Solution of GATE-ST 2023 Q58

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Consider the following regression model

$$y_t = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + \epsilon_t, \qquad t = 1, 2, \ldots, n \tag{1}$$

where α_0 , α_1 and α_2 are unknown parameters and ϵ_t's are independent and identically distributed random variables each having $\mathcal{N}(\mu, 1)$ distribution with μ unknown. Then which of the following statements is/are true?

1) There exists an unbiased estimator of α_1
2) There exists an unbiased estimator of α_2
3) There exists an unbiased estimator of α_0
4) There exists an unbiased estimator of μ

Solution: Assuming that the model is

$$y_t = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + \epsilon_t \tag{2}$$

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & A_{11} & A_{12} \\ 1 & A_{21} & A_{22} \\ \vdots & & \\ 1 & A_{n1} & A_{n2} \end{bmatrix} \begin{bmatrix} \alpha_0 \\ \alpha_1 \\ \alpha_2 \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_n \end{bmatrix} \tag{3}$$

Finding mean of the $\boldsymbol{\epsilon}$,

$$\mathbf{y} = A\boldsymbol{x} + \boldsymbol{\epsilon} \tag{4}$$

$$E(\mathbf{y}) = E(A\boldsymbol{x} + \boldsymbol{\epsilon}) \tag{5}$$

$$= A\mathbf{x} + E(\boldsymbol{\epsilon}) \tag{6}$$

$$E(\boldsymbol{\epsilon}) = \begin{bmatrix} E(\epsilon_1) \\ E(\epsilon_2) \\ \vdots \\ E(\epsilon_n) \end{bmatrix} = \begin{bmatrix} \mu \\ \mu \\ \vdots \\ \mu \end{bmatrix} = \mu \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix}$$

$$\mathbf{C_y} = \mathbf{C}_{\boldsymbol{\epsilon}} \tag{7}$$

Since the $\boldsymbol{\epsilon}$'s are independent vectors,

$$\text{Cov}(\epsilon_i, \epsilon_j) = 0, \qquad \forall i \neq j \tag{8}$$

$$\text{Var}(\epsilon_i) = 1, \qquad \forall 1 \leq i \leq n \tag{9}$$

$$\mathbf{C_y} = I_{n\times n} \tag{10}$$

$$\mathbf{y} \sim \mathcal{N}(A\mathbf{x} + E(\boldsymbol{\epsilon}), I) \tag{11}$$

$$p(\mathbf{y}) = \frac{1}{\sqrt{(2\pi)^n \det(\mathbf{C_y})}} \exp -\frac{1}{2}(\mathbf{y} - \boldsymbol{\mu}_\mathbf{y})^T \mathbf{C_y}^{-1}(\mathbf{y} - \boldsymbol{\mu}_\mathbf{y}) \tag{12}$$

where $\mathbf{C_y}$ is the covariance matrix for $\mathbf{y}$, and $\boldsymbol{\mu}_\mathbf{y}$ is the expectance vector for $\mathbf{y}$ The maximum likelihood function can be written as:

$$L(\mathbf{y}) = \frac{1}{(2\pi)^{\frac{n}{2}}} e^{-\frac{(\mathbf{y}-\boldsymbol{\mu}_\mathbf{y})^T(\mathbf{y}-\boldsymbol{\mu}_\mathbf{y})}{2}} \tag{13}$$

$$lnL(\mathbf{y}) = -\frac{n}{2} ln(2\pi) - \frac{1}{2}(\mathbf{y} - \boldsymbol{\mu}_\mathbf{y})^T(\mathbf{y} - \boldsymbol{\mu}_\mathbf{y}) \tag{14}$$

$$\frac{\partial lnL(\mathbf{y})}{\partial \mathbf{x}} = A^T A\mathbf{x} - A^T \mathbf{y} \tag{15}$$

The normal equation is

$$\frac{\partial lnL(\mathbf{y})}{\partial \mathbf{x}} = 0 \tag{16}$$

$$A^T A\mathbf{x} = A^T \mathbf{y} \tag{17}$$

$$\mathbf{x} = \left(A^T A\right)^{-1} A^T \mathbf{y} \tag{18}$$