

11.24 Restricting ourselves to Ω_0 , we find the likelihood function to be

$$L(\Omega_0) = \frac{1}{(2\pi)^{n/2} \sigma^n} \exp \left[-\frac{1}{2\sigma^2} \sum_{i=1}^n (y_i - \beta_0)^2 \right]$$

One may verify that maximum likelihood estimates of β_0 and σ^2 are

$$\hat{\beta}_0 = \bar{Y} \quad \text{and} \quad \hat{\sigma}_0^2 = \frac{\sum_{i=1}^n (Y_i - \bar{Y})^2}{n} \quad \text{so that}$$

$$L(\hat{\Omega}_0) = \frac{1}{(2\pi)^{n/2} (\hat{\sigma}_0^2)^{n/2}} e^{-n/2}.$$

For β_1 in the unrestricted space Ω , the likelihood function is given in the solution to Exercise 11.16, and the maximum likelihood estimates of β_0 and β_1 are the least squares estimates

$$\hat{\beta}_0 = \bar{Y} - \hat{\beta}_1 \bar{x} \quad \text{and} \quad \hat{\beta}_1 = \frac{S_{xy}}{S_{xx}}$$

The maximum likelihood estimate of σ^2 is $\hat{\sigma}^2 = \frac{\sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)^2}{n}$ so that

$$L(\hat{\Omega}) = \frac{1}{(2\pi)^{n/2} (\hat{\sigma}^2)^{n/2}} e^{-n/2}.$$

Hence

$$\lambda^{2/n} = \frac{\hat{\sigma}_0^2}{\hat{\sigma}^2} = \frac{\sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)^2}{S_{yy}} = \frac{SSE}{S_{yy}}$$

Then

$$\begin{aligned} S_{yy} &= \sum_{i=1}^n [y_i - \bar{y} - \hat{\beta}_1(x_i - \bar{x}) + \hat{\beta}_1(x_i - \bar{x})]^2 \\ &= \sum_{i=1}^n [y_i - \bar{y} - \hat{\beta}_1(x_i - \bar{x})]^2 + \hat{\beta}_1^2 S_{xx} + 2\hat{\beta}_1 S_{xy} - 2\hat{\beta}_1^2 S_{xx} \\ &= SSE + 2\hat{\beta}_1 S_{xy} - \hat{\beta}_1^2 S_{xx} \end{aligned}$$

But $\hat{\beta}_1 = \frac{S_{xy}}{S_{xx}}$ so that

$$S_{yy} = SSE + 2 \frac{S_{xy}^2}{S_{xx}} - \frac{S_{xy}^2}{S_{xx}} = SSE + \frac{S_{xy}^2}{S_{xx}}.$$

Now

$$\lambda^{2/n} = \frac{SSE}{SSE + \left(\frac{S_{xy}^2}{S_{xx}}\right)} = \frac{1}{1 + \left(\frac{T^2}{n-2}\right)}$$

where $T^2 = \frac{S_{xy}^2}{S_{xx} \left(\frac{SSE}{n-2}\right)} = \frac{\beta_1^2 \sum (x_i - \bar{x})^2}{\frac{SSE}{n-2}}$. Hence as λ gets small, T^2 will get large (either positively or negatively), and rejecting H_0 for large or small values of T will be equivalent to rejecting H_0 for small values of λ . Note that

$$T = \frac{\hat{\beta}_1}{\sqrt{\frac{\hat{\sigma}^2}{\sum_{i=1}^n (x_i - \bar{x})^2}}}$$

is the t test given in Section 11.6.

11.27 Using the coding $x = \frac{\text{year}-1971.5}{5}$, we obtain the following calculations:

$$\begin{array}{lll} \sum x = 0 & \sum y = 215.9 & \sum xy = -174.9 \\ \sum x^2 = 330 & \sum y^2 = 4760.43 & n = 10 \\ S_{xy} = -174.9 & S_{xx} = 330 & S_{yy} = 99.149 \end{array}$$

Then $\hat{\beta}_1 = \frac{S_{xy}}{S_{xx}} = \frac{-174.9}{330} = -.53$ and
 $SSE = 99.149 - (-.53)(-174.9) = 6.452$

and

$$s^2 = \frac{SSE}{8} = .8065.$$

To test the hypothesis

$$H_0: \beta_1 = 0 \quad \text{vs.} \quad H_a: \beta_1 < 0$$

we use the test statistic

$$t = \frac{\hat{\beta}_1}{\sqrt{\frac{s^2}{\sum (x_i - \bar{x})^2}}} = \frac{-.53}{\sqrt{\frac{.8065}{330}}} = -10.72.$$

The rejection region with $\alpha = .05$ is $t < -1.86$ and H_0 is rejected. We conclude that the rate of tuberculosis is decreasing with time.

