

# Simple Linear Regression Model

The model is

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i \quad i = 1, 2, 3, 4, \dots, n$$

Simple since there is only one  $X_i$

It is linear in  $\beta_0$  and  $\beta_1$

$E(Y_i) = \beta_0 + \beta_1 X_i$  is linear

$Y = \beta_0 + \beta_1 X_1 + e^{\beta_2 X_2} + \varepsilon_i$  is not linear

$Y = \beta_0 + e^{\beta_1 X_1} + \varepsilon_i$  is not linear also.

- A simple linear regression model assumes that the following specification is true in the population

$$Y = \beta_0 + \beta_1 X_i + \varepsilon$$

- Where other unobserved factors determining  $Y$  are captured by the error term  $\varepsilon$ .

- To estimate the parameters  $\beta_0$  &  $\beta_1$  in the model Assumptions 1-5, Linearity, identification, exogeneity, spherical error terms and data generation are required for Ordinary least Squares (OLS)

- Assumptions 1-6, i.e. including normality are required to use Maximum likelihood to estimate  $\beta_0$  &  $\beta_1$  (MLE)

Assumptions summarized

- i  $E(\varepsilon_i) = 0$  for all  $i = 1, 2, \dots, n \Rightarrow E(Y_i) = \beta_0 + \beta_1 X_i$
- ii  $\text{Var}(\varepsilon_i) = \sigma^2$  for all  $i = 1, 2, \dots, n \Rightarrow \text{Var}(Y_i) = \sigma^2$  Constant
- iii  $\text{Covariance}(\varepsilon_i, \varepsilon_j) = 0$  for  $i \neq j \Rightarrow \text{Cov}(Y_i, Y_j) = 0$  uncorrelatedness
- iv Normality  $\varepsilon_i \sim N(0, \sigma^2)$ ,  $\varepsilon_i$  and  $Y_i$  are independent and uncorrelated.

Ordinary least squares estimator

- Least squares Method does not require any distributional assumptions. (It does not require normality)
- MLE estimation requires the normality assumption (6)
- Ordinary least squares estimates  $\beta_0$  and  $\beta_1$ . Minimizes the sum of squared residuals (SSR)

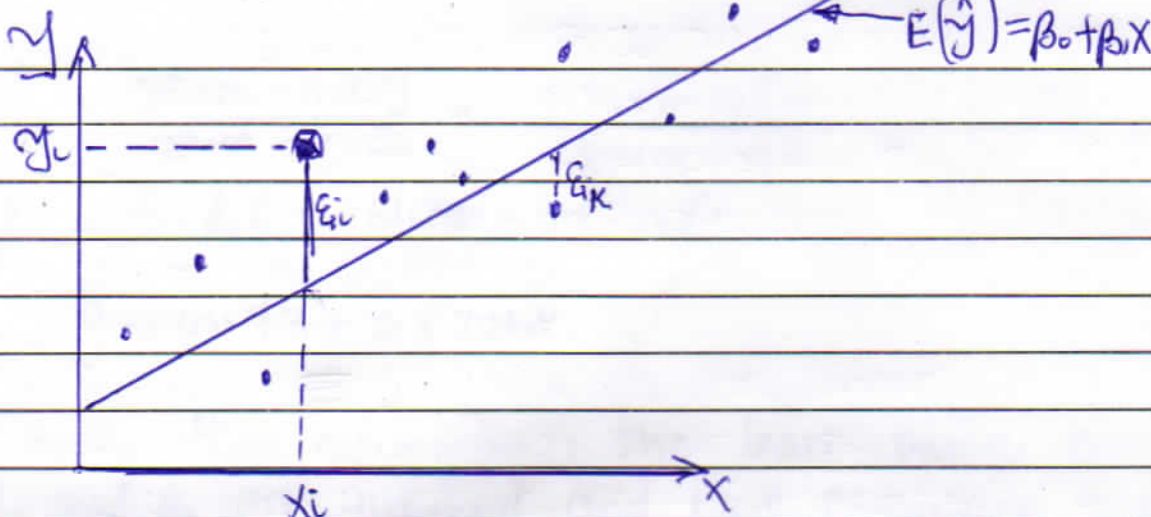
$$Q = \sum_{i=1}^n \hat{\varepsilon}_i^2 = \hat{\varepsilon}' \hat{\varepsilon} = \sum_{i=1}^n (Y_i - \hat{\beta}_0 - \hat{\beta}_1 X_i)^2 = \sum_{i=1}^n (Y_i - \hat{Y}_i)^2$$



Write on both sides of the paper

Question

②

Do not write  
in either  
margin

$\hat{y}_i$  estimates  $E(y_i) = \beta_0 + \beta_1 x_i$ , not  $\beta_0 + \beta_1 x_i + e_i$ .

