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Logistic Regression

Introduction

The simple and multiple linear regression methods we studied in Chapters 10 and 11 are used to model the relationship between a *quantitative* response variable and one or more explanatory variables. In this chapter, we describe similar methods that are used when the response variable is a *categorical* variable with two possible values, such as a student applicant receives or does not receive financial aid, a patient lives or dies during emergency surgery, or your cell phone coverage is acceptable or not.

In general, we call the two outcomes of the response variable “success” and “failure” and represent them by 1 (for a success) and 0 (for a failure). The mean is then the proportion of 1s, $p = P(\text{success})$. If our data are n independent observations, we have the *binomial setting*. What is new in this chapter is that the data now include at least one explanatory variable x and the *probability* p depends on the value of x . For example, suppose that we are studying whether a student applicant receives ($y = 1$) or is denied ($y = 0$) financial aid. Here, p is the probability that an applicant receives aid, and possible explanatory variables include (a) the financial support of the parents, (b) the income and savings of the applicant, and (c) whether the applicant has received financial aid before. Just as in multiple linear regression, the explanatory variables can be either categorical or quantitative. Logistic regression is a statistical method for describing these kinds of relationships.¹

- 14.1 The Logistic Regression Model
- 14.2 Inference for Logistic Regression



binomial
setting,
p. 312

14.1 The Logistic Regression Model

When you complete this section, you will be able to:

- Find the odds from a single probability.
- Describe the statistical model for logistic regression with a single explanatory variable.
- Find the odds ratio for comparing two proportions.

Binomial distributions and odds

In Chapter 5 we studied binomial distributions, and in Chapter 8 we learned how to do statistical inference for the proportion p of successes in the binomial setting. We start with a brief review of some of these ideas that we will need in this chapter.

EXAMPLE 14.1

Recommend the service. Exercise 8.16 (page 501) describes a survey of 250 customers of an automobile dealership. The customers were asked if they would recommend the service department to a friend. The number who responded Yes was 210.

In the notation of Chapter 5, p is the proportion of customers in the *population* of customers from which the sample was drawn who would respond Yes to the question. The number of customers who would respond Yes in a simple random sample (SRS) of size n has the binomial distribution with parameters n and p . The sample size of customers is $n = 250$, and the number who responded Yes is the count $X = 210$. The sample proportion is

$$\hat{p} = \frac{210}{250} = 0.84$$



Logistic regressions work with odds rather than proportions. The odds are simply the ratio of the proportions for the two possible outcomes. If \hat{p} is the proportion for one outcome, then $1 - \hat{p}$ is the proportion for the second outcome:

$$\text{odds} = \frac{\hat{p}}{1 - \hat{p}}$$

A similar formula for the population odds is obtained by substituting p for \hat{p} in this expression.

EXAMPLE 14.2

Odds of responding Yes. For the customer service data, the proportion of customers who would recommend the service in the sample of customers is $\hat{p} = 0.84$, so the proportion of customers who would not recommend the service department

$$1 - \hat{p} = 1 - 0.84 = 0.16$$

Therefore, the odds of recommending the service department are

$$\begin{aligned} \text{odds} &= \frac{\hat{p}}{1 - \hat{p}} \\ &= \frac{0.84}{0.16} \\ &= 5.25 \end{aligned}$$

When people speak about odds, they often round to integers or fractions. If we round 5.25 to $5 = 5/1$, we would say that the odds are approximately 5 to 1 that a customer would recommend the service to a friend. In a similar way, we could describe the odds that a customer would *not* recommend the service as 1 to 5.

USE YOUR KNOWLEDGE

14.1 Odds of drawing a heart. If you deal one card from a standard deck, the probability that the card is a heart is $13/52 = 1/4$.

(a) Find the odds of drawing a heart.

(b) Find the odds of drawing a card that is not a heart.

14.2 Given the odds, find the probability. If you know the odds, you can find the probability by solving the odds equation for the probability. So, $\hat{p} = \text{odds}/(\text{odds} + 1)$. If the odds of an outcome are 2.5 (or 5 to 2), what is the probability of the outcome?

Odds for two groups

In Example 8.11 (page 507), we compared the use of Instagram for young women and men. Using the methods of Chapter 8, we compared the proportions of female and male Instagram users with a confidence interval in (page 507) or significance test (page 512).

EXAMPLE 14.3



INSTAGR

Comparing the proportions of female and male Instagram users. Figure 14.1 contains output from JMP for this comparison. The sample proportion of women who are Instagram users is given as 61.08%, and the sample proportion for men is 43.98%. The difference is 0.170951, and the 95% confidence interval is (0.111429, 0.2292). We can summarize this result by saying, “In this sample of young adults, the percent of women who use Instagram is 17% higher the percent of men who use Instagram. This difference is statistically significant ($P < 0.0001$).”

LOOK BACK

indicator
variable,
p. 610

Another way to analyze these data is to use logistic regression. The explanatory variable is sex, a categorical variable. To use this in a regression (logistic or otherwise), we need to use a numeric code. The usual way to do this is with an *indicator variable*. For our problem, we will use an indicator of whether or not the adult is a woman:

$$x = \begin{cases} 1 & \text{if the person is a woman} \\ 0 & \text{if the person is a man} \end{cases}$$

The response variable is the proportion of Instagram users. For use in a logistic regression, we perform two transformations on this variable. First, we convert to odds. For women,

$$\begin{aligned} \text{odds} &= \frac{\hat{p}}{1 - \hat{p}} \\ &= \frac{0.6108}{1 - 0.6108} \\ &= 1.5694 \end{aligned}$$

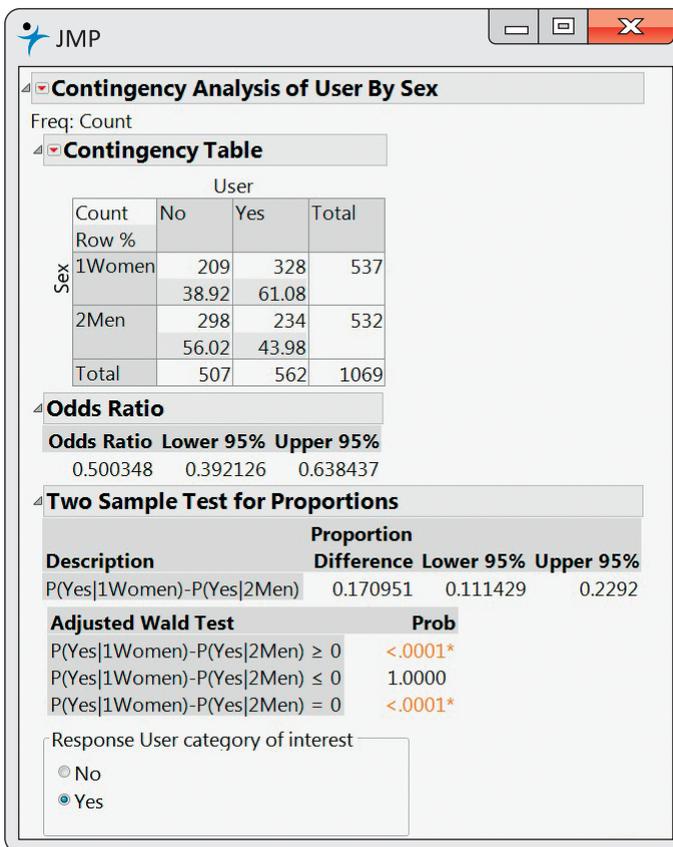


FIGURE 14.1 JMP output for the comparison of the proportions of female and male Instagram users, Example 14.3.

Similarly, for men we have

$$\begin{aligned}
 \text{odds} &= \frac{\hat{p}}{1 - \hat{p}} \\
 &= \frac{0.4398}{1 - 0.4398} \\
 &= 0.7851
 \end{aligned}$$

USE YOUR KNOWLEDGE

14.3 Energy drink commercials. A study was designed to compare two energy drink commercials. Each participant was shown the commercials, A and B, in random order and asked to select the better one. There were 150 women and 140 men who participated in the study. Commercial A was selected by 71 women and by 87 men. Find the odds of selecting Commercial A for the men. Do the same for the women.

14.4 Find the odds. Refer to the previous exercise. Find the odds of selecting Commercial B for the men. Do the same for the women.

Model for logistic regression

In simple linear regression, we modeled the mean μ_y of the response variable y as a linear function of the explanatory variable: $\mu = \beta_0 + \beta_1x$. When y is just 1 or 0 (success or failure), the mean is the probability p of a success. Logistic regression models the mean p in terms of an explanatory variable x . We might try to relate p and x as in simple linear regression: $p = \beta_0 + \beta_1x$. Unfortunately, this is not a good model. Whenever $\beta_1 \neq 0$, extreme values of x will give values of $\beta_0 + \beta_1x$ that fall outside the range of possible values of $p, 0 \leq p \leq 1$.

The logistic regression solution to this difficulty is to transform the odds ($p/(1 - p)$) using the natural logarithm. We use the term **log odds** or **logit** for this transformation.

As we did with linear regression, we use y for the response variable. So for women,

$$y = \log(\text{odds}) = \log(1.5694) = 0.4507$$

and for men,

$$y = \log(\text{odds}) = \log(0.7851) = -0.2419$$

In these expressions for the log odds, we use y as the observed value of the response variable, the log odds of using Instagram. We are now ready to build the logistic regression model.

