Confidence Intervals for Coefficients

We can also find confidence intervals for the regression coefficients, β_i for $i = 0, \ldots, k$, on the assumption that the residuals are independent and normally distributed.

To find a level C confidence interval, we first calculate

- b_i, the least squares estimate of β_i.
- $SE(b_i)$, the standard error for b_i, calculated from the x values, and s, the estimated standard deviation of the residuals.
- t^*, the value such that the area under the t distribution density curve with $n-k-1$ df between $-t^*$ and t^* is C.

Using these values, we compute the level C confidence interval for β_i as

$$(b_i \;-\; t^*\,SE(b_i),\;\; b_i \;+\; t^*\,SE(b_i))$$

Predicting the Response in a New Case When the True Parameters are Known

Suppose we find out the values of the explanatory variables for a new case, and wish to predict the response variable.

If the explanatory variables for the new case are $x'_1, \ldots, x'_k$, and if we knew the *true* values of the regression coefficients (β_i), we would predict the response, y, by its mean:

$$\mu_y \;=\; \beta_0 + \beta_1 x'_1 + \cdots + \beta_p x'_k$$

We could express the uncertainty in this prediction by the standard deviation of the residuals, whose true value is σ.

C. I. for the Mean Response

In practice, we don't know the β_i, so we don't know μ_y.

We can find a level C confidence interval for μ_y however, as follows:

$$(\hat{y} \;-\; t^*\,SE(\hat{y}),\;\; \hat{y} \;+\; t^*\,SE(\hat{y}))$$

where $\hat{y}$ is our estimate of the mean response at x' based on our estimates for the regression coefficients:

$$\hat{y} \;=\; b_0 + b_1 x'_1 + \cdots + b_p x'_k$$

and $SE(\hat{y})$ is our estimate of the standard deviation of $\hat{y}$, which will depend on x', on the x values in the observed cases, and on the estimated standard deviation of the residuals, s.

As before, t^* is the value such that C is the area between $-t^*$ and t^* that lies under the t distribution density curve with $n-k-1$ df.

C. I. for a New Observation

We can also find a level C prediction interval for a new observation, y, at x'. This is *not* the same thing as a C. I. for the mean of this new observation — predicting a particular y is harder than guessing the mean of y for this x'.

The prediction interval is centred at the same place as the C. I. for μ_y, however:

$$\hat{y} \;=\; b_0 + b_1 x'_1 + \cdots + b_k x'_k$$

The prediction interval is $(\hat{y} - t^* PE,\; \hat{y} + t^* PE)$, where t^* is as before, and PE is analogous to a standard error, but isn't the same as $SE(\hat{y})$.

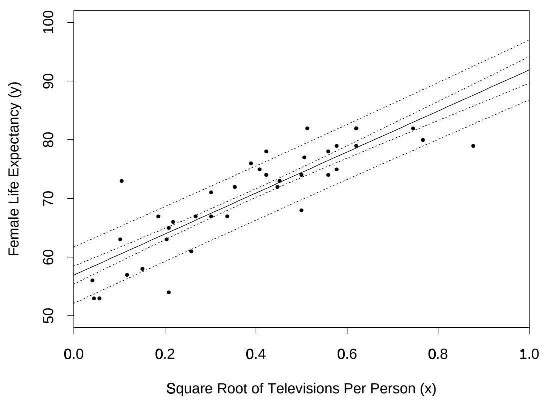
With one explanatory variable:

$$SE(\hat{y}) \;=\; s\sqrt{\frac{1}{n} + \frac{(x' - \bar{x})^2}{\sum (x_i - \bar{x})^2}}$$

$$PE \;=\; s\sqrt{1 + \frac{1}{n} + \frac{(x' - \bar{x})^2}{\sum (x_i - \bar{x})^2}}$$

Example: Prediction from the Data on Life Expectancy in 38 Countries

Here again is the regression line of female life expectancy on the square root of televisions per person. Also shown are $\widehat{y}$ plus or minus $SE(\widehat{y})$ and plus or minus PE, for each x' value:



Behaviour of Predictions

- For what x' are predictions most accurate?
- What happens to $SE(\widehat{y})$ as n gets bigger?
- What happens to PE as n gets bigger?