CHAPTER 5

GRAPHS AND TABLES

OBJECTIVES

You will learn how to read graphs and tables presenting information. Science articles report most information in tabular and graphic formats. If you understand the basics of tabular and graphic construction you can grasp more effectively the information presented, and gauge more speedily the information hidden or downplayed.

It is a truism that we live in an information society. At times, we seem awash in factoids. Graphs and tables convey much of the information pumped at us by the media. They also are especially important for scientific communication. Researchers use them extensively in reports, journal articles, and presentations. In this chapter you examine the logic behind the construction of these items, and the rules of "good form."

ORGANIZATION OF THE CHAPTER

You examine five types of graphs: pie charts, bar charts, line charts, histograms, and scatterplots. You will encounter good and bad examples of each. You will learn rules for deciding which type of chart to use in different situations. You will go on to consider data tables. They report scores on one, two, or three variables. They can show relationships between scores on two or three variables.

Graphs and tables both represent excellent tools for a variety of purposes. They can summarize data, providing descriptive overviews of scores on one or more variables. They can be used in hypothesis testing, following Einstein's logic of scientific inquiry, to examine how scores on an independent variable link to scores on a dependent variable. You also can use them to explore relationships among variables, following Holmes's logic of scientific inquiry.

We continue in this chapter with our hypothetical scenario concerning community policing in an urban neighborhood. You find that a local researcher recently has surveyed households in this locale on a range of topics related to community policing and victimization. You also examine national level data on some of these same topics, for the purposes of comparison. Furthermore, you have available information from 100 officers who have been trained recently as community police officers (CPOs) and are beginning work in that capacity. The information you have about them relates directly to the theory you developed to explain satisfaction with community policing assignments. (See Chapter 3.) You use two-way and three-way tables to examine key hypotheses in your theory.

On the workdisk you will find the datafiles used to construct most of the charts and graphs appearing in this chapter. I also have placed there suggestions for exercises. I have included additional datafiles on drunk-driving arrests, and on government spending on drug control strategies. Exercises on the workdisk encourage you to engage in grounded theorizing, and to test hypotheses, using graphs constructed from these datafiles. I hope you actively explore these materials. The more you do, the more you will understand the process.

Graphs can be poorly presented or even misleading. Cognitive psychology has learned a considerable amount in the last 20 years about how we organize and perceive visual information. This knowledge suggests how to construct graphs so they communicate effectively. [1, 2, 3] I combine the general implications of work in this area, with comments on deception in graphical presentation, to offer a list of "do's" and "don'ts" to follow when constructing graphs. [4]

CHARTS AND GRAPHS

The Type of Data and Number of Variables Suggest the Recommended Graph

You decide what type of graph to use based, in part, on the kind of data you have. First, you consider how many variables you will examine at a time. Do you just want to look at how people score on one variable? Or are you interested in two? Or three? Second, you consider the *type* of data. For graphical purposes, data are of two different types: *categorical* and *continuous*.

> Continuous data come from a scale of values that can be any real number from minus to plus infinity. Categorical data may be numerals or characters but their distinguishing feature is that they fall into a few unordered discrete categories. [5]

Sex, race, political party affiliation, region of the country, suburban vs. rural vs. urban, convicted vs. not convicted, or incarcerated vs. not incarcerated represent categorical variables. Age, scores on a satisfaction scale, scores on a personality inventory measuring sociability, or scores on a scale measuring police cynicism represent continuous variables.

Once you have answered these two questions—the type or types of data examined, and the number of variables—you can decide the type of graph best suited to your purpose. Table 5.1 shows recommended graph types once you have answered these two questions.

You will note from the table that, for some data situations, more than one of the graphs discussed here are recommended. You have choices. You also will see that, in some situations, I comment on the number of possible response categories. A variable may be continuous but allow only a few response categories. For example, in a survey you may ask about the level of officer satisfaction with the community-policing role but only allow responses ranging from 1 (not at all satisfied) to 10 (completely satisfied). Some kinds of graphs are "messy" and difficult to interpret if the variables contain a large number of response categories. I suggest that pie charts should be avoided if the number of categories exceeds 5, and bar charts should be avoided if the number of categories exceed 15. These represent arbitrary cutoff points, and you

TABLE 5.1
Types of Data, N of Variables, and Recommended Graph Types[1]

Type(s) of Data	Number of Response Categories	Number of Variables: One	Two	Three
Categorical	< 5	Pie	Multiple Pie Charts	Multiple Pie Charts
	< 15	Bar	Bar	Bar
Continuous	Any	Histogram (Density)	Scatterplot Line	Line
	< 5	Pie	Multiple Pie Charts	Multiple Pie Charts
	< 15	Bar	Bar	Bar
Mixed			Bar	Bar Scatterplot

Note: Adapted from Wilkinson, L. (1988). *SYGRAPH*. Evanston, IL: SYSTAT, Inc. p. 66.

[1] The types of graphs examined here represent just a small portion of those currently available for displaying numerical information. Additional types include: box-and-whiskers plots, stem-and-leaf plots, polar plots, Chernoff faces, quantile plots, density traces, and more. I discuss in this chapter the types of graphs that are most commonly used in scientific literature as well as in the general press.

may not agree with them. Personal tastes vary widely in this area.

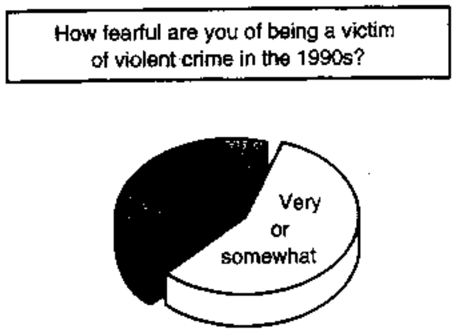
Pie Charts

Purposes You use pie charts to display the portions of a whole in different individual categories. When people make judgements about portions or proportions, pie charts can be as effective as other types of charts. [6]

Scenario You have learned that a criminal justice professor at a local university recently surveyed 1,000 households in the neighborhood which was the site of your community-policing initiative. In a 1989 survey interviewers asked household members: "How fearful are you of being a victim of violent crime in the 1990s?" People could reply "very fearful," "somewhat fearful," or "not at all fearful." The professor has supplied you with the results for this question. You want to learn how the concerns about victimization expressed by household members compared to the concerns expressed by household members across the country. You come across data from a national survey conducted at the same time [7]. Figure 5.1 provides two depictions of answers to this question on the national survey.

Bad Form The top pie is misleading for several reasons.

- First, it presents the pie floating in *three dimensions*. In general, three-dimensional charts are more difficult to interpret than two-dimensional charts.
- Second, a piece of the pie has *exploded;* it has been separated from the rest of the pie. This makes it more difficult to make judgements about proportions.
- Third, *data have been collapsed*. "Very fearful" and "Somewhat fearful" responses have been collapsed into one piece of pie, rather than appearing as two separate pieces.
- Fourth, the *pieces are not labeled*. You do not



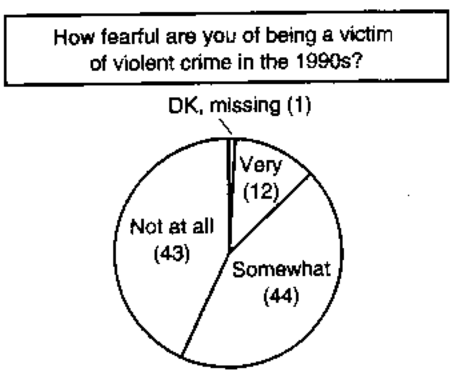


FIGURE 5.1
Pie charts showing fear of violent victimization, based on a national survey conducted in 1989. Top pie is *less* informative; bottom pie is *more* informative. (*Source*: Bennack, F. A., Jr. (1989). *The American public's hopes and fears for the 1990s*. New York: Hearst Corporation. Table 58 (p. 38). Reprinted in Flanagan, T. J., and Maguire, K., eds. (1992). *Sourcebook of criminal justice statistics 1991*. Washington: USGPO. Table 2.24 (p. 191)).

know the actual percentage or count associated with each piece.

- Fifth, one of the pieces has been shaded. *Shading* that differs across pieces interferes with judgements about proportions.
- Finally, *missing data have been excluded*. You do not know it from the chart, but 1 percent of the sample did not answer this question.

Good Form The bottom pie chart is correctly displayed. It is presented in two dimensions. Each portion has a clearly labeled percentage. The data are not collapsed across categories. There is no different shading across pieces. Missing data are included and labeled. No pieces are "exploding" out of the pie. I guess this is not a high energy food (tic).

