STATISTICAL ANALYSIS:

Microsoft® Excel® 2013

que®

Conrad Carlberg

Statistical Analysis: Microsoft® Excel® 2013

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Contents at a Glance

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About the Author

Conrad Carlberg started writing about Excel, and its use in quantitative analysis, before workbooks had worksheets. As a graduate student, he had the great good fortune to learn something about statistics from the wonderfully gifted Gene Glass. He remembers much of that and has learned more since. This is a book he has wanted to write for years, and he is grateful for the opportunity.

Dedication

For Toni, who has been putting up with this sort of thing for 17 years now, with all my love.

Acknowledgments

I'd like to thank Loretta Yates, who guided this book's overall progress, and who treats my self-imposed crises with an unexpected sort of pragmatic optimism. Michael Turner's technical edit was just right, and it was a delight to see how, at the stats lab anyway, the more things change...well, you know. Keith Cline kept the prose on track, despite my occasional howls of protest, with his copy edit. And in the end, Elaine Wiley somehow managed to get the whole thing put together. My thanks to each of you.

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Introduction

There was no reason I shouldn't have already written a book about statistical analysis using Excel. But I didn't, although I knew I wanted to. Finally, I talked Pearson into letting me write it for them.

Be careful what you ask for. It's been a struggle, but at last I've got it out of my system, and I want to start by talking here about the reasons for some of the choices I made in writing this book.

Using Excel for Statistical Analysis

The problem is that it's a huge amount of material to cover in a book that's supposed to be only 400 to 500 pages. The text used in the first statistics course I took was about 600 pages, and it was purely statistics, no Excel. In 2001, I co-authored a book about Excel (no statistics) that ran to 750 pages. To shoehorn statistics *and* Excel into 400 pages or so takes some picking and choosing.

Furthermore, I did not want this book to be an expanded Help document, like one or two others I've seen. Instead, I take an approach that seemed to work well in an earlier book of mine, *Business Analysis with Excel*. The idea in both that book and this one is to identify a topic in statistical (or business) analysis; discuss the topic's rationale, its procedures, and associated issues; and only then get into how it's carried out in Excel.

You shouldn't expect to find discussions of, say, the Weibull function or the lognormal distribution here. They have their uses, and Excel provides them as statistical functions, but my picking and choosing forced me to ignore them—at my peril, probably—and to use the space saved for material on more bread-and-butter topics such as statistical regression.

About You and About Excel

How much background in statistics do you need to get value from this book? My intention is that you need none. The book starts out with a discussion of different ways to measure things—by categories, such as models of cars, by ranks, such as first place through tenth, by numbers, such as degrees Fahrenheit—and how Excel handles those methods of measurement in its worksheets and its charts.

This book moves on to basic statistics, such as averages and ranges, and only then to intermediate statistical methods such as t-tests, multiple regression, and the analysis of covariance. The material assumes knowledge of nothing more complex than how to calculate an average. You do not need to have taken courses in statistics to use this book.

As to Excel itself, it matters little whether you're using Excel 97, Excel 2013, or any version in between. Very little statistical functionality changed between Excel 97 and Excel 2003. The few changes that did occur had to do primarily with how functions behaved when the user stress-tested them using extreme values or in very unlikely situations.

The Ribbon showed up in Excel 2007 and is still with us in Excel 2013. But nearly all statistical analysis in Excel takes place in worksheet functions—very little is menu driven—and there was almost no change to the function list, function names, or their arguments between Excel 97 and Excel 2007. The Ribbon does introduce a few differences, such as how to get a trendline into a chart. This book discusses the differences in the steps you take using the traditional menu structure and the steps you take using the Ribbon.

In Excel 2010, several apparently new statistical functions appeared, but the differences were more apparent than real. For example, through Excel 2007, the two functions that calculate standard deviations are STDEV() and STDEVP(). If you are working with a sample of values, you should use STDEV(), but if you happen to be working with a full population, you should use STDEVP(). Of course, the *P* stands for *population*.

Both STDEV() and STDEVP() remain in Excel 2010 and 2013, but they are termed *compatibility functions*. It appears that they may be phased out in some future release. Excel 2010 added what it calls *consistency functions*, two of which are STDEV.S() and STDEV.P(). Note that a period has been added in each function's name. The period is followed by a letter that, for consistency, indicates whether the function should be used with a sample of values or a population of values.

Other consistency functions were added to Excel 2010, and the functions they are intended to replace are still supported in Excel 2013. There are a few substantive differences between the compatibility version and the consistency version of some functions, and this book discusses those differences and how best to use each version.

Clearing Up the Terms

Terminology poses another problem, both in Excel and in the field of statistics (and, it turns out, in the areas where the two overlap). For example, it's normal to use the word *alpha* in a statistical context to mean the probability that you will decide that there's a true difference

between the means of two groups when there really isn't. But Excel extends *alpha* to usages that are related but much less standard, such as the probability of getting some number of heads from flipping a fair coin. It's not wrong to do so. It's just unusual, and therefore it's an unnecessary hurdle to understanding the concepts.

The vocabulary of statistics itself is full of names that mean very different things in slightly different contexts. The word *beta*, for example, can mean the probability of deciding that a true difference does *not* exist, when it does. It can also mean a coefficient in a regression equation (for which Excel's documentation unfortunately uses the letter *m*), and it's also the name of a distribution that is a close relative of the binomial distribution. None of that is due to Excel. It's due to having more concepts than there are letters in the Greek alphabet.

You can see the potential for confusion. It gets worse when you hook Excel's terminology up with that of statistics. For example, in Excel the word *cell* means a rectangle on a worksheet, the intersection of a row and a column. In statistics, particularly the analysis of variance, *cell* usually means a group in a factorial design: If an experiment tests the joint effects of sex and a new medication, one cell might consist of men who receive a placebo, and another might consist of women who receive the medication being assessed. Unfortunately, you can't depend on seeing "cell" where you might expect it: *within cell error* is called *residual error* in the context of regression analysis.

So this book presents you with some terms you might otherwise find redundant: I use *design cell* for analysis contexts and *worksheet cell* when referring to the software context where there's any possibility of confusion about which I mean.

For consistency, though, I try always to use *alpha* rather than *Type I error* or *statistical significance*. In general, I use just one term for a given concept throughout. I intend to complain about it when the possibility of confusion exists: when *mean square* doesn't mean *mean square*, you ought to know about it.

Making Things Easier

If you're just starting to study statistical analysis, your timing's much better than mine was. You have avoided some of the obstacles to understanding statistics that once—as recently as the 1980s—stood in the way. I'll mention those obstacles once or twice more in this book, partly to vent my spleen but also to stress how much better Excel has made things.

Suppose that 25 years ago you were calculating something as basic as the standard deviation of twenty numbers. You had no access to a computer. Or, if there was one around, it was a mainframe or a mini, and whoever owned it had more important uses for it than to support a Psychology 101 assignment.

So you trudged down to the Psych building's basement, where there was a room filled with gray metal desks with adding machines on them. Some of the adding machines might even have been plugged into a source of electricity. You entered your twenty numbers very carefully because the adding machines did not come with Undo buttons or Ctrl+Z. The

electricity-enabled machines were in demand because they had a memory function that allowed you to enter a number, square it, and add the result to what was already in the memory.

It could take half an hour to calculate the standard deviation of twenty numbers. It was all incredibly tedious and it distracted you from the main point, which was the concept of a standard deviation and the reason you wanted to quantify it.

Of course, 25 years ago our teachers were telling us how lucky we were to have adding machines instead of having to use paper, pencil, and a box of erasers.

Things are different in 2013, and truth be told, they have been changing since the mid 1980s when applications such as Lotus 1-2-3 and Microsoft Excel started to find their way onto personal computers' floppy disks. Now, all you have to do is enter the numbers into a worksheet—or maybe not even that, if you downloaded them from a server somewhere. Then, type **=STDEV.S(** and drag across the cells with the numbers before you press Enter. It takes half a minute at most, not half an hour at least.

Several statistics have relatively simple *definitional* formulas. The definitional formula tends to be straightforward and therefore gives you actual insight into what the statistic means. But those same definitional formulas often turn out to be difficult to manage in practice if you're using paper and pencil, or even an adding machine or hand calculator. Rounding errors occur and compound one another.

So statisticians developed *computational* formulas. These are mathematically equivalent to the definitional formulas, but are much better suited to manual calculations. Although it's nice to have computational formulas that ease the arithmetic, those formulas make you take your eye off the ball. You're so involved with accumulating the sum of the squared values that you forget that your purpose is to understand how values vary around their average.

That's one primary reason that an application such as Excel, or an application specifically and solely designed for statistical analysis, is so helpful. It takes the drudgery of the arithmetic off your hands and frees you to think about what the numbers actually mean.

Statistics is conceptual. It's not just arithmetic. And it shouldn't be taught as though it is.

The Wrong Box?

But should you even be using Excel to do statistical calculations? After all, people have been moaning about inadequacies in Excel's statistical functions for twenty years. The Excel forum on CompuServe had plenty of complaints about this issue, as did the Usenet newsgroups. As I write this introduction, I can switch from Word to Firefox and see that some people are still complaining on Wikipedia talk pages, and others contribute angry screeds to publications such as *Computational Statistics & Data Analysis*, which I believe are there as a reminder to us all of the importance of taking our prescription medication.

I have sometimes found myself as upset about problems with Excel's statistical functions as anyone. And it's true that Excel has had, and in some cases continues to have, problems with the algorithms it uses to manage certain functions such as the inverse of the F distribution.

But most of the complaints that are voiced fall into one of two categories: those that are based on misunderstandings about either Excel or statistical analysis, and those that are based on complaints that Excel isn't accurate enough.

If you read this book, you'll be able to avoid those kinds of misunderstandings. As to inaccuracies in Excel results, let's look a little more closely at that. The complaints are typically along these lines:

> I enter into an Excel worksheet two different formulas that should return the same result. Simple algebraic rearrangement of the equations proves that. But then I find that Excel calculates two different results.

Well, for the data the user supplied, the results differ at the fifteenth decimal place, so Excel's results disagree with one another by approximately five in 111 trillion.

Or this:

> I tried to get the inverse of the F distribution using the formula FINV(0.025,4198986,1025419), but I got an unexpected result. Is there a bug in FINV?

