

$$\begin{aligned}\hat{y} &= \hat{\beta}_0 + \hat{\beta}_1 x \\ \sum_{i=1}^n \hat{e}_i^2 &= \sum_{i=1}^n (y_i - \hat{y}_i)^2 \\ \hat{\beta}_1 &= \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2} \\ \hat{\beta}_0 &= \bar{y} - \hat{\beta}_1 \bar{x}\end{aligned}$$

$$\hat{e}_i = y_i - \hat{y}_i = y_i - (\hat{\beta}_0 + \hat{\beta}_1 x_i) = y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i$$

$$S_e^2 = \frac{1}{n-2} \sum_{i=1}^n (\hat{e}_i^2) = \frac{RSS}{n-2}$$

where  $RSS = \sum_{i=1}^n \hat{e}_i^2$  is the residual sum of squares.

$$t = \frac{\text{estimate} - \text{null}}{\text{std. error}}$$

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

$$t = \frac{\hat{\beta}_1}{s_{\hat{\beta}_1}}$$

$$PE(\hat{y}_0) = s_e \sqrt{1 + \frac{1}{n} + \frac{(x_0 - \bar{x})^2}{\sum_{i=1}^n (x_i - \bar{x})^2}}$$

$$\hat{y}_0 \pm t_{(1-\frac{\alpha}{2}, n-2)} \times PE(\hat{y}_0)$$

$$\begin{aligned}r &= \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \sum_{i=1}^n (y_i - \bar{y})^2}} \\ &= \frac{S_{xy}}{S_x S_y}\end{aligned}$$

$$TSS = \sum_{i=1}^n (y_i - \bar{y})^2$$

$$RSS = \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

$$R^2 = \frac{ESS}{TSS} = 1 - \frac{RSS}{TSS}$$

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

$$p = \frac{e^{\beta_0 + \beta_1 x}}{1 + e^{\beta_0 + \beta_1 x}}$$

$$z = x \frac{\hat{\beta}_1}{s_{\hat{\beta}_1}}$$

$$Y = \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k + e$$

$$\mu_Y = \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k$$

$$\sum_{i=1}^n (y_i - \hat{y}_i)^2$$

$$RSS = \sum_{i=1}^n \hat{e}_i^2$$

$$s_e^2 = \frac{RSS}{n-k-1}$$