We model the log odds as a linear function of the explanatory variable:

$$\log\left(\frac{p}{1 - p}\right) = \beta_0 + \beta_1x$$

Figure 14.2 graphs the relationship between p and x for some different values of β_0 and β_1 . For logistic regression, we use *natural* logarithms. There are tables of natural logarithms, and many calculators have a built-in function for this transformation.

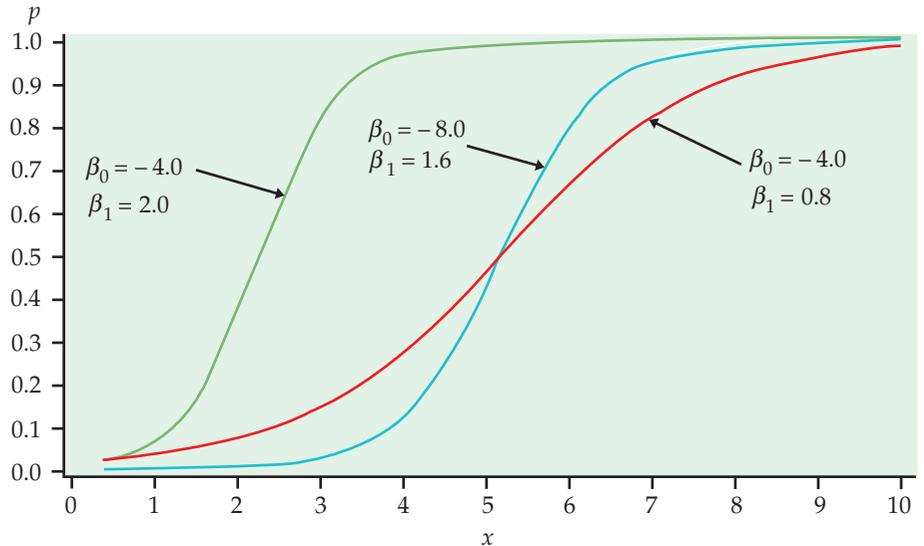


FIGURE 14.2 Plot of p versus x for different logistic regression models.

USE YOUR KNOWLEDGE

- 14.5 Find the odds.** Refer to Exercise 14.3. Find the log odds for the men and the log odds for the women.
- 14.6 Find the odds.** Refer to Exercise 14.4. Find the log odds for the men and the log odds for the women.

LOGISTIC REGRESSION MODEL

The **statistical model for logistic regression** is

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x$$

where p is a binomial proportion and x is the explanatory variable. The parameters of the logistic regression model are β_0 and β_1 .

EXAMPLE 14.4

Model for Instagram users. For our Instagram example, there are $n = 1069$ young persons in the sample. The explanatory variable is sex, which we have coded using an indicator variable with values $x = 1$ for women and $x = 0$ for men. The response variable, y , is also an indicator variable. Thus, each person either is an Instagram user or is not an Instagram user. Think of a process of selecting a young person at random and recording y and x . The model says that the probability, p , that this person is an Instagram user can depend upon the user's sex ($x = 1$ or $x = 0$). So there are two possible values for p —say, p_{women} and p_{men} .

Logistic regression with an indicator explanatory variable is a very special case. It is important because many multiple logistic regression analyses focus on one or more such variables as the primary explanatory variables of interest. For now, we use this special case to understand a little more about the model.

The logistic regression model specifies the relationship between p and x . Because there are only two values for x , we write both equations. For women,

$$\log\left(\frac{p_{\text{women}}}{1-p_{\text{women}}}\right) = \beta_0 + \beta_1$$

and for men,

$$\log\left(\frac{p_{\text{men}}}{1-p_{\text{men}}}\right) = \beta_0$$

Note that there is a β_1 term in the equation for women because $x = 1$, but it is missing in the equation for men because $x = 0$.

Fitting and interpreting the logistic regression model

In general, the calculations needed to find estimates b_0 and b_1 for the parameters β_0 and β_1 are complex and require the use of software. When the explanatory variable has only two possible values, however, we can easily find the estimates. This simple framework also provides a setting where we can learn what the logistic regression parameters mean.

EXAMPLE 14.5

Log odds for Instagram use. In the Instagram example, we found the log odds for women,

$$\log\left(\frac{\hat{p}_{\text{women}}}{1 - \hat{p}_{\text{women}}}\right) = 0.4507$$

and for men,

$$\log\left(\frac{\hat{p}_{\text{men}}}{1 - \hat{p}_{\text{men}}}\right) = -0.2419$$

The logistic regression model for women is

$$\log\left(\frac{p_{\text{women}}}{1 - p_{\text{women}}}\right) = \beta_0 + \beta_1$$

and for men it is

$$\log\left(\frac{p_{\text{men}}}{1 - p_{\text{men}}}\right) = \beta_0$$

To find the estimates b_0 and b_1 , we match the female and male model equations with the corresponding data equations. Thus, we see that the estimate of the intercept b_0 is simply the log odds for the men:

$$b_0 = -0.2419$$

and the estimate of the slope is the difference between the log odds for the women and the log odds for the men:

$$b_1 = 0.4507 - (-0.2419) = 0.6926$$

The fitted logistic regression model is

$$\log(\text{odds}) = -0.2419 + 0.6926x$$

The slope in this logistic regression model is the difference between the log odds for men and the log odds for women. Most people are not comfortable thinking in the log odds scale, so interpretation of the results in terms of the regression slope is difficult. Usually, we apply a transformation to help us. With a little algebra, it can be shown that

$$\frac{\text{odds}_{\text{women}}}{\text{odds}_{\text{men}}} = e^{0.6926} = 1.999$$

The transformation $e^{0.6926}$ undoes the logarithm and transforms the logistic regression slope into an **odds ratio**—in this case, the ratio of the odds that a woman uses Instagram to the odds that a man uses Instagram. In other words, we can multiply the odds for men by the odds ratio to obtain the odds for women:

$$\text{odds}_{\text{women}} = 1.999 \times \text{odds}_{\text{men}}$$

In this case, we would say that the odds for women are about twice the odds for men.

Notice that we have chosen the coding for the indicator variable so that the regression slope is positive. This will give an odds ratio that is greater than 1.

Had we coded men as 1 and women as 0, the sign of the slope would be reversed and the odds ratio would be $e^{-0.6926} = 0.500$. The odds for men are about half of the odds for women.

Logistic regression with an explanatory variable having two values is a very important special case. Here is an example where the explanatory variable is quantitative.

EXAMPLE 14.6



MOVIES

Is a movie going to be profitable? The MOVIES data file includes both the movie's budget and the total U.S. revenue for 76 recent movies. For this example, we will classify each movie as "profitable" ($y = 1$) if U.S. revenue is larger than the budget and not profitable ($y = 0$) otherwise. Profit is our response variable. The data file contains several explanatory variables, but we will focus here on the natural logarithm of the opening weekend revenue. Figure 14.3 is a scatterplot of the data with a scatterplot smoother. The probability that a movie is profitable increases with the log opening weekend revenue. Let's fit the logistic regression model

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x$$

where p is the probability that the movie is profitable and x is the log opening-weekend revenue. The model for estimated log odds fitted by software is

$$\log(\text{odds}) = b_0 + b_1 x = -2.56 + 1.125x$$

The odds ratio is $e^{b_1} = 3.08$. This means that if log opening weekend revenue x increases by one unit (roughly \$2.71 million), the odds that the movie will be profitable increase by a factor of 3.08.

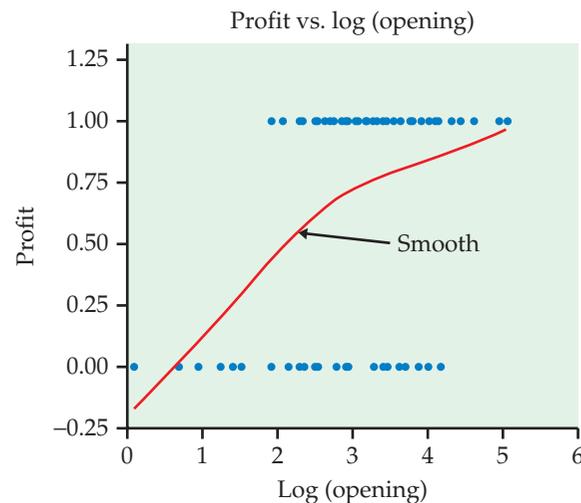


FIGURE 14.3 Scatterplot of profit ($Y = 1, N = 0$) versus the log opening weekend revenue $\text{Log}(\text{opening})$ with a smooth function, Example 14.6.

USE YOUR KNOWLEDGE

- 14.7 Find the logistic regression equation and the odds ratio.** Refer to Exercises 14.3 and 14.5. Find the logistic regression equation and the odds ratio.
- 14.8 Find the logistic regression equation and the odds ratio.** Refer to Exercises 14.4 and 14.6. Find the logistic regression equation and the odds ratio.

14.2 Inference for Logistic Regression

When you complete this section, you will be able to:

For a logistic regression with a single explanatory variable, use software to:

- Identify the estimates of the regression parameters and write the equation for the fitted model.
- Identify the 95% confidence interval for the regression slope and the significance test results for the null hypothesis that the slope is zero.
- Identify and interpret the odds ratio and the 95% confidence interval for the odds ratio.

For a logistic regression with several explanatory variables, use software to:

- Identify the estimates of the regression parameters and write the equation for the fitted model.
- Identify the significance test results for the null hypothesis that all regression slopes are zero.
- Identify the 95% confidence intervals for the regression coefficients and the significance test results for the null hypothesis that each of the regression coefficients is zero.
- Identify and interpret the odds ratio and the 95% confidence interval for the odds ratio for each explanatory variable.

