Student Number

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## STA 302f 2015 Quiz 4

- 1. (5 points) Let **Y** be a  $p \times 1$  random vector with  $E(\mathbf{Y}) = \boldsymbol{\mu}_y$  and  $cov(\mathbf{Y}) = \boldsymbol{\Sigma}_y$ . Let **T** be a  $q \times 1$  random vector with  $E(\mathbf{T}) = \boldsymbol{\mu}_t$  and  $cov(\mathbf{T}) = \boldsymbol{\Sigma}_t$ . Note that in general,  $p \neq q$ . Only one of the following statements is always true; the others are not true in general. Choose the true statement and prove it, starting with the definition of  $cov(\mathbf{Y}, \mathbf{T})$  on the formula sheet.
  - (a)  $cov(\mathbf{Y}, \mathbf{T}) = cov(\mathbf{T}, \mathbf{Y}).$
  - (b)  $cov(\mathbf{Y},\mathbf{T}) = \mathbf{0}.$
  - (c)  $cov(\mathbf{Y}, \mathbf{T}) = E(\mathbf{YT}') E(\mathbf{Y})E(\mathbf{T})'.$
  - (d)  $cov(\mathbf{Y}, \mathbf{T}) = \Sigma_y \Sigma_t$ .

 $C_{ov}(Y,\overline{I}) = \overline{E} \underbrace{\xi(Y - \mu_{y})(T - \mu_{t})}_{\xi}$ = E & YT' - Y M' - My T' + My M' 3 = E (YT') - E(Y)M\* - My Mrs Mx E(7- Ma My E(YT')- Mis Mit  $E(YT') - \mu_0 \mu_t$ 

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- 2. (5 points) The simple linear regression model is  $Y_i = \beta_0 + \beta_1 x_i + \epsilon_i$  for i = 1, ..., n, where  $\epsilon_1, ..., \epsilon_n$  are a random sample from a distribution with expected value zero and variance  $\sigma^2$ . The numbers  $x_1, ..., x_n$  are known, observed constants, while the parameters  $\beta_0$   $\beta_1$  and  $\sigma^2$  are unknown constants (parameters).
  - (a) Find  $E(Y_i)$ . Show a little work.

$$E(Y_{i}) = E(P_{i} + P_{i}x_{i} + E_{i}) = P_{i} + P_{i}x_{i} + E(E_{i})$$
  
=  $P_{i} + P_{i}x_{i}$ 

(b) Find  $E(\overline{Y})$ . Show your work.  $E(\overline{Y}) = E(\underbrace{f}_{n} \underbrace{z}_{n} \underbrace{Y}_{n}) = \underbrace{f}_{n} \underbrace{z}_{n} E(Y_{n})$  $= \underbrace{f}_{n} \underbrace{z}_{n} (\beta_{n} + \beta_{n} x_{n}) = \beta_{n} + \beta_{n} \overline{x}_{n}$ 

(c) In homework, you obtained the least-squares estimate  $\hat{\beta}_1 = \frac{\sum_{i=1}^n (x_i - \overline{x})(Y_i - \overline{Y})}{\sum_{i=1}^n (x_i - \overline{x})^2}$ . Is  $\hat{\beta}_1$  an unbiased estimate of  $\beta_1$ ? Answer Yes or No and show your work.

$$E(\beta, ) = E \begin{cases} \frac{2}{\Sigma} (x_{i} - \bar{x})(Y_{i} - \bar{y}) \\ \frac{2}{\Sigma} (x_{i} - \bar{x})^{2} \end{cases}$$

$$= \frac{\sum_{i=1}^{n} (x_{i} - \bar{x})E(Y_{i} - \bar{y})}{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}} = \frac{\sum_{i=1}^{n} (y_{i} - \bar{y})(E(y_{i}) - E(y))}{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}}$$

$$= \frac{\sum_{i=1}^{n} (x_{i} - \bar{x})(\beta_{0} + \beta_{1} x_{i} - (\beta_{0} + \beta_{1} \bar{x}))}{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}} = \beta_{i} \frac{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}}{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}} = \beta_{i} \frac{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}}{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}} = \beta_{i} \frac{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}}{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}} = \beta_{i} \frac{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}}{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}} = \beta_{i} \frac{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}}{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}} = \beta_{i} \frac{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}}{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}} = \beta_{i} \frac{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}}{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}} = \beta_{i} \frac{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}}{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}} = \beta_{i} \frac{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}}{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}} = \beta_{i} \frac{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}}{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}} = \beta_{i} \frac{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}}{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}} = \beta_{i} \frac{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}}{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}} = \beta_{i} \frac{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}}{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}} = \beta_{i} \frac{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}}{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}} = \beta_{i} \frac{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}}{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}} = \beta_{i} \frac{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}}{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}} = \beta_{i} \frac{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}}{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}} = \beta_{i} \frac{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}}{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}}} = \beta_{i} \frac{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}}{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}}} = \beta_{i} \frac{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}}{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}}} = \beta_{i} \frac{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}}{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}}} = \beta_{i} \frac{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}}}{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}}} = \beta_{i} \frac{\sum_{i=1}^{n} (x_{i} - \bar{x})^{2}}}{\sum_{i=1}^{n} (x$$