that individuals typically assume that future outcomes (for example, this year's sales) will be directly predictable from past outcomes (last year's sales). Thus, we tend to naïvely develop predictions based on the assumption of perfect correlation with past data.

In some unusual situations, individuals do intuitively expect a regression-to-the-mean effect. In 2001, when Barry Bonds hit seventy-three home runs in a single season, few expected him to repeat this performance the following year. When Wilt Chamberlain scored 100 points in a single game, most people did not expect him to score 100 points in his next game. When a historically 3.0 student got a 4.0 one semester, her parents did not expect a repeat performance the following semester. When a real-estate agent sold five houses in one month (an abnormally high performance), his fellow agents did not expect equally high sales from him the following month. Why is regression to the mean more intuitive in these cases? When a performance is extreme, we know it cannot last. Thus, under unusual circumstances, we expect performance to regress, but we generally do not recognize the regression effect in less extreme cases.

Consider Kahneman and Tversky's (1973) classic example in which misconceptions about regression led to overestimation of the effectiveness of punishment and the underestimation of the power of reward. In a discussion about flight training, experienced instructors noted that praise for an exceptionally smooth landing was typically followed by a poorer landing on the next try, while harsh criticism after a rough landing was usually followed by an improvement on the next try. The instructors concluded that verbal rewards were detrimental to learning, while verbal punishments were beneficial. Obviously, the tendency of performance to regress to the mean can account for the results; verbal feedback may have had absolutely no effect. However, to the extent that the instructors were prone to biased decision making, they were liable to reach the false conclusion that punishment is more effective than positive reinforcement in shaping behavior.

What happens when managers fail to acknowledge the regression principle? Consider an employee who performs extremely well during one evaluation period. He (and his boss) may inappropriately expect similar performance in the next period. What happens when the employee's performance regresses toward the mean? He (and his boss) will begin to make excuses for not meeting expectations. Managers who fail to recognize the tendency of events to regress to the mean are likely to develop false assumptions about future results and, as a result, make inappropriate plans. They will have inappropriate expectations for employee performance.

Bias 7: The Conjunction Fallacy

Problem 8. Linda is thirty-one years old, single, outspoken, and very smart. She majored in philosophy. As a student, she was deeply concerned with issues of discrimination and social justice, and she participated in antinuclear demonstrations.

Rank the following eight descriptions in order of the probability (likelihood) that they describe Linda:

- **a.** Linda is a teacher in an elementary school.
- **b.** Linda works in a bookstore and takes yoga classes.
- **c.** Linda is active in the feminist movement.
- **d.** Linda is a psychiatric social worker.
- **e.** Linda is a member of the League of Women Voters.
- **f.** Linda is a bank teller.
- **g.** Linda is an insurance salesperson.
- **h.** Linda is a bank teller who is active in the feminist movement.

Examine your rank orderings of descriptions C, F, and H. Most people rank order C as more likely than H and H as more likely than F. Their rationale for this ordering is that C–H–F reflects the degree to which the descriptions are representative of the short profile of Linda. Linda's profile was constructed by Tversky and Kahneman to be representative of an active feminist and unrepresentative of a bank teller. Recall from the representativeness heuristic that people make judgments according to the degree to which a specific description corresponds to a broader category within their minds. Linda's profile is more representative of a feminist than of a feminist bank teller, and is more representative of a feminist bank teller than of a bank teller. Thus, the representativeness heuristic accurately predicts that most individuals will rank order the items C–H–F.

The representativeness heuristic also leads to another common systematic distortion of human judgment—the conjunction fallacy (Tversky & Kahneman, 1983). This is illustrated by a reexamination of the potential descriptions of Linda. One of the simplest and most fundamental laws of probability is that a subset (for example, being a bank teller and a feminist) cannot be more likely than a larger set that completely includes the subset (for example, being a bank teller). In other words, a conjunction (a combination of two or more descriptors) cannot be more probable than any one of its descriptors; all feminist bank tellers are also bank tellers. By contrast, the "conjunction fallacy" predicts that a conjunction will be judged more probable than a single component descriptor when the conjunction *appears* more representative than the component descriptor. Intuitively, thinking of Linda as a feminist bank teller "feels" more correct than thinking of her as only a bank teller.

The conjunction fallacy can also be triggered by a greater availability of the conjunction than of one of its unique descriptors (Yates & Carlson, 1986). That is, if the conjunction creates more intuitive matches with vivid events, acts, or people than a component of the conjunction, the conjunction is likely to be perceived, falsely, as more probable than the component. Here's an example. Participants in a study by Tversky and Kahneman (1983) judged the chances of a massive flood somewhere in North America, in 1989, in which 1,000 people drown, to be less likely than the chances of an earthquake in California, sometime in 1989, causing a flood in which more than a thousand people drown. Yet, note that the latter possibility (California earthquake leading to flood) is a subset of the former; many other events could cause a flood in North America. Tversky and Kahneman (1983) have shown that the conjunction fallacy is likely to lead to deviations from rationality in judgments of sporting events, criminal behavior, international relations, and medical decisions. The obvious concern arising from the conjunction fallacy is that it leads us to poor predictions of future outcomes, causing us to be ill-prepared to cope with unanticipated events.