Different Interpretations The two different pie charts suggest different pictures. The top chart suggests that Americans are extremely fearful of violent victimization. The bottom chart provides a different depiction. It suggests that only a small portion of Americans, about 12 percent, are extremely fearful of being a victim of a violent crime. But at the same time, a roughly equal portion of Americans are not at all fearful (43%) or only somewhat fearful (44%).

Bar Charts

Purposes *One variable* When displaying one variable, a bar chart depicts the percentage, count, or proportion of cases, or average, for each category or level of a variable. The height of each bar reflects the count, proportion or percentage of cases; or the average for cases in that category. Figure 5.2 presents information from the pie chart in Figure 5.1 in the form of a bar graph.

Two or More Variables With two variables, bar charts depict relationships between scores on one independent variable, and scores on a dependent variable. Each bar represents one category or range of the independent variable. The height of each bar reflects how cases in that category of the independent variable, or in that range of the independent variable, score on the dependent variable. The score on the dependent variable may be a percentage, a proportion, a count, an average, or some other statistic.

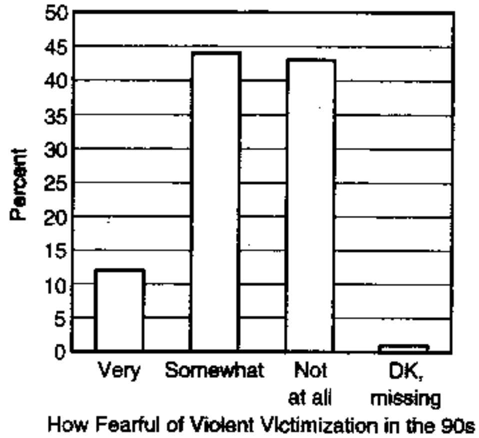


FIGURE 5.2
Bar chart of responses to the question "How fearful are you of becoming a victim of violent crime in the 1990s?" (*Source*: See Figure 5.1).

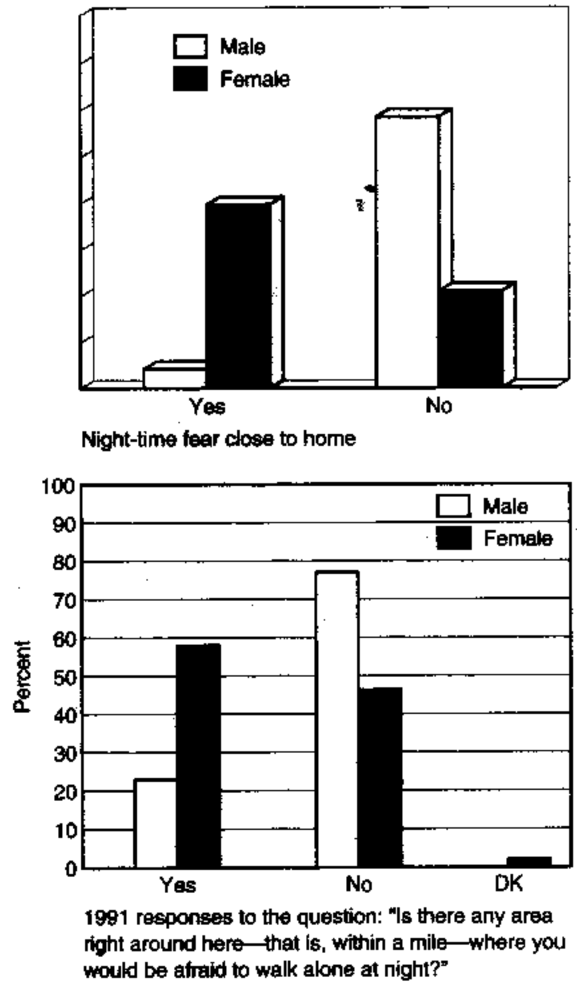


FIGURE 5.3
Bar chart of sex differences in places to avoid while walking alone at night. Top graph represents *bad* form; bottom graph represents *good* form. (*Source*: 1991 General Social Survey, conducted by the National Opinion Research Center. From tabulations in Flanagan, T. J., and Maguire, K, eds. (1992). *Sourcebook of criminal justice statistics 1991*. Washington: USGPO. Table 2.28 (p. 197)).

Scenario You learn that the local researcher who surveyed households in the neighborhood where your community-policing initiative took place also asked respondents about places to avoid while walking the streets. He asked them: "Is there any area right around here—that is, within a mile—where you would be afraid to walk alone at night?" You find in the data that women express higher avoidance than men. You seek a context in which to interpret these data. You find that the same question was asked of a national sample of respondents in 1991. Figure 5.3 shows two bar charts constructed from that national sample.

In the top figure, the left-hand pair of bars indicates the percentages of men and women in the sample who said "yes" in response to the question; the right-hand pair of bars shows the percentages of men and women saying "no" in response to the question. Dark bars represent women; light bars represent men.

Bad Form The top bar graph is inadequate in several respects.

- Most importantly, the Y or *vertical axis is not labeled*; you do not know that the different heights correspond to.
- Second, the Y axis *does not start at 0*, but instead starts at 20. You would not learn

this unless you had the bottom chart to compare with the top one.

- Third, the graph is again presented in *three dimensions*, making the bars blocky. With such bars it is even more difficult to gauge height exactly than it is in the two dimensional case. [8]
- Difficulty in gauging bar height is compounded by the *lack of a horizontal grid* running along the back.
- Finally, *missing data are excluded*.

Good Form The bottom bar graph avoids the above mistakes. The Y axis is clearly labeled and begins at 0. Missing data are included. The graph appears in two rather than three dimensions. A horizontal grid is provided.

Different Interpretations Both graphs depict the same general picture. Women, as compared to men, are more likely to report avoiding a place while walking alone at night. But the graphs also reveal differences. In the top graph men look more fearless than in the bottom graph. The bottom graph reveals that almost a quarter of men report a place to avoid while walking alone at night. The bottom graph also reveals a small proportion of respondents who were unable or unwilling to answer this question.

Histograms

Purpose and Construction Histograms look like bar charts. And, like bar charts, they can be used to represent scores on one continuous variable. Nevertheless, they are different from bar charts in their construction and in their purpose. Whereas bar charts provide information about scores or counts at specific values of the variable, or at specific ranges of the variable, histograms provide general information about the *shape* of the distribution. They display the sample density for a continuous variable. [9] They tell you where, along the range of the variable, most of the data appear. The height of each bar tells you how many cases score at that value of the variable, or at that range of the variable. Thus, they have a more specialized purpose than bar charts. They show how *scores* are *distributed* along a variable.

There are also important differences in construction. Most programs that construct histograms, like MYSTAT or SPSS-PC, will "automatically" select an interval for each bar in order to best show the distribution of the data. A second important difference is that the bars are shown touching each other, rather than separate. The bars are contiguous because they represent a continuous variable. Third, with a histogram, each bar should represent an equal range of scores on the variable. The bars should be of equal width.

Scenario The survey conducted by a local researcher in the neighborhood where your department initiated community policing included 1,000 households. They reported how many years they had lived in the neighborhood. The histogram in Figure 5.4 displays the results. Each bar represents an interval of five years.

Interpretation The bulk of respondents are newcomers to the neighborhood, with about 70 percent of the respondents reporting a length of residence of 5 years or less. Fewer respondents report longer stays in the neighborhood. Most of the data are at the lower end of the variable.

Line Graphs

Purposes Line graphs depict relationships between two continuous variables. They are often used effectively when the independent variable is time and the purpose is to show changes on the dependent variable over

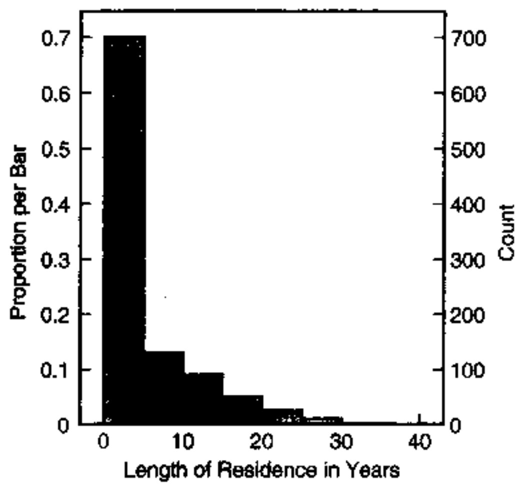


FIGURE 5.4
Histogram of 1,000 responses to the question: "How many years have you lived in this neighborhood?" Artificial data. Right-hand Y axis shows count. Left-hand Y axis shows proportion of all cases per bar.

some unit of time. Scores on the dependent variable, or percentages, or proportions, or counts, appear on the Y or vertical axis. Scores on the independent variable, often some unit of time, appear on the X or horizontal axis.