The minimum is acquired by

$$\frac{\partial Q}{\partial \beta_0} = -2 \sum (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i) = 0$$

$$\frac{\partial Q}{\partial \hat{\beta}_1} = -2 \sum x_i (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i) = 0$$

Simplify

$$n \hat{\beta}_0 + \hat{\beta}_1 \sum x_i = \sum y_i$$

$$\hat{\beta}_0 \sum x_i + \hat{\beta}_1 \sum x_i^2 = \sum x_i y_i$$

OR

Solving for

$$\hat{\beta}_1 = \frac{S_{xy}}{S_{xx}} = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2}$$

$$\hat{\beta}_1 = \frac{\sum x_i y_i - n \bar{x} \bar{y}}{\sum x_i^2 - n \bar{x}^2}$$

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x}$$

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x$$

Note

$$S_{xx} = \sum (x_i - \bar{x})^2 = \sum x_i^2 - \frac{(\sum x_i)^2}{n}$$

$$S_{xy} = \sum x_i y_i - \frac{(\sum x_i)(\sum y_i)}{n}$$

$$S_{yy} = \sum y_i^2 - \frac{(\sum y_i)^2}{n}$$

Example: Is a student's performance in final exam ( $y$ ) determined by continuous assessment ( $x$ )

$y$  95 80 0 0 79 77 72 66 98 90 0 95 35 50 72 55 75 66

$x$  96 77 0 0 78 64 89 47 90 93 18 86 0 30 59 77 74 67

$x^2$

$xy$

$y^2$

$\sum y =$

$\sum x =$

$\sum x^2 =$

$\sum xy =$

$\sum y^2 =$

$$\hat{\beta}_1 = \frac{\sum x_i y_i - n \bar{x} \bar{y}}{\sum x_i^2 - n \bar{x}^2} = \frac{81195 - 18(58.056)(61.389)}{80199 - 18(58.056)^2} = 0.8726$$

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x} = 61.389 - 0.8726(58.056) = 10.73$$

$$\hat{y} = 10.73 + 0.8726x$$

With the three assumptions the least squares estimators  $\hat{\beta}_0$  and  $\hat{\beta}_1$  are unbiased and have minimum variance among all linear unbiased estimators "MVUE"

$$E(\hat{\beta}_1) = \beta_1$$

$$E(\hat{\beta}_0) = \beta_0$$

$$\text{Var}(\hat{\beta}_1) = \frac{\sigma^2}{\sum (x_i - \bar{x})^2} = \frac{\sigma^2}{S_{xx}}$$

$$\text{Var}(\hat{\beta}_0) = \sigma^2 \left( \frac{1}{n} + \frac{\bar{x}^2}{\sum (x_i - \bar{x})^2} \right) = \sigma^2 \left( \frac{1}{n} + \frac{\bar{x}^2}{S_{xx}} \right)$$

If  $\sigma^2 = E(y_i - E(y_i))^2$  using  $\hat{y}$  as estimate for  $E(y_i)$  we estimate  $\sigma^2$  by  $s^2 = \frac{\sum (y_i - \hat{y}_i)^2}{n-2}$

Note

$$\text{Var}(y_i) = E(y_i - E(y_i))^2 = E(y_i - \beta_0 - \beta_1 x_i)^2 = E(\hat{\epsilon}_i^2) = \sigma^2$$

$$s^2 = \frac{\sum (y_i - \hat{y}_i)^2}{n-2} = \frac{\sum (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)^2}{n-2} = \frac{\text{SSE}}{n-2}$$

$\hat{\epsilon}_i = (y_i - \hat{y}_i)$  is referred to residuals

$$E(s^2) = E \frac{\text{SSE}}{n-2} = \frac{(n-2)\sigma^2}{n-2} = \sigma^2 \quad \text{unbiased}$$