We have examined five biases that emanate from the use of the representativeness heuristic: insensitivity to base rates, insensitivity to sample size, misconceptions of chance, regression to the mean, and the conjunction fallacy. The representativeness heuristic can often serve us well. After all, the likelihood of a specific occurrence is usually related to the likelihood of similar types of occurrences. Unfortunately, we tend to overuse this simplifying heuristic when making decisions. The five biases we have just explored illustrate the systematic irrationalities that can occur in our judgments when we are unaware of this tendency.

BIASES EMANATING FROM THE CONFIRMATION HEURISTIC

Bias 8: The Confirmation Trap

Imagine that the sequence of three numbers below follows a rule, and that your task is to diagnose that rule (Wason, 1960). When you write down other sequences of three numbers, your instructor will tell you whether or not your sequences follow the rule.

2–4–6

What sequences would you write down? How would you know when you had enough evidence to guess the rule? Wason's study participants tended to offer fairly few sequences, and the sequences tended to be consistent with the rule that they eventually guessed. Commonly proposed rules included "numbers that go up by two" and "the difference between the first two numbers equals the difference between the last two numbers."

In fact, Wason's rule was much broader: "any three ascending numbers." This solution requires participants to accumulate disconfirming, rather than confirming, evidence. For example, if you think the rule is "numbers that go up by two," you must try sequences that do not conform to this rule to find the actual rule. Trying the sequences 1–3–5, 10–12–14, 122–124–126, and so on, will only lead you into the "confirmation trap." Similarly, if you think the rule is "the difference between the first two numbers equals the difference between the last two numbers," you must try sequences that do not conform to this rule to find the actual rule. Trying the sequences 1–2–3, 10–15–20, 122–126–130, and so on, again would only bring you feedback that strengthens your hypothesis. Only six out of Wason's twenty-nine participants found the correct rule on their first guess. Wason concluded that obtaining the correct solution necessitates "a willingness to attempt to falsify hypotheses, and thus to test those intuitive ideas that so often carry the feeling of certitude" (p. 139).

As teachers, we have presented this task hundreds of times in classes. The first volunteer typically guesses "numbers going up by two" and is quickly eliminated. The second volunteer is often just as quick with a wrong answer. Interestingly, at this stage, it is rare that a volunteer will have proposed a sequence that doesn't conform to the rule. Why? Because people naturally tend to seek information that confirms their expectations and hypotheses, even when disconfirming or falsifying information is more useful.

When we encounter information that is consistent with our beliefs, we usually accept it with an open mind and a glad heart. If we scrutinize it at all, we ask, in Gilovich's (1991) words, "May I believe it?" We accept information uncritically unless there is an unavoidable reason to doubt it. Yet when we discover facts that force us to question our beliefs, we ask a very different question: "*Must* I believe it?" In other words, we wonder whether we can dismiss this troublesome tidbit.

There are two reasons that we fall prey to the confirmation trap. The first has to do with the way the human mind is designed to retrieve information from memory. The mere consideration of certain hypotheses makes information that is consistent with these hypotheses selectively accessible (Gilbert, 1991). Indeed, research shows that the human tendency to entertain provisional hypotheses as true even makes it possible to implant people with false memories. In one study, Loftus (1975) had participants watch a film of an automobile accident. Half of them were asked, "How fast was the white sports car going when it passed the barn while traveling along the country road?" There was, in fact, no barn in the film. Those asked about the nonexistent barn were substantially more likely to recall having seen it than those who were not asked about a barn.

We also succumb to the confirmation trap due to how we search for information. Because there are limits to our attention and cognitive processing, we must search for information selectively, searching first where we are most likely to find the most useful information. One consequence is the retrievability bias we discussed earlier. Another consequence is that people search selectively for information or give special credence to information that allows them to come to the conclusion they desire to reach (Kunda, 1990). Casual observation tells us that political conservatives are the most likely group to listen to conservative talk-show host Rush Limbaugh on the radio and also most likely to avoid the humor of liberal comedian Al Franken. It seems equally likely that political liberals are the group that most enjoys Franken's humor and that avoids listening to Limbaugh. Political partisans, like all of us, prefer to have their beliefs affirmed rather than undermined.

The biased search for and interpretation of evidence is particularly striking when it comes to political partisanship. Those who were most outraged by President Bill Clinton's false statements about his relationship with Monica Lewinsky were less outraged when it emerged that President George W. Bush and his administration had falsely led the nation to believe that Saddam Hussein possessed weapons of mass destruction. Similarly, those most outraged by Bush's misstatements found it easier to forgive Clinton's.

