

CSE-S12 HW-5

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Q1)

a) $y_i = x + z_i$ (x is constant)

$$z_i = y_i - x$$

Given $z_i \sim N(0, 1)$

\Rightarrow As x is constant, $y_i - x$ will also be a $N(0, 1)$.

$$\therefore (y_i - x) \sim N(0, 1)$$

Normal distribution, $p(x) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$

$$(\mu=0, \sigma=1) \Rightarrow \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}$$

$$\text{Likelihood, } L(y_i) = \prod_{i=1}^m e^{-\frac{(y_i - x)^2}{2}}$$

Taking log on both sides, we get,

$$\log(L(y_i)) = \sum_{i=1}^m -\frac{(y_i - x)^2}{2}$$

For maximum, equate derivative to 0.

$$\frac{\partial}{\partial x} (\log(L(y_i))) = 0$$

$$\Rightarrow \frac{\partial}{\partial x} \left(\sum_{i=1}^m -\frac{(y_i - x)^2}{2} \right) = 0$$

$$\sum_{i=1}^m -\frac{2(y_i - x)}{2} = 0$$

$$-\left(\sum_{i=1}^m y_i - mx \right) = 0$$

$$x_{MLE} = \frac{\sum_{i=1}^m y_i}{m}$$

$$\text{Bias} = E[\hat{x}] - x$$

$$E[\hat{x}] = E\left[\frac{1}{m} \sum_{i=1}^m y_i\right]$$

$$= \frac{1}{m} E\left[\sum_{i=1}^m y_i\right]$$

$$= \frac{1}{m} \times m \times E[y_i]$$

$$= E[y_i] \quad \left\{ \begin{array}{l} y_i = x + z_i \\ y_i \sim N(x, 1) \end{array} \right\} \rightarrow \begin{array}{l} \text{Shifted} \\ \text{standard} \\ \text{normal} \end{array}$$

$$= x$$

$$\boxed{\text{Bias} = x - x = 0}$$

Variance, $\hat{\sigma}^2$

It can also be written as

$$\hat{\sigma}^2(\hat{\theta}) = \sigma^2 \left(\frac{1}{m} \sum_{i=1}^m y_i \right)$$

$$= \frac{1}{m^2} \sigma^2 \left(\sum_{i=1}^m y_i \right)$$

$$= \frac{1}{m^2} \times m \times 1 = \frac{1}{m}$$

as $m \rightarrow \infty$, variance = 0

Bias: 0

variance: $\frac{1}{m}$

as $m \rightarrow \infty$

Bias: 0

variance: 0

$$(b) \text{ minimize } \frac{1}{m} \sum_{i=1}^m (y_i - x)^2 + \frac{\rho}{2} (x - \bar{x})^2$$

For x_{MAP} , take derivative and equate to 0.

$$\Rightarrow \frac{1}{m} * 2 * \sum_{i=1}^m (y_i - x) (-1) + \frac{\rho}{2} * 2 * (x - \bar{x}) (1) = 0$$

$$\Rightarrow \frac{2}{m} \sum_{i=1}^m (y_i - x) = \rho (x - \bar{x})$$

$$\Rightarrow \frac{2}{m} \sum_{i=1}^m y_i - \frac{2}{m} x_{MAP} = \rho x_{MAP} - \rho \bar{x}$$

$$\Rightarrow 2 \sum_{i=1}^m y_i - 2m x_{MAP} = \rho m x_{MAP} - \rho \bar{x} m$$

$$x_{MAP} = \frac{2 \sum_{i=1}^m y_i + \rho m \bar{x}}{m(\rho + 2)}$$

$$\text{Bias, } \Rightarrow E[\hat{x}] - x$$

$$= E\left[\frac{2 \sum_{i=1}^m y_i + \rho m \bar{x}}{m(\rho + 2)}\right] - x$$

$$= \frac{\rho m \bar{x}}{m(\rho + 2)} + \frac{2}{m(\rho + 2)} E\left[\sum_{i=1}^m y_i\right] - x$$