Statistical inference for logistic regression is very similar to statistical inference for simple linear regression. We calculate estimates of the model parameters and standard errors for these estimates. Confidence intervals are formed in the usual way, but we use standard Normal z^* -values rather than critical values from the t distributions. The ratio of the estimate of the slope to the standard error is the basis for hypothesis tests. Often, the test statistics are given as the squares of these ratios, and in this case, the P -values are obtained from the chi-square distribution with 1 degree of freedom.

Confidence intervals and significance tests**CONFIDENCE INTERVALS AND SIGNIFICANCE TESTS FOR LOGISTIC REGRESSION PARAMETERS**

A level C confidence interval for the slope β_1 is

$$b_1 \pm z^*SE_{b_1}$$

The ratio of the odds for a value of the explanatory variable equal to $x + 1$ to the odds for a value of the explanatory variable equal to x is the **odds ratio**.

A **level C confidence interval for the odds ratio e^{β_1}** is obtained by transforming the confidence interval for the slope:

$$(e^{b_1 - z^* SE_{b_1}}, e^{b_1 + z^* SE_{b_1}})$$

In these expressions, z^* is the value for the standard Normal density curve with area C between $-z^*$ and z^* .

To test the hypothesis $H_0: \beta_1 = 0$, compute the **test statistic**

$$z = \frac{b_1}{SE_{b_1}}$$

The P -value for the significance test of H_0 against $H_a: \beta_1 \neq 0$ is computed using the fact that, when the null hypothesis is true, z has approximately a standard Normal distribution.

Wald statistic

Note that, unlike other standard errors that we have used, the computation of standard errors for logistic regression parameters is complicated and requires software. This test statistic z is sometimes called a **Wald statistic**. Output from some statistical software reports the significance test result in terms of the square of the z statistic.

$$X^2 = z^2$$



chi-square
statistic,
p. 534

This statistic is called a chi-square statistic. When the null hypothesis is true, it has a distribution that is approximately a χ^2 distribution with 1 degree of freedom, and the P -value is calculated as $P(\chi^2 \geq X^2)$. Because the square of a standard Normal random variable has a χ^2 distribution with 1 degree of freedom, the z statistic and the chi-square statistic give the same results for statistical inference.

We have expressed the hypothesis-testing framework in terms of the slope β_1 because this form closely resembles what we studied in simple linear regression. In many applications, however, the results are expressed in terms of the odds ratio. A slope of 0 is the same as an odds ratio of 1, so we often express the null hypothesis of interest as “the odds ratio is 1.” This means that the two odds are equal and the explanatory variable is not useful for predicting the odds.

EXAMPLE 14.7



Software output. Figure 14.4 gives the output from Minitab for the Instagram example described in Example 14.5. Note that the variable SEXNUM in the output has values 1 for women and 0 for men. The parameter estimates are given as $b_0 = -0.2418$ and $b_1 = 0.692$. The standard errors are 0.0873 and 0.1240, respectively.

The 95% confidence interval for the slope is

$$\begin{aligned} b_1 \pm z^* SE_{b_1} &= 0.692 \pm (1.96)(0.1240) \\ &= 0.692 \pm 0.24304 \end{aligned}$$

We are 95% confident that the slope is between 0.449 and 0.935. Note that Minitab reports the significance test results using a chi-squared statistic.

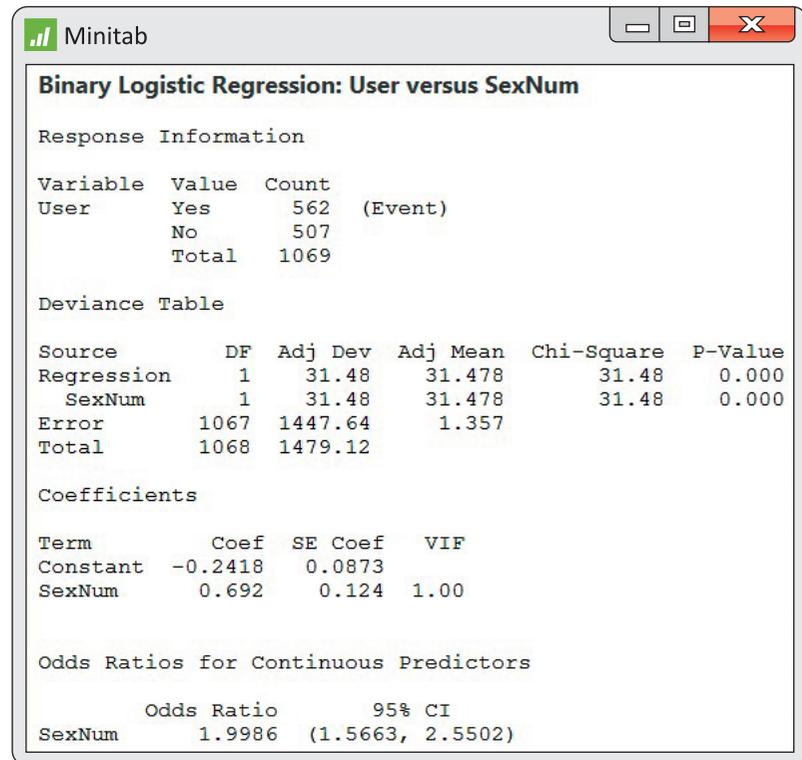


FIGURE 14.4 Logistic regression output from Minitab for the Instagram data, Example 14.7.

The output also provides the odds ratio 1.9986 and a 95% confidence interval, 1.5663 to 2.5502. For this problem we would report, “Women are more likely than men to be Instagram users (odds ratio = 2.00, 95% CI = 1.57 to 2.55).”

Note that there are some differences between the estimates given by Minitab in Figure 14.4 and the calculations that we performed in Exercise 14.5. These generally occur only in the last digit and are due to roundoff errors in our calculations.

USE YOUR KNOWLEDGE

14.9 Verify the calculation of the odds ratio. Refer to Example 14.7. Verify that the odds ratio, 1.9986, is e^{b_1} . (Use $b_1 = 0.69245$ for your calculation.)

14.10 Verify the calculation of the confidence interval. Refer to Example 14.7. Verify that the 95% confidence interval for the odds ratio, 1.57 to 2.55, is

$$(e^{b_1 - z^* SE_{b_1}}, e^{b_1 + z^* SE_{b_1}})$$

where $z^* = 1.96$. Explain why we use this value of z^* in the calculation.

In applications such as these, it is standard to use 95% for the confidence coefficient. With this convention, the confidence interval gives us the result of testing the null hypothesis that the odds ratio is 1 for a significance level of 0.05.

If the confidence interval does not include 1, we reject H_0 and conclude that the odds for the two groups are different; if the interval does include 1, the data do not provide enough evidence to distinguish the groups in this way.

The following example is typical of many applications of logistic regression. Here, there is a designed experiment with five different values for the explanatory variable.

EXAMPLE 14.8



Nigel Cattini / Alamy



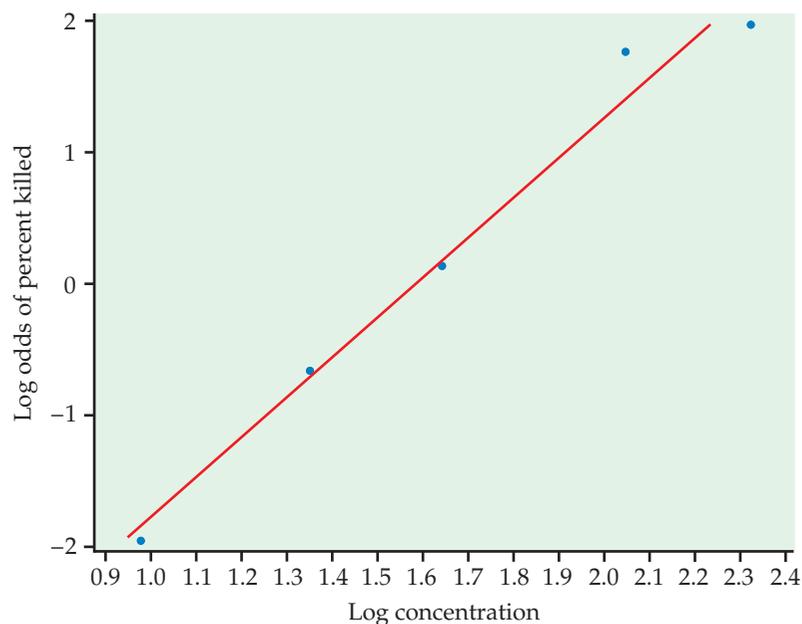
INSECTS

An insecticide for aphids. An experiment was designed to examine how well the insecticide rotenone kills an aphid, called *Macrosiphoniella sanborni*, that feeds on the chrysanthemum plant.² The explanatory variable is the concentration (in log of milligrams per liter) of the insecticide. At each concentration, approximately 50 insects were exposed. Each insect was either killed or not killed. We summarize the data using the number killed. The response variable for logistic regression is the log odds of the proportion killed. Here are the data:

Concentration (log)	Number of insects	Number killed
0.96	50	6
1.33	48	16
1.63	46	24
2.04	49	42
2.32	50	44

If we transform the response variable (by taking log odds) and use least squares, we get the fit illustrated in Figure 14.5. The logistic regression fit is given in Figure 14.6. It is a transformed version of Figure 14.5 with the fit calculated using the logistic model.

FIGURE 14.5 Plot of log odds of percent killed versus log concentration for the insecticide data, Example 14.8.



