

1. Consider a random sample $\{X_1, \dots, X_n\}$ of size $n > 1$ with an unknown mean $\mu \in (-\infty, \infty)$ and unknown variance $\sigma^2 \in (0, \infty)$. Show that S_n^2 has a smaller MSE than S_{n-1}^2 .

$$\begin{aligned}
& MSE(S_{n-1}^2) - MSE(S_n^2) \\
&= Var(S_{n-1}^2) + Bias(S_{n-1}^2) - Var\left(\frac{n-1}{n}S_n^2\right) - Bias\left(\frac{n-1}{n}S_n^2\right) \\
&= \frac{1}{n}\left(\mu_4 - \frac{n-3}{n-1}\sigma^4\right) + 0 - \left(\frac{n-1}{n}\right)^2 \frac{1}{n}\left(\mu_4 - \frac{n-3}{n-1}\sigma^4\right) - \left(\frac{\sigma^2}{n}\right)^2 \\
&= \frac{1}{n}\mu_4 - \frac{n-3}{n(n-1)}\sigma^4 - \frac{(n-1)^2}{n^3}\mu_4 + \frac{(n-1)(n-3)}{n^3}\sigma^4 - \frac{\sigma^4}{n^2} \\
&= \frac{n^2 - n^2 + 2n - 1}{n^3}\mu_4 + \frac{-n^2(n-3) + (n-1)^2(n-3) - n(n-1)}{n^3(n-1)}\sigma^4 \\
&= \frac{2n-1}{n^3}\mu_4 + \frac{n(8-3n)-3}{(n-1)n^3}\sigma^4
\end{aligned}$$

where for big n ,

$$\begin{aligned}
\lim_{n \rightarrow \infty} \frac{MSE(S_{n-1}^2) - MSE(S_n^2)}{n^2} &= -3\sigma^4 + 2\mu_4 = 2\mu_4 - 3\sigma^4 \cdot \kappa \cdot \kappa^{-1} \\
&= 2\mu_4 - 3\sigma^4 \frac{\mu_4}{\sigma^4} \cdot \kappa^{-1} \\
&= 2\mu_4 - 3\mu_4 \cdot \kappa^{-1} \\
&= \mu_4 \left(2 - \frac{3}{\kappa}\right)
\end{aligned}$$

which is only greater than 0 when $\kappa > 1.5$, while the lower bound of κ is just 1.

$\therefore S_n^2$ has a smaller MSE than S_{n-1}^2 for large n if $\kappa > 1.5$

(I tested on Bernoulli distribution with $p=0.5$, which should have $\kappa = 1$, which indeed show the MSE of S_n^2 to be bigger than S_{n-1}^2 for $n>5$)

2. Consider a random sample $\{X_1, \dots, X_n\}$ of size $n>2$ from $U[0, \theta]$, where θ is positive and finite. We found that X_n is the MLE of θ , and it is easy to see that $2\bar{X}$ is the MME of θ . In the sense of MSE, which one is better ? Please justify your answer.

$$f_{X_{(n)}} = n f_X(x) F_X(x)^{n-1} = \frac{n x^{n-1}}{\theta^n}$$

$$\begin{aligned} E(X_{(n)}) &= \int_0^\theta x \cdot \frac{n x^{n-1}}{\theta^n} dx \\ &= \frac{n}{\theta^n} \left[\frac{x^{n+1}}{n+1} \right]_0^\theta \\ &= \frac{n}{\theta^n} \frac{\theta^{n+1}}{n+1} \\ &= \frac{n}{n+1} \cdot \theta \end{aligned}$$