$s^2$  is an unbiased estimator of  $\sigma^2$

$$\text{SSE} = \sum (y_i - \hat{y}_i)^2 = S_{yy} - \frac{S_{xy}^2}{S_{xx}} \quad s^2 = \frac{\text{SSE}}{n-2}$$



## Hypothesis Testing and Confidence Intervals for $\hat{\beta}_1$

$$H_0: \beta_1 = 0 \text{ vs } H_1: \beta_1 \neq 0:$$

$H_0: \beta_1 = 0$  There is no linear relationship between  $y$  and  $x$   
Assuming  $\epsilon \sim N(0, \sigma^2)$  or  $y_i \sim N(\beta_0 + \beta_1 x_i, \sigma^2)$

(i)  $\hat{\beta}_1$  is  $N[\hat{\beta}_1, \frac{\sigma^2}{S_{xx}}]$

(ii)  $\frac{(n-2)s^2}{\sigma^2}$  is  $\chi^2(n-2)$

(iii)  $\hat{\beta}_1$  and  $s^2$  are independent.

Test statistics for  $H_0: \beta_1 = 0$  vs  $\beta_1 \neq 0$

$$t = \frac{\hat{\beta}_1}{s/\sqrt{S_{xx}}} \sim t(n-2) \text{ if } \beta = 0$$

Note

$$t = \frac{\text{Estimate}}{\text{Standard error of estimate}} = \frac{\hat{\beta}_1}{\text{Se}(\hat{\beta}_1)}$$

Reject  $H_0$  if  $|t| \geq t_{\alpha/2}(n-2)$

### Detailed Hypothesis

Case 1:  $H_0: \beta_1 \leq 0$  vs  $H_1: \beta_1 > 0$

Case 2:  $H_0: \beta_1 \geq 0$  vs  $H_1: \beta_1 < 0$

Case 3:  $H_0: \beta_1 = 0$  vs  $H_1: \beta_1 \neq 0$

Test statistic (T.S)  $t = \frac{\hat{\beta}_1 - 0}{\text{Se}(\hat{\beta}_1)/\sqrt{S_{xx}}}$

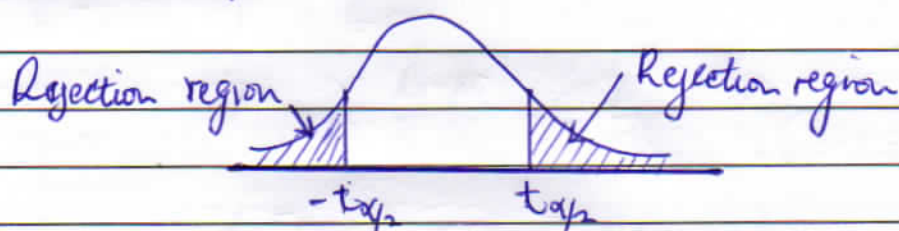
Rejection Region For d.f.  $n-2$  and type 1 error  $\alpha$

Case 1. Reject  $H_0$  if  $t > t_\alpha$

2. Reject  $H_0$  if  $t < -t_\alpha$

3. Reject  $H_0$  if  $|t| > t_{\alpha/2}$

For case 3:  $H_0: \beta_1 = 0$  vs  $H_1: \beta_1 \neq 0$



Example on Marks above: Test  $H_0: \beta_1 = 0$  vs  $H_1: \beta_1 \neq 0$

$$t = \frac{\hat{\beta}_1}{S/\sqrt{S_{xx}}} = \frac{0.8726}{13.8547/\sqrt{139.753}} = 8.8025$$