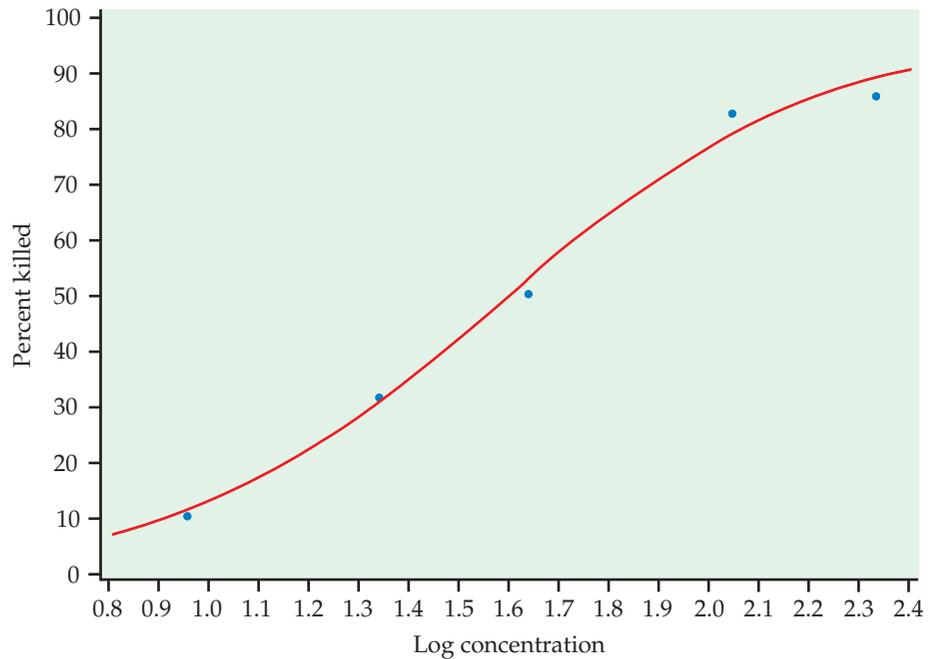


FIGURE 14.6 Plot of the percent killed versus log concentration with the logistic fit for the insecticide data, Example 14.8.

One of the major themes of this text is that we should present the results of a statistical analysis with a graph. For the insecticide example, we have done this with Figure 14.6, and the results appear to be convincing. But suppose that rotenone has no ability to kill *Macrosiphoniella sanborni*. What is the chance that we would observe experimental results at least as convincing to what we observed if this supposition were true? The answer is the P -value for the test of the null hypothesis that the logistic regression slope is zero. If this P -value is not small, our graph may be misleading. Statistical inference provides what we need.

EXAMPLE 14.9



INSECTS

Software output. Figure 14.7 gives the output from Minitab, SPSS, and JMP for the logistic regression analysis of the insecticide data. The model is

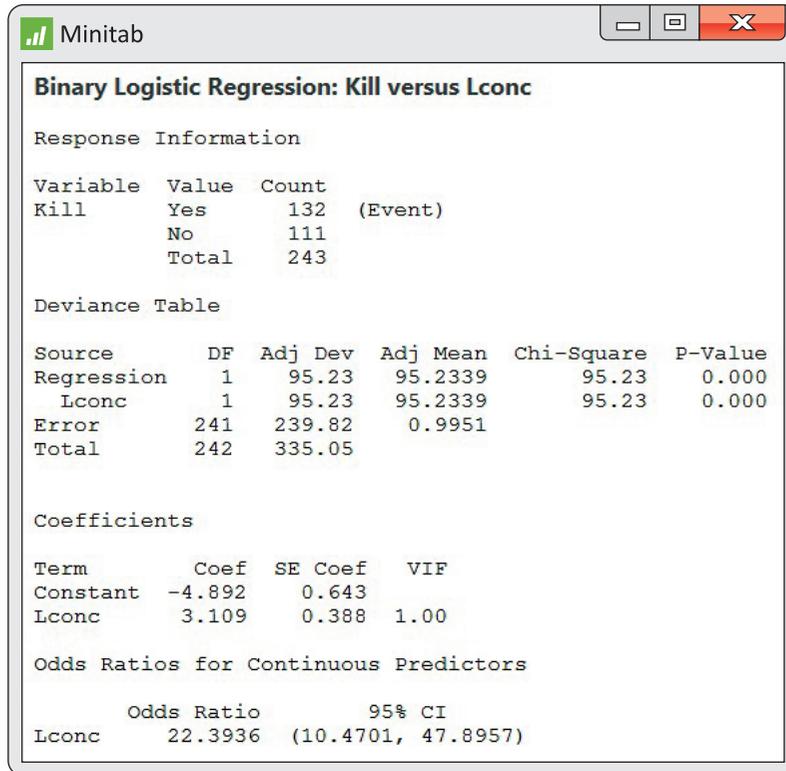
$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x$$

where the values of the explanatory variable x are 0.96, 1.33, 1.63, 2.04, and 2.32. From the output in Minitab and SPSS, we see that the fitted model is

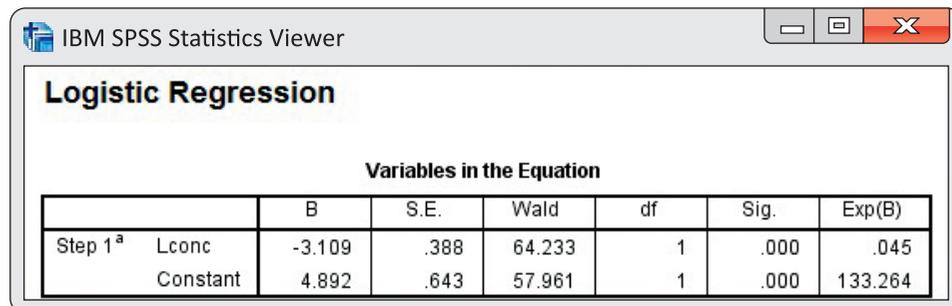
$$\log(\text{odds}) = b_0 + b_1 x = -4.89 + 3.11x$$

This is the fit that we plotted in Figure 14.6. The null hypothesis that $\beta_1 = 0$ is clearly rejected ($X^2 = 95.23$ in Minitab, Wald $X^2 = 64.233$ in SPSS, and $X^2 = 64.23$ in JMP; $P < 0.001$ for all). Note that Minitab uses a statistic that is quite different from the one used by JMP and SPSS, although the conclusion that we draw is the same. We calculate a 95% confidence interval

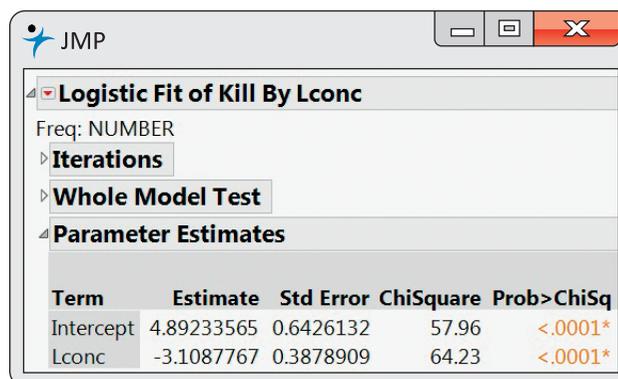
FIGURE 14.7 Logistic regression output from (a) Minitab, (b) SPSS, and (c) JMP for the insecticide data, Example 14.9.



(a)



(b)



(c)

for β_1 using the estimate $b_1 = 3.1088$ and its standard error $SE_{b_1} = 0.3879$ given in the output:

$$\begin{aligned} b_1 \pm z^*SE_{b_1} &= 3.1088 \pm (1.96)(0.3879) \\ &= 3.1088 \pm 0.7603 \end{aligned}$$

We are 95% confident that the true value of the slope is between 2.35 and 3.87.

The odds ratio is given on the Minitab output as 22.39. An increase of one unit in the log concentration of insecticide (x) is associated with a 22-fold increase in the odds that an insect will be killed. Minitab gives the 95% confidence interval for the odds ratio, 10.47 to 47.90. We could calculate this from the confidence interval for the slope:

$$\begin{aligned} (e^{b_1 - z^*SE_{b_1}}, e^{b_1 + z^*SE_{b_1}}) &= (e^{2.3485}, e^{3.8691}) \\ &= (10.47, 47.90) \end{aligned}$$

Note again that the test of the null hypothesis that the slope is 0 is the same as the test of the null hypothesis that the odds are 1. If we were reporting the results in terms of the odds, we could say, “The odds of killing an insect increase by a factor of 22.4 for each unit increase in the log concentration of insecticide ($X^2 = 64.23$, $P < 0.001$; 95% CI = 10.5 to 47.9).”

Note that SPSS and JMP give the fitted model as

$$\log(\text{odds}) = 4.89 - 3.11x$$

We see that the regression coefficients b_0 and b_1 are -1 times the coefficients given by Minitab. The reason for this is that SPSS and JMP model the log odds that an insect is *not* killed rather than the log odds that an insect is killed, as shown in the other two outputs. *Always examine software output carefully to be sure that the results you are getting correspond exactly to the analysis that you are trying to perform.* For this analysis, we know from our graph in Figure 14.6 that the slope should be positive.



In Example 14.6, we studied the problem of predicting whether or not a movie was going to make a profit using the log opening weekend revenue as the explanatory variable. We now revisit this example and show how statistical inference is an important part of the conclusion.

