

## Least-Squares Estimates

It is a statistical method used to find the best-fitting line or curve for a set of data points by minimizing the sum of the squares of the residuals (the differences between observed & predicted values)

→ For a <sup>simple</sup> linear regression, the model is

$$y = \beta_0 + \beta_1 x + \epsilon \quad \text{--- (1)}$$

where  $\beta_0$  &  $\beta_1$  are the parameters to estimate. (ie estimate parameters)

$\epsilon \rightarrow$  error term

the residuals  $(y_i - \hat{y}_i)$  are estimates of the error term  $\epsilon_i$ ,  $i = 1, \dots, n$

→ Now,  $y_i = \beta_0 + \beta_1 x_i + \epsilon_i \quad i = 1, \dots, n$

→ the sum of squared errors

$$SSE_p = \sum_{i=1}^n \epsilon_i^2$$

$$= \sum_{i=1}^n (y_i - \beta_0 - \beta_1 x_i)^2 \quad \text{--- (2)}$$

find the values of  $\beta_0$  &  $\beta_1$  that minimizes the  $\epsilon_i$ . So we have to use Partial

derivatives of eqn (2) w.r. to  $\beta_0$  &  $\beta_1$  .  $\beta_0$

$$\frac{\partial SSE_P}{\partial \beta_0} = -2 \sum_{i=1}^n (y_i - \beta_0 - \beta_1 x_i)$$

$$\frac{\partial SSE_P}{\partial \beta_1} = -2 \sum_{i=1}^n x_i (y_i - \beta_0 - \beta_1 x_i)$$

(3)

the values for the estimates  $b_0$  &  $b_1$  , set the eqn (3) equal to zero .

$$\sum_{i=1}^n (y_i - b_0 - b_1 x_i) = 0$$

$$\sum_{i=1}^n x_i (y_i - b_0 - b_1 x_i) = 0$$

Distributing the summation gives us

$$\sum_{i=1}^n y_i - nb_0 - b_1 \sum_{i=1}^n x_i = 0$$

$$\sum_{i=1}^n x_i y_i - b_0 \sum_{i=1}^n x_i - b_1 \sum_{i=1}^n x_i^2 = 0$$

$$\Rightarrow \left. \begin{aligned} b_0 n + b_1 \sum_{i=1}^n x_i &= \sum_{i=1}^n y_i \\ b_0 \sum_{i=1}^n x_i + b_1 \sum_{i=1}^n x_i^2 &= \sum_{i=1}^n x_i y_i \end{aligned} \right\} \text{--- (4)}$$

Solving eqn (4) for  $b_1$  &  $b_0$  we have

$$b_1 = \frac{\sum x_i y_i - [(\sum x_i)(\sum y_i)]/n}{\sum x_i^2 - (\sum x_i)^2/n} \quad \text{--- (5)}$$

$$b_0 = \bar{y} - b_1 \bar{x} \quad \text{--- (6)}$$

Q

~~$b_0 = 59.853$ ,  $b_1 = 2.4614$~~

fit the regression model

X	Y
1	2
2	4
3	5
4	4
5	6

$$y_i = b_0 + b_1 x_i + e_i$$

$$\underline{\underline{S-1}} \quad b_1 = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2}$$

$$b_0 = \bar{y} - b_1 \bar{x}$$

$$\bar{x} = 3, \bar{y} = 4.2$$

$$b_1 = \frac{8}{10} = 0.8, \quad b_0 = 4.2 - (0.8)3 = 1.8$$

$$\text{So, } \boxed{\hat{y} = 1.8 + 0.8x}$$

S-2 compute predicted values & Residuals

$$e_i = y_i - \hat{y}_i$$

X	Y	$\hat{y} = 1.8 + 0.8(X)$	Residual ( $e_i$ )	$(\frac{e_i}{\hat{y}_i})$ $x_i e_i$
1	2	2.6	-0.6	-0.6
2	4	3.4	0.6	1.2
3	5	4.2	0.8	2.4
4	4	5.0	-1.0	-4.0
5	6	5.8	0.2	1.0

