Chapter 4

Tools of the Trade

In This Chapter

- Seeing statistics as a process, not just as numbers
- Getting familiar with some basic statistical jargon

In today's world, the buzzword is *data*, as in, “Do you have any data to support your claim?” “What data do you have on this?” “The data supported the original hypothesis that …,” “Statistical data show that …,” and “The data bear this out ….” But the field of statistics is not just about data.

Statistics is the entire process involved in gathering evidence to answer questions about the world, in cases where that evidence happens to be data.

In this chapter, you see firsthand how statistics works as a process and where the numbers play their part. You're also introduced to the most commonly used forms of statistical jargon, and you find out how these definitions and concepts all fit together as part of that process. So the next time you hear someone say, “This survey had a margin of error of plus or minus 3 percentage points,” you'll have a basic idea of what that means.

Statistics: More than Just Numbers

Statisticians don't just “do statistics.” Although the rest of the world views them as number crunchers, they think of themselves as the keepers of the scientific method. Of course, statisticians work with experts in other fields to satisfy their need for data, because man cannot live by statistics alone, but crunching someone's data is only a small part of a statistician's job. (In fact, if that's all we did all day, we'd quit our day jobs and moonlight as casino consultants.) In reality, statistics is involved in every aspect of the *scientific method* — formulating good questions, setting up studies, collecting good data, analyzing the data properly, and making appropriate conclusions. But aside from analyzing the data properly, what do any of these aspects have to do with statistics? In this chapter you find out.

All research starts with a question, such as:

- Is it possible to drink too much water?
- What's the cost of living in San Francisco?
- Who will win the next presidential election?
- Do herbs really help maintain good health?
- Will my favorite TV show get renewed for next year?

None of these questions asks anything directly about numbers. Yet each question requires the use of data and statistical processes to come up with the answer.

Suppose a researcher wants to determine who will win the next U.S. presidential election. To answer with confidence, the researcher has to follow several steps:

1. **Determine the population to be studied.**
   In this case, the researcher intends to study registered voters who plan to vote in the next election.
2. **Collect the data.**
   This step is a challenge, because you can't go out and ask every person in the United States whether they plan to vote, and if so, for whom they plan to vote. Beyond that, suppose someone says, “Yes, I plan to vote.” Will that person *really* vote come Election Day? And will that same person tell you whom he actually plans to vote for? And what if

that person changes his mind later on and votes for a different candidate?

3. **Organize, summarize, and analyze the data.**
   After the researcher has gone out and collected the data she needs, getting it organized, summarized, and analyzed helps the researcher answer her question. This step is what most people recognize as the business of statistics.
4. **Take all the data summaries, charts, graphs, and analyses and draw conclusions from them to try to answer the researcher's original question.**
   Of course, the researcher will not be able to have 100% confidence that her answer is correct, because not every person in the United States was asked. But she can get an answer that she is *nearly* 100% sure is correct. In fact, with a sample of about 2,500 people who are selected in a fair and *unbiased* way (that is, every possible sample of size 2,500 had an equal chance of being selected), the researcher can get accurate results within plus or minus 2.5% (if all the steps in the research process are done correctly).

In making conclusions, the researcher has to be aware that every study has limits and that — because the chance for error always exists — the results could be wrong. A numerical value can be reported that tells others how confident the researcher is about the results and how accurate these results are expected to be. (See **Chapter 12** for more information on margin of error.)

After the research is done and the question has been answered, the results typically lead to even more questions and even more research. For example, if men appear to favor one candidate but women favor the opponent, the next questions may be: “Who goes to the polls more often on Election Day — men or women — and what factors determine whether they will vote?"

The field of statistics is really the business of using the scientific method to answer research questions about the world. Statistical methods are involved in every step of a good study, from designing the research to collecting the data, organizing and summarizing the information, doing an analysis, drawing conclusions, discussing limitations, and, finally, designing the next study in order to answer new questions that arise. Statistics is more than just numbers — it's a process.

Grabbing Some Basic Statistical Jargon

Every trade has a basic set of tools, and statistics is no different. If you think about the statistical process as a series of stages that you go through to get from question to answer, you may guess that at each stage you'll find a group of tools and a set of terms (or jargon) to go along with it. Now if the hair is beginning to stand up on the back of your neck, don't worry. No one is asking you to become a statistics expert and plunge into the heavy-duty stuff, or to turn into a statistics nerd who uses this jargon all the time. Hey, you don't even have to carry a calculator and pocket protector in your shirt pocket (because statisticians really don't do that; it's just an urban myth).

But as the world becomes more numbers-conscious, statistical terms are thrown around more in the media and in the workplace, so knowing what the language really means can give you a leg up. Also, if you're reading this book because you want to find out more about how to calculate some statistics, understanding basic jargon is your first step. So, in this section, you get a taste of statistical jargon; I send you to the appropriate chapters elsewhere in the book to get details.

Data

Data are the actual pieces of information that you collect through your study. For example, I asked five of my friends how many pets they own, and the data they gave me are the following: 0, 2, 1, 4, 18. (The fifth friend counted each of her aquarium fish as a separate pet.) Not all data are numbers; I also recorded the gender of each of my friends, giving me the following data: male, male, female, male, female.