EXAMPLE 14.10



MOVIES

Software output. Figure 14.8 gives the output from Minitab for a logistic regression analysis using log opening-weekend revenue as the explanatory variable to predict the log odds that the movie will be profitable. From the Minitab output, we see that the fitted model is

$$\log(\text{odds}) = b_0 + b_1x = -2.56 + 1.125x$$

In the output, the significance test results are given as chi-squared statistics. The P -value for log opening weekend revenue is given as 0.000, which we would report as $P < 0.0005$, so we can reject the null hypothesis that $\beta_1 = 0$. The value of the test statistic is $X^2 = 14.82$ with 1 degree of freedom. We use the estimate $b_1 = 1.125$ and its standard error $SE_{b_1} = 0.339$ to compute the 95% confidence interval for β_1 :

$$\begin{aligned} b_1 \pm z^*SE_{b_1} &= 1.125 \pm (1.96)(0.339) \\ &= 1.125 \pm 0.664 \end{aligned}$$

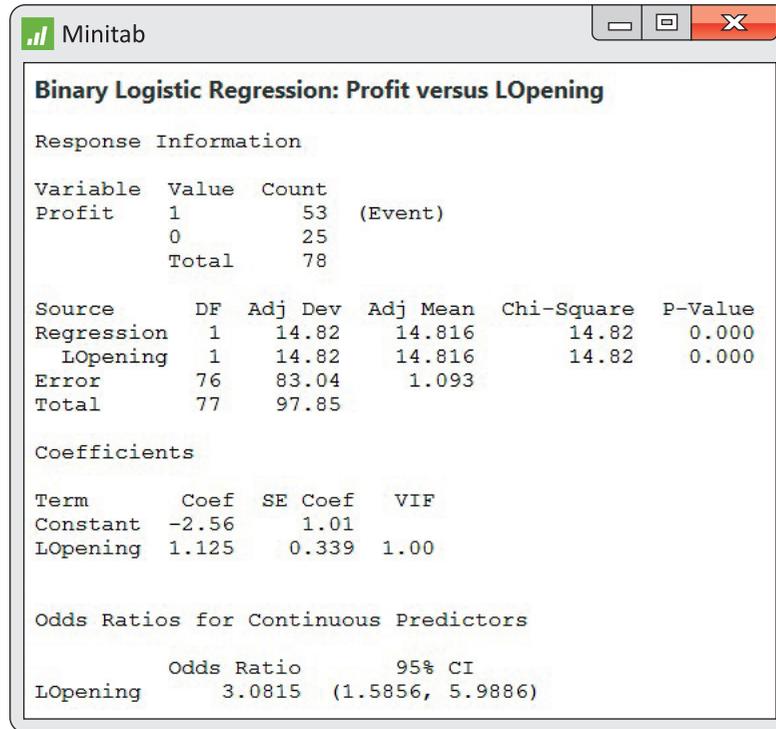


FIGURE 14.8 Logistic regression output from Minitab for the movie profitability data with log opening-weekend revenue as the explanatory variable, Example 14.10.

Our estimate of the slope is 1.125, and we are 95% confident that the true value is between 0.461 and 1.789. For the odds ratio, the estimate on the output is 3.0815. The 95% confidence interval is given as (1.5856, 5.9886).

We estimate that an opening-weekend revenue that is one unit larger (roughly \$2.71 million) will increase the odds that a movie is profitable by about three times. The data, however, do not give us a very accurate estimate. The odds ratio could be as small as 1.6 or as large as 6.0 with 95% confidence. We have evidence to conclude that movies with higher opening-weekend revenues are more likely to be profitable, but establishing the relationship accurately would require more data.

Multiple logistic regression

The movie example that we just considered naturally leads us to the next topic. The MOVIES data file includes additional explanatory variables. Do these other explanatory variables contain additional information that will give us a better prediction of profitability? We use **multiple logistic regression** to answer this question. Generating the computer output is easy, just as it was when we generalized simple linear regression with one explanatory variable to multiple linear regression with more than one explanatory variable in Chapter 11. The statistical concepts are similar, although the computations are more complex. Here is the example.

multiple logistic regression

LOOK BACK

multiple linear
regression
p. 610

EXAMPLE 14.11

MOVIES

Software output. As in Example 14.10, we predict the odds that a movie is profitable. The explanatory variables are log opening-weekend revenue (LOpening), number of theaters (Theaters), and a rating (Opinion) of the movie on a 1 to 10 scale (10 being best). Figure 14.9 gives the outputs from Minitab and SPSS. The fitted model is

$$\begin{aligned}\log(\text{odds}) &= b_0 + b_1 \text{LOpening} + b_2 \text{Theaters} + b_3 \text{Opinion} \\ &= -0.404 + 2.001 \text{LOpening} - 0.001 \text{Theaters} - 0.214 \text{Opinion}\end{aligned}$$

Binary Logistic Regression: Profit versus LOpening, Theaters, Opinion

Source	DF	Adj Dev	Adj Mean	Chi-Square	P-Value
Regression	3	18.4972	6.1657	18.50	0.000
LOpening	1	14.2148	14.2148	14.21	0.000
Theaters	1	3.6433	3.6433	3.64	0.056
Opinion	1	0.6064	0.6064	0.61	0.436
Error	74	79.3547	1.0724		
Total	77	97.8518			

Coefficients

Term	Coef	SE Coef	VIF
Constant	-0.40	1.99	
LOpening	2.001	0.620	3.12
Theaters	-0.001156	0.000631	2.87
Opinion	-0.214	0.279	1.22

Odds Ratios for Continuous Predictors

	Odds Ratio	95% CI
LOpening	7.3953	(2.1944, 24.9225)
Theaters	0.9988	(0.9976, 1.0001)
Opinion	0.8076	(0.4678, 1.3942)

(a)

Logistic Regression

Variables in the Equation

	B	S.E.	Wald	df	Sig.	Exp(B)
Step 1 ^a LOpening	2.001	.620	10.419	1	.001	7.395
Theaters	-.001	.001	3.354	1	.067	.999
Opinion	-.214	.279	.588	1	.443	.808
Constant	-.404	1.992	.041	1	.839	.667

(b)

FIGURE 14.9 Logistic regression output from (a) Minitab and (b) SPSS for the movie profitability data with log opening-weekend revenue, number of theaters, and the movie's rating as the explanatory variables, Example 14.11.



When analyzing data using multiple linear regression, we first examine the hypothesis that all the regression coefficients for the explanatory variables are zero. We do the same for multiple logistic regression. The hypothesis

$$H_0: \beta_1 = \beta_2 = \beta_3 = 0$$

is tested by a chi-square statistic with 3 degrees of freedom. (The degrees of freedom are 3 because there are three coefficients that are set to zero in the null hypothesis.) For Minitab, this is given near the top of the output on the line titled “Regression” under the label “Chi-square.” The value is 18.50, and the P -value is given as 0.000. We would report this as $P < 0.0005$. We reject H_0 and conclude that one or more of the explanatory variables can be used to predict the odds that a movie is profitable.

We now examine the coefficients for each variable and the tests that each of these is zero *in a model that contains the other two*. The P -values are 0.000 (< 0.0005), 0.056, and 0.436. The null hypotheses $H_0: \beta_2 = 0$ and $H_0: \beta_3 = 0$ cannot be rejected. That is, log opening-weekend revenue is the only predictor that adds significant predictive ability once the other two are already in the model.

Our initial multiple logistic regression analysis told us that the explanatory variables contain information that is useful for predicting whether or not the movie is profitable. Because the explanatory variables are correlated, however, we cannot clearly distinguish which variables or combinations of variables are important. Further analysis of these data using subsets of the three explanatory variables is needed to clarify the situation. We leave this work for the exercises.

CHAPTER 14 SUMMARY

- If \hat{p} is the sample proportion, then the **odds** are $\hat{p}/(1 - \hat{p})$, the ratio of the proportion of times the event happens to the proportion of times the event does not happen.
- The **logistic regression model** relates the **log of the odds** to the explanatory variable:

$$\log\left(\frac{p_i}{1 - p_i}\right) = \beta_0 + \beta_1 x_i$$

where the response variables for $i = 1, 2, \dots, n$ are independent binomial random variables with parameters 1 and p_i ; that is, they are independent with distributions $B(1, p_i)$. The explanatory variable is x .

- The **parameters** of the logistic model are β_0 and β_1 .
- The **odds ratio** is e^{β_1} , where β_1 is the slope in the logistic regression model.
- A **level C confidence interval for the intercept** β_0 is

$$b_0 \pm z^* SE_{b_0}$$

A **level C confidence interval for the slope** β_1 is

$$b_1 \pm z^* SE_{b_1}$$

A **level C confidence interval for the odds ratio** e^{β_1} is obtained by transforming the confidence interval for the slope:

$$(e^{b_1 - z^* SE_{b_1}}, e^{b_1 + z^* SE_{b_1}})$$

In these expressions, z^* is the value for the standard Normal density curve with area C between $-z^*$ and z^* .

- To test the hypothesis $H_0: \beta_1 = 0$, compute the **test statistic**

$$z = \frac{b_1}{SE_{b_1}}$$

and use the fact that z has a distribution that is approximately the standard Normal distribution when the null hypothesis is true. This statistic is sometimes called the **Wald statistic**. An alternative equivalent procedure is to report the square of z ,

$$X^2 = z^2$$

This statistic has a distribution that is approximately a χ^2 distribution with 1 degree of freedom, and the P -value is calculated as $P(\chi^2 \geq X^2)$. This is the same as testing the null hypothesis that the odds ratio is 1.