S-3 sum of residuals = 0

$$\sum e_i = (-0.6) + 0.6 + 0.8 - 1.0 + 0.2 = 0$$

$\frac{42}{9}$

S-4 sum of  $X_i \cdot e_i = 0$

$$\sum X_i e_i = -0.6 + 1.2 + 2.4 - 4.0 + 1.0 = 0$$

$$SSE = \sum e_i^2$$

total prediction  
error of the  
regression model = 2.40

$\downarrow$   
 $= 0.36 + 0.36 + 0.64 + 1.00 + 0.04$

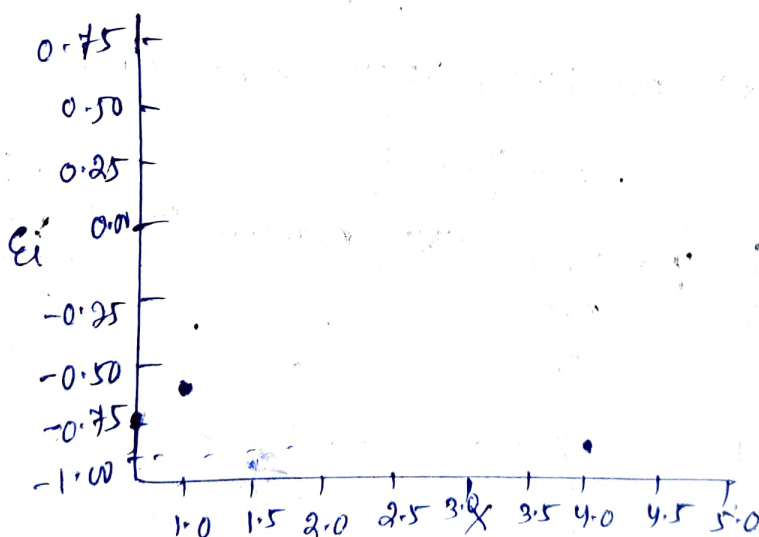
x	$e_i$	$e_i^2$
1	-0.6	0.36
2	0.6	0.36
3	0.8	0.64
4	-1.0	1.00
5	0.2	0.04

### Interpretation

Smaller SSE  $\rightarrow$  better fit

SSE = 0  $\rightarrow$  Perfect Prediction

\* Residual plot for Simple Linear Regression



## 2 Extrapolation

It is a statistical and analytical technique used to predict values beyond the range of observed data, based on the existing trend or pattern.

Ex

<u>Hours Studied</u>	<u>Exam score</u>
2	40
4	55
6	70

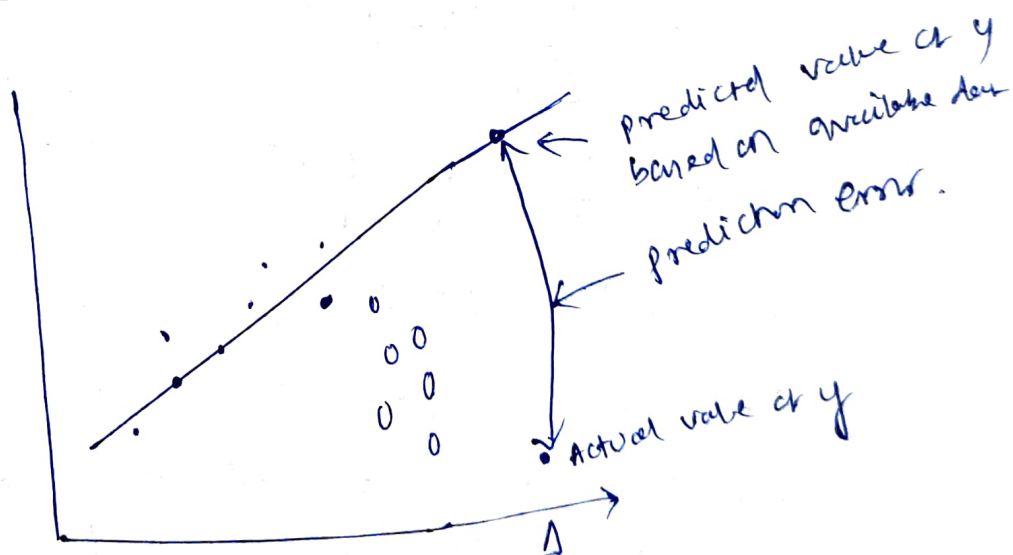
If we predict the score for 8 hours of study, this is extrapolation. because 8 is outside the observed range.

Ex

$$\hat{y} = 10x + 20$$

$$\text{for } x = 8, \quad \hat{y} = 10 \times 8 + 20 = 100$$

This prediction is extrapolated.



→ Extrapolation should be avoided if possible. If prediction outside the given range of  $x$  must be performed, the end user of the prediction needs to be informed that no  $x$ -data is available to support such a prediction.