Most data fall into one of two groups: numerical or categorical. (I present the main ideas about these variables here; see **Chapter 5** for more details.)

- **Numerical data:** These data have meaning as a measurement, such as a person's height, weight, IQ, or blood pressure; or they're a count, such as the number of stock shares a person owns, how many teeth a dog has, or how many pages you can read of your favorite book before you fall asleep. (Statisticians also call numerical data *quantitative data.*)
  Numerical data can be further broken into two types: discrete and continuous.
  - *Discrete data* represent items that can be counted; they take on possible values that can be listed out. The list of possible values may be fixed (also called *finite*); or it may go from 0, 1, 2, on to infinity (making it *countably infinite*). For example, the number of heads in 100 coin flips takes on values from 0 through 100 (finite case), but the number of flips needed to get 100 heads takes on values from 100 (the fastest scenario) on up to infinity. Its possible values are listed as 100, 101, 102, 103,… (representing the countably infinite case).
  - *Continuous data* represent measurements; their possible values cannot be counted and can only be described using intervals on the real number line. For example, the exact amount of gas purchased at the pump for cars with 20-gallon tanks represents nearly-continuous data from 0.00 gallons to 20.00 gallons, represented by the interval [0, 20], inclusive. (Okay, you *can* count all these values, but why would you want to? In cases like these, statisticians bend the

definition of continuous a wee bit.) The lifetime of a C battery can be anywhere from 0 to infinity, technically, with all possible values in between. Granted, you don't expect a battery to last more than a few hundred hours, but no one can put a cap on how long it can go (remember the Energizer Bunny?).

- **Categorical data:** Categorical data represent characteristics such as a person's gender, marital status, hometown, or the types of movies they like. Categorical data can take on numerical values (such as “1” indicating male and “2” indicating female), but those numbers don't have meaning. You couldn't add them together, for example. (Other names for categorical data are *qualitative data*, or *Yes/No data.*)

Ordinal data mixes numerical and categorical data. The data fall into categories, but the numbers placed on the categories have meaning. For example, rating a restaurant on a scale from 0 to 4 stars gives ordinal data. Ordinal data are often treated as categorical, where the groups are ordered when graphs and charts are made. I don't address them separately in this book.

Data set

A *data set* is the collection of all the data taken from your sample. For example, if you measured the weights of five packages, and those weights were 12, 15, 22, 68, and 3 pounds, those five numbers (12, 15, 22, 68, 3) constitute your data set. If you only record the general size of the package (for example, small, medium, or large), your data set may look like this: medium, medium, medium, large, small.

Variable

A *variable* is any characteristic or numerical value that varies from individual to individual. A variable can represent a count (for example, the number of pets you own); or a measurement (the time it takes you to wake up in the morning). Or the variable can be categorical, where each individual is placed into a group (or category) based on certain criteria (for example, political affiliation, race, or marital status). Actual pieces of information recorded on individuals regarding a variable are the data.

Population

For virtually any question you may want to investigate about the world, you have to center your attention on a particular group of individuals (for example, a group of people, cities, animals, rock specimens, exam scores, and so on). For example:

- What do Americans think about the president's foreign policy?
- What percentage of planted crops in Wisconsin did deer destroy last year?
- What's the prognosis for breast cancer patients taking a new experimental drug?
- What percentage of all cereal boxes get filled according to specification?

In each of these examples, a question is posed. And in each case, you can identify a specific group of individuals being studied: the American people, all planted crops in Wisconsin, all breast cancer patients, and all cereal boxes that are being filled, respectively. The group of individuals you want to study in order to answer your research question is called a *population.* Populations, however, can be hard to define. In a good study, researchers define the population very clearly, whereas in a bad study, the population is poorly defined.

The question of whether babies sleep better with music is a good example of how difficult defining the population can be. Exactly how would you define a baby? Under three months old? Under a year? And do you want to study babies only in the United States, or all babies worldwide? The results may be different for older and younger babies, for American versus European versus African babies, and so on.

Many times researchers want to study and make conclusions about a broad population, but in the end — to save time, money, or just because they don't know any better — they study only a narrowly defined population. That shortcut can lead to big trouble when conclusions are drawn. For example, suppose a college professor wants to study how TV ads persuade consumers to buy products. Her study is based on a group of her own students who participated to get five points extra credit. This test group may be convenient, but her results can't be generalized to any population beyond her own students, because no other population was represented in her study.

Sample, random, or otherwise

When you sample some soup, what do you do? You stir the pot, reach in with a spoon, take out a little bit of the soup, and taste it. Then you draw a conclusion about the whole pot of soup, without actually having tasted all of it. If your sample is taken in a fair way (for example, you didn't just grab all the good stuff) you will get a good idea how the soup tastes without having to eat it all. Taking a sample works the same way in statistics. Researchers want to find out something about a population, but they don't have time or money to study every single individual in the population. So they select a subset of individuals from the population, study those individuals, and use that information to draw conclusions about the whole population. This subset of the population is called a *sample.*

Although the idea of a selecting a sample seems straightforward, it's anything but. The way a sample is selected from the population can mean the difference between results that are correct and fair and results that are garbage. Example: Suppose you want a sample of teenagers' opinions on whether they're spending too much time on the Internet. If you send out a survey using text messaging, your results won't represent the opinions of *all teenagers,* which is your intended population. They will represent only those teenagers who have access to text messages. Does this sort of statistical mismatch happen often? You bet.