- In **multiple logistic regression**, the response variable has two possible values, as in logistic regression, but there can be several explanatory variables.

CHAPTER 14 EXERCISES

For Exercises 14.1 and 14.2, see page 14-3; for Exercises 14.3 and 14.4, see page 14-4; for Exercises 14.5 and 14.6, see page 14-6; for Exercises 14.7 and 14.8, see page 14-9; and for Exercises 14.9 and 14.10, see page 14-11.

14.11 How did you use your cell phone? A Pew Internet Poll asked cell phone owners about how they used their cell phones. One question asked whether or not, during the past 30 days, they had used their phone while in a store to call a friend or family member for advice about a purchase they were considering. The poll surveyed 1003 adults living in the United States by telephone. Of these, 462 responded that they had used their cell phone while in a store within the last 30 days to call a friend or family member for advice about a purchase they were considering.³

- What proportion of those surveyed reported that they used their cell phone while in a store within the last 30 days to call a friend or family member for advice about a purchase they were considering?
- Find the odds for the probability that you found in part (a).

14.12 Find some odds. For each of the following probabilities, find the odds: 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9. Make a plot of the odds versus the probabilities and describe the relationship.

14.13 A logistic model for cell phones. Refer to Exercise 14.11. Suppose that you want to investigate differences in cell phone use among customers of different ages. You create an indicator explanatory variable x that has the value 1 if the customer is 25 years of age or less and is 0 if the customer over 25 years of age.

- Describe the statistical model for logistic regression in this setting.
- Explain the relationship between the regression coefficients and the odds ratios for the two groups of customers defined by x .

14.14 Another logistic model for cell phones and age. Refer to the previous exercise. Suppose that you use the actual value of age in years as the explanatory variable in a logistic regression model.

- Describe the statistical model for logistic regression in this setting.

(b) Interpret the regression slope in terms of an effect based on a difference in age of one year.

(c) This model requires an assumption that is not needed in the model that you described in the previous exercise. Explain the assumption and describe a method for examining whether or not it is a reasonable assumption to make for these data. (*Hint*: Refer to Example 14.8 and Figure 14.5, page 14–12.)

14.15 A logistic regression for teeth and military service. Exercise 8.62 (page 520) describes data on the numbers of U.S. recruits who were rejected for service in a war against Spain because they did not have enough teeth. The exercise compared the rejection rate for recruits who were under the age of 20 with the rate for those who were 40 or over. To run a logistic regression for this setting, we define an indicator explanatory variable x with values 0 for age under 20 and 1 for age 40 or over. Figure 14.10 gives output from Minitab for this analysis.  **TEETH1**

(a) How many recruits were examined? How many were rejected and how many were not rejected?

(b) Write the fitted logistic regression model.

14.16 Inference for teeth and military service. Refer to the previous exercise.

(a) Using the information provided in the output in Figure 14.10, calculate and interpret the 95% confidence interval for the regression slope.

(b) Describe and interpret the results of the significance test for the regression slope. Be sure to give the null and alternative hypotheses, the test statistic, and the P -value with your conclusion.

14.17 Odds ratio for teeth and military service. Refer to the two previous exercises.

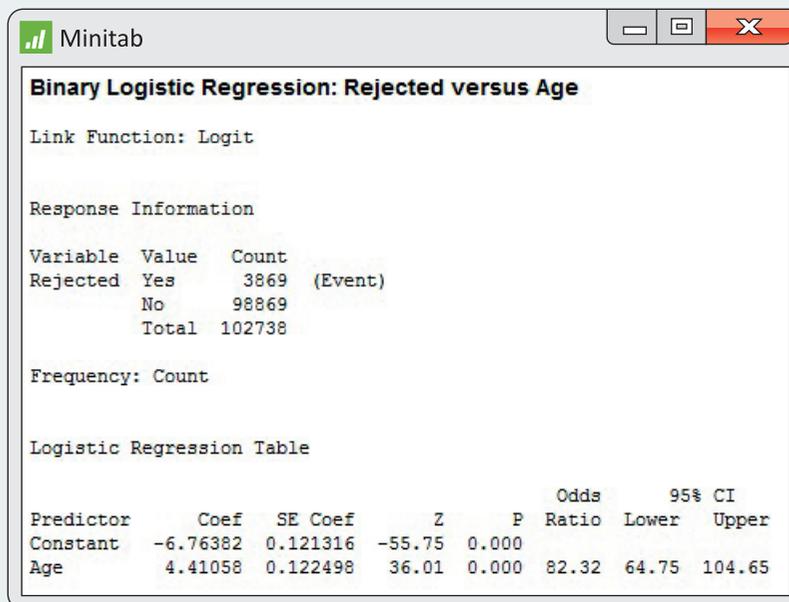
(a) Give the odds ratio for this analysis.

(b) Give the 95% confidence interval for the odds ratio.

(c) Give a brief description of the meaning of the odds ratio in this analysis.

14.18 Teeth and military service with six age categories. In Exercises 14.15, 14.16, and 14.17, we used logistic regression to study the relationship between being rejected for military service because a recruit did not have enough teeth and age categorized into two groups, under 20 and 40 or over. Data are available for all recruits categorized into six age groups. Let's look at a logistic regression that uses all the data to predict rejection for military service based on teeth. There are six age groups: under 20, 20–25, 25–30, 30–35, 35–40, and 40 or over. We define indicator explanatory variables for the last five groups. This is similar to defining a single indicator explanatory variable for an analysis of two groups.  **TEETH2**

Figure 14.11 gives the Minitab output for the logistic regression to predict rejection using the five age indicator explanatory variables.



Binary Logistic Regression: Rejected versus Age

Link Function: Logit

Response Information

Variable	Value	Count	
Rejected	Yes	3869	(Event)
	No	98869	
	Total	102738	

Frequency: Count

Logistic Regression Table

Predictor	Coef	SE Coef	Z	P	Odds Ratio	95% CI	
						Lower	Upper
Constant	-6.76382	0.121316	-55.75	0.000			
Age	4.41058	0.122498	36.01	0.000	82.32	64.75	104.65

FIGURE 14.10 Logistic regression output from Minitab for predicting recruit rejection using age in two categories, Exercises 14.15, 14.16, and 14.17.

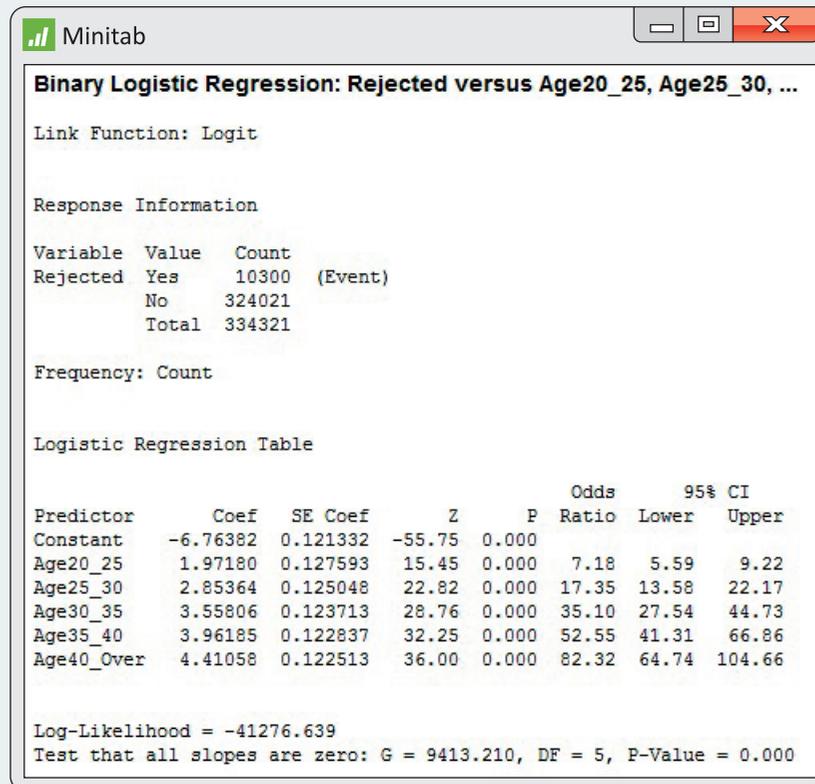


FIGURE 14.11 Logistic regression output from Minitab for predicting recruit rejection using age in six categories, Exercises 14.18 through 14.21.

- (a) Use the output to find the fitted model.
 (b) Is there a pattern in the values of the regression slopes? If yes, describe it.

14.19 Inference for the multiple logistic regression model. Refer to the previous exercise.

- (a) Describe and interpret the significance test that tests the null hypothesis that all regression coefficients are zero.
 (b) Using the information provided in the output in Figure 14.11, calculate and interpret the 95% confidence interval for each of the regression slopes.
 (c) Describe and interpret the results of the significance test for each regression slope. Be sure to give the null and alternative hypotheses, the test statistic, and the P -value with your conclusion.

14.20 Odds ratios for the multiple logistic regression model. Refer to the two previous exercises.

- (a) Give the odds ratio for each explanatory variable.
 (b) Give the 95% confidence interval for each odds ratio.

- (c) Give a brief description of the meaning of each odds ratio in this analysis.

14.21 Compare the multiple logistic regression analysis with the two-way table. The data analyzed in Figure 14.11 were analyzed in Exercise 9.42 and Figure 9.11 (page 552) using a 2×6 table of counts. Compare these two approaches to the analysis of these data. Describe some strengths and weaknesses of each approach. Which do you prefer? Give reasons for your answer.