No. Once upon a time, FINV returned the #NUM! error value for those arguments, but no longer. However, that's not the point. With so many degrees of freedom (over four million and one million, respectively), the person who asked the question was effectively dealing with populations, not samples. To use that sort of inferential technique with so many degrees of freedom is a striking instance of "unclear on the concept."

Would it be better if Excel's math were more accurate—or at least more internally consistent? Sure. But even the finger-waggers admit that Excel's statistical functions are acceptable at least, as the following comment shows.

> They can rarely be relied on for more than four figures, and then only for $0.001 < p < 0.999$, plenty good for routine hypothesis testing.

Now look. Chapter 6, "Telling the Truth with Statistics," goes into this issue further, but the point deserves a better soapbox, closer to the start of the book. Regardless of the accuracy of a statement such as "They can rarely be relied on for more than four figures," it's pointless to make it. It's irrelevant whether a finding is "statistically significant" at the 0.001 level instead of the 0.005 level, and to worry about whether Excel can successfully distinguish between the two findings is to miss the context.

There are many possible explanations for a research outcome other than the one you're seeking: a real and replicable treatment effect. Random chance is only one of these. It's one that gets a lot of attention because we attach the word *significance* to our tests to rule out chance, but it's not more important than other possible explanations you should be concerned about when you design your study. It's the design of your study, and how well you implement it, that allows you to rule out alternative explanations such as selection bias and disproportionate dropout rates. Those explanations—bias and dropout rates—are just two

examples of possible explanations for an apparent treatment effect: explanations that might make a treatment look like it had an effect when it actually didn't.

Even the strongest design doesn't enable you to rule out a chance outcome. But if the design of your study is sound, and you obtained what looks like a meaningful result, you'll want to control chance's role as an alternative explanation of the result. So, you certainly want to run your data through the appropriate statistical test, which *does* help you control the effect of chance.

If you get a result that doesn't clearly rule out chance—or rule it in—you're much better off to run the experiment again than to take a position based on a borderline outcome. At the very least, it's a better use of your time and resources than to worry in print about whether Excel's F tests are accurate to the fifth decimal place.

Wagging the Dog

And ask yourself this: Once you reach the point of planning the statistical test, are you going to reject your findings if they might come about by chance five times in 1,000? Is that too loose a criterion? What about just one time in 1,000? How many angels are on that pinhead anyway?

If you're concerned that Excel won't return the correct distinction between one and five chances in 1,000 that the result of your study is due to chance, you allow what's really an irrelevancy to dictate how, and using what calibrations, you're going to conduct your statistical analysis. It's pointless to worry about whether a test is accurate to one point in a thousand or two in a thousand. Your decision rules for risking a chance finding should be based on more substantive grounds.

Chapter 9, "Testing Differences Between Means: Further Issues," goes into the matter in greater detail, but a quick summary of the issue is that you should let the risk of making the wrong decision be guided by the costs of a bad decision and the benefits of a good one—not by which criterion appears to be the more selective.

What's in This Book

You'll find that there are two broad types of statistics. I'm not talking about that scurrilous line about lies, damned lies and statistics—both its source and its applicability are disputed. I'm talking about *descriptive* statistics and *inferential* statistics.

No matter if you've never studied statistics before this, you're already familiar with concepts such as averages and ranges. These are descriptive statistics. They describe identified groups: The average age of the members is 42 years; the range of the weights is 105 pounds; the median price of the houses is $270,000. A variety of other sorts of descriptive statistics exists, such as standard deviations, correlations, and skewness. The first five chapters of this book take a fairly close look at descriptive statistics, and you might find that they have some aspects that you haven't considered before.

Descriptive statistics provides you with insight into the characteristics of a restricted set of beings or objects. They can be interesting and useful, and they have some properties that aren't at all well known. But you don't get a better understanding of the world from descriptive statistics. For that, it helps to have a handle on inferential statistics. That sort of analysis is based on descriptive statistics, but you are asking and perhaps answering broader questions. Questions such as this:

> The average systolic blood pressure in this group of patients is 135. How large a margin of error must I report so that if I took another 99 samples, 95 of the 100 would capture the true population mean within margins calculated similarly?

Inferential statistics enables you to make inferences about a population based on samples from that population. As such, inferential statistics broadens the horizons considerably.

Therefore, I have prepared two new chapters on inferential statistics for this 2013 edition of *Statistical Analysis: Microsoft Excel*. Chapter 12, "Experimental Design and ANOVA," explores the effects of fixed versus random factors on the nature of your F tests. It also examines crossed and nested factors in factorial designs, and how a factor's status in a factorial design affects the mean square you should use in the F ratio's denominator.

I have also expanded coverage of the topic of statistical power, and this edition devotes an entire chapter to it. Chapter 13, "Statistical Power," discusses how to use Excel's worksheet functions to generate F distributions with different noncentrality parameters. (Excel's native F() functions all assume a noncentrality parameter of zero.) You can use this capability to calculate the power of an F test without resorting to 80-year-old charts.

But you have to take on some assumptions about your samples, and about the populations that your samples represent, to make the sort of generalization that inferential statistics makes available to you. From Chapter 6 through the end of this book, you'll find discussions of the issues involved, along with examples of how those issues work out in practice. And, by the way, how you work them out using Microsoft Excel.

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About Variables and Values

1

IN THIS CHAPTER

Variables and Values

It must seem odd to start a book about statistical analysis using Excel with a discussion of ordinary, everyday notions such as variables and values. But variables and values, along with scales of measurement (covered in the next section), are at the heart of how you represent data in Excel. And how you choose to represent data in Excel has implications for how you run the numbers.

With your data laid out properly, you can easily and efficiently combine records into groups, pull groups of records apart to examine them more closely, and create charts that give you insight into what the raw numbers are really doing. When you put the statistics into tables and charts, you begin to understand what the numbers have to say.

When you lay out your data without considering how you will use the data later, it becomes much more difficult to do any sort of analysis. Excel is generally very flexible about how and where you put the data you're interested in, but when it comes to preparing a formal analysis, you want to follow some guidelines. In fact, some of Excel's features don't work at all if your data doesn't conform to what Excel expects. To illustrate one useful arrangement, you won't go wrong if you put different variables in different columns and different records in different rows.

A *variable* is an attribute or property that describes a person or a thing. Age is a variable that describes you. It describes all humans, all living organisms, all objects—anything that exists for some period of time. Surname is a variable, and so are Weight in Pounds and Brand of Car. Database jargon often

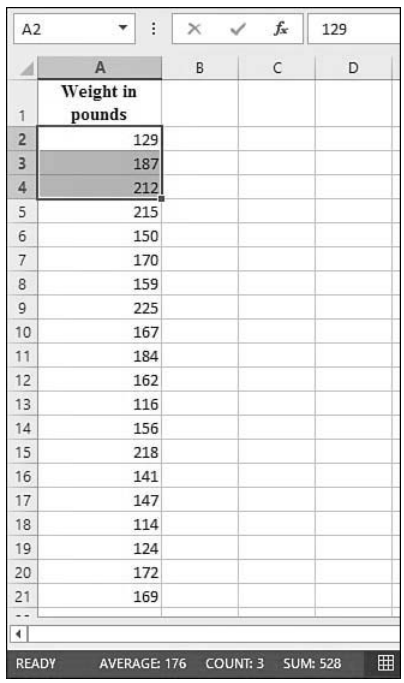
refers to variables as *fields*, and some Excel tools use that terminology, but in statistics you generally use the term *variable*.

Variables have *values*. The number 20 is a value of the variable Age, the name Smith is a value of the variable Surname, 130 is a value of the variable Weight in Pounds, and Ford is a value of the variable Brand of Car. Values vary from person to person and from object to object—hence the term *variable*.

Recording Data in Lists

When you run a statistical analysis, your purpose is generally to summarize a group of numeric values that belong to the same variable. For example, you might have obtained and recorded the weight in pounds for 20 people, as shown in Figure 1.1.

Figure 1.1
This layout is ideal for analyzing data in Excel.



The way the data is arranged in Figure 1.1 is what Excel calls a *list*—a variable that occupies a column, records that each occupy a different row, and values in the cells where the records' rows intersect the variable's column. (The *record* is the individual being, object, location—whatever—that the list brings together with other, similar records. If the list in Figure 1.1 is made up of students in a classroom, each student constitutes a record.)

A list always has a *header*, usually the name of the variable, at the top of the column. In Figure 1.1, the header is the label Weight in Pounds in cell A1.

> **NOTE** A *list* is an informal arrangement of headers and values on a worksheet. It's not a formal structure that has a name and properties, such as a chart or a pivot table. Excel 2007 through 2013 offer a formal structure called a *table* that acts much like a list, but has some bells and whistles that a list doesn't have. This book has more to say about tables in subsequent chapters.

There are some interesting questions that you can answer with a single-column list such as the one in Figure 1.1. You could select all the values and look at the status bar at the bottom of the Excel window to see summary information such as the average, the sum, and the count of the selected values. Those are just the quickest and simplest statistical analyses you might do with this basic single-column list.

> **TIP** You can turn the display of indicators such as simple statistics on and off. Right-click the status bar and select or deselect the items you want to show or hide. However, you won't see a statistic unless the current selection contains at least two values. The status bar of Figure 1.1 shows the average, count, and sum of the selected values. (The worksheet tabs have been suppressed to unclutter the figure.)

Again, this book has much more to say about the richer analyses of a single variable that are available in Excel. But first, suppose that you add a second variable, Sex, to the list in Figure 1.1.

You might get something like the two-column list in Figure 1.2. All the values for a particular record—here, a particular person—are found in the same row. So, in Figure 1.2, the person whose weight is 129 pounds is female (row 2), the person who weighs 187 pounds is male (row 3), and so on.

Using the list structure, you can easily do the simple analyses that appear in Figure 1.3, where you see a *pivot table* and a *pivot chart*. These are powerful tools and well suited to statistical analysis, but they're also very easy to use.