Some of the biggest culprits of statistical misrepresentation caused by bad sampling are surveys done on the Internet. You can find thousands of surveys on the Internet that are done by having people log on to a particular Web site and give their opinions. But even if 50,000 people in the U.S. complete a survey on the Internet, it doesn't represent the population of all Americans. It represents only those folks who have Internet access, who logged on to that particular Web site, and who were interested enough to participate in the survey (which typically means that they have strong opinions about the topic in question). The result of all these problems is *bias* — systematic favoritism of certain individuals or certain outcomes of the study.

How do you select a sample in a way that avoids bias? The key word is *random.* A *random sample* is a sample selected by equal opportunity; that is, every possible sample the same size as yours had an equal chance to be selected from the population. What *random* really means is that no group in the population is favored in or excluded from the selection process.

Non-random (in other words *bad*) *samples* are samples that were selected in such a way that some type of favoritism and/or automatic exclusion of a part of the population was involved. A classic example of a non-random sample comes from polls for which the media asks you to phone in your opinion on a certain issue (“call-in” polls). People who choose to participate in call-in polls do not represent the population at large because they had to be watching that program, and they had to feel strongly enough to call in. They technically don't represent a sample at all, in the statistical sense of the word, because no one selected them beforehand — they selected themselves to participate, creating a *volunteer* or *self-selected* sample. The results will be skewed toward people with strong opinions.

To take an authentic random sample, you need a randomizing mechanism to select the individuals. For example, the Gallup Organization starts with a computerized list of all telephone exchanges in America, along with estimates of the number of residential households that have those exchanges. The computer uses a procedure called *random digit dialing* (RDD) to randomly create phone numbers from those exchanges, and then selects samples of telephone numbers from those. So what really happens is that the computer creates a list of *all possible* household phone numbers in America and then selects a subset of numbers from that list for Gallup to call.

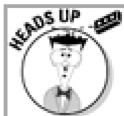
Another example of random sampling involves the use of random number generators. In this process, the items in the sample are chosen using a computer-generated list of random numbers, where each sample of items has the same chance of being selected. Researchers may use this type of randomization to assign patients to a treatment group versus a control group in an experiment. This process is equivalent to drawing names out of a hat or drawing numbers in a lottery.

> No matter how large a sample is, if it's based on non-random methods, the results will not represent the population that the researcher wants to draw conclusions about. Don't be taken in by large samples — first check to see how they were selected. Look for the term *random sample*. If you see that term, dig further into the fine print to see how the sample was actually selected and use the preceding definition to verify that the sample was, in fact, selected randomly. A small random sample is better than a large non-random one.

Statistic

A *statistic* is a number that summarizes the data collected from a sample. People use many different statistics to summarize data. For example, data can be summarized as a percentage (60% of U.S. households sampled own more than two cars), an average (the average price of a home in this sample is …), a median (the median salary for the 1,000 computer scientists in this sample was …), or a percentile (your baby's weight is at the 90th percentile this month, based on data collected from over 10,000 babies).

The type of statistic calculated depends on the type of data. For example, percentages are used to summarize categorical data, and means are used to summarize numerical data. The price of a home is a numerical variable, so you can calculate its mean or standard deviation. However, the color of a home is a categorical variable; finding the standard deviation or median of color makes no sense. In this case, the important statistics are the percentages of homes of each color.



Not all statistics are correct or fair, of course. Just because someone gives you a statistic, nothing guarantees that the statistic is scientific or legitimate. You may have heard the saying, “Figures don't lie, but liars figure.”

Parameter

Statistics are based on sample data, not on population data. If you collect data from the entire population, that process is called a *census.* If you then summarize the entire census information from one variable into a single number, that number is a *parameter,* not a statistic. Most of the time, researchers are trying to estimate the parameters using statistics. The U.S. Census Bureau wants to report the total number of people in the U.S., so it conducts a census. However, due to logistical problems in doing such an arduous task (such as being able to contact homeless folks), the census numbers can only be called *estimates* in the end, and they're adjusted upward to account for people the census missed.

Bias

Bias is a word you hear all the time, and you probably know that it means something bad. But what really constitutes bias? *Bias* is systematic favoritism that is present in the data collection process, resulting in lopsided, misleading results. Bias can occur in any of a number of ways:

- **In the way the sample is selected:** For example, if you want to estimate how much holiday shopping people in the United States plan to do this year, and you take your clipboard and head out to a shopping mall on the day after Thanksgiving to ask customers about their shopping plans, you have bias in your sampling process. Your sample tends to favor those die-hard shoppers at that particular mall who were braving the massive crowds on that day known to retailers and shoppers as “Black Friday.”
- **In the way data are collected:** Poll questions are a major source of bias. Because researchers are often looking for a particular result, the questions they ask can often reflect and lead to that expected result. For example, the issue of a tax levy to help support local schools is something every voter faces at one time or another. A poll question asking, “Don't you think it would be a great investment in our future to support the local schools?” has a bit of bias. On the other hand, so does “Aren't you tired of paying money out of your pocket to educate other people's children?” Question wording can have a huge impact on results.