Scenario A local neighborhood leader has been complaining vociferously about "increasing rates of street crime in this neighborhood and across the country." Her comments have prompted you to investigate recent trends in robbery and assault victimizations. You turned to data from the *National Crime Survey*. It is a national survey that asks people about recent victimization experiences. You will learn more about it in Chapter 12. Researchers have constructed *victimization rates* from these data. A victimization rate divides the number of victimization incidents by the number of people, and generates a rate of victimization incidents per 1,000 persons or households. You have obtained information about national victimization rates and graphed them. The results appear in Figure 5.5.

Bad Form The top graph is inadequate in several respects.

- The three-dimensional perspective turns each line into a "ribbon." But the three-dimensional perspective makes it difficult to connect the ribbon with actual scores on the Y axis.
- Although the units on the Y axis are numbered, the axis itself is not labeled.
- The lines representing different scores on the Y axis do not extend across the back, making it harder to interpret scores.
- The figure lacks a legend clearly stating that the "solid" ribbon represents the assault rate, and the "dotted" ribbon the robbery rate.

Good Form The bottom figure corrects these problems.

- The figure appears in two dimensions rather than three.
- The units on the Y axis are now labeled as well as numbered.
- Lines for different Y values extend across the figure, making it easier to interpret Y scores at different points on the line.
- A legend is provided.

Different Interpretations The top graph suggests that assault rates have perhaps declined slightly over the period, while the robbery rate has stayed steady. The bottom graph suggests a slightly different and more precise interpretation. Assault rates have declined about 10 percent from the beginning of the period to the end. Robbery rates have declined by roughly a third. When assault rates increased in the late 1970s, robbery rates did not show a corresponding increase. But when assault rates increased in the early 1980s, from 1981 to 1984, robbery rates also increased.

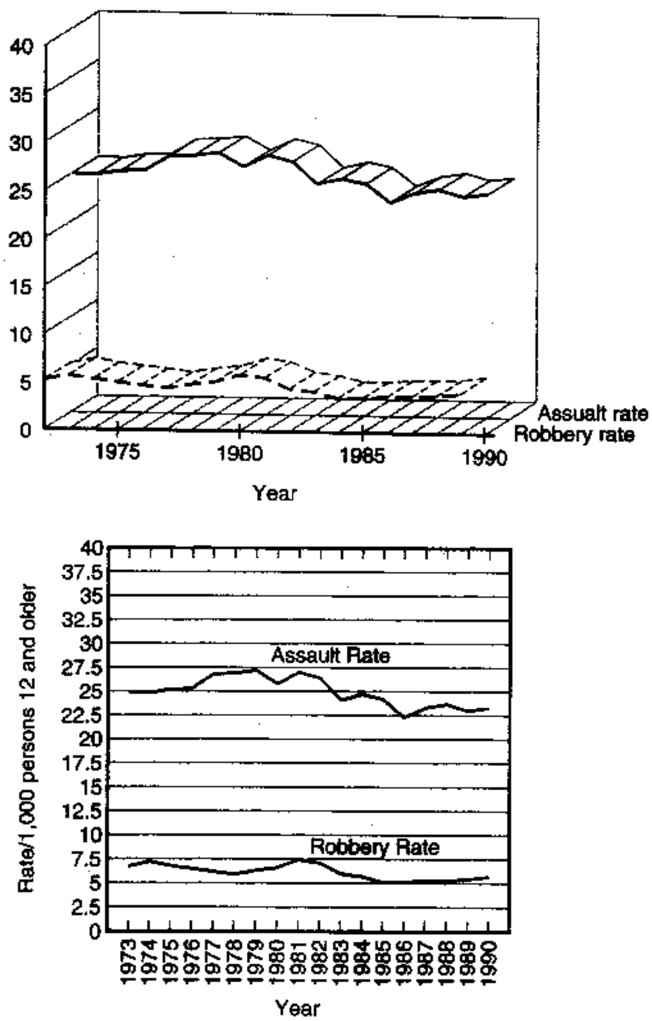


FIGURE 5.5 Line graph of national victimization rates: Assault and robbery. Top graph depicts *bad* form. Bottom graph depicts *good* form. (*Source.* Flanagan, T. J., and Maguire, K., eds. (1992). *Sourcebook of criminal justice statistics 1991*. Washington: USGPO. Table 3.2 (p. 257)).

Line Graphs of Change Researchers and policy makers have strong interests in reporting and interpreting yearly changes in victimization or crime rates. Every January rings in not only the new year, but also a spate of reports from police departments in major cities describing changes in the crime rate for the preceding year. Sometimes agencies also report longer term trends. Agencies can report changes in different ways. The way they choose to report these changes can result in widely different interpretations. Two choices you make in constructing line graphs of change are particularly important.

One way to report change is to compare subsequent years, or months, or quarters to a fixed period. In the top panel of Figure 5.6, one line graph of changes in assault uses 1973 as the rate against which the assault rates for subsequent years, 1980 through 1990, are compared (solid line). The other graph uses 1979 as the base year (dotted line). Since the assault rate in 1979 was higher than in 1973, the dotted line reveals a more substantial drop over the decade of the 1980s (about 14%) than does the solid line (about a 6% drop).

A second way to report change is to compare each period to the immediately preceding period. The solid line graph in the bottom panel of Figure 5.6 compares the assault victimization rate for each year to the preceding year. The dotted line graph in the panel is the same in the top panel: assault rates in 1980 through 1990 are compared to 1979. The two line graphs suggest markedly different trends in assault over the decade of the 1980s. The yearly change line suggests no net change; the line based on comparisons with 1979 suggests a sizable decline.

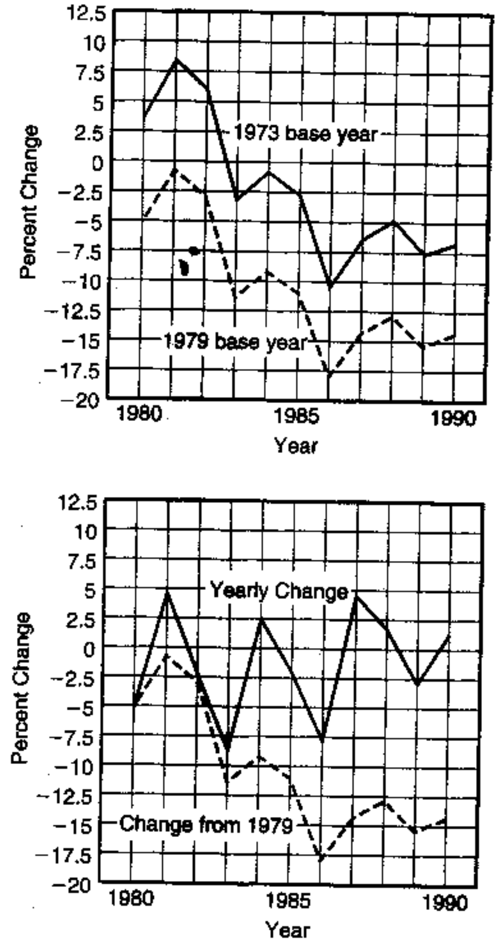


FIGURE 5.6 Different line graphs showing changes in the national assault victimization rate. In the top panel rates are compared to a specific base year, either 1973 or 1979. Although the *shape* of each trend is similar, using 1979 as a base year produces a more significant drop than using 1973 does. The bottom panel contrasts yearly changes (solid line), with changes based on one base year (1979—dotted line). The yearly change graph (solid line) shows no net change over the period, whereas the comparisons with 1979 show a substantial drop over the period (dotted line). (*Source*: Data from Flanagan, T. J., and Maguire, K., eds. (1992). *Sourcebook of criminal justice statistics 1991*. Washington: USGPO. Table 3.2 (p. 257)).

Scatterplots

Purposes Scatterplots display relationships between two continuous variables. They show a **bivariate distribution**—how scores on *two* variables are arrayed or *distributed* vis-à-vis one another. Each data point is positioned in the plot depending on its exact score on each variable. Scores on the predictor or independent variable are arrayed along the horizontal or X axis. Cases scoring low on X appear on the left; cases scoring high on X appear on the right. Scores on the dependent or outcome variable are arrayed vertically along the Y axis. Cases scoring low on Y appear in the lower part of the plot; cases

High Y	Low X, High Y	Medium X, High Y	High X, High Y
Medium Y	Low X, Medium Y	Medium X, Medium Y	High X, Medium Y
Low Y	Low X, Low Y	Medium X, Low Y	High X, Low Y
	Low X	Medium X	High X

scoring high on Y appear in the upper part of the plot.

If a case scores low on *both* X and Y, it appears in the *lower left* portion of the plot. If a case scores high on both X and Y, it appears in the *upper right* portion of the plot. In short, where a case appears in the plot depends on its position on *both* variables. The figure above shows how data points are positioned within the scatterplot depending on their X and Y scores.