$$\begin{aligned} Var(X_{(n)}) &= \int_0^\theta \left(x - \frac{n}{n+1} \theta \right)^2 \frac{n x^{n-1}}{\theta^n} dx \\ &= \left[\frac{n x^{n+2}}{(n+2) \theta^n} \right]_0^\theta - \frac{2n}{n+1} \theta \left[\frac{n x^{n+1}}{(n+1) \theta^n} \right]_0^\theta + \left(\theta \cdot \frac{n}{n+1} \right)^2 \left[\frac{x^n}{\theta^n} \right]_0^\theta \\ &= \frac{n \theta^2}{n+2} - \frac{2n \theta \cdot n \theta}{(n+1)^2} + \frac{n^2 \theta^2}{(n+1)^2} \\ &= \frac{n \theta^2}{n+2} - \frac{n^2 \theta^2}{(n+1)^2} \end{aligned}$$

$$E(2\bar{X}) = 2 \frac{\theta}{2} = \theta$$

$$Var(2\bar{X}) = 4 Var(\bar{X}) = \frac{4}{12n} \theta^2 = \frac{\theta^2}{3n}$$

$$\begin{aligned}
MSE(X_{(n)}) &= \frac{n\theta^2}{n+2} - \frac{n^2\theta^2}{(n+1)^2} + \left(\frac{\theta}{n+1}\right)^2 \\
&= \frac{2\theta^2}{(n+2)(n+1)} \in O\left(\frac{1}{n^2}\right) \\
MSE(2\bar{X}) &= Var(2\bar{X}) = \frac{\theta^2}{3n} \in O\left(\frac{1}{n}\right)
\end{aligned}$$

Since MSE of $X_{(n)}$ is smaller for big n , it is a better estimator

3. Consider a random sample $\{X_1, \dots, X_n\}$ of size $n > 1$ from a uniform distribution on an interval $[\mu - \sqrt{3}\sigma, \mu + \sqrt{3}\sigma]$, where $\mu \in (-\infty, \infty)$ and $\sigma \in (0, \infty)$. Find
- a. the MMEs of μ and σ , and

$$\begin{aligned}
E(X) &= \mu \\
\therefore \hat{\mu} &= \frac{\sum_{i=1}^n x_i}{n}
\end{aligned}$$

$$\begin{aligned}
Var(X) &= \frac{1}{12}(\mu + \sqrt{3}\sigma - \mu + \sqrt{3}\sigma)^2 = \frac{\sigma^2}{4} \\
\therefore \hat{\sigma} &= \sqrt{4S_n(X)}
\end{aligned}$$

- b. the MLEs of μ and σ

$$\begin{aligned}
L &= \prod_{i=1}^n f_X(x_i|\theta) \\
&= \prod_{i=1}^n \frac{1}{2\sqrt{3}\sigma} \text{ if } \forall i \in n, x_i \in [\mu - \sqrt{3}, \mu + \sqrt{3}], 0 \text{ otherwise} \\
\frac{\partial}{\partial \sigma} \log L &= -n \log(2\sqrt{3}\sigma)
\end{aligned}$$

which is monotonic decreasing when σ increases \implies the likelihood is maximized when $\forall i \in n, x_i \in [\mu - \sqrt{3}, \mu + \sqrt{3}]$ and σ is minimized \iff the range is minimized

$$\implies X_{(1)} = \mu - \sqrt{3}, X_{(n)} = \mu + \sqrt{3}$$

$$\hat{\mu} = \frac{X_{(1)} + X_{(n)}}{2}$$

$$\hat{\sigma} = \frac{X_{(n)} - X_{(1)}}{2\sqrt{3}}$$

4. Consider a random sample $\{X_1, \dots, X_n\}$ from a distribution with a pdf defined by

$$f(X|\theta) = \begin{cases} \theta x^{\theta-1} & , \text{ for } x \in (0, 1) \\ 0 & , \text{ otherwise} \end{cases}$$

where $0 < \theta < \infty$. Let $g(\theta) = \frac{1}{\theta}$

a) Find the MLE of $g(\theta)$

$$L = \prod_{i=1}^n \theta x_i^{\theta-1}$$

$$\log L = n \log \theta + \sum_{i=1}^n (\theta - 1) \log x_i$$

$$\frac{\partial L}{\partial \theta} = \frac{n}{\theta} + \sum_{i=1}^n \log x_i$$