14.22 What purchases will be made? A poll of 1000 adults aged 18 or older asked about purchases they intended to make for the upcoming holiday season.⁴ A total of 463 adults listed gift card as a planned purchase.

- (a) What proportion of adults plan to purchase a gift card as a present?
 (b) What are the odds that an adult will purchase a gift card as a present?
 (c) What proportion of adults do not plan to purchase a gift card as a present?

(d) What are the odds that an adult will not buy a gift card as a present?

(e) How are your answers to parts (b) and (d) related?

14.23 High blood pressure and cardiovascular disease.

There is much evidence that high blood pressure is associated with increased risk of death from cardiovascular disease. A major study of this association examined 3338 men with high blood pressure and 2676 men with low blood pressure. During the period of the study, 21 men in the low-blood-pressure group and 55 in the high-blood-pressure group died from cardiovascular disease.

(a) Find the proportion of men who died from cardiovascular disease in the high-blood-pressure group. Then calculate the odds.

(b) Do the same for the low-blood-pressure group.

(c) Now calculate the odds ratio with the odds for the high-blood-pressure group in the numerator. Describe the result in words.

14.24 High blood pressure and cardiovascular disease.

Refer to the study of cardiovascular disease and blood pressure in Exercise 14.23. Computer output for a logistic regression analysis of these data gives the estimated slope $b_1 = 0.7505$ with standard error $SE_{b_1} = 0.2578$.

(a) Give a 95% confidence interval for the slope.

(b) Calculate the X^2 statistic for testing the null hypothesis that the slope is zero and use Table F to find an approximate P -value.

(c) Write a short summary of your results and conclusions.

14.25 High blood pressure and cardiovascular disease.

The results describing the relationship between blood pressure and cardiovascular disease are given in terms of the change in log odds in Exercise 14.24.

(a) Transform the slope to the odds ratio and the 95% confidence interval for the slope to a 95% confidence interval for the odds ratio.

(b) Write a conclusion using the odds to describe the results.

14.26 Exergaming in Canada. Exergames are active video games such as rhythmic dancing games, virtual bicycles, balance board simulators, and virtual sports simulators that require a screen and a console. A study of exergaming by students in grades 10 and 11 in Montreal, Canada, examined many factors related to participation in exergaming.⁵ Of the 358 students who reported that they stressed about their health, 29.9% said that they were exergamers. Of the 851 students who reported that they did not stress about their health, 20.8% said that they were exergamers. Analyze these data using logistic regression and write a summary of your analytical approach, your results, and your conclusions.

14.27 More exergaming in Canada. Refer to the previous exercise. Another explanatory variable reported in this study was the amount of television watched per day. Of the 54 students who reported that they watched no TV, 11.1% were exergamers; for the 776 students who watched some TV but less than two hours, 20.6% were exergamers; and for the 370 students who watched two or more hours, 31.1% were exergamers. Use logistic regression to examine the relationship between TV watching and exergaming. Write a summary of your analytical approach, your results, and your conclusions.

14.28 What's wrong? For each of the following, explain what is wrong and why.

(a) If $b_1 = 5$ in a logistic regression analysis with one explanatory variable, we estimate that the probability of an event is multiplied by 5 when the value of the explanatory variable increases by one unit.

(b) The intercept β_0 is equal to the odds of an event when $x = 0$.

(c) The odds of an event are 1 minus the probability of the event.

14.29 What's wrong? For each of the following, explain what is wrong and why.

(a) For a multiple logistic regression with four explanatory variables, the null hypothesis that the regression coefficients of all the explanatory variables are zero is tested with an F test.

(b) For a logistic regression, we assume that the model has a Normally distributed error term.

(c) In logistic regression with one explanatory variable, we can use a chi-square statistic to test the null hypothesis $H_0: b_1 = 0$ versus a one-sided alternative.

(d) In multiple logistic regression, we do not need to worry about correlation among explanatory variables when interpreting model coefficient estimates.

 **14.30 Interpret the fitted model.** If we apply the exponential function to the fitted model in Example 14.6 (page 14-8), we get

$$\text{odds} = e^{-2.56+1.125x} = e^{-2.56} \times e^{1.125x}$$

Show that for any value of the quantitative explanatory variable x , the odds ratio for increasing x by 1,

$$\frac{\text{odds}_{x+1}}{\text{odds}_x}$$

is $e^{1.125} = 3.08$. This justifies the interpretation given at the end of Example 14.6.

14.31 Will a movie be profitable? In Example 14.6 (page 14-8), we developed a model to predict whether a movie is profitable based on log opening-weekend

revenue. What are the predicted odds of a movie being profitable if the opening-weekend revenue is

- \$20 million dollars ($LO_{\text{opening}} = 3.00$)?
- \$40 million dollars ($LO_{\text{opening}} = 3.69$)?
- \$60 million dollars ($LO_{\text{opening}} = 4.09$)?

14.32 Converting odds to probability. Refer to the previous exercise. For each opening-weekend revenue, compute the estimated probability that the movie is profitable.

14.33 Salt intake and cardiovascular disease. In Example 9.12 (page 542), the relative risk of developing cardiovascular disease (CVD) for people with low- and high-salt diets was estimated. Let's reanalyze these data using the methods in this chapter. Here are the data:

	Salt in diet		Total
	Low	High	
Developed CVD			
Yes	88	112	200
No	1081	1134	2215
Total	1169	1246	2415

- For each salt level, find the probability of developing CVD.
- Convert each of the probabilities that you found in part (a) to odds.
- Find the log of each of the odds that you found in part (b).

14.34 Salt in the diet and CVD. Refer to the previous exercise. Use $x = 1$ for the high-salt diet and $x = 0$ for the low-salt diet.

- Find the estimates b_0 and b_1 .
- Give the fitted logistic regression model.
- What is the odds ratio for a high-salt versus low-salt diet?
- When the probability of an event is very small, the odds ratio and relative risk are similar. Compare this odds ratio with the relative risk estimate in Example 9.12. Are they close? Explain your answer.

14.35 Give a 99% confidence interval for β_1 . Refer to Example 14.9 (page 14-13). Suppose that you wanted to report a 99% confidence interval for β_1 . Show how you would use the information provided in the outputs shown in Figure 14.7 to compute this interval.  INSECTS

14.36 Give a 95% confidence interval for the odds ratio. Refer to Example 14.9 and the outputs in Figure 14.7 (page 14-14). Using the estimate b_1 and its standard error, find the 95% confidence interval for the odds ratio and verify that this agrees with the interval given by the software.

 **14.37 z and the X^2 statistic.** Use the three outputs in Figure 14.7 (page 14-14) to explore the relationship between the z statistic and the X^2 statistic that we have discussed in this chapter (page 14-10).

- Use the information in each output to calculate the z statistic. Verify that they are essentially the same (with no roundoff, they would be equal). This z statistic has approximately the standard Normal distribution if the null hypothesis (slope 0) is true.
- Show that the square of z is close to the Wald statistic reported by SPSS and the X^2 statistic reported by JMP.
- Note that Minitab uses a different calculation to obtain a X^2 statistic. Does the P -value for this statistic reported by Minitab lead to a different conclusion than the X^2 values given by SPSS and JMP? Explain your answer.

(d) Comment on the reporting of P values as 0.000 by Minitab and .000 by SPSS versus <0.0001 by JMP. Which do you prefer? Give reasons for your answer.

14.38 Finding the best model? In Example 14.11 (page 14-17), we looked at a multiple logistic regression for movie profitability based on three explanatory variables. Complete the analysis by looking at the three models that include two explanatory variables and the three models that include only one variable. Create a table that includes the parameter estimates and their P -values as well as the overall X^2 statistic and degrees of freedom. Based on the results, which model do you feel is the best? Explain your answer.  MOVIES

14.39 Tipping behavior in Canada. The Consumer Report on Eating Share Trends (CREST) contains data from all provinces of Canada detailing away-from-home food purchases by roughly 4000 households per quarter. Researchers recently restricted their attention to restaurants at which tips would normally be given.⁶ From a total of 73,822 observations, "high" and "low" tipping variables were created based on whether the observed tip rate was above 20% or below 10%, respectively. They then used logistic regression to identify explanatory variables associated with either "high" or "low" tips. The following table summarizes what they termed the stereotype-related variables for the low-tip analysis:

Explanatory variable	Odds ratio
Senior adult	1.099
Sunday	1.098
English as second language	1.142
French-speaking Canadian	1.163
Alcoholic drinks	0.713
Lone male	0.858

All coefficients were significant at the 0.01 level. Write a short summary explaining these results in terms of the odds of leaving a low tip.

14.40 An example of Simpson's paradox. Here is an example of Simpson's paradox: *the reversal of the direction of a comparison or an association when data from several groups are combined to form a single group.* The data concern two hospitals, A and B, and whether or not patients undergoing surgery died or survived. Here are the data for all patients:

	Hospital A	Hospital B
Died	63	16
Survived	2037	784
Total	2100	800

And here are the more detailed data where the patients are categorized as being in good condition or poor condition:

	Good condition		Poor condition	
	Hospital A	Hospital B	Hospital A	Hospital B
Died	6	8	57	8
Survived	594	592	1443	192
Total	600	600	1500	200

(a) Use a logistic regression to model the odds of death with hospital as the explanatory variable. Summarize the results of your analysis and give a 95% confidence interval for the odds ratio of Hospital A relative to Hospital B.