Scenario In preparation for a possible expansion of department community-policing activities, a total of 100 officers has received extensive training in community-policing techniques. During their training they completed a battery of inventories, including a sociability scale and a police cynicism scale. They also answered a question about policing, saying whether crime fighting was always the most important part of the job of policing. They also rated, on a 10-point scale, how satisfied they were with their role as a community-policing officer. Lower scores represented dissatisfaction; higher scores represented satisfaction. You can use this information to assess empirically the hypotheses you developed in Chapter 3 about factors associated with high levels of satisfaction as a community-policing officer.

The artificial data shown in these scatterplots were generated by me, and do *not* represent results from an actual study.

Positive Correlation Your theory predicts a positive association between sociability and satisfaction with community policing. Those officers scoring higher on the sociability inventory should anticipate more satisfaction with the community-policing assignment. Thus, those who score low on sociability should score low on satisfaction, appearing in the lower left hand portion of the scatterplot. Those scoring high on sociability also should report high satisfaction, appearing in the upper right portion of the plot.

Figure 5.7 displays the results. The top plot displays just the data points. There tend to be more points in the upper right and lower left portions of the plot than there are in the upper left and bottom right portions. Thus, there is a weak tendency for scores on Y (satisfaction) to increase as scores on X (sociability) increase. There is a positive albeit weak correlation between X and Y.

The bottom plot displays the same data points as the top plot but also adds the **regression line**. This line shows the linear relationship between the X and Y variables. The line is made up of points that would be generated if scores on Y (satisfaction) could be predicted perfectly from scores on X (sociability). These data points along the line are not actual data points but are rather $Y_{\text{predicted}}$ data points. The points making up such a line could be generated from an equation of the form:

$$Y_{\text{predicted}} = A + (B * X)$$

A represents the score on Y (satisfaction) when X (sociability) = 0. It is called the **intercept** because it is the predicted score on Y, on the line, when $X = 0$. B represents the **slope** of the line. It tells you how many units on the Y variable you increase, when you increase

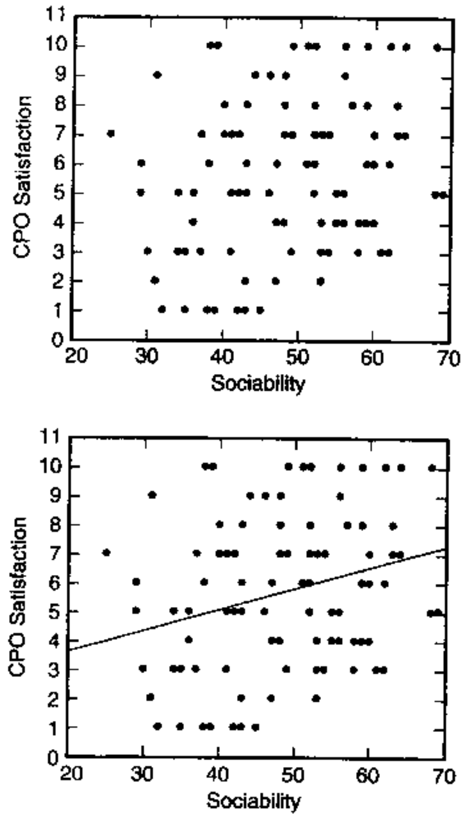


FIGURE 5.7 Positive correlation between sociability and satisfaction with community policing role: 100 community-policing officers.

one unit on the X variable. For these 100 officers the actual equation describing the regression line is:

$$\text{Satisfaction}_{\text{predicted}} = 2.51 + (.06 * \text{Sociability})$$

The line rises from left to right, supporting your hypothesized positive relationship between sociability and satisfaction. Those who are more sociable report a higher level of satisfaction. For every one unit increase on the sociability scale, scores on satisfaction are predicted to increase .06 of a point. (If this slope strikes you as small, just remember that scores on satisfaction range from 1 to 10, whereas scores on the sociability scale range from 20 to about 70.)

When you look at the top plot, you might feel that it is hard to judge if there is a positive association, or no association, between the two variables. This is because the correlation, albeit positive, is a weak one. The connection between the two variables is not strong. The weakness of the correlation also is reflected in the fact that the data points do not cluster strongly about the regression line; many of them are quite distant from it.

Figure 5.8 displays a stronger positive correlation. It shows the association between age and cynicism about police work among the 100 officers. Again, the top panel shows the data points themselves; the bottom panel displays the data along with the regression line. Research has shown that older officers tend to be more cynical about the effectiveness of police work. [10] The data here support the same conclusion. You also can see that the correlation is stronger than the one between sociability and satisfaction, as the data points cluster more strongly about the regression line. You do not "need" the regression line to decide that there is a positive correlation between the two variables. The correlation between these two variables is described by the equation:

$$\text{Cynicism}_{\text{predicted}} = 41.50 + (.21 * \text{Age})$$

Thus, an officer aged 40 would be predicted to have a cynicism score of 49.9 (41.50 + (.21 * 40)). A 50-year-old officer would have a predicted cynicism score of 52.0. For every single-year increase, cynicism is predicted to increase by .21 units; for every ten-year increase in age, cynicism is predicted to increase 2.1 units.

Negative Correlation Your theory predicts a *negative* correlation between age (X) and

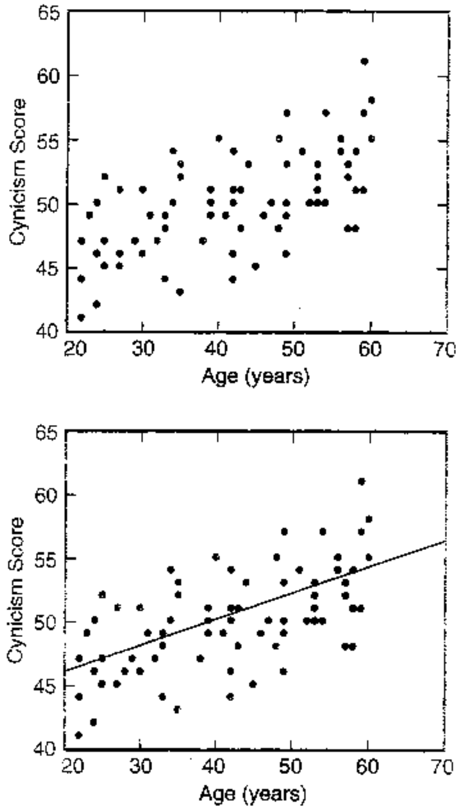


FIGURE 5.8 Strong, positive correlation between age and cynicism about police work: 100 community-policing officers. The top panel contains just the data points; the bottom panel also shows the regression line.

satisfaction with a community policing assignment (Y). As age increases, satisfaction with cor ımunity policing should decrease. With a negative correlation, as scores *increase* on the X or horizontal axis they *decrease* on the vertical of Y axis.

Figure 5.9 displays the relevant data for the 100 officers. The negative relationship is evident in both the top panel, displaying just the data, and the bottom panel, which also includes the regression line. That line is defined by the equation:

$$\text{Satisfaction}_{\text{predicted}} = 13.31 + (-.19 * \text{Age})$$

For every additional year, satisfaction, on average, decreases by 1/5 of a point. Thus the predicted satisfaction score for an officer of 30 years of age would be 7.61 (13.31 + ((− .19)∗(30))), whereas the predicted satisfaction score for a 50-year-old officer would be 3.81 (13.31 + ((− 19)∗50))).

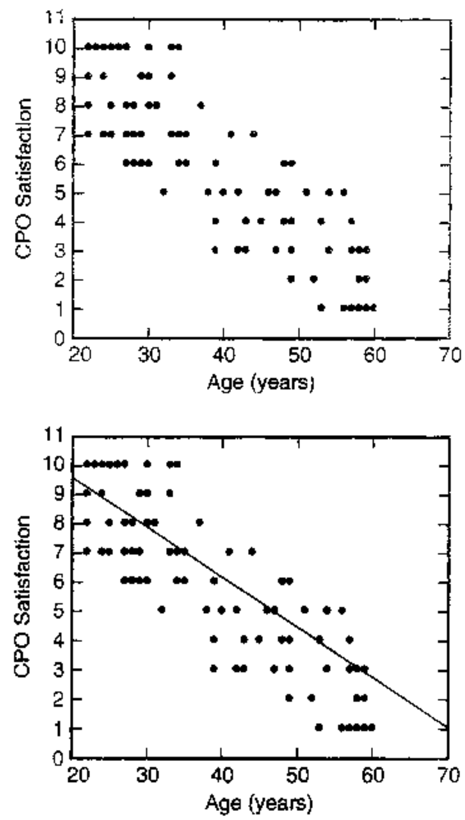


FIGURE 5.9 Strong, negative correlation between age and satisfaction with police work: 100 community-policing officers. The top panel contains just the data points; the bottom panel also shows the regression line.