11.28a. Using the uncoded x 's given in Exercise 11.3, we obtain $\hat{\beta}_1 = 4.8417$ and $S_{xx} = 42$. Then from Exercise 11.13, we obtain $s^2 = 3.0476$. To test the hypothesis

$$H_0: \beta_1 = 0 \quad \text{vs.} \quad H_a: \beta_1 > 0$$

we use the test statistic

$$t = \frac{\hat{\beta}_1 - 0}{\sqrt{\frac{s^2}{S_{xx}}}} = \frac{4.841667}{\sqrt{\frac{3.0476}{42}}} = 17.97$$

The rejection region is $t > t_{0.05, 6} = 3.143$, and H_0 is rejected. There is evidence of an increase.

b. The 99% confidence interval for β_1 is

$$\hat{\beta}_1 \pm t_{0.005} \sqrt{\frac{s^2}{S_{xx}}} = 4.84 \pm 3.707(.26937) = 4.84 \pm 1.00,$$

or $[3.84, 5.84]$.

11.31 $V(a_0\hat{\beta}_0 + a_1\hat{\beta}_1) = \left(\frac{a_0^2 \frac{\sum x_i^2}{n} + a_1^2 - 2a_0a_1\bar{x}}{S_{xx}} \right)$

Letting $a_0 = 1$ and $a_1 = x^*$, we have

$$\begin{aligned} V(\hat{\beta}_0 + \hat{\beta}_1 x^*) &= \frac{\frac{\sum x_i^2}{n} + (x^*)^2 - 2x^*\bar{x}}{S_{xx}} = \frac{\frac{\sum x_i^2}{n} - \frac{1}{n}(\sum x_i)^2 + (x^*)^2 - 2x^*\bar{x} + \bar{x}^2}{S_{xx}} \\ &= \frac{S_{xx} + (x^* - \bar{x})^2}{S_{xx}} = \frac{1}{n} + \frac{(x^* - \bar{x})^2}{S_{xx}}. \end{aligned}$$

Since $(x^* - \bar{x})^2 \geq 0$ for all x^* , $V(\hat{\beta}_0 + \hat{\beta}_1 x^*)$ is minimized for $(x^* - \bar{x})^2 = 0$ or $x^* = \bar{x}$.

11.32 Refer to Exercises 11.13, 11.20, and 11.31. When $x^* = 5$, $\hat{y} = 452.119 - 29.402(5) = 305.11$. From Exercise 11.31,

$$\begin{aligned} V(\hat{y}) &= V(\hat{\beta}_0 + \hat{\beta}_1 x) = \left[\frac{1}{14} + \frac{(5 - \frac{86.48}{14})^2}{732.4876 - (\frac{86.48}{14})^2} \right] s^2 = \left(\frac{1}{14} + \frac{1.3857}{198.288} \right) (5138.97) \\ &= 402.98 \end{aligned}$$

Thus, a 90% confidence interval for $E(Y)$ is

$$\hat{y} \pm t_{.05, 12} \sqrt{V(\hat{y})} = 305.11 \pm 1.782 \sqrt{402.98} = 305.11 \pm 35.773.$$

11.38 In Exercise 11.31, we showed that

$$V(\widehat{\beta}_0 + \widehat{\beta}_1 x) = \frac{1}{n} + \frac{(x - \bar{x})^2}{S_{xx}}.$$

Hence, the prediction interval can be written as

$$\widehat{y} \pm t_{\alpha/2} s \sqrt{1 + \frac{1}{n} + \frac{(x - \bar{x})^2}{S_{xx}}}.$$

as shown in the text. When $x = \bar{x}$, the length of this interval is

$$2t_{\alpha/2} s \sqrt{1 + \frac{1}{n}}.$$

which is the minimum value the length can take on. Notice as long as the confidence coefficient stays the same, the width of the interval is controlled by $\frac{(x - \bar{x})^2}{S_{xx}}$, which is minimized at $x = \bar{x}$. I.e. our prediction will be the best at the mean of the independent variable.

11.39 Refer to Exercises 11.3 and 11.13. When $x = 9$, $\widehat{y} = 65.15$, and the 95% prediction interval is

$$65.15 \pm 2.447 \sqrt{3.05 \left[1 + \frac{1}{8} + \frac{(9 - 4.5)^2}{42} \right]} = 65.15 \pm 5.42$$

or $[59.73, 70.57]$.