Here's another example of the confirmation trap. Lord, Ross, and Lepper (1979) asked participants in their study to review evidence for and against the effectiveness of the death penalty in deterring crime. Those who identified themselves as supporters of the death penalty found research evidence that the death penalty was ineffective at deterring crime completely unpersuasive. They criticized the studies as poorly designed and the findings as unreliable. Meanwhile, participants who entered the study as opponents of the death penalty found the same evidence to be valid and persuasive. Instead, they had problems with research showing the effectiveness of the death penalty at deterring crime, and they found plenty of reasons to disregard the evidence. In the end, those on both sides of the issue left the experiment even more solidly assured of their opening opinions.

Once you become aware of the confirmation trap, you are likely to find that it pervades your decision-making processes. When you make a tentative decision (to buy a new car, to hire a particular employee, to start research and development on a new product line, etc.), do you search for data that support your decision before making the final commitment? Most of us do. However, the search for disconfirming evidence will provide the most useful insights. For example, when you are seeking to confirm your decision to hire a particular employee, you probably will have no trouble finding positive information about the individual, such as enthusiastic recommendations from past employers. In fact, it may be more important for you to determine whether negative information about this individual, such as a criminal record, also exists, as well as positive information about another potential applicant. Now consider the last car you purchased. Imagine that the day after you drove your new car home, your local newspaper printed two lists ranking cars by performance—one by fuel efficiency and one by crash-test results. Which list would you pay more attention to? Most of us would pay more attention to whichever list confirms that we made a good purchase.

Our colleage Dick Thaler has identified a business opportunity to help managers avoid the confirmation trap. Thaler's idea is to form two new consulting firms. One of them, called "Yes Person," would respond to all requests for advice by telling the clients that all their ideas are great. In fact, to speed service and ensure satisfaction, Yes

Person would allow clients to write the consulting report themselves if they liked. The other consulting firm, called "Devil's Advocate," would disapprove of any plans currently being considered by a client. Reports by Devil's Advocate would consist of a list of the top ten reasons the client should not pursue the plan under consideration.

Which consulting style would be more useful to the client? Thaler insists that Devil's Advocate would provide a much more important service than Yes Person, and it is hard to disagree. In reality, however, consulting engagements often bear a closer resemblance to the Yes Person format than to that of Devil's Advocate, in part because consulting firms know that clients like to hear how good their ideas are. Our desire to confirm our initial ideas is so strong that we will pay people to back us up! When pressed, Thaler conceded that he wouldn't start either consulting firm, since neither could succeed. After all, he pointed out, no client would ever hire Devil's Advocate, and Yes Person already has too much competition from established consulting firms.

Bias 9: Anchoring

> **Problem 9.** Take the last three digits of your phone number. Add the number one to the front of the string, so that now you have four digits. Think of that number as a year. Now try to estimate the year that the Taj Mahal was completed. Was it before or after the date made by your phone number?
>
> ____________ Before____________ After
>
> On the line below, please make your best estimate of the actual year in which the Taj Mahal was completed: ____________

Was your answer affected by your phone number? Most people who answer this question are influenced by this obviously irrelevant information. Reconsider how you would have responded if your phone number resulted in the year 1978 or the year 1040. On average, individuals whose final three digits are high give more recent estimates for the Taj Mahal's completion than do individuals with lower phone numbers. In fact, the Taj Mahal was completed in 1648 in Agra, India, after fifteen years of construction.

Why do we pay attention to irrelevant "anchors" such as digits in a phone number? There are at least two reasons that anchors affect our decisions. First, we often develop estimates by starting with an initial anchor that is based on whatever information is provided and adjust from the anchor to yield a final answer (Epley, 2004; Epley & Gilovich, 2001). Adjustments away from anchors are usually not sufficient (Tversky & Kahneman, 1974). Second, Mussweiler and Strack (1999) show that the existence of an anchor leads people to think of information that is consistent with that anchor (e.g., reasons why the Taj Mahal may have been completed around the year formed by the end of your telephone number) rather than accessing information that is inconsistent with the anchor (e.g., reasons why the Taj Mahal's completion date was different from the number formed by your phone number). This phenomenon occurs even when anchors are presented subliminally (Mussweiler & Englich, 2005).

In their classic demonstration of anchoring, Tversky and Kahneman (1974) asked participants to estimate the percentage of African countries belonging to the United Nations. For each participant, a random number (obtained by a spin of a roulette wheel, observed by the participant) was given as a starting point. From there, participants were asked to state whether the actual quantity was higher or lower than this random value and then develop their best estimate. The arbitrary values from the roulette wheel had a substantial impact on participants' estimates. For example, among those who started with the number ten from the roulette wheel, the median estimate was 25 percent African countries in the U.N. Among those who started with the number sixty-five from the wheel, the median estimate was 45 percent. Thus, even though participants were aware that the anchor was random and unrelated to the judgment task, the anchor had a dramatic effect on their judgment. Interestingly, paying participants according to their accuracy did not reduce the magnitude of the anchoring effect.