No Correlation If there is no correlation between scores on two variables, data points will be distributed evenly within the scatterplot. As scores on *X* increase, scores on *Y* will neither increase nor decrease.

Figure 5.10 contains an example. Your theory predicts no relationship between age and sociability. Although you predict older officers will be more cynical, you do not predict that they will be more sociable, or less sociable, than younger officers. The data support this expectation. Note that the regression line in the bottom panel is almost perfectly flat. $\text{Sociability}_{\text{predicted}}$ neither increases nor decreases as age increases.

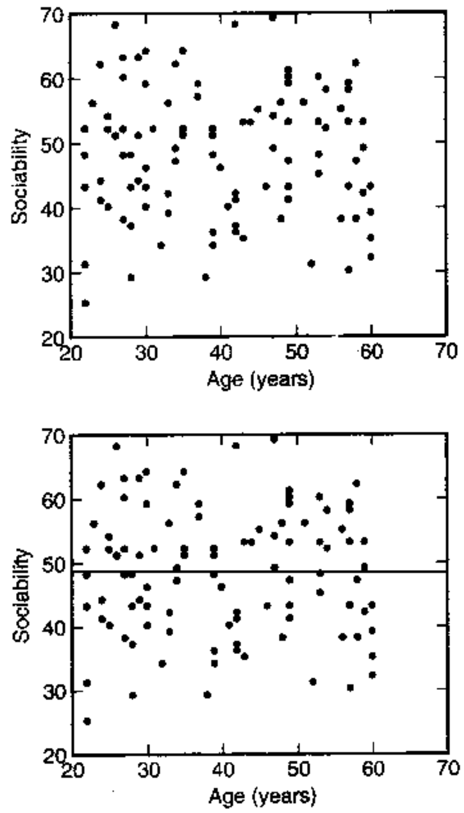


FIGURE 5.10
No correlation between age and sociability. The top panel contains just the data points; the bottom panel also shows the regression line.

Good Form and Scatterplots All of the scatterplots presented have followed these basic rules of good form in construction of scatterplots.

- Mention if missing data are not included in the plot, stating how many cases have been excluded.
- Extend the *X* and *Y* axes so that no data points are located on the "frame" surrounding the scatterplot. Depending on the plotting symbol used, it may be difficult to "pick up" a data point if it "touches" an edge of the plot.
- Attend to the relationship between the cluster of data and the total size of the plot. Ideally, the data points should extend 70 percent to 90 percent of both the *X* and *Y* axes. Perception of the degree of relationship can be influenced by the size of the frame around the data points. The correlation looks stronger between two variables if the surrounding frame is larger because the data points contrast more strongly with the background. [2]
- Clearly label *X* and *Y* axes.

SUMMARY

Graphs can inform or mislead. They can confuse or embody effective communication. Table 5.2 summarizes the "do's and don'ts" discussed above.

TABLES

We turn now to the *tabular* as compared to the graphical presentation of data. You will examine data tables containing one, two, and

TABLE 5.2
"Do's and Don'ts" for Graph Construction

Type of Graph	Do	Don't
Pie Chart	Label percentage or count associated with each portion. Include missing data.	Shade pieces differently. Present in 3 dimensions. Collapse data.
Bar Graph	Include missing data. Start *Y* axis at 0. Clearly label units on the *Y* axis. Provide horizontal grid.	Present in 3 dimensions.
Line graph	Start *Y* axis at 0. Clearly label units on the *X* and *Y* axes. Provide horizontal grid. Provide legend for each series.	Present in 3 dimensions.
Scatterplot	Maintain proper relationship between data and frame. Clearly label axes. Mention excluded data.	Have data points touching the frame.

three variables. When you have more than one variable, these tables are also called **cross-tabulations** or **contingency tables**.

When do you use tabular rather than graphical presentation of your data? Tabular presentation is warranted if you are examining two or three variables, and all the variables are categorical rather than continuous. You also can use tabular presentation if you have a continuous variable but wish to recode it into a smaller number of categories.

One Variable

Single variables are presented in **frequency distributions**. Recall that Figure 5.4 presented a histogram displaying the length of residence for 1,000 households residing in the neighborhood where your initial community policing initiative took place. Table 5.3 presents the same information in a frequency distribution.

The first two columns show the categories into which the data have been grouped. These categories are of equal width. They are also *mutually exclusive*. A data point can appear in only one category. Finally, they are *exhaustive*. All scores on the variable have been included in at least one category. No scores are too high or too low to fit into a category.

As in the histogram, each category represents a 5-year time span. These are the *apparent limits*. More precise boundaries for the data categories are provided in columns 3 and 4. These represent the *real limits*. To decide how to categorize specific cases, you refer to the real limits, not the apparent limits. Column 5 shows the number of cases that score within each interval. For example, 90 households reported a length of residence between 9.5 years and 14.5 years. These numbers are converted into percentages of the total in Column 6. These 90 households represented 9 percent of the total sample.

TABLE 5.3
Frequency Distribution:
Length of Residence in Neighborhood for 1,000 Households

1	2	3	4	5	6	7
Apparent Limits (in years)		Real Limits (in years)		N of Cases Within Interval	Percentage of Cases Within Interval	Cumulative Percentage of Cases Within Interval
From	To	From	To			
0	5	−.5	4.5	696	69.6	69.6
5	10	4.5	9.5	133	13.3	82.9
10	15	9.5	14.5	90	9	91.9
15	20	14.5	19.5	51	5.1	97
20	25	19.5	24.5	22	2.2	99.2
25	30	24.5	29.5	7	.1	99.9
30	35	29.5	34.5	1	.1	100
			TOTAL	1,000	100	

Column 7 reports the *cumulative percentage*—the percentage of cases scoring at that value of the variable or lower. 91.9 percent of the sample reported a length of residence of 9.5–14.5 years or less.

Frequency distributions present the same information as histograms, but for a different purpose. The histogram provides you with a rough estimate of where your data appear. By contrast, the frequency distribution shows exactly how many cases appear at each segment of the variable.

Two Variables

The purpose of two-way or bivariate contingency tables is the same as the purpose of scatterplots: to see how scores on one variable relate to scores on another variable. We first examine a two-variable contingency table where both variables are categorical. In a second example we inspect two continuous variables that each have been recoded into a small number of categories.

Categorical Variables

Scenario The 100 police officers trained in community policing were asked to answer a question about their views on police as "crime fighters." The question was: "A police officer's most important job at all times is to be a crime fighter." You are interested in seeing if men and women officers answer this question similarly.

Frequencies Table 5.4 displays the association between the two variables. In a cross-tabulation you typically use the categories of the independent variable to create the columns, and the categories of the dependent variable to create the rows. Here you treat sex of the officer as the independent variable, and agreement or disagreement with the "crime fighter" question as the dependent variable.

Appearing *outside* the table, in the margins, are the **marginal frequencies**. These are the frequency distributions for each variable.

TABLE 5.4
Sex by Crime-Fighting Views: Frequencies

		Sex		
		F	M	
Crime Fighting Most Important?	N	6	31	37
	Y	16	47	63
		22	78	100

TABLE 5.5
Sex by Crime-Fighting Views: Column Percentages

		Sex	
		F	M
Crime Fighting Most Important?	N	27%	40%
	Y	73%	60%
		100%	100%

You can see that 22 of the 100 officers trained in community policing were women. Sixty-three of the 100 officers felt that crime fighting was the police officer's most important job at all times.

Appearing *inside* the table are the **cell frequencies**, telling you exactly how many people appear in each of the four possible cells. You see, for example, that 16 of the 22 women officers agreed that crime fighting was the police officer's most important job. Forty-seven of the 78 men felt similarly.

You want to know if women officers, as compared to men, are more likely to feel that crime fighting is an officer's most important job. It is hard to compare directly the responses of men and women in this table because there are unequal numbers of each. Is 16/22 a greater fraction than 47/78?

You can control for the different number of cases in each category of the independent variable by computing **column percentages.** If the cases in each column add to 100%, what percentage of those cases appear in each cell? In other words, you percentage *down.* Table 5.5 displays the column percentages.

Here is a general formula for interpreting two-way tables when column percentages have been computed:

> Whereas ____ percent of the [READ FIRST CATEGORY OF THE INDEPENDENT VARIABLE] [READ MOST IMPORTANT CATEGORY OF THE DEPENDENT VARIABLE], ____ percent of the [READ NEXT CATEGORY OF THE INDEPENDENT VARIABLE] [READ *SAME* MOST IMPORTANT CATEGORY OF THE DEPENDENT VARIABLE].
>
> This suggests the following interpretation for Table 5.6:
>
> Whereas 73 percent of the female officers felt that crime fighting was an officer's most important job, 60 percent of the male officers felt that crime fighting was an officer's most important job.