Other issues that result in bias with polls are timing, length, level of question difficulty, and the manner in which the individuals in the sample were contacted (phone, mail, house-to-house, and so on). See Chapter 16 for more information on designing and evaluating polls and surveys.

> When examining polling results that are important to you or that you're particularly interested in, find out what questions were asked and exactly how the questions were worded before drawing your conclusions about the results.

Mean (Average)

The mean, also referred to by statisticians as the *average,* is the most common statistic used to measure the center, or middle, of a numerical data set. The *mean* is the sum of all the numbers divided by the total number of numbers. The mean of the entire population is called the *population mean,* and the mean of a sample is called the *sample mean.* (See **Chapter 5** for more on the mean.)

The mean may not be a fair representation of the data, because the average is easily influenced by *outliers* (very small or large values in the data set that are not typical).

Median

The median is another way to measure the center of a numerical data set. A statistical median is much like the median of an interstate highway. On many highways, the median is the middle, and an equal number of lanes lay on either side of it. In a numerical data set, the *median* is the point at which there are an equal number of data points whose values lie above and below the median value. Thus, the median is truly the middle of the data set. See **Chapter 5** for more on the median.

The next time you hear an average reported, look to see whether the median is also reported. If not, ask for it! The average and the median are two different representations of the middle of a data set and can often give two very different stories about the data, especially when the data set contains outliers (very large or small numbers that are not typical).

Standard deviation

Have you heard anyone report that a certain result was found to be "two standard deviations above the mean"? More and more, people want to report how significant their results are, and the number of standard deviations above or below average is one way to do it. But exactly what is a standard deviation?

The *standard deviation* is a measurement statisticians use for the amount of variability (or spread) among the numbers in a data set. As the term implies, a standard deviation is a standard (or typical) amount of deviation (or distance) from the average (or mean, as statisticians like to call it). So the standard deviation, in very rough terms, is the average distance from the mean.

The formula for standard deviation (denoted by s) is as follows, where n equals the number of values in the data set, each x represents a number in the data set, and $\bar{x}$ is the average of all the data:

$$s = \sqrt{\sum \frac{(x-\bar{x})^2}{n-1}}$$

For detailed instructions on calculating the standard deviation, see **Chapter 5**.

The standard deviation is also used to describe where most of the data should fall, in a relative sense, compared to the average. For example, if your data have the form of a bell-shaped curve (also known as a *normal distribution*), about 95% of the data lie within two standard deviations of the mean. (This result is called the *empirical rule,* or the *68–95–99.7% rule.* See **Chapter 5** for more on this.)

The standard deviation is an important statistic, but it is often absent when statistical results are reported. Without it, you're getting only part of the story about the data. Statisticians like to tell the story about the man who had one foot in a bucket of ice water and the other foot in a bucket of boiling water. He said on average he felt just great! But think about the variability in the two temperatures for each of his feet. Closer to home, the average house price, for example, tells you nothing about the range of house prices you may encounter when house-hunting. The average salary may not fully represent what's really going on in your company, if the salaries are extremely spread out.

Don't be satisfied with finding out only the average — be sure to ask for the standard deviation as well. Without a standard deviation, you have no way of knowing how spread out the values may be. (If you're talking starting salaries, for example, this could be very important!)

Percentile

You've probably heard references to percentiles before. If you've taken any kind of standardized test, you know that when your score was reported, it was presented to you with a measure of where you stood compared to the other people who took the test. This comparison measure was most likely reported to you in terms of a percentile. The *percentile* reported for a given score is the percentage of values in the data set that fall below that certain score. For example, if your score was reported to be at the 90th percentile, that means that 90% of the other people who took the test with you scored lower than you did (and 10% scored higher than you did). The median is right in the middle of a data set, so it represents the 50th percentile. For more specifics on percentiles, see **Chapter 5**.

Percentiles are used in a variety of ways for comparison purposes and to determine *relative standing* (that is, how an individual data value compares to the rest of the group). Babies' weights are often reported in terms of percentiles, for example. Percentiles are also used by companies to see where they stand compared to other companies in terms of sales, profits, customer satisfaction, and so on.

Standard score

The standard score is a slick way to put results in perspective without having to provide a lot of details — something that the media loves. The *standard score* represents the number of standard deviations above or below the mean (without caring what that standard deviation or mean actually are).

For example, suppose Bob took his statewide 10th-grade test recently and scored 400. What does that mean? Not much, because you can't put 400 into perspective. But knowing that Bob's standard score on the test is +2 tells you everything. It tells you that Bob's score is two standard deviations above the mean. (Bravo, Bob!) Now suppose Emily's standard score is –2. In this case, this is not good (for Emily), because it means her score is two standard deviations *below* the mean.

The process of taking a number and converting it to a standard score is called *standardizing*. For the details on calculating and interpreting standard scores when you have a normal (bell-shaped) distribution, see Chapter 9.