Mussweiler and Strack (2000) have shown that the power of anchoring can be explained by the confirmation heuristic and by the selective accessibility in our minds of hypothesis-consistent information. In one experiment, they asked participants to estimate the average price of a new car in Germany. Half of the participants were provided with a high anchor (40,000 German marks) and half were provided with a low anchor (20,000 German marks). Participants who received the high anchor were quicker to recognize words (such as "Mercedes" and "BMW") associated with expensive cars. Participants who got the low anchors, on the other hand, were quicker to recognize words (such as "Golf" and "VW") associated with inexpensive cars, suggesting that concepts related to the anchors provided were more active in their minds and more mentally accessible.

Graduating MBA students routinely complain about the effect of anchoring on their salary negotiations. Hiring organizations typically are interested in knowing these students' pre-MBA salaries. Inevitably, these figures influence the post-MBA offers that the students receive, despite the fact that these figures are only marginally relevant to their future performance. A more informative figure would be what the student could earn elsewhere with his or her MBA experience, perhaps as measured by the offers that his or her classmates are receiving. Once they accept jobs, future pay increases usually come in the form of percentage increases based on current salary. Those MBA students who negotiate aggressively on the way intend to obtain higher salaries, which then serve as anchors for future years' salaries. Their propensity to negotiate from the start may be quite unrelated to their performance on the job. For instance, evidence suggests that women are less likely to negotiate than are men (Babcock & Laschever, 2007). Furthermore, the research findings suggest that when an employer is deciding what offer to make to a potential employee, any anchor that creeps into the discussion, such as an off-hand comment by an uninformed spouse or secretary, is likely to affect the eventual offer, even if the employer tries to ignore the anchor as being irrelevant.

There are numerous examples of anchoring in everyday life. For example:

- In education, children are tracked by a school system that may categorize them by ability at an early age. One study showed that teachers tend to expect children assigned to the lowest group to achieve little and have much higher expectations of children in the top group (Darley & Gross, 1983). These expectations influence actual performance in profound ways, as revealed by studies in which students were randomly assigned to groups of varying levels. Teachers, who were unaware that the assignment was random, treated students differently depending on which group they belonged to (Rosenthal, 1974; Rosenthal & Jacobson, 1968).

- We have all fallen victim to the first-impression syndrome when meeting someone for the first time. We often place so much emphasis on initial impression anchors that we fail to adjust our opinion appropriately at a later date when we have the chance to do so (Dougherty, Turban, & Callender, 1994).
- A person's race serves as an anchor with respect to our expectations of their behavior, and we tend to adjust insufficiently from that anchor. Due to deeply ingrained stereotypes about people of African descent, Americans perceive the very same behavior when exhibited by an African-American as more aggressive than when that behavior is exhibited by a European-American (Duncan, 1976).

Joyce and Biddle (1981) have provided empirical support for the presence of the anchoring effect among practicing auditors of major accounting firms. Auditors participating in one condition were asked the following questions (adapted from the original to keep the problem current):

> It is well known that many cases of management fraud go undetected even when competent annual audits are performed. The reason, of course, is that Generally Accepted Auditing Standards are not designed specifically to detect executive-level management fraud. We are interested in obtaining an estimate from practicing auditors of the prevalence of executive-level management fraud as a first step in ascertaining the scope of the problem.
>
> **1.** Based on your audit experience, is the incidence of significant executive-level management fraud more than 10 in each 1,000 firms (that is, 1 percent) audited by Big Four accounting firms?
> **a.** Yes, more than 10 in each 1,000 Big Four clients have significant executive-level management fraud.
> **b.** No, fewer than 10 in each 1,000 Big Four clients have significant executive-level management fraud.
>
> **2.** What is your estimate of the number of Big Four clients per 1,000 that have significant executive-level management fraud? (Fill in the blank below with the appropriate number.)
> ___ in each 1,000 Big Four clients have significant executive-level management fraud.

The second condition differed from the first only in that participants were asked whether the fraud incidence was more or less than 200 per 1,000 firms audited, rather than 10 per 1,000. Prior to the auditing scandals that started to emerge in 2001, participants in the first condition estimated a fraud incidence of 16.52 per 1,000 on average, compared with an estimated fraud incidence of 43.11 per 1,000 in the second condition! In our own use of these problems with executive classes, answers to both versions have roughly doubled since the fall of Enron, but the differences between the two versions of the problem remain large. It seems that even seasoned experts, including professional auditors, can be affected by anchors. In fact, Englich and her collegues (Englich & Mussweiler, 2001; Englich, Mussweiler, & Strack, 2006) show that judges' sentencing decisions are influenced by anchors as irrelevant as a roll of the dice.

Epley (2004) discusses two different processes that lead to the anchoring bias. Specifically, he shows that when an anchor is externally set (that is, not set by the decision maker), the anchor leads to a biased search for information compatible with the anchor (Mussweiler & Strack, 1999, 2000, 2001). For example, when you view a house whose list price is dramatically above its market value, the high anchor is likely to lead you to see the positive features of the house that are consistent with a high valuation. In contrast, when someone develops her own anchor, she will start with that anchor and insufficiently adjust away from it (Epley & Gilovich, 2001). For example, when considering the question of when George Washington was elected president of the United States, most Americans begin with the year in which the country declared its independence from England (1776) and adjust up from that to arrive at an estimate.