In short, in this sample of 100 cases, women were somewhat more likely than men to endorse crime fighting as an officer's primary responsibility. To learn if this relationship was significant beyond this sample, you would conduct statistical analyses.

Continuous Variables You might examine the relationship between two continuous variables using a cross-tabulation. To do this you would first need to **recode** the scores on the continuous variables into a smaller number of categories. Say you want to examine the relationship between age and satisfaction with community policing using a cross-tab table. You want to examine satisfaction scores by decade of age. You could recode

TABLE 5.6
Age by Satisfaction with Community Policing:
Frequencies and Column Percentages

		Age (decades)				
		20s	30s	40s	50s	TOTAL
Satisfaction	Low	0 **0%**	6 **24%**	19 **79%**	25 **100%**	50
	High	26 **100%**	19 **76%**	5 **21%**	0 **0%**	50
		26 **100%**	25 **100%**	24 **100%**	25 **100%**	100

Note. Column percentages in bold.

actual age into the relevant decade (20s, 30s, and so on). You could recode scores on satisfaction into halves (lower half, upper half), thirds (lower third, middle third, upper third), fourths, or fifths.

Table 5.6 shows the relationship between age and satisfaction with being a community police officer. Satisfaction scores have been recoded into halves: those scoring 1–5 have been recoded into a "Low" group; those scoring 6–10 have been recoded into a "High" group. Age has been recoded into decades. The table shows marginal frequencies, cell frequencies, and column percentages in bold. The table allows you to make statements such as the following:

> Whereas 100 percent of those officers in their 20s express a high level of satisfaction with the community-policing role, 76 percent of those in their 30s express similar satisfaction, and 21 percent of those in their 40s express similar satisfaction. No officers in their 50s express a high level of satisfaction with the role.

Therefore, as age increases, satisfaction with the community-policing role decreases.

Independent and Dependent Variables Not Clear There may be situations where you are *un*able to identify clearly your independent and dependent variables. In these situations your decision about which variable to use for the columns, and which variable to use for the rows, is somewhat arbitrary. In these situations **row percentages** or **total percentages** may be useful in a table. With row percentages all the cases in a single row of a table sum to 100 percent. If you are using row percentages you compare up and down. With total percentages all the cases in all the cells in the table add to 100 percent.

You may be interested in the relationship between age and sex of the 100 officers receiving community policing training. The table can be organized in different ways. For example, Table 5.7 shows the frequencies and, in bold, the row percentages. You can see that, whereas 63 percent (31% + 32%) of the men are in their 40s and 50s, none of the women officers fall into this age group.

Rules of Tabular Construction The bulk of the examples discussed above assume that you can identify clearly your independent variable and your dependent variable. In these cases:

- Categories of your independent variable become your columns.

TABLE 5.7

Age by Sex of 100 Community Police Officers: Frequencies and Row Percentages

			Age (decades)				
			20s	30s	40s	50s	TOTAL
Sex	F	N	13	9	0	0	22
		Row %	**59%**	**41%**	**0%**	**0%**	**100%**
	M	N	13	16	24	25	78
		Row %	**17%**	**20%**	**31%**	**32%**	**100%**
			26	25	24	25	100

Note. Row percentages in bold.

- Categories of your dependent variable become your rows.
- You percentage down, calculating the percentage of cases in a column that are in each cell, such that the percentages in each column sum to 100 percent. This step standardizes for the different number of cases in each column. You are percentaging *within* each category of the independent variable.
- You compare percentages across, focusing on the *same* row of interest.

Three Variables

The tables you have examined so far have focused on two variables. Usually one variable functions as an independent variable (X), and the other as a dependent variable (Y). For example, you examined the relationship between age (X) and satisfaction (Y) with the community-policing role.

Cross-tab tables also can be used to look at three variables simultaneously: these show **trivariate** relationships. Why might you want to look at three variables simultaneously?

Reasons for Examining Three Variables Simultaneously When you examine trivariate relationships, you are looking at how a relationship between two variables may be influenced by a third variable. The nature of this influence can vary. This amounts to, in effect, further elaborating, specifying, delimiting, or testing the hypothesis of central interest. In general terms you think of these reasons for including a third variable as ways of *elaborating* the hypothesis in question. Not surprisingly the use of three-way tables has been called the *elaboration model*. [11, 12] The theorist is elaborating the conditions and processes surrounding the central relationship of interest. The third variable is also sometimes called a **test variable**—it allows the researcher to test under which conditions the relationship of central interest holds or doesn't hold.

The Third Variable Is an Intervening Variable First, you might hypothesize that a third variable, Z, *intervenes* between X and Y. In other words X leads to Y because X leads to Z, which in turns leads to Y. Graphically:

$$X \longrightarrow Z \longrightarrow Y$$

You may recall that, in Chapter 3, you hypothesized that age (X) led to decreased satisfaction with community policing (Y) *because*

Yes, such transformations are permissible, but only in one direction. You can convert observed scores on a variable from higher levels of measurement into lower levels (e.g., ratio to ordinal). You cannot, however, do the reverse. The information required for the latter treatment is simply not in the data.

INDEXES AND SCALING

In the remainder of the chapter you will examine two specific *types* of operational indicators—indexes and scales. **Indexes** are summary indicators, comprised of more than one variable. As a researcher you do not make distinctions between the different variables that make up the index. Most often, each variable you use in the index contributes about equally to the index summary score. Scores on an index represent a theoretical construct more general than scores on a single observed variable. After you construct an index you can array cases along the general variable or attribute tapped by the index.

The goal of **scale construction** is also to sort out the people being studied on the variable or attribute of interest. But the process involves two steps. First, the researcher learns the relationship of different items to one another. Then, based on their responses to particular items, people or items or both can be sorted on the variable. In short, with scales the researcher has to first *order* or *organize* the items being used before beginning to collect people's responses to the items. You will examine this process more closely later in the chapter.

Test Theory and Multiple Variables

Your insight into the conceptual foundations of scale and index construction will benefit if we spend more time with test theory. The equation on p. 102 showed that an observed score on one item reflected both a true score and measurement error. You can expand this equation to a situation where you have more than one variable.

As noted above, in the HCEM scenario, arrestees in your jurisdiction receive mandatory drug testing. Tests examine for four different substances: cocaine or crack-cocaine, heroin, amphetamines ("speed"), and marijuana. Each arrestee's urine sample is tested for each of these drugs, resulting in four different test results. Arrestees could test positive for any one of the four drugs.

You want to examine the drug-testing scores of convicted offenders assigned to HCEM. You want to develop one overall variable for the offenders showing the extent of their drug problem. You conceive of a construct: general involvement in drug abuse. You expect that you could operationalize this indicator of a concept by adding up the results of the different drug-testing results to produce one general drug test score.

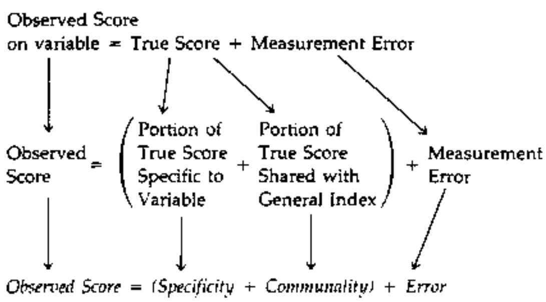
Operationally, this is easy. You have four different drug test results for each offender. Each observed score is a dummy variable at the nominal level of measurement, showing drug positive or not (1 or 0), for each drug type, for each case. You add the observed scores on each case to obtain scores on an index "General Drug Involvement."

When you construct this index you are making some assumptions about each variable contributing to the index. By postulating the concept "General Drug Involvement" and choosing each of these four variables to contribute to an indicator of it, you assume that the true score of each variable has two portions. One portion is specific to the drug tested. The other emerges from a tendency toward or against general drug involvement; the first represents the *specificity* of the item, the second reflects what is *shared* between the specific concept (e.g., cocaine use) and the more general concept (general drug involvement). Therefore, if you are thinking of spe-

Creating a "General Drug Involvement" Index: Sample Cases

	Scores on Variables				Score on Summary Index
Case	Cocaine	Heroin	Speed	Marijuana	
A	0	0	0	0	0
B	0	0	0	1	1
C	0	1	0	0	1
D	1	1	1	0	3
E	1	0	0	1	2

cific variables in the light of a more general index, reflecting a more general concept, we can elaborate our equation for classical test theory as follows [7]:



The portion of the item's true score that is unique to the item is called **specificity**. The portion of its true score that it shares with other items, and the more general concept indicated in the set of items, is called **communality**.