$$= \frac{\rho m \bar{x}}{m(\rho + 2)} + \frac{2}{m(\rho + 2)} * m * E[y_i] - x$$

$$= \frac{\sum y_i \bar{x}}{m(p+2)} + \frac{2\mu}{p+2} - \mu$$

$$= \frac{\sum \bar{x} + 2\mu - \sum \mu - 2\mu}{p+2}$$

$$= \frac{\sum (\bar{x} - \mu)}{p+2}$$

$$\therefore \text{Bias} = \frac{\sum (\bar{x} - \mu)}{p+2}$$

Variance ,

$$= \sigma^2 \left(\frac{2 \sum y_i + \sum m \bar{x}}{(p+2)m} \right)$$

$$= \sigma^2 \left(\frac{\sum m \bar{x}}{(p+2)m} \right) + \sigma^2 \left(\frac{2 \sum y_i}{(p+2)m} \right)$$

$$= 0 \left(\begin{matrix} \uparrow \\ \text{constant} \end{matrix} \right) + \frac{4}{(p+2)^2 m^2} \sigma^2 (\sum y_i)$$

$$= \frac{4}{(p+2)^2 m^2} m \cdot 1 = \frac{4}{(p+2)^2 m}$$

$$\text{Bias} = \frac{\rho(\bar{x} - x)}{\rho + 2} \quad \text{as } m \rightarrow \infty$$

$$\text{Bias} = \frac{\rho(\bar{x} - x)}{\rho + 2}$$

$$\text{Variance:- } \frac{4}{(\rho + 2)^2 m}$$

$$\text{Variance:- } 0$$

$$\begin{aligned} (c) E[(x - \hat{x})^2] &= E[(x - E(\hat{x}) + E(\hat{x}) - \bar{x})^2] \\ &= (x - E(\hat{x}))^2 - 2E[(x - E(\hat{x}))(E(\hat{x}) - \bar{x})] \\ &\quad + E[(E(\hat{x}) - \bar{x})^2] \\ &= (x - E(\hat{x}))^2 - 2(x - E(\hat{x}))E[E(\hat{x}) - \bar{x}] \\ &\quad + E[(E(\hat{x}) - \bar{x})^2] \end{aligned}$$

$$E[E(\hat{x}) - \bar{x}] = 0$$

$$\begin{aligned} &= \underbrace{(x - E(\hat{x}))^2}_{B^2} + E[(E(\hat{x}) - \bar{x})^2] \\ &= B^2 + V \end{aligned}$$

here, $B = x - E(\hat{x}) \rightarrow$ estimator bias

$$V = (E(\hat{x}) - \hat{x})^2$$

$$(2) \text{ Bias}(B) = \frac{\beta(x - \bar{x})}{\beta + 2}, \text{ variance } (V) = \frac{4}{(\beta + 2)^2 m}$$

$$B^2 = \frac{\beta^2 (x - \bar{x})^2}{(\beta + 2)^2}, \quad V = \frac{4}{m(\beta + 2)^2}$$

$$\frac{\partial}{\partial \beta} (B^2 + V) = \frac{\partial}{\partial \beta} \left(\frac{\beta^2 (x - \bar{x})^2}{(\beta + 2)^2} + \frac{4}{m(\beta + 2)^2} \right)$$

↑
Result from 1c

$$\Rightarrow \frac{(\beta + 2)^2 \cdot 2\beta(x - \bar{x})^2 - 2(\beta + 2)\beta^2(x - \bar{x})^2}{(\beta + 2)^4} + \frac{-4m \cdot 2(\beta + 2)}{m^2(\beta + 2)^4}$$

$$\Rightarrow \frac{4\beta(x - \bar{x})^2}{(\beta + 2)^3} - \frac{4}{m} \left(\frac{2}{(\beta + 2)^3} \right) = 0$$

$$\Rightarrow \frac{4\beta \cancel{(\beta + 2)^3}}{\cancel{(\beta + 2)^3}} = \frac{4}{m} \left(\frac{2}{\cancel{(\beta + 2)^3}} \right)$$

$$\boxed{\beta = \frac{2}{m \Delta^2}}$$