Findings from Nisbett and Ross (1980) suggest that the anchoring bias itself dictates that it will be very difficult for this book to convince you to change your decision-making strategies. They would argue that the heuristics we identify here are cognitive anchors that are central to your judgment processes. Thus, any cognitive strategy that we suggest must be presented and understood in a manner that will force you to break your existing cognitive anchors. The evidence presented in this section suggests that this should be a difficult challenge—but one that is important enough to be worth the effort!

Bias 10: Conjunctive- and Disjunctive-Events Bias

Problem 10. Which of the following instances appears most likely? Which appears second most likely?

- **a.** Drawing a red marble from a bag containing 50 percent red marbles and 50 percent white marbles.
- **b.** Drawing a red marble seven times in succession, with replacement (i.e., a selected marble is put back into the bag before the next marble is selected), from a bag containing 90 percent red marbles and 10 percent white marbles.
- **c.** Drawing at least one red marble in seven tries, with replacement, from a bag containing 10 percent red marbles and 90 percent white marbles.

The most common ordering of preferences is B–A–C. Interestingly, the correct order of likelihood is C (52 percent), A (50 percent), and B (48 percent)—the exact opposite of the most common intuitive pattern! This result illustrates a general bias to overestimate the probability of conjunctive events, or events that must occur in conjunction with one another (Bar-Hillel, 1973), and to underestimate the probability of disjunctive events, or events that occur independently (Tversky & Kahneman, 1974). Thus, when multiple events all need to occur (choice B), we overestimate the true likelihood of this happening, while if only one of many events needs to occur (choice C), we underestimate the true likelihood of this event.

The overestimation of conjunctive events offers a powerful explanation for the problems that typically occur with projects that require multistage planning. Individuals, businesses, and governments frequently fall victim to the conjunctive-events bias in terms of timing and budgets. Home remodeling, new product ventures, and public works projects seldom finish on time or on budget.

Consider the following real-life scenarios:

- After three years of study, doctoral students typically dramatically overestimate the likelihood of completing their dissertations within a year. This occurs even when they plan how long each component of the project will take. Why do they not finish in one year?
- A partner managed a consulting project in which five teams were each analyzing a different strategy for a client. The alternatives could not be compared until all of the teams completed their analysis. As the client's deadline approached, three of the five teams were behind schedule, but the partner assured the client that all five would be ready on time. In the end, the manager presented only three of the five alternatives to the client (two were still missing). Unimpressed, the client dropped the consulting firm. Whose fault was it that the project failed?
- The City of Boston undertook a massive construction project to move Interstate Highway 93 below ground as it passes through the city (The Big Dig). City officials developed a $2.5 billion budget based on each subcontractor's estimate. Nevertheless, the Big Dig finished roughly five years late and $12 billion over budget. What went wrong?

Why are we so optimistic in our assessments of a project's cost and time frame? Why are we so surprised when a seemingly unlikely setback occurs? Because of the human tendency to underestimate disjunctive events. "A complex system, such as a nuclear reactor or the human body, will malfunction if any of its essential components fails," argue Tversky and Kahneman (1974). "Even when the likelihood of failure in each component is slight, the probability of an overall failure can be high if many components are involved."

An awareness of our underestimation of disjunctive events sometimes makes us too pessimistic. Consider the following scenario:

> It's Monday evening (10:00 P.M.). Your boss calls to tell you that you must be at the Chicago office by 9:30 A.M. the next morning. You call all five airlines that have flights that get into Chicago by 9:00 A.M. Each has one flight, and all the flights are booked. When you ask the probability of getting on each of the flights if you show up at the airport in the morning, you are disappointed to hear probabilities of 30 percent, 25 percent, 15 percent, 20 percent, and 25 percent. Consequently, you do not expect to get to Chicago on time.

In this case, the disjunctive bias leads you to expect the worst. In fact, if the probabilities given by the airlines are unbiased and independent, you have a 73 percent chance of getting on one of the flights (assuming that you can arrange to be at the right ticket counter at the right time).

Bias 11: Overconfidence

> **Problem 11.** Ten uncertain quantities are listed below. Do not look up any information about these items. For each, write down your best estimate of the quantity. Next, put a lower and upper bound around your estimate, so that you are confident that your 98 percent range surrounds the actual quantity.