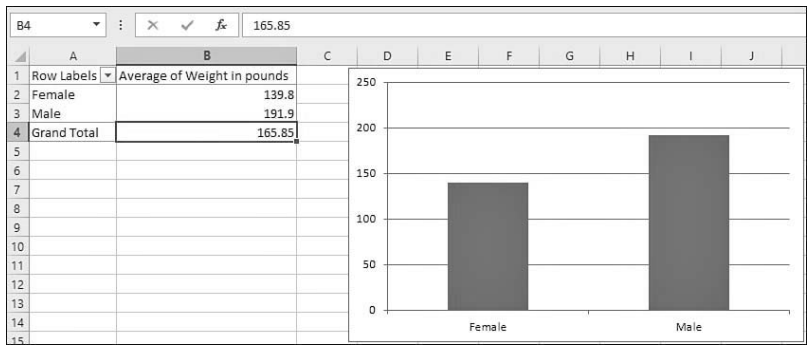
All that's needed for the pivot chart and pivot table in Figure 1.3 is the simple, informal, unglamorous list in Figure 1.2. But that list, and the fact that it keeps related values of weight and sex together in records, makes it possible to do the analyses shown in Figure 1.3. With the list in Figure 1.2, you're just a few clicks away from analyzing and charting average weight by sex.

> **NOTE** In Excel 2013, it's eleven clicks if you do it all yourself; you save a click if you start with the Recommended Pivot Tables button on the Ribbon's Insert tab. And if you select the full list or even just a subset of the records in the list (say, cells A4:B4) the Quick Analysis tool gets you a weight-by-sex pivot table in only three clicks.

Figure 1.2
The list structure helps you keep related values together.

	A	B	C	D	E
1	Weight in pounds	Sex			
2	129	Female			
3	187	Male			
4	212	Male			
5	215	Male			
6	150	Female			
7	170	Male			
8	159	Female			
9	225	Male			
10	167	Male			
11	184	Male			
12	162	Female			
13	116	Female			
14	156	Female			
15	218	Male			
16	141	Female			
17	147	Female			
18	114	Female			
19	124	Female			
20	172	Male			
21	169	Male			

Figure 1.3
The pivot table and pivot chart summarize the individual records shown in Figure 1.2.



	A	B
1	Row Labels	Average of Weight in pounds
2	Female	139.8
3	Male	191.9
4	Grand Total	165.85

Note that you cannot create a standard Excel column chart directly from the data as displayed in Figure 1.2. You first need to get the average weight of men and women, then associate those averages with the appropriate labels, and finally create the chart. A pivot chart is much quicker, more convenient, and more powerful.

Scales of Measurement

There's a difference in how weight and sex are measured and reported in Figure 1.2 that is fundamental to all statistical analysis—and to how you bring Excel's tools to bear on the numbers. The difference concerns scales of measurement.

Category Scales

In Figures 1.2 and 1.3, the variable Sex is measured using a *category* scale, often called a *nominal* scale. Different values in a category variable merely represent different groups, and there's nothing intrinsic to the categories that does anything but identify them. If you throw out the psychological and cultural connotations that we pile onto labels, there's nothing about Male and Female that would lead you to put one on the left and the other on the right in Figure 1.3's pivot chart, the way you'd put June to the left of July.

Another example: Suppose that you want to chart the annual sales of Ford, General Motors, and Toyota cars. There is no order that's necessarily implied by the names themselves: They're just categories. This is reflected in the way that Excel might chart that data (see Figure 1.4).

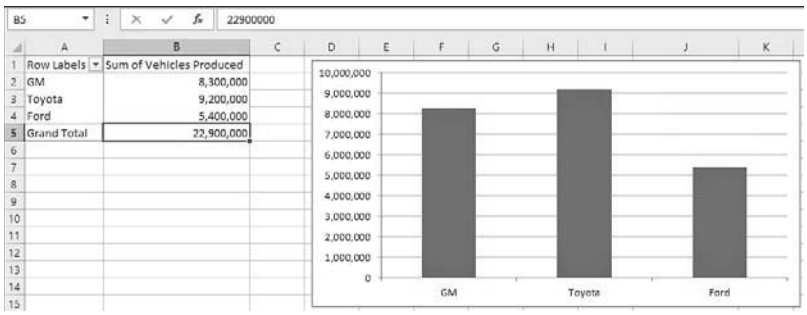


Figure 1.4
Excel's Column charts always show categories on the horizontal axis and numeric values on the vertical axis.

Notice these two aspects of the car manufacturer categories in Figure 1.4:

- Adjacent categories are equidistant from one another. No additional information is supplied by the distance of GM from Toyota, or Toyota from Ford.
- The chart conveys no information through the order in which the manufacturers appear on the horizontal axis. There's no implication that GM has less "car-ness" than Toyota, or Toyota less than Ford. You could arrange them in alphabetical order if you wanted, or in order of number of vehicles produced, but there's nothing intrinsic to the scale of manufacturers' names that suggests any rank order.

> **NOTE** This is one of many quirks of terminology in Excel. The name Ford is of course a value, but Excel prefers to call it a category and to reserve the term value for numeric values only.

In contrast, the vertical axis in the chart shown in Figure 1.4 is what Excel terms a *value* axis. It represents numeric values.

Notice in Figure 1.4 that a position on the vertical, value axis conveys real quantitative information: the more vehicles produced, the taller the column. The vertical and the

horizontal axes in Excel's Column charts differ in several ways, but the most crucial is that the vertical axis represents numeric quantities, while the horizontal axis simply indicates the existence of categories.

In general, Excel charts put the names of groups, categories, products, or any other designation on a category axis and the numeric value of each category on the value axis. But the category axis isn't always the horizontal axis (see Figure 1.5).

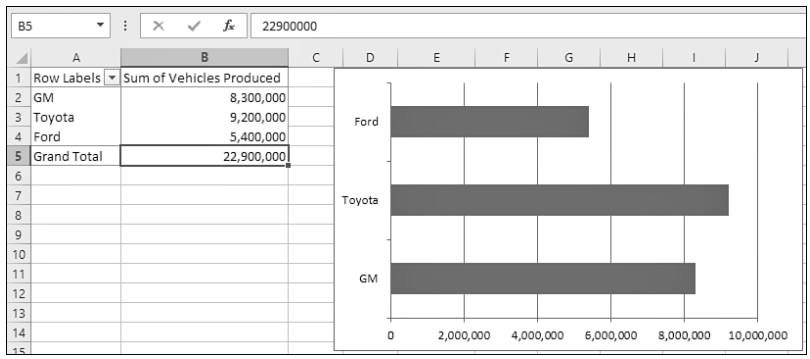


Figure 1.5
In contrast to Column charts, Excel's Bar charts always show categories on the vertical axis and numeric values on the horizontal axis.

The Bar chart provides precisely the same information as does the Column chart. It just rotates this information by 90 degrees, putting the categories on the vertical axis and the numeric values on the horizontal axis.

I'm not belaboring the issue of measurement scales just to make a point about Excel charts. When you do statistical analysis, you choose a technique based in large part on the sort of question you're asking. In turn, the way you ask your question depends in part on the scale of measurement you use for the variable you're interested in.

For example, if you're trying to investigate life expectancy in men and women, it's pretty basic to ask questions such as, "What is the average life span of males? of females?" You're examining two variables: sex and age. One of them is a category variable, and the other is a numeric variable. (As you'll see in later chapters, if you are generalizing from a sample of men and women to a population, the fact that you're working with a category variable and a numeric variable might steer you toward what's called a *t-test*.)

In Figures 1.3 through 1.5, you see that numeric summaries—average and sum—are compared across different groups. That sort of comparison forms one of the major types of statistical analysis. If you design your samples properly, you can then ask and answer questions such as these:

- Are men and women paid differently for comparable work? Compare the average salaries of men and women who hold similar jobs.
- Is a new medication more effective than a placebo at treating a particular disease? Compare, say, average blood pressure for those taking an alpha blocker with that of those taking a sugar pill.

- Do Republicans and Democrats have different attitudes toward a given political issue? Ask a random sample of people their party affiliation, and then ask them to rate a given issue or candidate on a numeric scale.

Notice that each of these questions can be answered by comparing a *numeric* variable across different *categories* of interest.

Numeric Scales

Although there is only one type of category scale, there are three types of numeric scales: ordinal, interval, and ratio. You can use the value axis of any Excel chart to represent any type of numeric scale, and you often find yourself analyzing one numeric variable, regardless of type, in terms of another variable. Briefly, the numeric scale types are as follows:

- Ordinal scales are often rankings, and tell you who finished first, second, third, and so on. These rankings tell you who came out ahead, but not how far ahead, and often you don't care about that. Suppose that in a qualifying race Jane ran 100 meters in 10.54 seconds, Mary in 10.83 seconds, and Ellen in 10.84 seconds. Because it's a preliminary heat, you might care only about their order of finish, and not about how fast each woman ran. Therefore, you might convert the time measurements to order of finish (1, 2 and 3), and then discard the timings themselves. Ordinal scales are sometimes used in a branch of statistics called *nonparametrics* but are used infrequently in the parametric analyses discussed in this book.
- Interval scales indicate differences in measures such as temperature and elapsed time. If the high temperature Fahrenheit on July 1 is 100 degrees, 101 degrees on July 2, and 102 degrees on July 3, you know that each day is one degree hotter than the previous day. So, an interval scale conveys more information than an ordinal scale. You know, from the order of finish on an ordinal scale, that in the qualifying race Jane ran faster than Mary and Mary ran faster than Ellen, but the rankings by themselves don't tell you how much faster. It takes elapsed time, an interval scale, to tell you that.
- Ratio scales are similar to interval scales, but they have a true zero point, one at which there is a complete absence of some quantity. The Celsius temperature scale has a zero point, but it doesn't indicate a complete absence of heat, just that water freezes there. Therefore, 10 degrees Celsius is not twice as warm as 5 degrees Celsius, so Celsius is not a ratio scale. Degrees kelvin does have a true zero point, one at which there is no molecular motion and therefore no heat. Kelvin is a ratio scale, and 100 degrees kelvin is twice as warm as 50 degrees kelvin. Other familiar ratio scales are height and weight.

It's worth noting that converting between interval (or ratio) and ordinal measurement is a one-way process. If you know how many seconds it takes three people to run 100 meters, you have measures on a ratio scale that you can convert to an ordinal scale—gold, silver, and bronze medals. You can't go the other way, though: If you know who won each medal, you're still in the dark as to whether the bronze medal was won with a time of 10 seconds or 10 minutes.