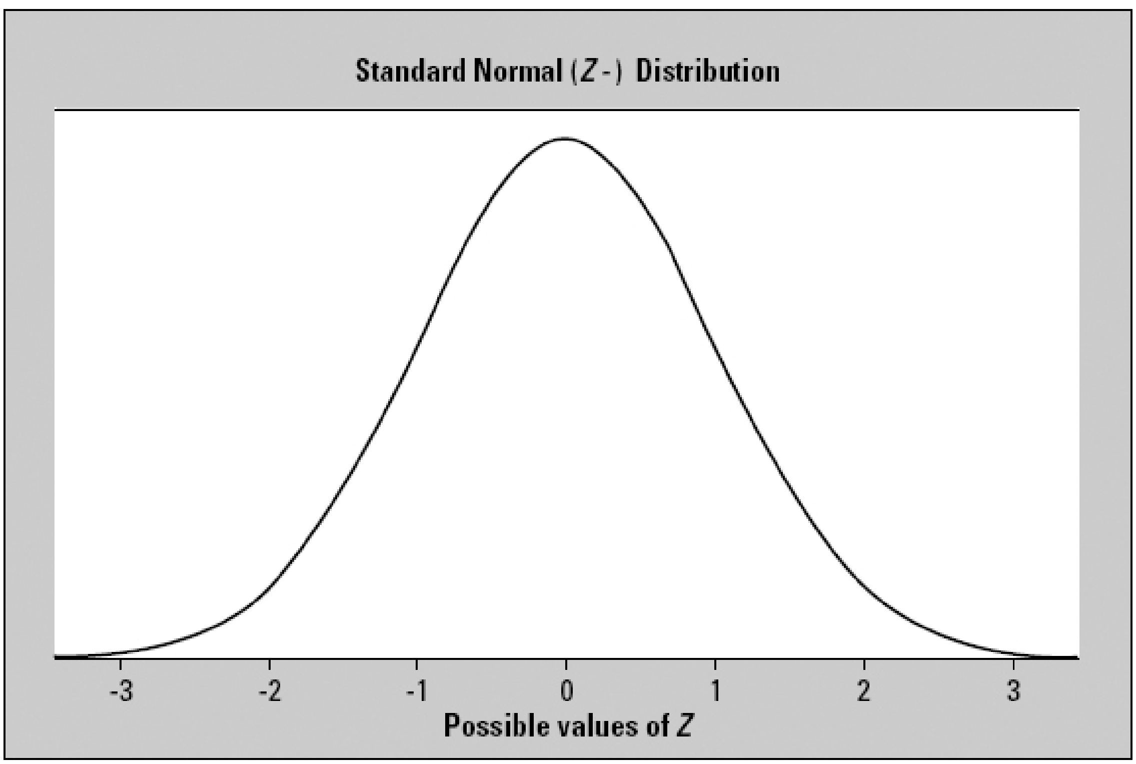
Distribution and normal distribution

The *distribution* of a data set (or a population) is a listing or function showing all the possible values (or intervals) of the data and how often they occur. When a distribution of categorical data is organized, you see the number or percentage of individuals in each group. When a distribution of numerical data is organized, they're often ordered from smallest to largest, broken into reasonably sized groups (if appropriate), and then put into graphs and charts to examine the shape, center, and amount of variability in the data.

The world of statistics includes dozens of different distributions for categorical and numerical data; the most common ones have their own names. One of the most well-known distributions is called the *normal distribution,* also known as the *bell-shaped curve.* The normal distribution is based on numerical data that is continuous; its possible values lie on the entire real number line. Its overall shape, when the data are organized in graph form, is a symmetric bell-shape. In other words, most (around 68%) of the data are centered around the mean (giving you the middle part of the bell), and as you move farther out on either side of the mean, you find fewer and fewer values (representing the downward sloping sides on either side of the bell).

The mean (and hence the median) is directly in the center of the normal distribution due to symmetry, and the standard deviation is measured by the distance from the mean to the *inflection point* (where the curvature of the bell changes from concave up to concave down). Figure 4-1 shows a graph of a normal distribution with mean 0 and standard deviation 1 (this distribution has a special name, the *standard normal distribution* or *Z-distribution*).The shape of the curve resembles the outline of a bell.

Figure 4.1: A standard normal (*Z*-) distribution has a bell-shaped curve with mean 0 and standard deviation 1.



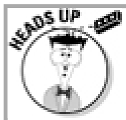
Because every distinct population of data has a different mean and standard deviation, an infinite number of different normal distributions exist, each with its own mean and its own standard deviation to characterize it. See **Chapter 9** for plenty more on the normal and standard normal distributions.

Central Limit Theorem

The normal distribution is also used to help measure the accuracy of many statistics, including the mean, using an important result in statistics called the *Central Limit Theorem.* This theorem gives you the ability to measure how much your sample mean will vary, without having to take any other sample means to compare it with (thankfully!). By taking this variability into account, you can now use your data to answer questions about the population, such as “What's the mean household income for the whole U.S.?”; or “This report said 75% of all gift cards go unused; is that really true?” (These two particular analyses made possible by the Central Limit Theorem are called *confidence intervals* and *hypothesis tests*, respectively, and are described in **Chapters 13** and **14**, respectively.)

The Central Limit Theorem (*CLT* for short) basically says that for non-normal data, your sample mean has an approximate normal distribution, no matter what the distribution of the original data looks like (as long as your sample size was large enough). And it doesn't just apply to the sample mean; the CLT is also true for other sample statistics, such as the sample proportion (see **Chapters 13** and **14**). Because statisticians know so much about the normal distribution (see the preceding section), these analyses are much easier. See **Chapter 11** for more on the Central Limit Theorem, known by statisticians as the “Crown jewel in the field of all statistics.” (Should you even bother to tell them to get a life?)

z-values



If a data set has a normal distribution, and you standardize all the data to obtain standard scores, those standard scores are called *z*-values. All *z*-values have what is known as a standard normal distribution (or *Z*-distribution). The *standard normal distribution* is a special normal distribution with a mean equal to 0 and a standard deviation equal to 1.