Estimate	Lower	Upper	
___	___	___	a. Wal-Mart's 2006 revenue
___	___	___	b. Microsoft's 2006 revenue
___	___	___	c. World population as of July 2007
___	___	___	d. Market capitalization (price per share times number of shares outstanding) of Best Buy as of July 6, 2007
___	___	___	e. Market capitalization of Heinz as of July 6, 2007
___	___	___	f. Rank of McDonald's in the 2006 *Fortune* 500
___	___	___	g. Rank of Nike in the 2006 *Fortune* 500
___	___	___	h. Number of fatalities due to motor vehicle accidents in the United States in 2005
___	___	___	i. The national debt of the U.S. federal government as of July 2007
___	___	___	j. The U.S. federal government budget for the 2008 fiscal year

How many of your ten ranges actually surround the true quantities? If you set your ranges so that you were 98 percent confident, you should expect to correctly bound approximately 9.8, or nine to ten, of the quantities. Let's look at the correct answers: (a) $351,139,000,000 ($351 billion); (b) $44,282,000,000 ($44 billion); (c) 6,602,224,175 people (6.6 billion); (d) $23,150,000,000 ($23 billion); (e) $15,230,000,000 ($15 billion); (f) 108; (g) 158; (h) 43,443; (i) $8,800,000,000,000 ($8.8 trillion); (j) $2,900,000,000,000 ($2.9 trillion).

How many of your ranges actually surrounded the true quantities? If you surrounded nine or ten, we can conclude that you were appropriately confident in your estimation ability. Most people surround only between three (30 percent) and seven (70 percent), despite claiming a 98 percent confidence that each range will surround the true value. Why? Most of us are overconfident in the precision of our beliefs and do not acknowledge our true uncertainty.[1]

In Alpert and Raiffa's (1969/1982) initial demonstration of overconfidence based on 1,000 observations (100 participants on 10 items), 42.6 percent of quantities fell outside 90 percent confidence ranges. Since then, overconfidence has been identified as a common judgmental pattern and demonstrated in a wide variety of settings. Why should you be concerned about overconfidence? After all, it has probably given you the courage to attempt endeavors that have stretched your abilities. Unwarranted confidence can indeed be beneficial in some situations. However, consider the potential adverse effects of excess confidence in the following situations:

- You are a surgeon who is trying to persuade a patient's family to agree to a difficult operation. When the family asks you to estimate the likelihood that the patient will survive the operation, you respond, "Ninety-five percent." If the patient dies on the

[1] Note that some researchers have used the term "overconfidence" to describe other phenomena, including believing that we are better than others or overestimating our control over events. We will use the word "overconfidence" to refer only to excessive confidence in the precision of subjective estimates, or what Moore and Healy (2007) call "overprecision."

operating table, was he one of the unlucky 5 percent, or are you guilty of malpractice for an overconfident projection?

- You are the chief legal counsel for a firm that has been threatened with a multimillion-dollar lawsuit. You are 98 percent confident that the firm will not lose in court. Is this degree of certainty sufficient for you to recommend rejecting an out-of-court settlement? Suppose you learn that, if you lose the case, your firm will go bankrupt. Based on what you know now, are you still comfortable with your 98 percent estimate?
- You have developed a marketing plan for a new product. You are so confident in your plan that you have not developed any contingencies for early market failure. When the first stage of your plan falters, will you expedite changes in the marketing strategy, or will your overconfidence blind you to its flaws?

These examples demonstrate the serious problems that can result from the tendency to be overconfident. While confidence in your abilities is necessary for achievement in life, and can inspire respect and confidence in others, overconfidence can be a barrier to effective professional decision making. Too sure that we know the right answer, we become impervious to new evidence or alternative perspectives. Odean (1998) has argued that overconfidence could explain the excessively high rate of trading in the stock market, despite the costs (Odean, 1999). Malmendier and Tate (2005) used overconfidence to explain the high rates of corporate mergers and acquisitions, despite the fact that such ventures so often fail. Plous (1993) suggests that overconfidence contributed to the nuclear accident at Chernobyl and to the explosion of the space shuttle *Challenger*. In his words, "No problem in judgment and decision making is more prevalent and more potentially catastrophic than overconfidence" (p. 217).

Overconfidence is related to the confirmation heuristic. Since the human mind is better at searching memory for confirming rather than disconfirming evidence, when people assess their confidence in any belief, it will be easier for them to generate supportive than contradictory evidence. Just as anchors facilitate recollection of anchor-consistent information, our initial guesses about uncertain quantities produce selective mental accessibility of information consistent with these guesses. Adjustment from these "self-generated anchors" is often insufficient (Epley & Gilovich, 2001), producing an excessive confidence that our initial estimates were, in fact, pretty good (Block & Harper, 1991). Thus bolstered by the availability of supportive evidence, we overestimate the accuracy of our knowledge and the truth of our tentative hypotheses (Koriat, Lichtenstein, & Fischhoff, 1980). In this way, the confirmation heuristic leads to overconfidence (Klayman, Soll, Gonzalez-Vallejo, & Barlas, 1999; Soll & Klayman, 2004). As with the other biases described in this chapter, this process tends to occur automatically, without conscious awareness.

Interventions that force people to think about alternative perspectives, interpretations, or hypotheses are often effective at shaking people's overconfidence and inducing more accurate levels of confidence (Griffin, Dunning, & Ross, 1990). In other words, thinking about why you might be wrong can help correct for the influence of confirmatory bias on confidence judgments.