Telling an Interval Value from a Text Value

Excel has an astonishingly broad scope, and not only in statistical analysis. As much skill as has been built in to it, though, it can't quite read your mind. It doesn't know, for example, whether the 1, 2, and 3 you just entered into a worksheet's cells represent the number of teaspoons of olive oil you use in three different recipes or 1st, 2nd, and 3rd place in a political primary. In the first case, you meant to indicate liquid measures on an interval scale. In the second case, you meant to enter the first three places in an ordinal scale. But they both look alike to Excel.

> **NOTE** This is a case in which you must rely on your own knowledge of numeric scales because Excel can't tell whether you intend a number as a value on an ordinal or an interval scale. Ordinal and interval scales have different characteristics—for one thing, ordinal scales do not follow a normal distribution, a "bell curve." An ordinal variable has one instance of the value 1, one instance of 2, one instance of 3, and so on, so its distribution is flat instead of curved. Excel can't tell the difference between an ordinal and an interval variable, though, so you have to take control if you're to avoid using a statistical technique that's wrong for a given scale of measurement.

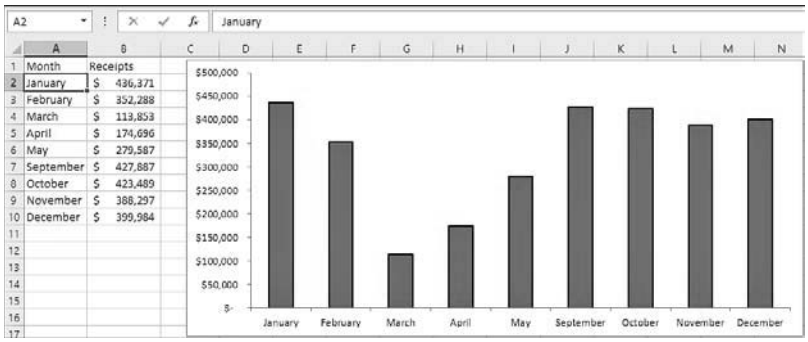
Text is a different matter. You might use the letters A, B and C to name three different groups, and in that case you're using text values on a nominal, category scale. You can also use numbers: 1, 2 and 3 to represent the same three groups. But if you use a number as a nominal value, it's a good idea to store it in the worksheet as a text value. For example, one way to store the number 2 as a text value in a worksheet cell is to precede it with an apostrophe: '2. (You'll see the apostrophe in the formula box but not in the cell.)

On a chart, Excel has some complicated decision rules that it uses to determine whether a number is only a number. (Excel 2013 has some additional tools to help you participate in the decision-making process, as you'll see later in this chapter). Some of those rules concern the type of chart you request. For example, if you request a Line chart, Excel treats numbers on the horizontal axis as though they were nominal, text values. But if instead you request an XY chart using the same data, Excel treats the numbers on the horizontal axis as values on an interval scale. You'll see more about this in the next section.

So, as disquieting as it may sound, a number in Excel may be treated as a number in one context and not in another. Excel's rules are pretty reasonable, though, and if you give them a little thought when you see their results, you'll find that they make good sense.

If Excel's rules don't do the job for you in a particular instance, you can provide an assist. Figure 1.6 shows an example.

Figure 1.6
You don't have data for all the months in the year.



Suppose that you run a business that operates only when public schools are in session, and you collect revenues during all months except June, July and August. Figure 1.6 shows that Excel interprets dates as categories—but only if they are entered as text, as they are in the figure. Notice these two aspects of the worksheet and chart in Figure 1.6:

- The dates are entered in the worksheet cells A2:A10 as text values. One way to tell is to look in the formula box, just to the right of the f_x symbol, where you see the text value January.
- Because they are text values, Excel has no way of knowing that you mean them to represent dates, and so it treats them as simple categories—just like it does for GM, Ford, and Toyota. Excel charts the dates-as-text accordingly, with equal distances between them: May is as far from April as it is from September.

Compare Figure 1.6 with Figure 1.7, where the dates are real numeric values, not simply text:

- You can see in the formula box that it's an actual date, not just the name of a month, in cell A2, and the same is true for the values in cells A3:A10.
- The Excel chart automatically responds to the type of values you have supplied in the worksheet. The program recognizes that the numbers entered represent monthly intervals and, although there is no data for June through August, the chart leaves places for where the data would appear if it were available. Because the horizontal axis now represents a numeric scale, not simple categories, it faithfully reflects the fact that in the calendar, May is four times as far from September as it is from April.

NOTE

A date value in Excel is just a numeric value: the number of days that have elapsed between the date in question and January 1, 1900. Excel assumes that when you enter a value such as 1/1/14, three numbers separated by two slashes, you intend it as a date. Excel treats it as a number but applies a date format such as mm/yy or mm/dd/yyyy to that number. You can demonstrate this for yourself by entering a legitimate date (not something such as 34/56/78) in a worksheet cell and then setting the cell's number format to Number with zero decimal places.

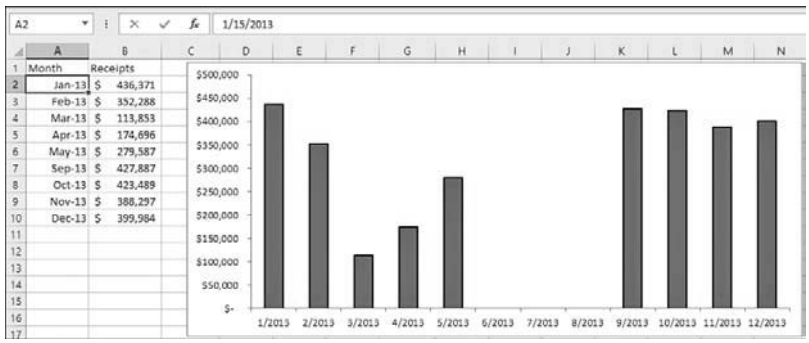


Figure 1.7
The horizontal axis accounts for the missing months.

Charting Numeric Variables in Excel

Several chart types in Excel lend themselves beautifully to the visual representation of numeric variables. This book relies heavily on charts of that type because most of us find statistical concepts that are difficult to grasp in the abstract are much clearer when they're illustrated in charts.

Charting Two Variables

Earlier this chapter briefly discussed two chart types that use a category variable on one axis and a numeric variable on the other: Column charts and Bar charts. There are other, similar types of charts, such as Line charts, that are useful for analyzing a numeric variable in terms of different categories—especially time categories such as months, quarters, and years. However, one particular type of Excel chart, called an *XY (Scatter)* chart, shows the relationship between exactly two numeric variables. Figure 1.8 provides an example.

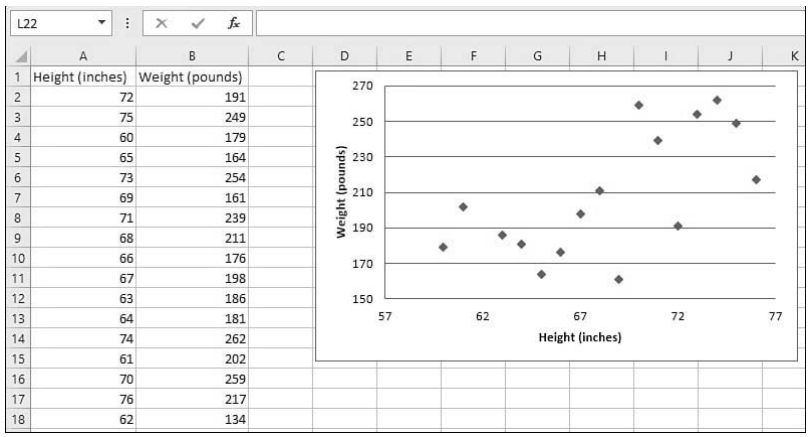


Figure 1.8
In an XY (Scatter) chart, both the horizontal and vertical axes are value axes.

NOTE

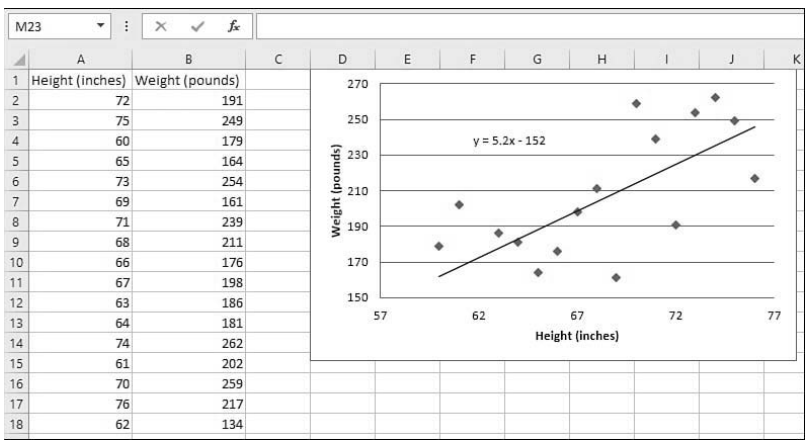
Since the 1990s at least, Excel has called this sort of chart an XY (Scatter) chart. In its 2007 version, Excel started referring to it as an XY chart in some places, as a Scatter chart in others, and as an XY (Scatter) chart in still others. For the most part, this book opts for the brevity of XY chart, and when you see that term you can be confident it's the same as an XY (Scatter) chart.

The markers in an XY chart show where a particular person or object falls on each of two numeric variables. The overall pattern of the markers can tell you quite a bit about the relationship between the variables, as expressed in each record's measurement. Chapter 4, "How Variables Move Jointly: Correlation," goes into considerable detail about this sort of relationship.

In Figure 1.8, for example, you can see the relationship between a person's height and weight: Generally, the greater the height, the greater the weight. The relationship between the two variables differs fundamentally from those discussed earlier in this chapter, where the emphasis is placed on the sum or average of a numeric variable, such as number of vehicles, according to the category of a nominal variable, such as make of car.

However, when you are interested in the way that two numeric variables are related, you are asking a different sort of question, and you use a different sort of statistical analysis. How are height and weight related, and how strong is the relationship? Does the amount of time spent on a cell phone correspond in some way to the likelihood of contracting cancer? Do people who spend more years in school eventually make more money? (And if so, does that relationship hold all the way from elementary school to post-graduate degrees?) This is another major class of empirical research and statistical analysis: the investigation of how different variables change together—or, in statistical jargon, how they *covary*.