$$t = 8.8025 > t_{0.025}(16) = 2.120 \text{ Reject } H_0.$$

Confidence interval for Slope  $\beta_1$

~~95%~~ A  $100(1-\alpha)\%$  confidence interval for  $\beta_1$  is

$$\hat{\beta}_1 \pm t_{\alpha/2}(n-1) \frac{S}{\sqrt{S_{xx}}}$$

$$\text{Where } S = \frac{S_{yy} - \frac{S_{xy}^2}{S_{xx}}}{n-2}$$

$$\beta_1 \pm t_{\alpha/2}(n-1) \frac{S}{\sqrt{S_{xx}}}$$

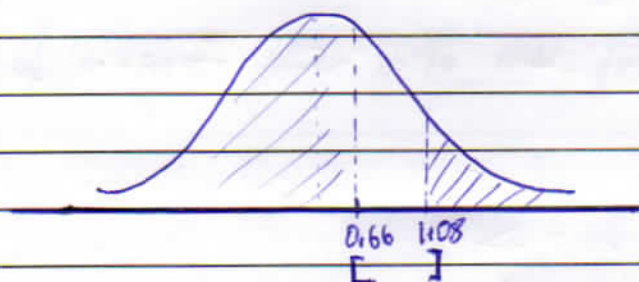
A 95% confidence interval for  $\beta_1$  for the marks example

$$\hat{\beta}_1 \pm t_{0.025}(16) \frac{S}{\sqrt{(x_i - \bar{x})^2}}$$

$$0.8726 \pm 2.120(0.09914)$$

$$0.8726 \pm 0.2102$$

$$(0.6624, 1.0828)$$





Confidence interval for slope  $\beta_1$

$$\left| \frac{\hat{\beta}_1 - \beta_1}{\text{se} \sqrt{1/s_{xx}}} \right| < t_{\alpha/2} \quad \text{is a } (1-\alpha)100\% \text{ Confidence I.}$$

$$-t_{\alpha/2} < \frac{\hat{\beta}_1 - \beta_1}{\text{se} \sqrt{1/s_{xx}}} < t_{\alpha/2}$$

$$-t_{\alpha/2} \text{se} \sqrt{1/s_{xx}} < \hat{\beta}_1 - \beta_1 < t_{\alpha/2} \text{se} \sqrt{1/s_{xx}}$$

$\hat{\beta}_1 - t_{\alpha/2} \text{se} \sqrt{1/s_{xx}} < \beta < \hat{\beta}_1 + t_{\alpha/2} \text{se} \sqrt{1/s_{xx}}$  is the  
(1- $\alpha$ )100% Confidence interval for  $\beta_1$  where  $t$  has  $n-2$  df.

F test for  $H_0: \beta_1 = 0$  (Recall ANOVA)

$$H_0: \beta_1 = 0 \quad \text{vs} \quad H_1: \beta_1 \neq 0$$

$$\text{Test Statistics } F = \frac{SS(\text{Regression})/n-1}{SS(\text{Error})/n-2} = \frac{MS_{\text{Reg}}}{MS_E}$$

Rejection Region: With  $df_1 = 1$   $df_2 = n-2$ , reject  $H_0$  if  $F > F_\alpha$

$$SS_{\text{Reg}} = \sum (\hat{y}_i - \bar{y})^2$$

$$SS_E = \sum (y_i - \bar{y})^2$$

Confidence interval for intercept  $\beta_0$

$$\sigma_{\hat{\beta}_0} = \text{se} \sqrt{\frac{1}{n} + \frac{\bar{x}^2}{s_{xx}}}$$

The (1- $\alpha$ )100% Confidence interval for  $\beta_0$  is given by

$$\hat{\beta}_0 \pm t_{\alpha/2} \text{se} \sqrt{\frac{1}{n} + \frac{\bar{x}^2}{s_{xx}}} \quad \text{for } t \text{ with } n-2 \text{ df.}$$

Determine the 95% CI for  $\hat{\beta}_1$  for example 1.1.

Inference about the Correlation coefficient  $\rho_{yx}$ 

The  $t$  statistic for  $\beta_1$  can be expressed in terms of  $r$  as follows

$$t = \frac{\hat{\beta}_1}{s / \sqrt{\sum (x_i - \bar{x})^2}}$$

$$t = r_{yx} \frac{\sqrt{n-2}}{\sqrt{1-r_{yx}^2}}$$

The sample correlation  $r_{yx}$  is the basis for estimation and significance testing of the population correlation  $\rho_{yx}$

