

# Ch 3: Linear Regression

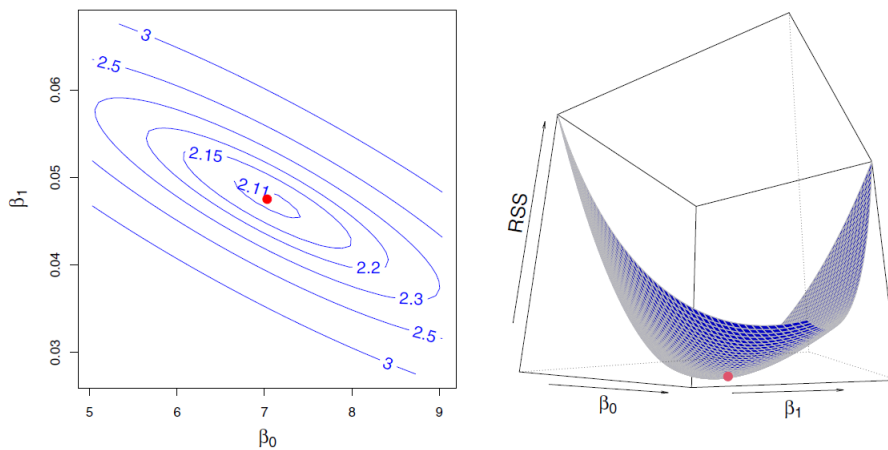
Alex Socarras

3/29/2022

**SLR:**  $Y \approx \beta_0 + \beta_1 X, \hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x$

**RSS:**  $RSS = e_1^2 + e_2^2 + \dots + e_n^2$ , where  $e_i = y_i - \hat{y}_i$

**LSCE:**  $\hat{\beta}_1 = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2}$  and  $\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x}$



**FIGURE 3.2.** Contour and three-dimensional plots of the RSS on the Advertising data, using sales as the response and TV as the predictor. The red dots correspond to the least squares estimates  $\hat{\beta}_0$  and  $\hat{\beta}_1$ , given by (3.4).

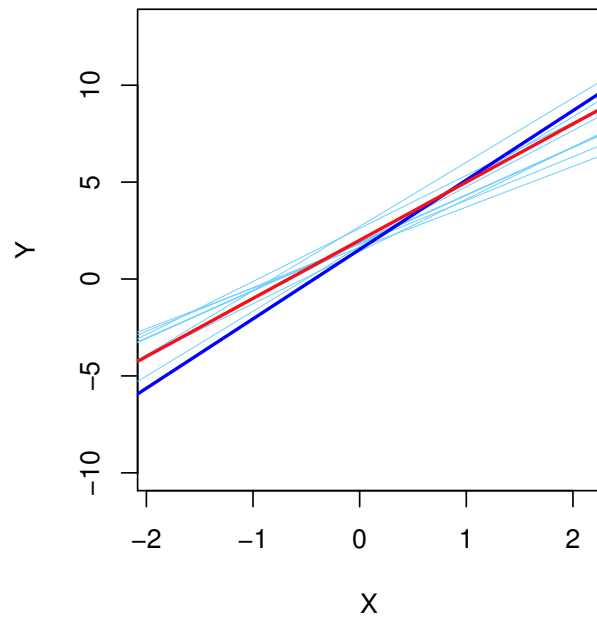
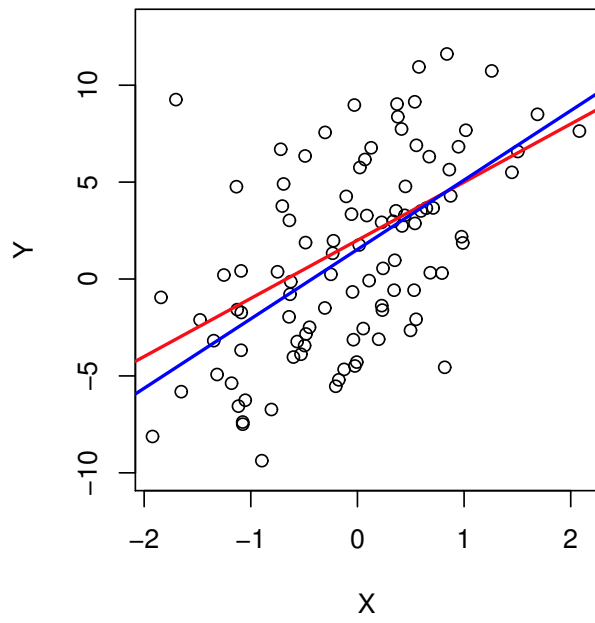
## Model Accuracy

population regression line:  $Y = \beta_0 + \beta_1 X + \epsilon$  (assume  $\epsilon$  is ind. of  $X$ )

Estimating  $\beta_0, \beta_1$  is analogous to estimating the population mean of a random variable by averaging estimates obtained over a large number of data sets (samples):

$$\text{Var}(\hat{\mu}) = \text{SE}(\hat{\mu})^2 = \frac{\sigma^2}{n},$$

where the *standard error* of  $\hat{\mu} = \text{SE}(\hat{\mu})$  indicates the average amount the estimated mean differs from the population mean. **Warning:** assumes  $n$  are uncorrelated.



.