Bias 12: Hindsight and the Curse of Knowledge

Imagine yourself in the following scenarios:

- You are an avid football fan, and you are watching a critical game in which your team is behind 35–31. With three seconds left and the ball on the opponent's three-yard line, the quarterback calls a pass play into the corner of the end zone. When the play fails, you shout, "I knew that was a bad play."
- You are driving in an unfamiliar area, and your spouse is behind the wheel. When you approach an unmarked fork in the road, your spouse decides to go to the right. Four miles and fifteen minutes later, it is clear that you are lost. You blurt out, "I knew you should have turned left at the fork."
- A manager who works for you hired a new supervisor last year. You were well aware of the choices she had at the time and allowed her to choose the new employee on her own. You have just received production data on every supervisor. The data on the new supervisor are terrible. You call in the manager and claim, "There was plenty of evidence that he was the wrong man for the job."
- As director of marketing in a consumer-goods organization, you have just presented the results of an extensive six-month study on current consumer preferences for the products manufactured by your company. At the conclusion of your presentation, a senior vice president responds, "I don't know why we spent so much time and money collecting these data. I could have told you what the results were going to be."

Do you recognize any of your own behaviors in these scenarios? Do you recognize someone else's remarks? Each scenario exemplifies "the hindsight bias" (Fischhoff, 1975), which often occurs when people look back on their own judgments and those of others. We typically are not very good at recalling or reconstructing the way an uncertain situation appeared to us before finding out the results of the decision. What play would you have called? Did you really know that your spouse should have turned left? Was there truly evidence that the selected supervisor was a bad choice? Could the senior vice president actually have predicted your study's results? While our intuition is occasionally accurate, we tend to overestimate what we knew beforehand based upon what we later learned.

Fischhoff (1975) examined the differences between hindsight and foresight in the context of judging the outcome of historical events. In one study, participants were divided into five groups and asked to read a passage about the war between the British and Gurka forces in 1814. One group was not told the result of the war. The remaining four groups of participants were told either that: (1) the British won, (2) the Gurkas won, (3) a military stalemate was reached with no peace settlement, or (4) a military stalemate was reached with a peace settlement. Obviously, only one group was told the truthful outcome—in this case, (1)—that the British won. Each participant was then asked what his or her subjective assessments of the probability of each of the outcomes would have been without the benefit of knowing the reported outcome. Participants tended to believe that even if they had not been told the outcome, they would have judged the outcome that they were later told had happened as being most likely. Based on this and other varied examples, it becomes clear that knowledge of an outcome increases an individual's belief about the degree to which he or she would have predicted that outcome without the benefit of that knowledge.

The processes that give rise to anchoring and overconfidence are also at work in producing the hindsight bias (Fiedler, 2000; Koriat, Fiedler, & Bjork, 2006). According to this explanation, knowledge of an event's outcome works as an anchor by which individuals interpret their prior judgments of the event's likelihood. Due to the selective accessibility of confirmatory information during information retrieval, adjustments to anchors are inadequate (Mussweiler & Strack, 1999). Consequently, hindsight knowledge biases our perceptions of what we remember knowing in foresight. Furthermore, to the extent that various pieces of data about the event vary in support of the actual outcome, evidence that is consistent with the known outcome may become cognitively more salient and thus more available in memory (Slovic & Fischhoff, 1977). This tendency will lead an individual to justify a claimed foresight in view of "the facts provided." Finally, the relevance of a particular piece of data may later be judged important to the extent to which it is representative of the final observed outcome.

In the short run, the hindsight bias can offer a number of advantages. For instance, it can be flattering to believe that your judgment is far better than it actually is! In addition, hindsight allows us to criticize other people's apparent lack of foresight. However, the hindsight bias reduces our ability to learn from the past and to evaluate decisions objectively. In general, individuals should be judged by the process and logic of their decisions, not just on their results. A decision maker who makes a high-quality decision that does not work out should be rewarded, not punished. Why? Because results are affected by a variety of factors outside the direct control of the decision maker. When the hindsight bias leads our knowledge of the result to color our evaluation of the decision maker's logic, we will make poorer evaluations than we would otherwise.

Closely related to the hindsight bias is the "curse of knowledge," which argues that when assessing others' knowledge, people are unable to ignore knowledge that they have that others do not have (Camerer, Loewenstein, & Weber, 1989). Available knowledge is hard to forget when you try to imagine how much others know about something; sophistication stands in the way of a fair assessment. This "curse" explains the difficulty that teachers often have adjusting their lessons according to students' level of knowledge and the tendency of product designers to overestimate the average person's ability to master high-tech devices. Indeed, evidence suggests that as many as half of high-tech devices that consumers return as malfunctioning are, in fact, in perfect working order—the consumer just couldn't figure out how to use it (den Ouden, 2006). Hoch (1988) found that marketing experts are generally worse at predicting the beliefs, values, and tastes of other consumers than nonexpert consumers are. This results from the marketing experts acting as if the nonexpert consumer understood as much about the products as they do.