## Hypothesis

Case 1:  $H_0: \rho_{yx} \leq 0$  vs.  $H_1: \rho_{yx} > 0$

Case 2:  $H_0: \rho_{yx} \geq 0$  vs.  $H_1: \rho_{yx} < 0$

Case 3:  $H_0: \rho_{yx} = 0$  vs.  $H_1: \rho_{yx} \neq 0$

Time Series T.S.  $t = r_{yx} \frac{\sqrt{n-2}}{\sqrt{1-r_{yx}^2}}$

R.R. With  $n-2$  df and type I error probability  $\alpha$ ,

1.  $t > t_{\alpha}$

2.  $t < -t_{\alpha}$

3.  $|t| > t_{\alpha/2}$

Check assumptions and draw conclusions

## Exercise

Soil pH :	3.3	3.4	3.4	3.5	3.6	3.6	3.7	3.7	3.8	3.8
Growth Ret :	17.78	21.59	23.84	15.13	23.45	20.87	17.78	20.09	17.78	12.46

Q<sub>i</sub> Examine the scatter plot and decide whether a straight line is reasonable model: Is regression significant?

Q<sub>ii</sub> Identify the Least squares model estimates for  $Y = \beta_0 + \beta_1 X + \epsilon$

Q<sub>iii</sub> Predict the growth retardation for a soil pH of 4.0



# Simple Linear Regression.

The Model: The simple linear regression model for  $n$  observations can be written as

$$Y_i = \beta_0 + \beta_1 X_i + \epsilon_i \quad i = 1, 2, 3, \dots, n$$

Linear in  $\beta_0$  and  $\beta_1$

$$Y = \beta_0 + \beta_1 x_i^2 + \epsilon_i \text{ is Linear in } \beta_0 \text{ \& } \beta_1$$

$$Y = \beta_0 + 2^{\beta_1} x_i + \epsilon_i \text{ is not Linear in } \beta_1$$

Model

$$Y_i = \beta_0 + \beta_1 x_i + \epsilon_i \quad i = 1, 2, \dots, n$$

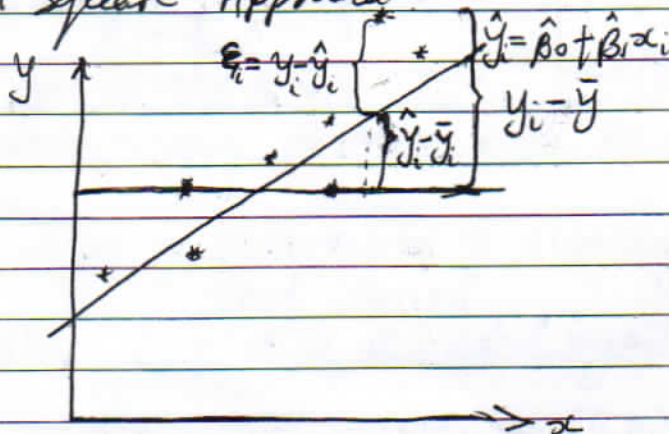
Assumption

- (i)  $E(\epsilon_i) = 0$  for all  $i = 1, 2, \dots, n$  or  $E(Y_i) = \beta_0 + \beta_1 x_i$
- (ii)  $\text{Var}(\epsilon_i) = \sigma^2$  for all  $i = 1, 2, \dots, n$  or  $\text{Var}(Y_i) = \sigma^2$  Homoscedastic
- (iii)  $\text{Cov}(\epsilon_i, \epsilon_j) = 0$  for all  $i \neq j$  or  $\text{Cov}(x_i, Y_i) = 0$

$$\text{Var}(Y_i) = E[Y_i - E(Y_i)]^2 = E(Y_i - \beta_0 - \beta_1 x_i)^2 = E(\epsilon_i^2) = \sigma^2$$

Estimation of  $\beta_0$ ,  $\beta_1$  and  $\sigma^2$

Least square Approach



Total variation =  $y_i - \bar{y}$   
 error (Residual) =  $y_i - \hat{y}_i$   
 explained by regression =  $\hat{y}_i - \bar{y}$

$$y_i - \hat{y}_i = (y_i - \bar{y}) - (\hat{y}_i - \bar{y}) \quad \text{from the sum}$$

$$(y_i - \bar{y}) = (y_i - \hat{y}_i) + (\hat{y}_i - \bar{y})$$



Sum of squares

$$\sum (y_i - \bar{y})^2 = \sum (\hat{y}_i - \bar{y})^2 + \sum (y_i - \hat{y}_i)^2 + 2 \underbrace{\sum (\hat{y}_i - \bar{y})(y_i - \hat{y}_i)}_0$$

$$\left( \begin{array}{l} \text{Sum of squares} \\ \text{about mean} \\ \text{SST corrected} \end{array} \right) = \left( \begin{array}{l} \text{Sum of squares} \\ \text{due to regression} \\ \text{SSR}(b_1/b_0) \end{array} \right) + \left( \begin{array}{l} \text{Sum of square} \\ \text{about regression} \\ \text{Residual SS} \end{array} \right)$$

$$SST = SSR + SSE$$

Therefore to test if regression is significant i.e.

$$H_0: \beta_1 = 0 \text{ Vs } H_1: \beta_1 \neq 0$$

We have the Anova.