Excel's XY charts can tell you a considerable amount about how two numeric variables are related. Figure 1.9 adds a trendline to the XY chart in Figure 1.8.



	Height (inches)	Weight (pounds)
2	72	191
3	75	249
4	60	179
5	65	164
6	73	254
7	69	161
8	71	239
9	68	211
10	66	176
11	67	198
12	63	186
13	64	181
14	74	262
15	61	202
16	70	259
17	76	217
18	62	134

Figure 1.9
A trendline graphs a numeric relationship, which is almost never an accurate way to depict reality.

The diagonal line you see in Figure 1.9 is a *trendline*. It is an idealized representation of the relationship between men's height and weight, at least as determined from the sample of 17 men whose measures are charted in the figure. The trendline is based on this formula:

Weight = 5.2 * Height – 152

Excel calculates the formula based on what's called the *least squares* criterion. You'll see much more about this in Chapter 4.

Suppose that you picked several—say, 20—different values for height in inches, plugged them into that formula, and then used the formula to calculate the resulting weight. If you now created an Excel XY chart that shows those values of height and weight, you would get a chart that shows a straight line similar to the trendline you see in Figure 1.9.

That's because arithmetic is nice and clean and doesn't involve errors. The formula applies arithmetic which results in a set of predicted weights that, plotted against height on a chart, describe a straight line. Reality, though, is seldom free from errors. Some people weigh more than a formula thinks they should, given their height. Other people weigh less. (Statistical analysis terms these discrepancies *errors* or *deviations*.) The result is that if you chart the measures you get from actual people instead of from a mechanical formula, you're going to get a set of data that looks like the somewhat scattered markers in Figures 1.8 and 1.9.

Reality is messy, and the statistician's approach to cleaning it up is to seek to identify regular patterns lurking behind the real-world measures. If those real-world measures don't precisely fit the pattern that has been identified, there are several explanations, including these (and they're not mutually exclusive):

- People and things just don't always conform to ideal mathematical patterns. Deal with it.
- There may be some problem with the way the measures were taken. Get better yardsticks.
- Some other, unexamined variable may cause the deviations from the underlying pattern. Come up with some more theory, and then carry out more research.

Understanding Frequency Distributions

In addition to charts that show two variables—such as numbers broken down by categories in a Column chart, or the relationship between two numeric variables in an XY chart—there is another sort of Excel chart that deals with one variable only. It's the visual representation of a *frequency distribution*, a concept that's absolutely fundamental to intermediate and advanced statistical methods.

A frequency distribution is intended to show how many instances there are of each value of a variable. For example:

- The number of people who weigh 100 pounds, 101 pounds, 102 pounds, and so on
- The number of cars that get 18 miles per gallon (mpg), 19 mpg, 20 mpg, and so on
- The number of houses that cost between $200,001 and $205,000, between $205,001 and $210,000, and so on

Because we usually round measurements to some convenient level of precision, a frequency distribution tends to group individual measurements into classes. Using the examples just given, two people who weigh 100.2 and 100.4 pounds might each be classed as 100 pounds; two cars that get 18.8 and 19.2 mpg might be grouped together at 19 mpg; and any number of houses that cost between $220,001 and $225,000 would be treated as in the same price level.

As it's usually shown, the chart of a frequency distribution puts the variable's values on its horizontal axis and the count of instances on the vertical axis. Figure 1.10 shows a typical frequency distribution.

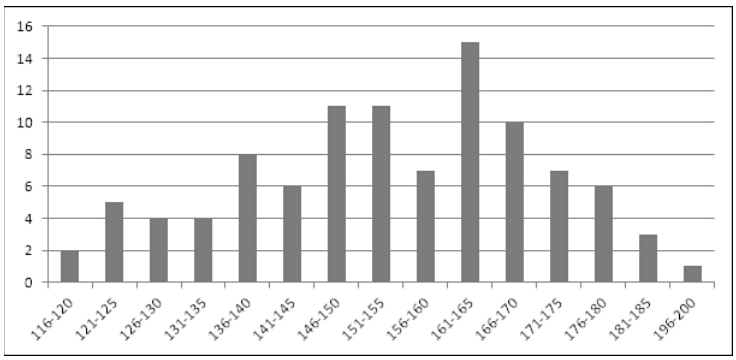


Figure 1.10
Typically, most records cluster toward the center of a frequency distribution.

You can tell quite a bit about a variable by looking at a chart of its frequency distribution. For example, Figure 1.10 shows the weights of a sample of 100 people. Most of them are between 140 and 180 pounds. In this sample, there are about as many people who weigh a lot (say, over 175 pounds) as there are whose weight is relatively low (say, up to 130). The range of weights—that is, the difference between the lightest and the heaviest weights—is about 85 pounds, from 116 to 200.

There are lots of ways that a different sample of people might provide different weights than those shown in Figure 1.10. For example, Figure 1.11 shows a sample of 100 vegans. (Notice that the distribution of their weights is shifted down the scale somewhat from the sample of the general population shown in Figure 1.10.)

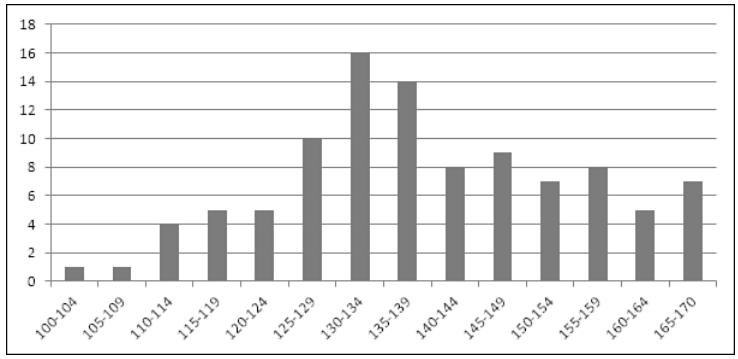


Figure 1.11
Compared to Figure 1.10, the location of the frequency distribution has shifted to the left.

The frequency distributions in Figures 1.10 and 1.11 are relatively symmetric. Their general shapes are not far from the idealized normal "bell" curve, which depicts the distribution of many variables that describe living beings. This book has much more to say in later chapters about the normal curve, partly because it describes so many variables of interest, but also because Excel has so many ways of dealing with the normal curve.

Still, many variables follow a different sort of frequency distribution. Some are skewed right (see Figure 1.12) and others left (see Figure 1.13).

Figure 1.12 shows counts of the number of mistakes on individual federal tax forms. It's normal to make a few mistakes (say, one or two), and it's abnormal to make several (say, five or more). This distribution is positively skewed.

Another variable, home prices, tends to be positively skewed, because although there's a real lower limit (a house cannot cost less than $0) there is no theoretical upper limit to the price of a house. House prices therefore tend to bunch up between $100,000 and $300,000, with fewer between $300,000 and $400,000, and fewer still as you go up the scale.

A quality control engineer might sample 100 ceramic tiles from a production run of 10,000 and count the number of defects on each tile. Most would have zero, one, or two defects, several would have three or four, and a very few would have five or six. This is another positively skewed distribution—quite a common situation in manufacturing process control.

Row Labels	Count of Mistakes
0	119
1	275
2	270
3	181
4	92
5	41
6	18
7	3
9	1
Grand Total	1000

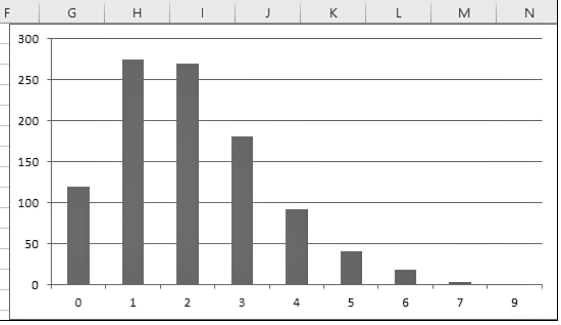
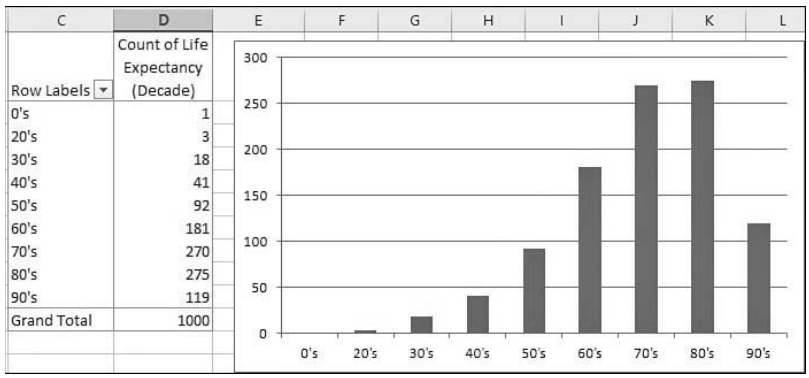


Figure 1.12
A frequency distribution that stretches out to the right is called positively skewed.



Row Labels	Count of Life Expectancy (Decade)
0's	1
20's	3
30's	18
40's	41
50's	92
60's	181
70's	270
80's	275
90's	119
Grand Total	1000

Figure 1.13
Negatively skewed distributions are not as common as positively skewed distributions.

Because true lower limits are more common than true upper limits, you tend to encounter more positively skewed frequency distributions than negatively skewed. But negative skews certainly occur. Figure 1.13 might represent personal longevity: Relatively few people die in their twenties, thirties and forties, compared to the numbers who die in their fifties through their eighties.

Using Frequency Distributions

It's helpful to use frequency distributions in statistical analysis for two broad reasons. One concerns visualizing how a variable is distributed across people or objects. The other concerns how to make inferences about a population of people or objects on the basis of a sample.

Those two reasons help define the two general branches of statistics: *descriptive* statistics and *inferential* statistics. Along with descriptive statistics such as averages, ranges of values, and percentages or counts, the chart of a frequency distribution puts you in a stronger position to understand a set of people or things because it helps you visualize how a variable behaves across its range of possible values.

In the area of inferential statistics, frequency distributions based on samples help you determine the type of analysis you should use to make inferences about the population. As you'll see in later chapters, frequency distributions also help you visualize the results of certain choices that you must make—choices such as the probability of coming to the wrong conclusion.

