

## Uncertainties in Least Squares Coefficients

Consider Bivariate data  $(x_i, y_i)$  for  $i=1,2,3,\dots,n$

$$y = \beta_0 + \beta_1 x$$

The line  $y_i = \beta_0 + \beta_1 x_i + \varepsilon_i$ ,  $\varepsilon_i$  is the error, that best fits the data in the sense of minimizing the sum of the squared errors. It is called the least squares regression line

$\widehat{\beta}_0, \widehat{\beta}_1$  are estimates of  $\beta_0, \beta_1$ .

$$\widehat{y}_i = \widehat{\beta}_0 + \widehat{\beta}_1 x_i = \text{Fitted line}$$

If  $\varepsilon_i$  tend to be large then  $(x_i, y_i)$  are widely scattered around the line.

If  $\varepsilon_i$  tend to be small then  $(x_i, y_i)$  are tightly clustered around the line.

The line  $y_i = \beta_0 + \beta_1 x_i + \varepsilon_i$  has Normal distribution with

$$\mu_{y_i} = \beta_0 + \beta_1 x_i$$

$$\sigma_{y_i}^2 = \sigma^2$$

$$\widehat{\beta}_1 = \sum_{i=1}^n \left[ \frac{x_i - \bar{x}}{\sum_{i=1}^n (x_i - \bar{x})^2} \right] y_i$$

$$\widehat{\beta}_0 = \sum_{i=1}^n \left[ \frac{1}{n} - \frac{\bar{x}(x_i - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2} \right] y_i$$

Mean of the estimates  $\widehat{\beta}_0, \widehat{\beta}_1$  are

$$\mu_{\widehat{\beta}_0} = \beta_0 \quad \mu_{\widehat{\beta}_1} = \beta_1$$

Uncertainty in the estimates  $\widehat{\beta}_0, \widehat{\beta}_1$  are

$$\sigma_{\widehat{\beta}_0} = \sigma \sqrt{\left[ \frac{1}{n} + \frac{\bar{x}^2}{\sum_{i=1}^n (x_i - \bar{x})^2} \right]}$$

$$\sigma_{\widehat{\beta}_1} = \sigma \sqrt{\left[ \frac{1}{\sum_{i=1}^n (x_i - \bar{x})^2} \right]}$$

Since the value of  $\sigma$  is unknown it is approximated with  $s$

$$s_{\widehat{\beta}_0} = s \sqrt{\left[ \frac{1}{n} + \frac{\bar{x}^2}{\sum_{i=1}^n (x_i - \bar{x})^2} \right]}$$

$$s_{\widehat{\beta}_1} = s \sqrt{\left[ \frac{1}{\sum_{i=1}^n (x_i - \bar{x})^2} \right]}$$

Where  $s$  is the estimate of the error standard deviation  $\sigma$  and

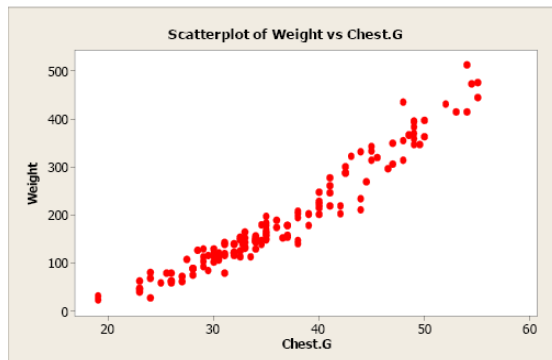
$$s = \sqrt{\frac{(1-r^2) \sum (y_i - \bar{y})^2}{n-2}}$$

$$s_{\widehat{\beta}_0} = s \sqrt{\left[ \frac{1}{n} + \frac{\bar{x}^2}{\sum_{i=1}^n (x_i - \bar{x})^2} \right]} \quad s_{\widehat{\beta}_1} = s \sqrt{\left[ \frac{1}{\sum_{i=1}^n (x_i - \bar{x})^2} \right]}$$

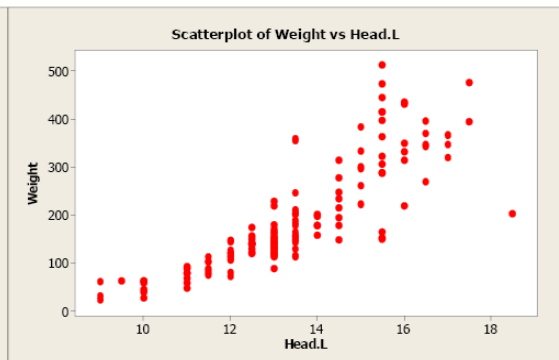
$$s_{\widehat{\beta}_1} \propto \frac{1}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

If  $x$  – values are more spread then the uncertainty of estimates  $\widehat{\beta}_0$  ,  $\widehat{\beta}_1$  are Smaller.

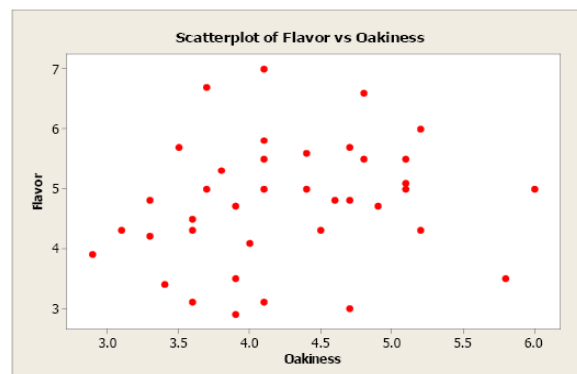
The standard deviation of  $x$  is more.



**Strong positive relationship**  
 **$r = 0.96$**



**Moderate positive relationship**  
 **$r = 0.67$**



**Very weak positive relationship**  
 **$r = 0.07$**

Problem: Two engineers are conducting independent experiments to estimate spring constant for a particular spring. The first engineer suggests measuring the length of the spring with no load, then applying loads of 0,1,2,3,& 4 lb. The second engineer suggests using loads of 0, 2, 4, 6 & 8 lb. Which will be more precise?

Sol: X ----- 0, 1, 2, 3, 4      Y----- 0, 2, 4, 6, 8

$\sigma_y$  is twice as great as  $\sigma_x$  .

Uncertainty of X is twice as large as the uncertainty of Y. Hence, the Engineer, Y 's estimate is twice as precise.