### 8.3 Coefficient of Determination, $r^2$

→  $r^2$ , for measuring the goodness of fit of the regression.

→  $r^2$  also known as coefficient of determination.

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

where  $SSE$  = sum of squares error  
 $SSR$  = sum of squares regression.

$$SST = \text{sum of squares total} \\ (y - \bar{y}) = (\hat{y} - \bar{y}) + (y - \hat{y})$$

$$SST = SSR + SSE$$

$$\text{ie } \Rightarrow SSR = SST - SSE$$

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

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

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

$$\rightarrow \text{Squares both sides \& summation} \\ \sum (y_i - \bar{y})^2 = \sum (\hat{y}_i - \bar{y})^2 + \sum (y_i - \hat{y}_i)^2$$

$$\Rightarrow SST = SSR + SSE$$

→ If  $SSE = 0$  then  $SST = SSR$ , so  $r^2 = 1$

maximum value of  $r^2$  is 1 which occurs when the regression is a perfect fit.

Subject	X = Time	Y = Distance	Predicted score $\hat{y} = 6 + 2x$	Error in prediction (Y - $\hat{y}$ )	Error in prediction (Y - $\hat{y}$ ) <sup>2</sup>
1	2	10	10	0	0
2	2	11	10	1	1
3	3	12	12	0	0
4	4	13	14	-1	1
5	4	14	14	0	0
6	4	14	14	-1	1
7	5	15	16	-1	1
8	6	20	18	-2	4
9	7	18	20	-2	4
10	8	22	22	0	0
	9	25	24	1	1

$ESF = \sum (y - \hat{y})^2 = 12$

T-2 calculate SST (page - 224)

X	Y	$\bar{y}$	(Y - $\bar{y}$ )	(Y - $\bar{y}$ ) <sup>2</sup>
		16	-6	36
		16	-5	25
		16	-4	16
		16	-3	9
		16	-2	4
		16	-1	1
		16	4	16
		16	2	4
		16	6	36
		16	9	81

$SST = \sum (Y - \bar{y})^2 = 228$

$$\underline{8.3} \quad SSR = SST - SSE = 228 - 12 = 216$$

$$\underline{8.4} \quad r^2 = \frac{216}{228} = 0.947$$

8.4 Standard error of the estimate, s

⇒  $r^2$  statistics measures the goodness of fit of the regression to the dataset.

→ 's' or standard error of the estimate is a measure of the accuracy of the estimates produced by the regression.

→ To find the value of 's' we find mean square error (MSE)

$$MSE = \frac{SSE}{(n-m-1)}$$

where m indicates the no. of predictor variables, which is 1 for simple linear regression greater than 1 for multiple regression case.

the standard error of the estimate is

$$s = \sqrt{MSE} = \sqrt{\frac{SSE}{(n-m-1)}}$$

ex

$$s = \sqrt{MSE} = \sqrt{\frac{12}{(10-1-1)}} = 1.2$$

### 8.5 correlation coefficient ( $r$ )

The correlation coefficient  $r$  (also known as the Pearson product moment correlation coefficient) is an indication of the strength of the linear relationship between two quantitative variables,

$$r = \frac{\sum (x - \bar{x})(y - \bar{y})}{(n-1) s_x s_y}$$

where  $s_x$  &  $s_y \rightarrow$  sample standard deviations of  $x$  &  $y$  data values respectively.

Q

$x$	23	23	27	27	39	41	47	49	50
$y$	9.5	26.5	7.8	17.8	31.4	25.9	27.4	27.2	31.2

$$n = 9$$

S-1  $\bar{x} = \frac{\sum x}{n} = 36.22$  ,  $\bar{y} = 22.74$

S-2  $\sum (x - \bar{x})(y - \bar{y}) = 571.51$

S-3

For Age  $x$

$$s_x = \sqrt{\frac{\sum (x - \bar{x})^2}{n-1}} = \sqrt{\frac{1019.81}{8}} = \sqrt{127.44} = 11.29$$

$$s_y = \sqrt{\frac{\sum (y - \bar{y})^2}{n-1}} = \sqrt{\frac{635.25}{8}} = \sqrt{79.41} = 8.91$$

S-4

$$r = \frac{\sum (x - \bar{x})(y - \bar{y})}{(n-1) s_x s_y}$$

$$= \frac{571.51}{(9-1)(11.29)(8.91)} = \frac{571.51}{8 \times 100.57}$$

$$= \frac{571.51}{804.56}$$

$$\approx 0.71$$