The standard normal distribution is useful for examining the data and determining statistics like percentiles, or the percentage of the data falling between two values. So if researchers determine that the data have a normal distribution, they usually first standardize the data (by converting each data point into a *z*-value) and then use the standard normal distribution to explore and discuss the data in more detail. See **Chapter 9** for more details on *z*-values.

Experiments

An *experiment* is a study that imposes a treatment (or control) to the subjects (participants), controls their environment (for example, restricting their diets, giving them certain dosage levels of a drug or placebo, or asking them to stay awake for a prescribed period of time), and records the responses. The purpose of most experiments is to pinpoint a cause-and-effect relationship between two factors (such as alcohol consumption and impaired vision; or dosage level of a drug and intensity of side effects). Here are some typical questions that experiments try to answer:

- Does taking zinc help reduce the duration of a cold? Some studies show that it does.
- Does the shape and position of your pillow affect how well you sleep at night? The Emory Spine Center in Atlanta says yes.
- Does shoe heel height affect foot comfort? A study done at UCLA says up to one-inch heels are better than flat soles.

In this section, I discuss some additional definitions of words that you may hear when someone is talking about experiments. **Chapter 17** is entirely dedicated to the subject. For now, just concentrate on basic experiment lingo.

Treatment group versus control group

Most experiments try to determine whether some type of experimental treatment (or important factor) has a significant effect on an outcome. For example, does zinc help to reduce the length of a cold? Subjects who are chosen to participate in the experiment are typically divided into two groups: a treatment group and a control group. (More than one treatment group is possible.)

- The *treatment group* consists of participants who receive the experimental treatment whose effect is being studied (in this case, zinc tablets).
- The *control group* consists of participants who do not receive the experimental treatment being studied. Instead, they get a placebo (a fake treatment; for example, a sugar pill); a standard, nonexperimental treatment (such as vitamin C, in the zinc study); or no treatment at all, depending on the situation.

In the end, the responses of those in the treatment group are compared with the responses from the control group to look for differences that are statistically significant (unlikely to have occurred just by chance).

Placebo

A *placebo* is a fake treatment, such as a sugar pill. Placebos are given to the control group to account for a psychological phenomenon called the *placebo effect*, in which patients receiving a fake treatment still report having a response, as if it were the real treatment. For example, after taking a sugar pill a patient experiencing the placebo effect might say, “Yes, I feel better already,” or “Wow, I *am* starting to feel a bit dizzy.” By measuring the placebo effect in the control group, you can tease out what portion of the reports from the treatment group were real and what portion were likely due to the placebo effect. (Experimenters assume that the placebo effect affects both the treatment and control groups.)

Blind and double-blind

A *blind experiment* is one in which the subjects who are participating in the study are not aware of whether they're in the treatment group or the control group. In the zinc example, the vitamin C tablets and the zinc tablets would be made to look exactly alike and patients would not be told which type of pill they were taking. A blind experiment attempts to control for bias on the part of the participants.

A *double-blind experiment* controls for potential bias on the part of both the patients *and* the researchers. Neither the patients nor the researchers collecting the data know which subjects received the treatment and which didn't. So who does know what's going on as far as who gets what treatment? Typically a third party (someone not otherwise involved in the experiment) puts together the pieces independently. A double-blind study is best, because even though researchers may claim to be unbiased, they often have a special interest in the results — otherwise they wouldn't be doing the study!

Surveys (Polls)

A *survey* (more commonly known as a *poll*) is a questionnaire; it's most often used to gather people's opinions along with some relevant demographic information. Because so many policymakers, marketers, and others want to "get at the pulse of the American public" and find out what the average American is thinking and feeling, many people now feel that they cannot escape the barrage of requests to take part in surveys and polls. In fact, you've probably received many requests to participate in surveys, and you may even have become numb to them, simply throwing away surveys received in the mail or saying "no" when asked to participate in a telephone survey.

If done properly, a good survey can really be informative. People use surveys to find out what TV programs Americans (and others) like, how consumers feel about Internet shopping, and whether the United States should allow someone under 35 to become president. Surveys are used by companies to assess the level of satisfaction their customers feel, to find out what products their customers want, and to determine who is buying their products. TV stations use surveys to get instant reactions to news stories and events, and movie producers use them to determine how to end their movies.

However, if I had to choose one word to assess the general state of surveys in the media today, I'd say it's *quantity* rather than *quality.* In other words, you'll find no shortage of bad surveys. But in this book you find no shortage of good tips and information for analyzing, critiquing, and understanding survey results, and for designing your own surveys to do the job right. (To take off with surveys, head to **Chapter 16**.)

Margin of error

You've probably heard or seen results like this: “This survey had a margin of error of plus or minus 3 percentage points.” What does this mean? Most surveys (except a census) are based on information collected from a sample of individuals, not the entire population. A certain amount of error is bound to occur — not in the sense of calculation error (although there may be some of that, too) but in the sense of *sampling error,* which is the error that occurs simply because the researchers aren't asking everyone. The *margin of error* is supposed to measure the maximum amount by which the sample results are expected to differ from those of the actual population. Because the results of most survey questions can be reported in terms of percentages, the margin of error most often appears as a percentage, as well.