ANOVA Table.

Source of variation	Degrees of freedom	Sum of squares SS	Mean square	F
Due to regression	1	$\sum (\hat{y}_i - \bar{y})^2$	$MS_{reg}$	$F_c = \frac{MS_{reg}}{S^2}$
About regression Residual	$n-2$	$\sum (y_i - \hat{y}_i)^2$	$S^2 = \frac{SSE}{n-2}$	
Total corrected for $\bar{y}$	$n-1$	$\sum (y_i - \bar{y})^2$		

An accompanying p value will be available (given)

p-value = probability of observing a value larger than that observed.

In this case it is a 2 sided hypothesis

$$p\text{-value} = 2 * P(F \geq F_c(1, n-2))$$

- If  $F_c$  is large reject  $H_0: \beta_1 = 0$  :  $\Rightarrow$  implying that most variation is caused by (explained by) regression.
- Reject  $H_0$  if p-value is too small



## Coefficient of Determination

Coefficient of Determination is defined as

$$r^2 = \frac{SSR}{SST} = \frac{\sum (\hat{y}_i - \bar{y})^2}{\sum (y_i - \bar{y})^2}$$

SSR - Regression sum of squares =  $\sum (\hat{y}_i - \bar{y})^2$

SST - Total sum of squares =  $\sum (y_i - \bar{y})^2$

$$SST = SSR + SSE$$

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

$$\sum (\hat{y} - \bar{y}) = \sum (y_i - \bar{y})^2 - \sum (y_i - \hat{y}_i)^2$$

$$SSR = SST - SSE$$

$$r^2 = \frac{SST - SSE}{SST} = 1 - \frac{SSE}{SST}$$

Proportion of variation in  $y$  explained by the model or accounted by regression.

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

$$r^2 = \frac{SSR}{SST} = \frac{14873.0}{17944} = 0.8288$$

$$t = \frac{\hat{\beta}_1}{s / \sqrt{\sum_{i=1}^n (x_i - \bar{x})^2}} = \frac{\sqrt{n-2} r}{\sqrt{1-r^2}}$$

The fit of the regression is "good" if the sum  $\sum \epsilon_i^2 (= SSE)$  is small i.e. the unexplained part of the variance of  $y$  is small. If SSE is small then  $R^2$  is close to 1.



# Coefficient of Determination (Multiple Correlation Coefficient)

$$r^2 = \frac{SSR}{SST} = \frac{\sum (\hat{y}_i - \bar{y})^2}{\sum (y_i - \bar{y})^2} \quad \text{Where } SST = SSR + SSE$$

$$SST = \sum (y_i - \bar{y})^2 = \sum (\hat{y}_i - \bar{y})^2 + \sum (y_i - \hat{y}_i)^2$$

$r^2$  gives the proportion of variation in  $y$  that is explained by the model or accounted for by regression on  $x$ .

Sample Correlation Coefficient  $r$  between  $x$  and  $y$

$$r = \frac{S_{xy}}{\sqrt{S_x^2 S_y^2}} = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{[\sum (x_i - \bar{x})^2][\sum (y_i - \bar{y})^2]}}$$

For Example 1.1  $r^2 = \frac{SSR}{SST} = \frac{4.1873.0}{17.244.3} = 0.8288$

$$r = \sqrt{0.8288} = 0.91$$

## Exercise

$y$	$x$	$x^2$	$y^2$	$xy$
25	10			
55	18			
50	25			
75	40			
110	50			
138	63			
90	42			
60	30			
10	5			
100	55			

(i) Determine the least square estimators  $\hat{\beta}_0$  and  $\hat{\beta}_1$

(ii) Determine  $r^2$  and explain how well your model fits the data

(iii) Use ANOVA to test whether regression is significant.