## C&EE 110 Homework 9

Warren Kim

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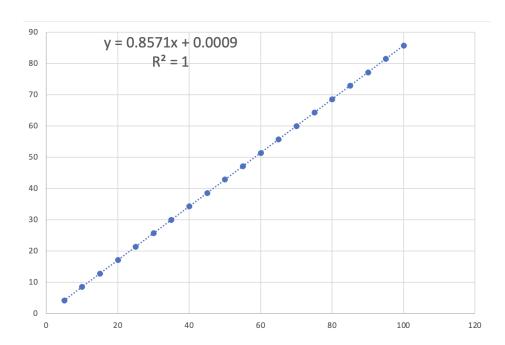
## Question 1

Using the Table, we get:

Sxy	14249.7	x	у	xiyi	xi^2	90									
Sxx	16625	5	4.29	21.45	25	80	У	= 0.8571	x + 0.	0009			.0	·•	
		10	8.57	85.7	100			R <sup>2</sup>	= 1						
Beta1	0.8571248	15	12.86	192.9	225	70									
		20	17.14	342.8	400	60	H				-	•			
Xbar	52.5	25	21.43	535.75	625	50	-				-				
ybar	45	30	25.71	771.3	900	40					.•				
		35	30	1050	1225					• • •					
Beta0	0.0009474	40	34.29	1371.6	1600	30	Г								
		45	38.57	1735.65	2025	20	$\vdash$		, ·						
		50	42.86	2143	2500	10	L								
		55	47.14	2592.7	3025			• ***							
		60	51.43	3085.8	3600		0	20		40	60	80		100	120
		65	55.71	3621.15	4225										
		70	60	4200	4900										
		75	64.29	4821.75	5625										
		80	68.57	5485.6	6400										
		85	72.86	6193.1	7225										
		90	77.14	6942.6	8100										
		95	81.43	7735.85	9025										
		100	85.71	8571	10000										

Then,

(a)



(b) Given:

$$\hat{\beta_1} = \frac{\sum_{i=1}^{N} (x_i - \overline{x})(y_i - \overline{y})}{\sum_{i=1}^{N} (x_i - \overline{x})^2}$$
$$= \frac{S_{xy}}{S_{xx}}$$

and  $\hat{\beta_0}=\overline{y}-\hat{\beta_1}\overline{x}=0.8571$  from excel. So, we get  $\hat{\beta_0}=0.0009,~\hat{\beta_1}=0.8571$  .

 $\beta_0$  is the deflection when a load of 0KN is applied to the beam.

 $\beta_1$  is the rate of change of the deflection when the load is increased on the beam.

## Question 2

*Proof.* We want to show that  $\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x$  always goes through the point  $(\overline{x}, \overline{y})$ . Given

$$\begin{split} \hat{y} &= \hat{\beta_0} + \hat{\beta_1} x \\ \overline{y} &= \hat{\beta_0} + \hat{\beta_1} \overline{x} \\ &= \overline{y} - \hat{\beta_1} \overline{x} + \hat{\beta_1} \overline{x} \end{split} \qquad \text{by definition} \\ &= \overline{y} - \hat{\beta_1} (\overline{x} - \overline{x}) \\ \overline{y} &= \overline{y} \end{split}$$

So,  $\hat{y}$  always goes through the point  $(\overline{x}, \overline{y})$ .

## Question 3

Proof.

$$E(\beta_1) = E\left(\frac{\sum\limits_{i=1}^{N} (x_i - \overline{x})Y_i}{S_{xx}}\right)$$

$$= \frac{\sum\limits_{i=1}^{N} (x_i - \overline{x})E(Y_i)}{S_{xx}}$$

$$= \frac{\sum\limits_{i=1}^{N} (x_i - \overline{x})(\beta_0 + \beta_1 x_i)}{S_{xx}}$$

$$= \beta_0 \frac{\sum\limits_{i=1}^{N} (x_i - \overline{x})}{S_{xx}} + \beta_1 \frac{\sum\limits_{i=1}^{N} (x_i - \overline{x})x_i}{S_{xx}}$$

$$= 0 + \beta_1 \frac{S_{xx}}{S_{xx}}$$

$$= 0 + \beta_1 \frac{S_{xx}}{S_{xx}}$$

$$\sum_{i=1}^{N} (x_i - \overline{x}) = 0$$

$$E(\beta_1) = \beta_1$$
(\*)

and

$$E(\hat{\beta}_0) = E(\overline{Y}) - E(\hat{\beta}_1)\overline{x}$$

$$= \beta_0 + \beta_1\overline{x} \qquad \text{from (*)}$$

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

Therefore,  $\hat{\beta}_0$ ,  $\hat{\beta}_1$  represent unbiased estimators of  $\beta_0$ ,  $\beta_1$