If the scores on each of the four specific drug tests are substantially influenced by general drug involvement, you will see positive associations between the four different drug results. This is because the true score of each item contains a large amount of communality. Offenders who tested positive for one drug will be likely also to test positive for a second, or third, or fourth drug. You will see cross-tabulation tables such as the following:

		Test Positive for Cocaine/Crack-Cocaine?	
		No	**Yes**
Test Positive for Amphetamines?	**No**	30 (60%)	10 (7%)
	Yes	20 (40%)	140 (93%)

Note. N and Column percentages shown. Artificial data.

Those who tested negative for cocaine or crack-cocaine were most likely also to test negative for amphetamines; 60% of those testing negative for crack or cocaine were also negative for amphetamines. Those who tested positive for cocaine or crack-cocaine were most likely also to test positive for amphetamines; 93% of those testing positive for cocaine or crack also tested positive for amphetamines. Scores on these two variables correlate with each other because each variable reflects not only specific drug usage, but also a more general tendency toward or away from general drug use.

In sum, scores from different variables may correlate with one another if they tap into the same, more general construct. Indexes are variables providing summary observed scores referring to these more general concepts. Given this background, you can consider more closely the reasons researchers use scales and indexes.

Why Do Researchers Resort to Scales and Indexes?

There are three reasons. [8]

Items Are Noisy Each individual variable you use includes some error, introduced by the measuring process. When you focus on an indicator of a general concept, the error associated with each specific variable, and the specificity of each variable, operate like so much "noise," interfering with your measurement goal. If you use several different variables to make such a judgement, however, it is likely that the "noise" involved in the responses to the different items will partially cancel each other out.[4] The categorization or score you assign to the case using an index score will be closer to the case's "true score" on the general concept than the categorization or score based on one item. You gain this precision, however, if and only if the index is based on several specific variables that correlate positively with one another.

Parsimony In Chapter 3 you learned about theoretical model building, and the criminal justice researchers' goal of building *parsimonious* or *simple* models. They also like to have simple *tests* of their models as well. The use of scales and indexes allows them to achieve this goal. A multifaceted or complex attribute can be represented with one summary score. In the example above, use of a summary "General Drug Involvement" index allows you to use just one concept in your theory, and one variable to reflect that concept.

Indexes Permit Discrimination By adding or averaging several variables, you can gauge scores on attributes with more precision than if you simply use one variable. If I have a variable showing a positive vs. a negative drug test result for one substance, then I can classify offenders into only two groups based on their results—those who tested positive, and those who did not. If I have four dummy variables, my general index will have scores ranging from 0 to 4; five different scores are possible. If I use the latter, the resulting ordering of offenders on the dimension will be more finely tuned to the true differences that exist.

Index Construction

An **index** is a summary indicator, based on several variables that correlate with one another and tap into the same general construct, where each component variable is treated as more or less equal.[5] You can use the *total* score based on the items in the index, or the *average* score. You want to verify that the different items reflect the *same* general attribute. You do so by verifying that scores on one variable correlate positively with scores from other variables referring to the same general concept. You can use cross-

[4] This is the case only if certain assumptions about the nature of the errors in each item, and across items, are valid.

[5] Depending upon the level of measurement and the range of possible scores for each variable, researchers may need to follow particular steps to ensure that each variable counts equally to the index. Typically, researchers standardize scores on each variable by converting scores to standard scores, also known as Z scores. See Chapter 10.

tab tables, as above, or scatterplots, for these examinations. If the different variables reflect the same general attribute, observed scores on the different variables will be generally consistent with one another. You will learn more about the mechanics of these procedures in Chapter 7 on Reliability.

Some Well-Known Criminal Justice Indexes Several indexes are widely used in criminal justice research.

UCR Index of Reported Crimes Police in almost all U.S. jurisdictions file monthly reports of crimes with the FBI. The FBI then totals these crimes in an index. The **Part 1 Crime Index** reports the total number of reported crimes occurring within a calendar year. The eight serious crimes added up to get the total number of serious crimes are: murder and nonnegligent manslaughter, forcible rape, robbery, aggravated assault; burglary; larceny–theft, motor vehicle theft, and, since October of 1978, arson. The index also can be expressed as a rate.[6] The Part 1 Index Crime Rate is calculated as follows:

$$\frac{\text{number of Part 1 index crimes in an area}}{\text{population in an area}} \times 100{,}000$$

The FBI provides further detail by separating out Part 1 crimes into a reported **Violent Crime Index** (murder, rape, robbery, aggravated assault), and a reported **Property Crime Index** (burglary, larceny, and motor vehicle theft). Of course, violence can occur during a property crime and property damage, or theft, can occur during a violent crime.

Victimization Indexes from the National Crime Survey The National Institute of Justice compiles the results of the *National Crime Survey,* a national survey conducted on an ongoing basis that asks people about victimization experiences. You will get a more detailed description of the NCS in Chapter 12. The Department of Justice constructs indexes from this survey.

The NCS asks about the following types of victimization incidents: rape, robbery, assault, burglary, personal and household larceny, and motor vehicle theft. [12] **Victimization counts** are calculated by adding up the number of victims of one or more crimes. Since a single crime incident can have more than one victim, victimization counts will be higher than victim incident counts. If a husband and wife both get robbed while walking home together one night, there is one victimization incident, but two victimization counts.

All victimizations are added up to get an index of **overall victimization counts** and generalizations are made *from* the surveyed population *to* the population of the country as a whole. For example, in 1988 there were approximately 35.8 million victimizations in the U.S. [13]

These victimization counts are then used to compute **victimization rates**. For personal crimes of rape, robbery, assault, and theft, *people* are used as the denominator to construct victimization rates of *personal* crimes. More specifically:

$$\text{Personal victimization rate} = \frac{\text{number of personal crime victimizations}}{\text{total population 12 and over}} \times 1{,}000$$

[6] There has been considerable discussion for several years about the inappropriateness of the denominator used to construct the Part 1 Index Crime Rate. [9, 10, 11] Although population may be the appropriate denominator for constructing a murder rate, it may not be appropriate when constructing a burglary rate, where occupied housing units should be used instead, or a forcible rape rate, where the number of women should be used. Of course, on the practical side it would be extremely difficult for law enforcement officials to collect information for the appropriate denominators for each of the eight Part 1 index crimes on a routine basis.

For household crimes—burglary, household larceny, motor vehicle theft—the number of *households* is used to as the denominator.

$$\text{Household victimization rate} = \frac{\text{number of household victimizations reported}}{\text{total number of households}} \times 1{,}000$$

Because of the way the survey sample is constructed, the researchers are able to extrapolate from the survey respondents to the entire U.S. population, and develop estimated victimization rates for the entire country.[7] How do they perform this magic? You'll see in Chapter 10.

These rates we have been discussing so far—the UCR reported crime rates for personal and property crimes, the household victimization rate, and the personal victimization rate—are all indicators of the *incidence* of victimization. An **incidence-based rate** divides the number of *incidents* by *a population count*, whether that be individuals or households. (As a mental exercise, you may wish to estimate the level of measurement of these indexes.) Thus, for the household victimization rate, one household being burgled 10 times during a year contributes the same amount to the property victimization rate as 10 households each being burgled once during the year.

The Department of Justice researchers also generate an overall index of the *prevalence* of crime that includes both personal and household crimes. A **prevalence-based rate** divides the *number of persons (or households) experiencing* the event by the *total number of persons (or households)*. Note that, conceptually, this is very different from an incidence-based index rate. If a particular household experiences 1 burglary during a year, or 10 different burglaries, that household contributes the same amount to the prevalence-based indicator.

One prevalence-based rate developed from the NCS is an index of **households touched by crime**: the proportion of households in the country that have experienced one or more victimizations during a calendar year. A household is counted as "touched by crime" during a year if one or more of its members experience one or more of the following victimization experiences: rape, personal robbery, assault, personal theft, or motor vehicle theft; or if the household is burglarized or victimized by a theft. [14] Homicide is not included. Researchers extrapolate from the results of the National Crime Survey to estimate, nationwide, the number of households touched by crime.

Figure 6.4 shows the proportion of households, nationwide, "touched by crime" during the period 1975 through 1988, by race of household. Whereas the proportion has dropped consistently for White households during the period, it has dropped less among African American households. In 1988 nearly 1/4 of U.S. households (24.6%) had been touched by a crime.

Problems with These Indexes Critics have pointed out shortcomings of these indexes. [15] (1) The general measures count attempted and completed crimes as equivalent. The proportion of attempted vs. successful crimes varies widely. Whereas roughly 90% of the household larcenies reported in the NCS were successfully completed, only about 35% of robberies reported in the NCS were successfully completed. (2) All these indexes add together "apples and oranges"—crimes that vary enormously in their severity, and in the type of victimization experience. In the personal victimization rate constructed from the NCS, a victimization incident of an attempted bicycle theft contributes the same

[7] Because of the way this extrapolation works the resulting estimates have some built-in imprecision. This built-in imprecision of the extrapolated rates is due to *sampling error*, which you will learn more about in Chapter 10.