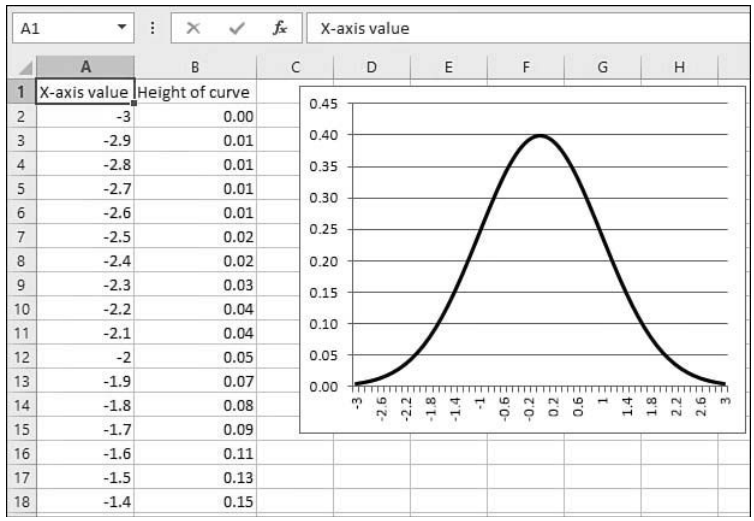
Visualizing the Distribution: Descriptive Statistics

It's usually much easier to understand a variable—how it behaves in different groups, how it may change over time, and even just what it looks like—when you see it in a chart. For example, here's the formula that defines the normal distribution:

$$u = (1 / ((2\pi)^{.5}) \sigma) e \text{ ^ } (- (X - \mu)^2 / 2 \sigma^2)$$

And Figure 1.14 shows the normal distribution in chart form.

Figure 1.14
The familiar normal curve is just a frequency distribution.



The formula itself is indispensable, but it doesn't convey understanding. In contrast, the chart informs you that the frequency distribution of the normal curve is symmetric and that most of the records cluster around the center of the horizontal axis.

NOTE

The formula was developed by a seventeenth-century French mathematician named Abraham De Moivre. Excel simplifies it to this:

```
=NORMDIST(1,0,1,FALSE)
```

In Excel 2010 and 2013, it's this:

```
=NORM.S.DIST(1,FALSE)
```

Those are *major* simplifications.

Again, personal longevity tends to bulge in the higher levels of its range (and therefore skews left as in Figure 1.13). Home prices tend to bulge in the lower levels of their range (and therefore skew right). The height of human beings creates a bulge in the center of the range, and is therefore symmetric and *not* skewed.

Some statistical analyses assume that the data comes from a normal distribution, and in some statistical analyses that assumption is an important one. This book does not explore the topic in great detail because it comes up infrequently. Be aware, though, that if you want to analyze a skewed distribution there are ways to normalize it and therefore comply with

the requirements of the analysis. Very generally, you can use Excel's SQRT() and LOG() functions to help normalize a negatively skewed distribution, and an exponentiation operator (for example, =A2^2 to square the value in A2) to help normalize a positively skewed distribution.

> **NOTE** Finding just the right transformation for a particular data set can be a matter of trial and error, however, and the Excel Solver add-in can help in conjunction with Excel's SKEW() function. See Chapter 2, "How Values Cluster Together," for information on Solver, and Chapter 7, "Using Excel with the Normal Distribution," for information on SKEW(). The basic idea is to use SKEW() to calculate the skewness of your transformed data and to have Solver find the exponent that brings the result of SKEW() closest to zero.

Visualizing the Population: Inferential Statistics

The other general rationale for examining frequency distributions has to do with making an inference about a population, using the information you get from a sample as a basis. This is the field of inferential statistics. In later chapters of this book, you will see how to use Excel's tools—in particular, its functions and its charts—to infer a population's characteristics from a sample's frequency distribution.

A familiar example is the political survey. When a pollster announces that 53% of those who were asked preferred Smith, he is reporting a descriptive statistic. Fifty-three percent of the sample preferred Smith, and no inference is needed.

But when another pollster reports that the margin of error around that 53% statistic is plus or minus 3%, she is reporting an inferential statistic. She is extrapolating from the sample to the larger population and inferring, with some specified degree of confidence, that between 50% and 56% of all voters prefer Smith.

The size of the reported margin of error, six percentage points, depends heavily on how confident the pollster wants to be. In general, the greater degree of confidence you want in your extrapolation, the greater the margin of error that you allow. If you're on an archery range and you want to be virtually certain of hitting your target, you make the target as large as necessary.

Similarly, if the pollster wants to be 99.9% confident of her projection into the population, the margin might be so great as to be useless—say, plus or minus 20%. And although it's not headline material to report that somewhere between 33% and 73% of the voters prefer Smith, the pollster can be confident that the projection is accurate.

But the size of the margin of error also depends on certain aspects of the frequency distribution in the sample of the variable. In this particular (and relatively straightforward) case, the accuracy of the projection from the sample to the population depends in part on the level of confidence desired (as just briefly discussed), in part on the size of the sample, and in part on the percent favoring Smith in the sample. The latter two issues, sample size and

percent in favor, are both aspects of the frequency distribution you determine by examining the sample's responses.

Of course, it's not just political polling that depends on sample frequency distributions to make inferences about populations. Here are some other typical questions posed by empirical researchers:

- What percent of the nation's existing houses were resold last quarter?
- What is the incidence of cardiovascular disease today among diabetics who took the drug Avandia before questions about its side effects arose in 2007? Is that incidence reliably different from the incidence of cardiovascular disease among those who never took the drug?
- A sample of 100 cars from a particular manufacturer, made during 2013, had average highway gas mileage of 26.5 mpg. How likely is it that the average highway mpg, for all that manufacturer's cars made during that year, is greater than 26.0 mpg?
- Your company manufactures custom glassware. Your contract with a customer calls for no more than 2% defective items in a production lot. You sample 100 units from your latest production run and find 5 that are defective. What is the likelihood that the entire production run of 1,000 units has a maximum of 20 that are defective?

In each of these four cases, the specific statistical procedures to use—and therefore the specific Excel tools—would be different. But the basic approach would be the same: Using the characteristics of a frequency distribution from a sample, compare the sample to a population whose frequency distribution is either known or founded in good theoretical work. Use the numeric functions in Excel to estimate how likely it is that your sample accurately represents the population you're interested in.

Building a Frequency Distribution from a Sample

Conceptually, it's easy to build a frequency distribution. Take a sample of people or things and measure each member of the sample on the variable that interests you. Your next step depends on how much sophistication you want to bring to the project.

Tallying a Sample

One straightforward approach continues by dividing the relevant range of the variable into manageable groups. For example, suppose that you obtained the weight in pounds of each of 100 people. You might decide that it's reasonable and feasible to assign each person to a weight class that is ten pounds wide: 75 to 84, 85 to 94, 95 to 104, and so on. Then, on a sheet of graph paper, make a tally in the appropriate column for each person, as suggested in Figure 1.15.

The approach shown in Figure 1.15 uses a *grouped* frequency distribution, and tallying by hand into groups was the only practical option as recently as the 1980s, before personal computers came into truly widespread use. But using an Excel function named FREQUENCY(), you can get the benefits of grouping individual observations without the tedium of manually assigning individual records to groups.

Figure 1.15
This approach helps clarify the process, but there are quicker and easier ways.

	A	B	C	D	E	F	G
1							
2				✓			
3				✓			
4				✓			
5			✓	✓			
6			✓	✓	✓		
7			✓	✓	✓		
8			✓	✓	✓		
9			✓	✓	✓		
10			✓	✓	✓		
11			✓	✓	✓		
12			✓	✓	✓		
13			✓	✓	✓		
14			✓	✓	✓		
15			✓	✓	✓		
16		✓	✓	✓	✓		
17		✓	✓	✓	✓		
18		✓	✓	✓	✓		
19		✓	✓	✓	✓		
20		✓	✓	✓	✓	✓	
21		✓	✓	✓	✓	✓	
22		✓	✓	✓	✓	✓	
23	✓	✓	✓	✓	✓	✓	
24	✓	✓	✓	✓	✓	✓	✓
25	✓	✓	✓	✓	✓	✓	✓
26	✓	✓	✓	✓	✓	✓	✓
27	✓	✓	✓	✓	✓	✓	✓
28	75 to 84	85 to 94	95 to 104	105 to 114	115 to 124	125 to 134	135 to 144

Grouping with FREQUENCY()

If you assemble a frequency distribution as just described, you have to count up all the records that belong to each of the groups that you define. Excel has a function, FREQUENCY(), that will do the heavy lifting for you. All you have to do is decide on the boundaries for the groups and then point the FREQUENCY() function at those boundaries and at the raw data.

Figure 1.16 shows one way to lay out the data.

In Figure 1.16, the weight of each person in your sample is recorded in column A. The numbers in cells C2:C8 define the upper boundaries of what this section has called *groups*, and what Excel calls *bins*. Up to 85 pounds defines one bin; from 86 to 95 defines another; from 96 to 105 defines another, and so on.

> **NOTE** There's no special need to use the column headers shown in Figure 1.16, cells A1, C1, and D1. In fact, if you're creating a standard Excel chart as described here, there's no great need to supply column headers at all. If you don't include the headers, Excel names the data Series1 and Series2. If you use the pivot chart instead of a standard chart, though, you will need to supply a column header for the data shown in column A in Figure 1.16.

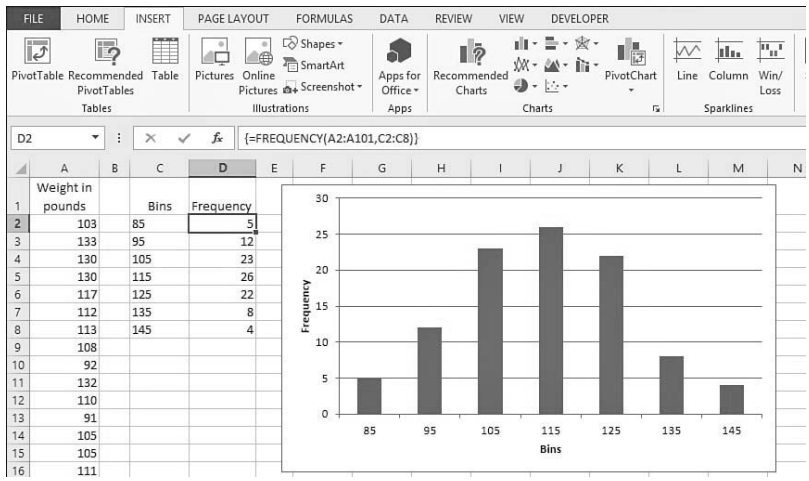


Figure 1.16
The groups are defined by the numbers in cells C2:C8.