How do you interpret a margin of error? Suppose you know that 51% of people sampled say that they plan to vote for Ms. Calculation in the upcoming election. Now, projecting these results to the whole voting population, you would have to add and subtract the margin of error and give a range of possible results in order to have sufficient confidence that you're bridging the gap between your sample and the population. Supposing a margin of error of plus or minus 3 percentage points, you would be pretty confident that between 48% (51% – 3%) and 54% (51% + 3%) of the population will vote for Ms. Calculation in the election, based on the sample results. In this case, Ms. Calculation may get slightly more or slightly less than the majority of votes and could either win or lose the election. This has become a familiar situation in recent years when the media want to report results on Election Night, but based on early exit polling results, the election is "too close to call." For more on the margin of error, see Chapter 12.

The margin of error measures accuracy; it does not measure the amount of bias that may be present (find a discussion of bias earlier in this chapter). Results that look numerically scientific and precise don't mean anything if they were collected in a biased way.

Confidence interval

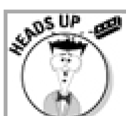
One of the biggest uses of statistics is to estimate a population parameter using a sample statistic. In other words, use a number that summarizes a sample to help you guesstimate the corresponding number that summarizes the whole population (the definitions of parameter and statistic appear earlier in this chapter). You're looking for a population parameter in each of the following questions:

- What's the average household income in America? (Population = all households in America; parameter = average household income.)
- What percentage of all Americans watched the Academy Awards this year? (Population = all Americans; parameter = percentage who watched the Academy Awards this year.)
- What's the average life expectancy of a baby born today? (Population = all babies born today; parameter = average life expectancy.)

- How effective is this new drug on adults with Alzheimer's? (Population = all people who have Alzheimer's; parameter = percentage of these people who see improvement when taking this drug.)

It's not possible to find these parameters exactly; they each require an estimate based on a sample. You start by taking a random sample from a population (say a sample of 1,000 households in America) and then finding the corresponding statistic from that sample (the sample's mean household income). Because you know that sample results vary from sample to sample, you need to add a “plus or minus something” to your sample results if you want to draw conclusions about the whole population (all households in America). This “plus or minus” that you add to your sample statistic in order to estimate a parameter is the margin of error.

When you take a sample statistic (such as the sample mean or sample percentage) and add/subtract a margin of error, you come up with what statisticians call a *confidence interval.* A confidence interval represents a range of likely values for the population parameter, based on your sample statistic. For example, suppose the average time it takes you to drive to work each day is 35 minutes, with a margin of error of plus or minus 5 minutes. You estimate that the average time to work would be anywhere from 30 to 40 minutes. This estimate is a confidence interval.



Some confidence intervals are wider than others (and wide isn't good, because it equals less accuracy). Several factors influence the width of a confidence interval, such as sample size, the amount of variability in the population being studied, and how confident you want to be in your results. (Most researchers are happy with a 95% level of confidence in their results.) For more on factors that influence confidence intervals, as well as instructions for calculating and interpreting confidence intervals, see Chapter 13.

Hypothesis testing

Hypothesis test is a term you probably haven't run across in your everyday dealings with numbers and statistics. But I guarantee that hypothesis tests have been a big part of your life and your workplace, simply because of the major role they play in industry, medicine, agriculture, government, and a host of other areas. Any time you hear someone talking about their study showing a "statistically significant result," you're encountering a hypothesis test. (A statistically significant result is one that is unlikely to have occurred by chance. See **Chapter 14** for the full scoop.)

Basically, a *hypothesis test* is a statistical procedure in which data are collected from a sample and measured against a claim about a population parameter. For example, if a pizza delivery chain claims to deliver all pizzas within 30 minutes of placing the order, on average, you could test whether this claim is true by collecting a random sample of delivery times over a certain period and looking at the average delivery time for that sample. To make your decision, you must also take into account the amount by which your sample results can change from sample to sample (which is related to the margin of error).

> HEADS UP
>
> Because your decision is based on a sample and not the entire population, a hypothesis test can sometimes lead you to the wrong conclusion. However, statistics are all you have, and if done properly, they can give you a good chance of being correct. For more on the basics of hypothesis testing, see **Chapter 14**.

A variety of hypothesis tests are done in scientific research, including *t*-tests (comparing two population means), paired *t*-tests (looking at before/after data), and tests of claims made about proportions or means for one or more populations. For specifics on these hypothesis tests, see **Chapter 15**.

p-values

Hypothesis tests are used to test the validity of a claim that is made about a population. This claim that's on trial, in essence, is called the *null hypothesis*. The *alternative hypothesis* is the one you would believe if the null hypothesis is concluded to be untrue. The evidence in the trial is your data and the statistics that go along with it. All hypothesis tests ultimately use a *p*-value to weigh the strength of the evidence (what the data are telling you about the population). The *p*-value is a number between 0 and 1 and interpreted in the following way:

- A small *p*-value (typically ≤ 0.05) indicates strong evidence against the null hypothesis, so you reject it.
- A large *p*-value (> 0.05) indicates weak evidence against the null hypothesis, so you fail to reject it.
- *p*-values very close to the cutoff (0.05) are considered to be marginal (could go either way). Always report the *p*-value so your readers can draw their own conclusions.