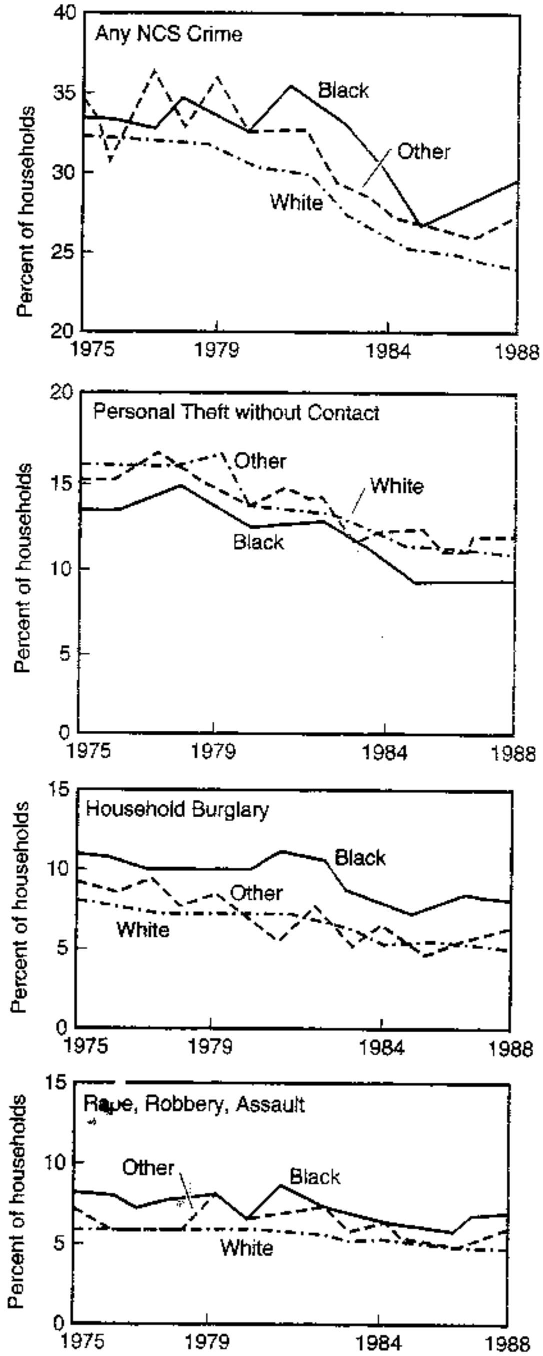


FIGURE 6.4
Source: Rand, M. (1989) Households touched by crime. Bureau of Justice Statistics Bulletin. Washington, DC: U.S. Department of Justice. Figure 2, p. 2.

amount to the rate as does a completed rape. The households touched by crime index, and the overall "Crime Index" calculated by the FBI from the UCR, are the two indexes that combine the broadest range of incidents.

This latter problem is inherent, somewhat, in every index. An index *always* adds variables that are, to some extent, unlike one another, to arrive at a more general variable. Thus, some blurring is inevitable. Such are the costs of seeking parsimony. In recognition of such costs, researchers have pursued the development of *scales*, to which we now turn.

Scale Construction

Scales are distinct from indexes. Scales consider the relationship *between items*. The items are ordered on an underlying attribute of interest. Numbers or categories are then assigned to the items based on their position on the variable. Psychologists over the decades have developed many procedures for scaling a wide variety of stimuli.

A scaling exercise may have one of three purposes: (1) to find the position of the item or stimulus itself on an underlying attribute or dimension, (2) to classify or position persons on an underlying attribute or dimension, or (3) to classify or position both persons and stimuli on an underlying attribute or dimension. [17] When the persons or items have been positioned on the underlying attribute of interest, they have been *scaled*.

Consider, for example, the scaling of crimes on a seriousness dimension. I may be interested in this simply to learn how serious people think heroin smuggling is compared to bicycle theft (scaling the items). Or I may be interested in finding how people differ in the perceived seriousness of a set of crimes, and then understanding those differences. Some may think that people convicted of bicycle theft should go to prison, whereas

BOX 6.1

A SAFETY INDEX FOR PHILADELPHIA'S SUBURBAN NEIGHBORHOODS

Who Decides Item Weights?

In December 1989 *Philadelphia* magazine published a guide to the safest suburban neighborhoods in the region. [16] They developed a "safety index" for each of the 251 locales surrounding Philadelphia.[8] Readers were encouraged to "find out . . . Just how safe is your town?"

The magazine developed their safety index in the following fashion. For each of the eight Part 1 UCR crimes they computed countywide rates. Then they calculated the UCR crime rates for each township within the larger counties. To get the relative safety of each township vis-à-vis its surrounding county, they divided each township's rate for each crime by its county rate. Thus, if the aggravated assault rate in a township was the same as in the larger county, the result would be 1.0; if it was half of the county rate, the result would be 0.5.

Each of these ratios was added up to calculate an "overall safety index." (Murder, rape and arson were excluded from the overall index.) In adding the crimes up, they weighted "the various crimes according to a 'worry factor'." Here is how their weighting went:

Crime	Index Weight According to "Worry" Factor
Robbery + Assault (combined)	50
Burglary	25
Auto Theft	15
Larceny or Theft	10

So according to the author of the study, a robbery is twice as worrisome as a burglary, and five times as worrisome as a larceny. But a burglary is only 67 percent more worrisome than an auto theft. Why were these relative weights chosen? Why not other weights? The use of a different weighting scheme would result in a different ordering of the communities on the index. You can try this out for yourself and see. The actual dataset appears in the file PHILASUB.WKS. The workdisk contains some suggested exercises that suggest ways you can test this out.

The main point is this: beware an index where the contributing variables have been assigned different weights, and a sound justification for those different weights is lacking. If the weights are arbitrary, so too are the resulting scores on the index.

[8] The area around the city of Philadelphia is divided up into seven large counties—three in New Jersey, and four in Pennsylvania. Each county is then further divided into townships. The units analyzed were these townships.

others may not (scaling persons). Or I may be interested in finding out how the crimes are arrayed along an underlying seriousness dimension, and what crime each person views as the most serious (scaling both items and people).

Suppose You Wanted to Measure Crime Seriousness Imagine you want to know about the seriousness of different offenses. This has been a topic of considerable interest to social scientists for some time. The great measurement psychologist Louis Thurstone published a paper on this in the 1920s [18, 19]. The most noted publication for criminologists in this area was Sellin and Wolfgang's seminal work on the topic, *The Measurement of Delinquency*, published in 1964. The 15 crimes in which you are interested appear in Table 6.2. You want to arrange these crimes so that you know which is more serious than the other, and by how much. What are the different ways you might want to go about this?

What I will do below is to describe different techniques that researchers might use to scale these 15 stimuli. For each technique I will discuss its advantages and its disadvantages.

Equal-Appearing Intervals *The Underlying Rationale* Louis Thurstone invented several different scaling procedures. The most widely used was the method of *equal-appearing intervals*. Underlying this procedure is a presumption called **the law of comparative judgements**. This law assumes that, for each stimulus, there exists a **modal** or **typical response**. In crime seriousness a modal-judged level of seriousness is assumed to exist for each crime. It is *not* assumed that everyone judging the stimulus provides the modal judgement. People can vary in how seriously they judge the crime. But those variations will center on that modal judgement, disperse evenly on either side, and taper off as you move away from the modal judgement. Most judgements for a crime will be close to the modal judgement for that crime.

In technical terms he assumed that judgements formed a *normal distribution* around the modal judgement. You can learn more about

TABLE 6.2
Fifteen Crimes in Which You Are Interested

A. A person using force, robs a victim of $10. The victim struggles and is shot to death.
B. A person disturbs the neighborhood with loud, noisy behavior.
C. A person steals property worth $1,000 from outside a building.
D. A father beats his young child with his fists. The child requires hospitalization.
E. A man forcibly rapes a woman. Her physical injuries require hospitalization.
F. A person steals property worth $10 from outside a building.
G. A person, using force, robs a victim of $10. No physical harm occurs.
H. A person plants a bomb in a public building. The bomb explodes, and 20 people are killed.
I. A person steals property worth $10,000 from outside a building.
J. A person smuggles heroin into the country.
K. A person steals property worth $50 from outside a building.
L. A factory knowingly gets rid of its wastes in a way that pollutes the water supply of a city. As a result 20 people become ill, but none require medical treatment.
M. A person steals an unlocked car and later abandons it.
N. A person steals property worth $100 from outside a building.
O. A person, using force, robs a victim of $10. The victim is hurt and requires hospitalization.