The count of records within each bin appears in D2:D8. You don't count them yourself—you call on Excel to do that for you, and you do that by means of a special kind of Excel formula, called an *array formula*. You'll read more about array formulas in Chapter 2, as well as in later chapters, but for now here are the steps needed to get the bin counts shown in Figure 1.16:

1. Select the range of cells that the results will occupy. In this case, that's the range of cells D2:D8.
2. Type, but don't yet enter, the following formula:

   =FREQUENCY(A2:A101,C2:C8)

   which tells Excel to count the number of records in A2:A101 that are in each bin defined by the numeric boundaries in C2:C8.
3. After you have typed the formula, hold down the Ctrl and Shift keys simultaneously and press Enter. Then release all three keys. This keyboard sequence notifies Excel that you want it to interpret the formula as an array formula.

> **NOTE** When Excel interprets a formula as an array formula, it places curly brackets around the formula in the formula box.

> **TIP** You can use the same range for the Data argument and the Bins argument in the FREQUENCY() function: for example, =FREQUENCY(A1:A101,A1:A101). Don't forget to enter it as an array formula. This is a convenient way to get Excel to treat every recorded value as its own bin, and you get the count for every unique value in the range A1:A101.

The results appear very much like those in cells D2:D8 of Figure 1.16, of course depending on the actual values in A2:A101 and the bins defined in C2:C8. You now have the frequency distribution but you still should create the chart.

Compared to earlier versions, Excel 2013 makes it quicker and easier to create certain basic charts such as the one shown in Figure 1.16. Assuming the data layout used in that figure, here are the steps you might use in Excel 2013 to create the chart:

1. Select the data you want to chart—that is, the range C1:D8. (If the relevant data range is surrounded by empty cells or worksheet boundaries, all you need to select is a single cell in the range you want to chart.)
2. Click the Insert tab, and then click the Recommended Charts button in the Charts group.
3. Click the Clustered Column chart example in the Insert Chart window, and then click OK.

You can get other variations on chart types in Excel 2013 by clicking, for example, the Insert Column Chart button (in the Charts group on the Insert tab). Click More Chart Types at the bottom of the drop-down to see various ways of structuring Bar charts, Line charts, and so on given the layout of your underlying data.

Things weren't as simple in earlier versions of Excel. For example, here are the steps in Excel 2010, again assuming the data is located as in Figure 1.16:

1. Select the data you want to chart—that is, the range C1:D8.
2. Click the Insert tab, and then click the Insert Column Chart button in the Charts group.
3. Choose the Clustered Column chart type from the 2-D charts. A new chart appears, as shown in Figure 1.17. Because columns C and D on the worksheet both contain numeric values, Excel initially thinks that there are two data series to chart: one named Bins and one named Frequency.

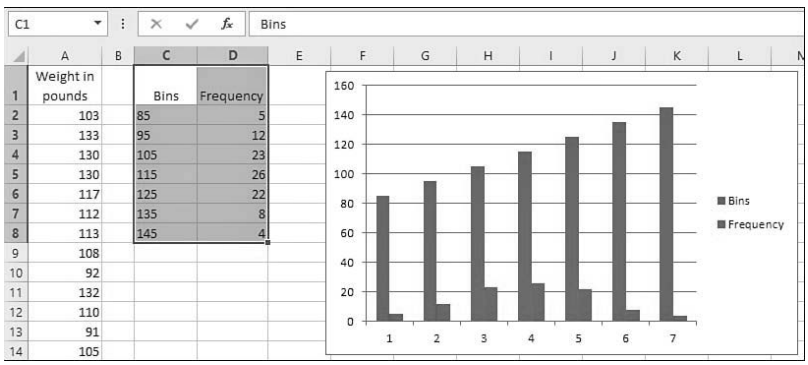


Figure 1.17
Values from both columns are charted as data series at first because they're all numeric.

4. Fix the chart by clicking Select Data in the Design tab that appears when a chart is active. The dialog box shown in Figure 1.18 appears.

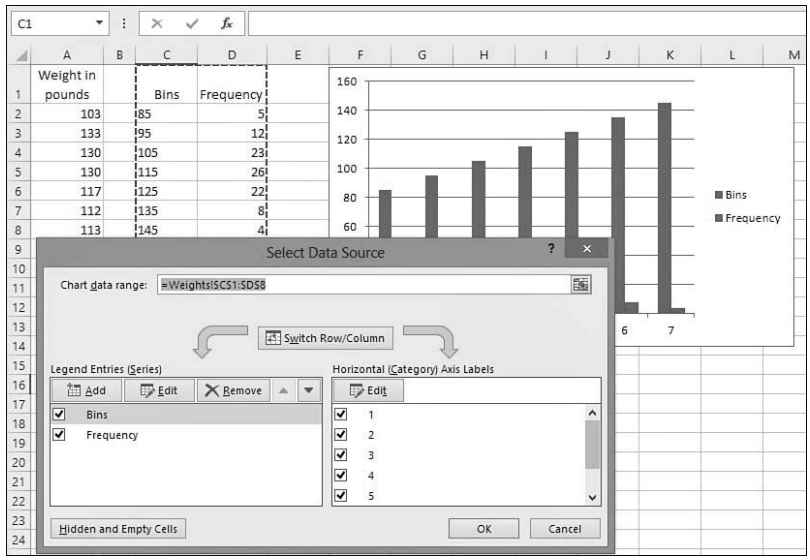


Figure 1.18
You can also use the Select Data dialog box to add another data series to the chart.

5. Click the Edit button under Horizontal (Category) Axis Labels. A new Axis Labels dialog box appears; drag through cells C2:C8 to establish that range as the basis for the horizontal axis. Click OK.
6. Click the Bins label in the left list box shown in Figure 1.18. Click the Remove button to delete it as a charted series. Click OK to return to the chart.
7. Remove the chart title and series legend, if you want, by clicking each and pressing Delete.

At this point, you will have a normal Excel chart that looks much like the one shown in Figure 1.16.

USING NUMERIC VALUES AS CATEGORIES

The differences between how Excel 2010 and Excel 2013 handle charts present a good illustration of the problems created by the use of numeric values as categories. The "Charting Two Variables" section earlier in this chapter alludes to the ambiguity involved when you want Excel to treat numeric values as categories.

In the example shown in Figure 1.16, you present two numeric variables—Bins and Frequency—to Excel's charting facility. Because both variables are numeric (and their values are stored as numbers rather than text), there are various ways that Excel can treat them in charts:

- Treat each *column*—the Bins variable and the Frequency variable—as data series to be charted. This is the approach you might take if you wanted to chart both Income and Expenses over time: you would have Excel treat each variable as a data series, and the different rows in the underlying data range would represent different time periods. You get this chart if you choose Clustered Chart in the Insert Column Chart drop-down.
- Treat each *row* in the underlying data range as a data series. Then, the columns are treated as different categories on the column chart's horizontal axis. You get this result if you click More Column Charts at the bottom of the Insert Column Chart drop-down—it's the third example chart in the Insert Chart window.
- Treat one of the variables—Bins or Frequency—as a category variable for use on the horizontal axis. This is the column chart you see in Figure 1.16 and is the first of the recommended charts.

Excel 2013, at least in the area of charting, recognizes the possibility that you will want to use numeric values as nominal categories. It lets you express an opinion without forcing you to take all the extra steps required by Excel 2010. Still, if you're to participate effectively, you need to recognize the differences between, say, interval and nominal variables. You also need to recognize the ambiguities that crop up when you want to use a number as a category.

Grouping with Pivot Tables

Another approach to constructing the frequency distribution is to use a pivot table. A related tool, the pivot chart, is based on the analysis that the pivot table provides. I prefer this method to using an array formula that employs FREQUENCY(). With a pivot table, once the initial groundwork is done, I can use the same pivot table to do analyses that go beyond the basic frequency distribution. But if all I want is a quick group count, FREQUENCY() is usually the faster way.

Again, there's more on pivot tables and pivot charts in Chapter 2 and later chapters, but this section shows you how to use them to establish the frequency distribution.

Building the pivot table (and the pivot chart) requires you to specify bins, just as the use of FREQUENCY() does, but that happens a little further on.

> NOTE
> A reminder: When you use the FREQUENCY() method described in the prior section, a header at the top of the column of raw data can be helpful but is not required. When you use the pivot table method discussed in this section, the header is required.

Begin with your sample data in A1:A101 of Figure 1.16, just as before. Select any one of the cells in that range and then follow these steps:

1. Click the Insert tab. Click the PivotChart button in the Charts group. (Prior to Excel 2013, click the PivotTable drop-down in the Tables group and choose PivotChart from the drop-down list.) When you choose a pivot chart, you automatically get a pivot table along with it. The dialog box in Figure 1.19 appears.

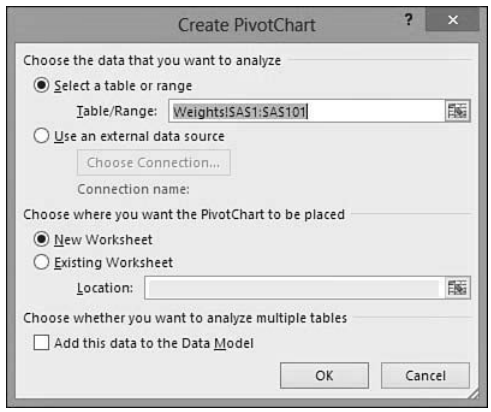


Figure 1.19
If you begin by selecting a single cell in the range containing your input data, Excel automatically proposes the range of adjacent cells that contain data.

2. Click the Existing Worksheet option button. Click in the Location range edit box. Then, to avoid overwriting valuable data, click some blank cell in the worksheet that has other empty cells to its right and below it.
3. Click OK. The worksheet now appears as shown in Figure 1.20.