(b) Rerun your analysis in part (a) using hospital and the condition of the patient as explanatory variables. Summarize the results of your analysis and give a 95% confidence interval for the odds ratio of Hospital A relative to Hospital B.

(c) Explain Simpson's paradox in terms of your results in parts (a) and (b).

14.41 Reducing the number of workers. To be competitive in global markets, many corporations are undertaking major reorganizations. Often, these involve "downsizing" or a "reduction in force" (RIF), where substantial numbers of employees are terminated. Federal and various state laws require that employees be treated equally regardless of their age. In particular, employees over the age of 40 are in a "protected" class, and many allegations of discrimination focus on comparing employees over 40 with their younger coworkers. Here are the data for a recent RIF:

Terminated	Over 40	
	No	Yes
Yes	7	41
No	504	765

(a) Write the logistic regression model for this problem using the log odds of a RIF as the response variable and an indicator for over and under 40 years of age as the explanatory variable.

(b) Explain the assumption concerning binomial distributions in terms of the variables in this exercise. To what extent do you think that these assumptions are reasonable?

(c) Software gives the estimated slope $b_1 = 1.3504$ and its standard error $SE_{b_1} = 0.4130$. Transform the results to the odds scale. Summarize the results and write a short conclusion.

(d) If additional explanatory variables were available—for example, a performance evaluation—how would you use this information to study the RIF?

14.42 Internet use in Canada. A recent study used data from the Canadian Internet Use Survey (CIUS) to explore the relationship between certain demographic variables and Internet use by individuals in Canada.⁷

The response variable refers to the use of the Internet from any location within the last 12 months. Explanatory variables included age (years), income (thousands of dollars), location (1 = urban, 0 = other), sex (1 = male, 0 = female), education (1 = at least some postsecondary education, 0 = other), language (1 = English, 0 = French), and children (1 = at least one child in household, 0 = no children). The following table summarizes the results:

Explanatory variable	b
Age	-0.063
Income	0.013
Location	0.367
Sex	-0.222
Education	1.080
Language	0.285
Children	0.049
Intercept	2.010

All but Children were significant at the 0.05 level.

(a) Interpret the sign of each of the coefficients (except the intercept) in terms of the probability that the individual uses the Internet.

(b) Compute the odds ratio for each of the variables in the table.

(c) What are the odds that a French-speaking, 23-year-old male, living alone in Montreal, and making \$50,000 a year his second year after college is using the Internet?

(d) Convert the odds in part (c) to a probability.

14.43 Predicting physical activity. Participation in physical activities typically declines between high school and young adulthood. This suggests that postsecondary

institutions may be an ideal setting to address physical activity. A study looked at the association between physical activity and several behavioral and perceptual characteristics among midwestern college students.⁸ Of 663 students who met the vigorous activity guidelines for the previous week, 169 reported eating fruit two or more times per day. Of the 471 who did not meet the vigorous activity guidelines in the previous week, 68 reported eating fruit two or more times per day. Model the log odds of vigorous activity using an indicator variable for eating fruit two or more times per day as the explanatory variable. Summarize your findings.

14.44 Online consumer spending. The Consumer Behavior Report is designed to provide insight into online shopping trends.⁹ A recent report asked the question, “In the past three months, how has the current state of the economy impacted your money spending on online purchasing?” Here are the results from 3156 online consumers:

Gender	Reduced spending	
	No	Yes
Female	586	708
Male	1074	788

- What proportion of individuals plan to reduce their spending in each gender?
- What is the odds ratio for comparing female individuals to male individuals?
- Write the logistic regression model for this problem using the log odds of reducing spending as the response variable and an indicator of gender as the explanatory variable.
- Software gives the estimated slope $b_1 = 0.4988$ and its standard error $SE_{b_1} = 0.0729$. Transform this result to the odds scale and compare it with your answer in part (b).
- Construct a 95% confidence interval for the odds ratio and write a short conclusion.

14.45 Proximity of fast-food restaurants to schools and adolescent overweight. A California study looked at the relationship between fast-food restaurants near schools (within a 0.5-mile radius) and overweight among middle and high school students.¹⁰ Overweight was determined based on each student’s responses to the California Healthy Kids Survey (CHKS). A database of latitude-longitude coordinates for schools and restaurants was used to determine proximity. Here are the data:

Fast-food nearby	n	$X(\text{overweight})$
No	238,215	65,080
Yes	291,152	83,143

Use logistic regression to study the question of whether or not overweight is related to the proximity of fast-food restaurants to schools. Write a short paragraph summarizing your conclusions.

14.46 Overweight and fast-food restaurants, continued. Refer to the previous exercise. In the article, the researchers commented that (1) CIs were adjusted to take into account that the students were from different schools; and (2) the analyses took into account the sex, age, and race/ethnicity of the students and other variables related to characteristics of the schools.

- What violation of the distribution of the response is Statement 1 addressing? Explain your answer.
- Explain why the researchers controlled for the variables described in Statement 2 when looking at the relationship between overweight and proximity.

The following four exercises use the GPAHI data file. We examine models for relating success as measured by the GPA to several explanatory variables. In Chapter 11, we used multiple regression methods for our analysis. Here, we define an indicator variable, HIGPA, to be 1 if the GPA is 3.0 or better and 0 otherwise.  GPAHI

 **14.47 Use high school grades to predict high grade point averages.** Use a logistic regression to predict HIGPA using the three high school grade summaries as explanatory variables.  GPAHI

- Summarize the results of the hypothesis test that the coefficients for all three explanatory variables are zero.
- Give the coefficient for high school math grades with a 95% confidence interval. Do the same for the two other predictors in this model.

(c) Summarize your conclusions based on parts (a) and (b).

 **14.48 Use SAT scores to predict high grade point averages.** Use a logistic regression to predict HIGPA using the SATM and SATCR scores as explanatory variables.  GPAHI

- Summarize the results of the hypothesis test that the coefficients for both explanatory variables are zero.
- Give the coefficient for the SATM score with a 95% confidence interval. Do the same for the SATCR score.
- Summarize your conclusions based on parts (a) and (b).

 **14.49 Use high school grades and SAT scores to predict high grade point averages.** Run a logistic regression to predict HIGPA using the three high school grade summaries and the two SAT scores as explanatory variables. We want to produce an analysis that is similar to that done for the case study in Chapter 11.  GPAHI

- (a) Test the null hypothesis that the coefficients of the three high school grade summaries are zero; that is, test $H_0: \beta_{HSM} = \beta_{HSS} = \beta_{HSE} = 0$.
- (b) Test the null hypothesis that the coefficients of the two SAT scores are zero; that is, test $H_0: \beta_{SATM} = \beta_{SATCR} = 0$.
- (c) What do you conclude from the tests in parts (a) and (b)?

 **14.50 Is there an effect of gender?** In this exercise, we investigate the effect of gender on the odds of getting a high GPA.  GPAHI

- (a) Use gender to predict HIGPA using a logistic regression. Summarize the results.
- (b) Perform a logistic regression using gender and the two SAT scores to predict HIGPA. Summarize the results.
- (c) Compare the results of parts (a) and (b) with respect to how gender relates to HIGPA. Summarize your conclusions.

CHAPTER 14 NOTES AND DATA SOURCES

1. Logistic regression models for the general case where there are more than two possible values for the response variable have been developed. These are considerably more complicated and are beyond the scope of our present study. For more information on logistic regression, see A. Agresti, *An Introduction to Categorical Data Analysis*, 2nd ed., Wiley, 2007; and D. W. Hosmer and S. Lemeshow, *Applied Logistic Regression*, 2nd ed., Wiley, 2000.

2. This example is taken from a classic text written by a contemporary of R. A. Fisher, the person who developed many of the fundamental ideas of statistical inference that we use today. The reference is D. J. Finney, *Probit Analysis*, Cambridge University Press, 1947. Although not included in the analysis, it is important to note that the experiment included a control group that received no insecticide. No aphids died in this group. We have chosen to call the response “dead.” In Finney’s book, the category is described as “apparently dead, moribund, or so badly affected as to be unable to walk more than a few steps.” This is an early example of the need to make careful judgments when defining variables to be used in a statistical analysis. An insect that is “unable to walk more than a few steps” is unlikely to eat very much of a chrysanthemum plant!

3. See www.pewinternet.org/2012/01/30/the-rise-of-in-store-mobile-commerce/.

4. Erin K. O’Loughlin et al., “Prevalence and correlates of exergaming in youth,” *Pediatrics*, 130 (2012), pp. 806–814.

5. Based on Leigh J. Maynard and Malvern Mupandawana, “Tipping behavior in Canadian restaurants,” *International Journal of Hospitality Management*, 28 (2009), pp. 597–603.

6. These results are from the Consumer Reports National Research Center, which conducted a telephone survey of a nationally representative probability sample of tele-phone households. One thousand interviews were completed among adults aged 18 and over. Interviewing took place October 15–18, 2009.

7. Anthony A. Noce and Larry McKeown, “A new benchmark for Internet use: A logistic modeling of factors influencing Internet use in Canada, 2005,” *Government Information Quarterly*, 25 (2008), pp. 462–476.

8. Dong-Chul Seo et al., “Relations between physical activity and behavioral and perceptual correlates among midwestern college students,” *Journal of American College Health*, 56 (2007), pp. 187–197.

9. These economic trend reports are from **mr.pricegrabber.com**. These results are based on the June 2009 report.

10. Brennan Davis and Christopher Carpenter, “Proximity of fast-food restaurants to schools and adolescent obesity,” *American Journal of Public Health*, 99 (2009), pp. 505–510.