Have you ever given someone what you believed were very clear directions to your home, only to find that he got lost? Keysar (1994) argues that when an individual sends an ambiguous message (which is clear to her) to another individual, based on information that the receiver does not possess, she assumes that her intent will be magically understood by the other party. Keysar (1994) had people read scenarios that provided them with privileged information about "David." They read that David had dinner at a particular restaurant based on a friend's recommendation. Half the participants in the experiment learned that David had really enjoyed his meal, and the other half learned that he had disliked it very much. All the participants read that David wrote his friend the following note: "About the restaurant, it was marvelous, just marvelous." The participants who knew that David had enjoyed the restaurant had a strong tendency to believe that the friend would take the comment as sincere. In contrast, participants who knew that David had disliked the restaurant had a strong tendency to believe that the friend would take the comment as sarcastic. This result occurred despite the fact that both groups of participants knew that the friend had access to the same note and no additional information about David's dining experience.

In organizations, a great deal of disappointment results from the failure to communicate clearly. This disappointment is caused in part by our false belief that people understand our ambiguous messages. It should come as no surprise that communication by e-mail, lacking the cues of intonation and body language, only makes this problem worse (Kruger, Epley, Parker, & Ng, 2005).

INTEGRATION AND COMMENTARY

Heuristics, or rules of thumb, are the cognitive tools we use to simplify decision making. The preceding pages have described twelve of the most common biases that result when we over-rely on these judgmental heuristics. These biases, along with their associated heuristics, are summarized in Table 2.2. Remember that more than one heuristic can operate on your decision-making processes at any given time.

The logic of heuristics is that, on average, any loss in decision quality will be outweighed by time saved. And, indeed, such "shortcuts" lead far more often to adequate decisions than to poor ones. However, as we have demonstrated in this chapter, a blanket acceptance of heuristics is unwise. First, as illustrated by the quiz items, there are many instances in which the loss in decision quality far outweighs the time saved by heuristics. Second, the foregoing logic suggests that we voluntarily accept the quality tradeoffs associated with heuristics. In reality, we do not: Most of us are unaware of their existence and their pervasive impact upon our decision making. Consequently, we fail to distinguish between situations in which they are beneficial and situations in which they are potentially harmful.

Why do we fail to apply heuristics selectively? In good part because our minds are wired to make reliance on these heuristics natural and comfortable. For instance, the biases related to the availability heuristic appear to be a natural function of the selectiveness of human memory. Our brains are better at remembering information that is interesting, emotionally arousing, or recently acquired. The human brain evolved over millennia using strategies that helped our ancestors survive and reproduce. Humans seem to be more self-aware than any other animals. Nevertheless, we remain profoundly ignorant of the internal workings of our minds and of the processes, such as recall from immediate memory and confirmatory hypothesis testing, that can have such important and negative consequences.

When the stakes are high and decision quality is important, it is worth engaging in more effortful thought processes that can avoid biases. The key to improved judgment lies in learning to distinguish between appropriate and inappropriate uses of heuristics, when your judgment is likely to rely on heuristics, and how to avoid them. This chapter gives you the foundation you need to make these distinctions.

TABLE 2-2 Summary of the Twelve Biases Presented in Chapter 2

Bias	Description
Biases Emanating from the Availability Heuristic	
1. Ease of recall	Individuals judge events that are more easily recalled from memory, based on vividness or recency, to be more numerous than events of equal frequency whose instances are less easily recalled.
2. Retrievability	Individuals are biased in their assessments of the frequency of events based on how their memory structures affect the search process.
Biases Emanating from the Representativeness Heuristic	
3. Insensitivity to base rates	When assessing the likelihood of events, individuals tend to ignore base rates if any other descriptive information is provided—even if it is irrelevant.
4. Insensitivity to sample size	When assessing the reliability of sample information, individuals frequently fail to appreciate the role of sample size.
5. Misconceptions of chance	Individuals expect that a sequence of data generated by a random process will look "random," even when the sequence is too short for those expectations to be statistically valid.
6. Regression to the mean	Individuals tend to ignore the fact that extreme events tend to regress to the mean on subsequent trials.
7. The conjunction fallacy	Individuals falsely judge that conjunctions (two events co-occurring) are more probable than a more global set of occurrences of which the conjunction is a subset.
Biases Emanating from the Confirmation Heuristic	
8. The confirmation trap	Individuals tend to seek confirmatory information for what they think is true and fail to search for disconfirmatory evidence.
9. Anchoring	Individuals make estimates for values based upon an initial value (derived from past events, random assignment, or whatever information is available) and typically make insufficient adjustments from that anchor when establishing a final value.
10. Conjunctive- and disjunctive-events bias	Individuals exhibit a bias toward overestimating the probability of conjunctive events and underestimating the probability of disjunctive events.
11. Overconfidence	Individuals tend to be overconfident of the infallibility of their judgments when answering moderately to extremely difficult questions.
12. Hindsight and the curse of knowledge	After finding out whether or not an event occurred, individuals tend to overestimate the degree to which they would have predicted the correct outcome. Furthermore, individuals fail to ignore information they possess that others do not when predicting others' behavior.