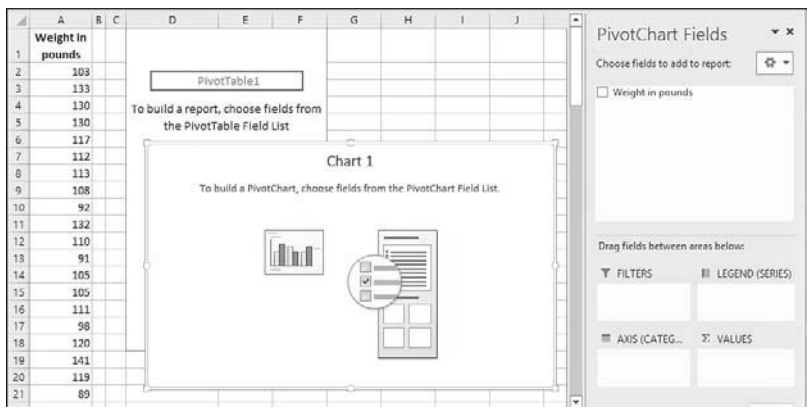


Figure 1.20
With one field only, you normally use it for both Axis Fields (Categories) and Summary Values.

4. Click the Weight In Pounds field in the PivotTable Fields list and drag it into the Axis (Categories) area.
5. Click the Weight In Pounds field again and drag it into the **Σ Values** area. Despite the uppercase Greek sigma, which is a summation symbol, the **Σ Values** in a pivot table can show averages, counts, standard deviations, and a variety of statistics other than the sum. However, Sum is the default statistic for a field that contains numeric values only.

6. The pivot table and pivot chart are both populated as shown in Figure 1.21. Right-click any cell that contains a row label, such as C2. Choose Group from the shortcut menu. The Grouping dialog box shown in Figure 1.22 appears.

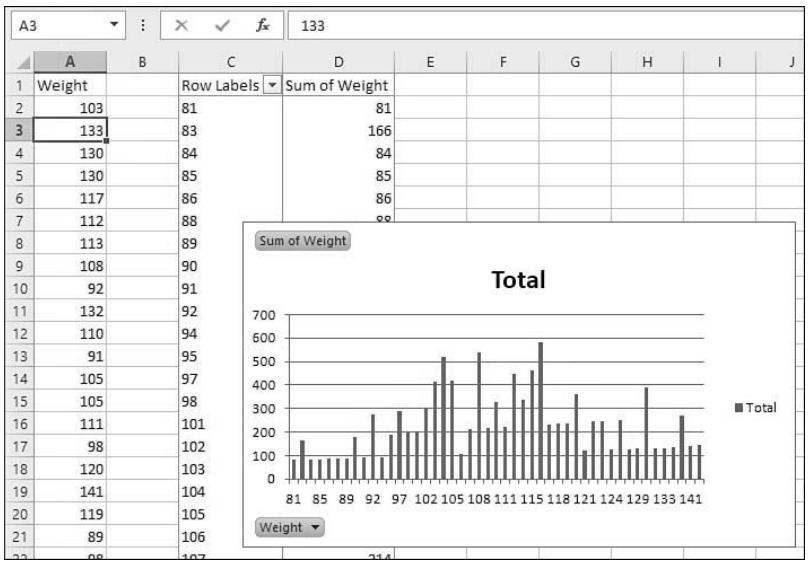


Figure 1.21
The Weight field contains numeric values only, so the pivot table defaults to Sum as the summary statistic.

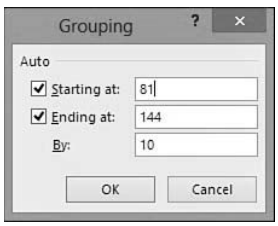


Figure 1.22
This step establishes the groups that the FREQUENCY() function refers to as *bins*.

7. In the Grouping dialog box, set the Starting At value to **81** and enter **10** in the By box. Click OK.
8. Right-click a cell in the pivot table under the header Sum of Weight. Choose Value Field Settings from the shortcut menu. Select Count in the Summarize Value Field By list box, and then click OK.
9. The pivot table and chart reconfigure themselves to appear as in Figure 1.23. To remove the field buttons in the upper- and lower-left corners of the pivot chart, select the chart, click the Analyze tab, click Field Buttons, and select Hide All.

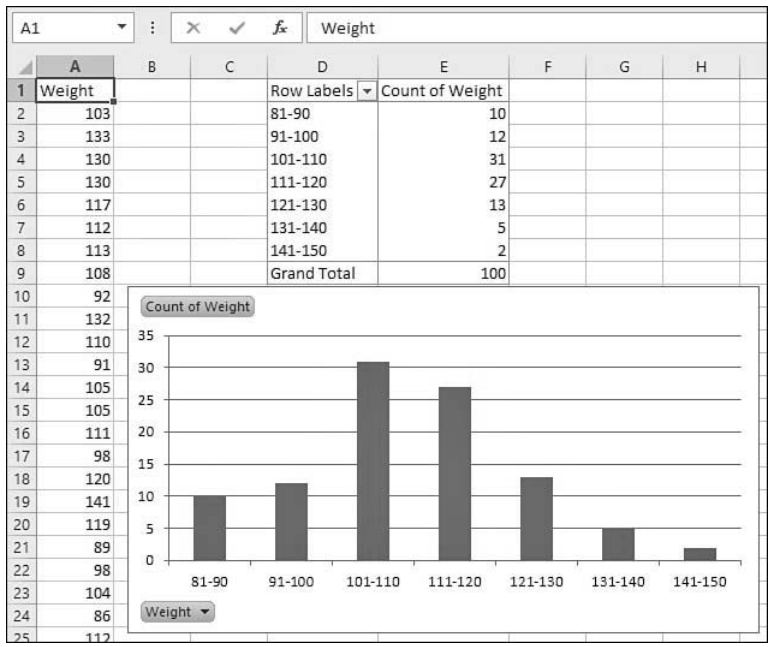


Figure 1.23
This sample's frequency distribution has a slight right skew but is reasonably close to a normal curve.

Building Simulated Frequency Distributions

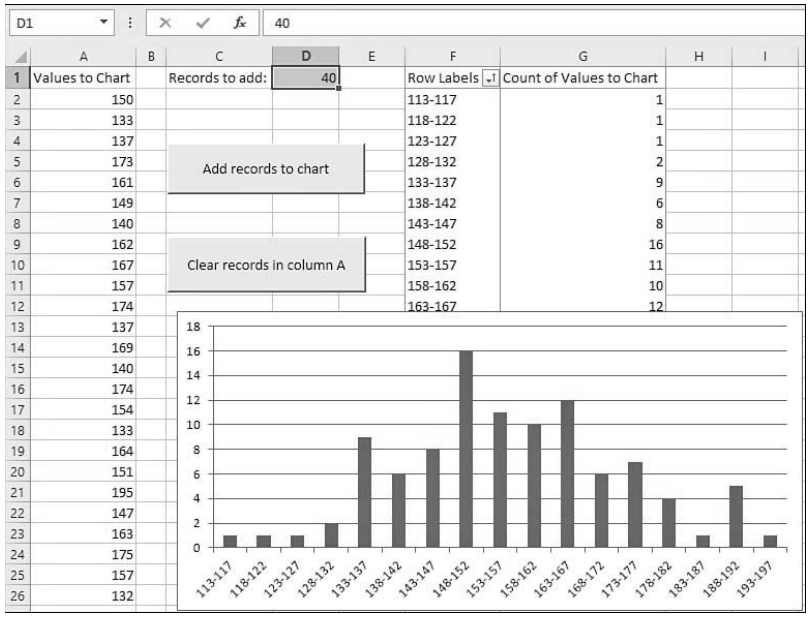
It can be helpful to see how a frequency distribution assumes a particular shape as the number of underlying records increases. *Statistical Analysis: Excel 2013* has a variety of worksheets and workbooks for you to download from this book's website (www.quepublishing.com/title/9780789753113). The workbook for Chapter 1 has a worksheet named Figure 1.24 that samples records at random from a population of values that follows a normal distribution. The following figure, as well as the worksheet on which it's based, shows how a frequency distribution comes closer and closer to the population distribution as the number of sampled records increases.

Begin by clicking the button labeled Clear Records in column A. All the numbers will be deleted from column A, leaving only the header value in cell A1. (The pivot table and pivot chart will remain as they were: It's a characteristic of pivot tables and pivot charts that they do not respond immediately to changes in their underlying data sources.)

Decide how many records you'd like to add, and then enter that number in cell D1. You can always change it to another number.

Click the button labeled Add Records to Chart. When you do so, several events take place, all driven by Visual Basic procedures that are stored in the workbook:

Figure 1.24
This frequency distribution is based on a population of records that follow a normal distribution.



- A sample is taken from the underlying normal distribution. The sample has as many records as specified in cell D1. (The underlying, normally distributed population is stored in a separate, hidden worksheet named Random Normal Values; you can display the worksheet by right-clicking a worksheet tab and selecting Unhide from the shortcut menu.)
- The sample of records is added to column A. If there were no records in column A, the new sample is written starting in cell A2. If there were already, say, 100 records in column A, the new sample would begin in cell A102.
- The pivot table and pivot chart are updated (or, in Excel terms, *refreshed*). As you click the Add Records to Chart button repeatedly, more and more records are used in the chart. The greater the number of records, the more nearly the chart comes to resemble the underlying normal distribution.

In effect, this is what happens in an experiment when you increase the sample size. Larger samples resemble more closely the population from which you draw them than do smaller samples. That greater resemblance isn't limited to the shape of the distribution: It includes the average value and measures of how the values vary around the average. Other things being equal, you would prefer a larger sample to a smaller one because it's likely to represent the population more closely.

But this effect creates a cost-benefit problem. It is usually the case that the larger the sample, the more accurate the experimental findings—and the more expensive the experiment. Many issues are involved here (and this book discusses them), but at some point the incremental accuracy of adding, say, ten more experimental subjects no longer justifies the incremental expense of adding them. One of the bits of advice that statistical analysis provides is to tell you when you're reaching the point when the returns begin to diminish.

With the material in this chapter—scales of measurement, the nature of axes on Excel charts, and frequency distributions—in hand, Chapter 2 moves on to the beginnings of practical statistical analysis, the measurement of central tendency.

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