Set $\frac{\partial L}{\partial \theta}$ to 0:

$$\frac{n}{\theta} = - \sum_{i=1}^n \log x_i$$

$$\frac{1}{\theta} = - \frac{\sum_{i=1}^n \log x_i}{n}$$

$$MLE(g(\theta)) = \frac{- \sum_{i=1}^n \log x_i}{n} = \overline{-\log X}$$

b) Is the MLE an unbiased estimator of $g(\theta)$

$$\begin{aligned}
E(-\overline{\log X}) &= E(-\log X) \\
&= \int_0^1 -\log x \cdot \theta x^{\theta-1} dx \\
&= -\theta \int_0^1 \log x \cdot d\frac{x^\theta}{\theta} \\
&= -\theta \left(\left[\frac{x^\theta}{\theta} \log x \right]_0^1 - \int_0^1 \frac{x^\theta}{\theta} d \log x \right) \\
&= -\theta \left(0 - \lim_{x \rightarrow 0} \frac{x^\theta}{\theta} \log x - \int_0^1 \frac{x^{\theta-1}}{\theta} dx \right) \\
&= -\theta \left(-\left[\frac{x^\theta}{\theta^2} \right]_0^1 \right) = \frac{1}{\theta} = g(\theta)
\end{aligned}$$

\therefore the MLE is unbiased

Given that the regularity conditions hold, then

c) Find the C-R inequality for $g(\theta)$

$$\begin{aligned}
\frac{\partial^2}{\partial \theta^2} L &= -\frac{n}{\theta^2} \\
-E\left(-\frac{n}{\theta^2}\right) &= \frac{n}{\theta^2} \\
Var(g(\theta)) &\geq \frac{\left(\frac{d}{d\theta} g(\theta)\right)^2}{\frac{n}{\theta^2}} \\
&= \frac{\theta^2 (-\theta^{-2})^2}{n} \\
&= \frac{1}{n\theta^2}
\end{aligned}$$

\therefore the lower bound $Var\left(\frac{1}{\theta}\right) = \frac{1}{n\theta^2}$

d) Show that the MLE found in (a) is the UMVUE of $g(\theta)$.

$$\begin{aligned}
\text{Var}(\overline{-\log X}) &= \frac{1}{n} \text{Var}(-\log X) \\
\text{Var}(-\log X) &= \int_0^1 (-\log x - \frac{1}{\theta})^2 \theta x^{\theta-1} dx \\
&= \int_0^1 (\log^2 x + \frac{2 \log x}{\theta} + \frac{1}{\theta^2}) \theta x^{\theta-1} dx \\
&= \int_0^1 \log^2 x \cdot \theta x^{\theta-1} dx + \int_0^1 2 \log x \cdot x^{\theta-1} dx + \int_0^1 \frac{1}{\theta} x^{\theta-1} dx \\
&= \int_0^1 \log^2 x dx + \int_0^1 2 \log x \cdot x^{\theta-1} dx + \int_0^1 \frac{1}{\theta} x^{\theta-1} dx \\
&= 0 - \lim_{x \rightarrow 0} x^\theta \log^2(x) - \int_0^1 2 \log x \cdot x^{\theta-1} dx + \int_0^1 2 \log x \cdot x^{\theta-1} dx + \int_0^1 \frac{1}{\theta} x^{\theta-1} dx \\
&= \int_0^1 \frac{1}{\theta} x^{\theta-1} dx \\
&= \frac{1}{\theta} [\frac{x^\theta}{\theta}]_0^1 \\
&= \frac{1}{\theta^2}
\end{aligned}$$

$$\text{Var}(\overline{-\log X}) = \frac{1}{n\theta^2}$$

which is indeed the lower bound given by CR inequality.

Hence, the MLE is indeed the UMBUE of $g(\theta)$