For example, suppose a pizza place claims their delivery times are 30 minutes or less on average but you think it's more than that. You conduct a hypothesis test because you believe the null hypothesis, H_o, that the mean delivery time is 30 minutes max, is incorrect. Your alternative hypothesis (H_a) is that the mean time is greater than 30 minutes. You randomly sample some delivery times and run the data through the hypothesis test, and your *p*-value turns out to be 0.001, which is much less than 0.05. You conclude that the pizza place is wrong; their delivery times are in fact more than 30 minutes on average, and you want to know what they're gonna do about it! (Of course you could be wrong by having sampled an unusually high number of late pizzas just by chance; but whose side am I on?) For more on *p*-values, head to **Chapter 14**.

Statistical significance

Whenever data are collected to perform a hypothesis test, the researcher is typically looking for something out of the ordinary. (Unfortunately, research that simply confirms something that was already well known doesn't make headlines.) Statisticians measure the amount by which a result is out of the ordinary using hypothesis tests (see **Chapter 14**). They define a *statistically significant* result as a result with a very small probability of happening just by chance, and provide a number called a *p*-value to reflect that probability (see the previous section on *p*-values).

For example, if a drug is found to be more effective at treating breast cancer than the current treatment is, researchers say that the new drug shows a statistically significant improvement in the survival rate of patients with breast cancer. That means that based on their data, the difference in the overall results from patients on the new drug compared to those using the old treatment is so big that it would be hard to say it was just a coincidence. However, proceed with caution: You can't say that these results necessarily apply to each individual or to each individual in the same way. For full details on statistical significance, see **Chapter 14**.

When you hear that a study's results are statistically significant, don't automatically assume that the study's results are important. *Statistically significant* means the results were unusual, but unusual doesn't always mean important. For example, would you be excited to learn that cats move their tails more often when lying in the sun than when lying in the shade, and that those results are statistically significant? This result may not even be important to the cat, much less anyone else!

Sometimes statisticians make the wrong conclusion about the null hypothesis because a sample doesn't represent the population (just by chance). For example, a positive effect that's experienced by a sample of people who took the new treatment may have just been a fluke; or in the example in the preceding section, the pizza company really was delivering those pizzas on time and you just got an unlucky sample of slow ones. However, the beauty of research is that as soon as someone gives a press release saying that she found something significant, the rush is on to try to replicate the results, and if the results can't be replicated, this probably means that the original results were wrong for some reason (including being wrong just by chance). Unfortunately, a press release announcing a "major breakthrough" tends to get a lot of play in the media, but follow-up studies refuting those results often don't show up on the front page.

One statistically significant result shouldn't lead to quick decisions on anyone's part. In science, what most often counts is not a single remarkable study, but a body of evidence that is built up over time, along with a variety of well-designed follow-up studies. Take any major breakthroughs you hear about with a grain of salt and wait until the follow-up work has been done before using the information from a single study to make important decisions in your life. The results may not be replicable, and even if they are, you can't know if they necessarily apply to each individual.

Correlation versus causation

Of all of the misunderstood statistical issues, the one that's perhaps the most problematic is the misuse of the concepts of correlation and causation.

Correlation, as a statistical term, is the extent to which two numerical variables have a linear relationship (that is, a relationship that increases or decreases at a constant rate). Following are three examples of correlated variables:

- The number of times a cricket chirps per second is strongly related to temperature; when it's cold outside, they chirp less frequently, and as the temperature warms up, they chirp at a steadily increasing rate. In statistical terms, you say number of cricket chirps and temperature have a strong positive correlation.
- The number of crimes (per capita) has often been found to be related to the number of police officers in a given area. When more police of-

ficers patrol the area, crime tends to be lower, and when fewer police officers are present in the same area, crime tends to be higher. In statistical terms we say the number of police officers and the number of crimes have a strong negative correlation.

- The consumption of ice cream (pints per person) and the number of murders in New York are positively correlated. That is, as the amount of ice cream sold per person increases, the number of murders increases. Strange but true!

But correlation as a statistic isn't able to explain *why* or *how* the relationship between two variables, x and y, exists; only that it does exist.

Causation goes a step further than correlation, stating that a change in the value of the x variable *will cause* a change in the value of the y variable. Too many times in research, in the media, or in the public consumption of statistical results, that leap is made when it shouldn't be. For instance, you can't claim that consumption of ice cream *causes* an increase in murder rates just because they are correlated. In fact, the study showed that temperature was positively correlated with both ice cream sales and murders. (For more on correlation and causation, see **Chapter 18**.) When can you make the causation leap? The most compelling case is when a well-designed experiment is conducted that rules out other factors that could be related to the outcomes (see **Chapter 17** for information on experiments showing cause-and-effect).

You may find yourself wanting to jump to a cause-and-effect relationship when a correlation is found; researchers, the media, and the general public do it all the time. However, before making any conclusions, look at how the data were collected and/or wait to see if other researchers are able to replicate the results (the first thing they try to do after someone else's "groundbreaking result" hits the airwaves).