

Stats - HW 1 - Solution

①

1) and 2) : integration by parts, obtain

$$m(\theta) = \frac{1}{\theta} ; \quad V(\theta) = \frac{1}{\theta^2}$$

3)

• By linearity of the expectation, we have

$$E[\hat{m}] = E\left[\frac{1}{n} \sum_{i=1}^n X_i\right] = \frac{1}{n} \sum_{i=1}^n E[X_i] = \frac{1}{n} \cdot n \cdot m(\theta) = m(\theta)$$

• Since the X_i 's are independent, we have

$$\begin{aligned} \text{Var}(\hat{m}) &= \text{Var}\left(\frac{1}{n} \sum_{i=1}^n X_i\right) = \frac{1}{n^2} \sum_{i=1}^n \text{Var}(X_i) \\ &= \frac{1}{n^2} \cdot n \cdot V(\theta) = \frac{V(\theta)}{n} \end{aligned}$$

• The consistency of \hat{m} follows from the ~~law~~ law of large numbers.

4) We can write

$$\begin{aligned} P(|\hat{m} - m(\theta)| \geq \varepsilon) &= P(\hat{m} - m(\theta) \geq \varepsilon) \cup (\hat{m} - m(\theta) \leq -\varepsilon) \\ &\leq P(\hat{m} - m(\theta) \geq \varepsilon) + P(\hat{m} - m(\theta) \leq -\varepsilon) \end{aligned}$$

Applying Bienaymé - Chebyshev inequality twice, we obtain

$$P(|\hat{m} - m(\theta)| \geq \varepsilon) \leq 2 \cdot \frac{V(\hat{m})}{\varepsilon^2} = \frac{2 \cdot V(\theta)}{\varepsilon^2 n}$$

Rem. The question and the result are correct, but not stated in an optimal fashion.

a) We do not need $E[Y] = 0$ in the assumption of the inequality

b) We have in fact $P(|Y| \geq t) \leq \frac{1}{t^2} E[Y^2]$ with an absolute value

So the sharper inequality $P(|\hat{m} - m(\theta)| \geq \varepsilon) \leq \frac{V(\theta)}{\varepsilon^2 n}$ is also true.

5. By linearity of the expectation, we have

$$\begin{aligned} \mathbb{E}[\hat{V}] &= \mathbb{E}\left[\frac{1}{n} \sum_{i=1}^n (X_i - \hat{m})^2\right] \\ &= \frac{1}{n} \sum_{i=1}^n \mathbb{E}[(X_i - \hat{m})^2] \end{aligned}$$

The variables $(X_i - \hat{m})^2$ are identically distributed, so

$$\mathbb{E}[\hat{V}] = \frac{1}{n} \cdot n \cdot \mathbb{E}[(X_1 - \hat{m})^2] = \mathbb{E}[(X_1 - \hat{m})^2]$$

To compute it, we write

$$(X_1 - \hat{m})^2 = X_1^2 + \hat{m}^2 - 2 X_1 \cdot \hat{m}$$

$$\begin{aligned} \text{We have } \mathbb{E}[X_1^2] &= \mathbb{E}[X_1]^2 + \text{Var}(X_1) \\ &= m(\theta)^2 + V(\theta) \end{aligned}$$

$$\begin{aligned} \mathbb{E}[\hat{m}^2] &= \mathbb{E}[\hat{m}]^2 + \text{Var}(\hat{m}) \\ &= m(\theta)^2 + \frac{V(\theta)}{n} \quad (\text{by Q. 3}) \end{aligned}$$

$X_1 \cdot \hat{m} = X_1 \cdot \left(\frac{1}{n} \sum_{i=1}^n X_i\right)$, and the X_i 's are independent

$$\begin{aligned} \mathbb{E}[X_1 \cdot \hat{m}] &= \frac{1}{n} \mathbb{E}[X_1^2] + \frac{1}{n} \sum_{i=2}^n \mathbb{E}[X_1 X_i] \\ &= \frac{1}{n} (m(\theta)^2 + V(\theta)) + \frac{n-1}{n} \mathbb{E}[X_1] \mathbb{E}[X_i] \\ &= \frac{1}{n} (m(\theta)^2 + V(\theta)) + \frac{n-1}{n} m^2(\theta) \\ &= \frac{V(\theta)}{n} + m^2(\theta) \end{aligned}$$

So

$$\begin{aligned} \mathbb{E}[\hat{V}] &= m(\theta)^2 + V(\theta) + m(\theta)^2 + \frac{V(\theta)}{n} - 2 \frac{V(\theta)}{n} - 2m(\theta)^2 \\ &= \boxed{V(\theta) \left(1 - \frac{1}{n}\right)} \end{aligned}$$

6. No, because $E[\hat{V}] \neq V(\theta)$

(2)

7. Yes, because $\lim_{n \rightarrow \infty} E[\hat{V}] = \lim_{n \rightarrow \infty} \left(1 - \frac{1}{n}\right) V(\theta) = V(\theta)$

8. let us write

$$\hat{V} = \frac{1}{n} \sum_{i=1}^n (X_i - \hat{m})^2$$

$$= \frac{1}{n} \sum_{i=1}^n (X_i - m(\theta) + m(\theta) - \hat{m})^2$$

$$= \frac{1}{n} \sum_{i=1}^n \left[(X_i - m(\theta))^2 + (m(\theta) - \hat{m})^2 + 2(X_i - m(\theta))(m(\theta) - \hat{m}) \right]$$

a) The quantity $\frac{1}{n} \sum_{i=1}^n (X_i - m(\theta))^2 \xrightarrow[n \rightarrow \infty]{\text{IP}} E[(X - m(\theta))^2] = V(\theta)$ by the law of large numbers applied to the r.v. $(X_i - m(\theta))^2$

b) $\frac{1}{n} \sum_{i=1}^n (m(\theta) - \hat{m})^2 = (m(\theta) - \hat{m})^2$ and we know that \hat{m} is a consistent estimator of $m(\theta)$, so $\hat{m} \xrightarrow[n \rightarrow \infty]{\text{IP}} m(\theta)$, which implies $(m(\theta) - \hat{m})^2 \xrightarrow[n \rightarrow \infty]{\text{IP}} 0$.

c) We have $\frac{1}{n} \sum_{i=1}^n 2(X_i - m(\theta)) \cdot (m(\theta) - \hat{m})$
 $= 2(m(\theta) - \hat{m}) \left[\frac{1}{n} \sum_{i=1}^n (X_i - m(\theta)) \right]$

$= -2(\hat{m} - m(\theta))^2 \xrightarrow[n \rightarrow \infty]{\text{IP}} 0$ by the same argument as above.

So $\hat{V} \xrightarrow[n \rightarrow \infty]{\text{IP}} V(\theta)$, it is a consistent estimator.

