

Probability and Statistics 2
Unit 1 and 2
Assignment Questions

1. Given: $X \sim \text{Poisson}(\theta)$
 $\frac{X - \theta}{\sqrt{\theta}} \sim \text{approx. } N(0, 1)$

$n=1, \hat{\lambda} = 200$

Here, $\frac{\hat{\lambda} - \lambda}{\sqrt{\lambda/n}} \sim N(0, 1)$

$\hat{\lambda} = \sum_{i=1}^n X_i$

Hence, $P(Z_{2.5\%} < Z < Z_{97.5\%}) = 0.95$
 $P(-1.96 < Z < 1.96) = 0.95$

$P\left(-1.96 < \frac{\hat{\lambda} - \lambda}{\sqrt{\lambda/n}} < 1.96\right) = 0.95$

$P\left(-1.96 \sqrt{\frac{\hat{\lambda}}{n}} < \hat{\lambda} - \lambda < 1.96 \sqrt{\frac{\hat{\lambda}}{n}}\right) = 0.95$

$P\left(\hat{\lambda} - 1.96 \sqrt{\frac{\hat{\lambda}}{n}} < \lambda < \hat{\lambda} + 1.96 \sqrt{\frac{\hat{\lambda}}{n}}\right) = 0.95$

$\hat{\lambda} = 200, n=1$

95% CI for $\lambda = \left(200 - 1.96 \sqrt{\frac{200}{1}}, 200 + 1.96 \sqrt{\frac{200}{1}}\right)$

$\Rightarrow (172.2814142, 227.7185858)$

2. $X_i, i = 1, 2, \dots, n$ iid's

mean $\rightarrow \mu$, var. $\rightarrow \sigma^2$

$$\bar{X} = \sum_{i=1}^n X_i, \quad S^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2$$

i) To show $\rightarrow E(\bar{X}) = \mu, \quad V(\bar{X}) = \frac{\sigma^2}{n}$

$$E(\bar{X}) = E\left(\frac{\sum X_i}{n}\right) = \frac{\sum E(X_i)}{n} = \frac{n\mu}{n} \Rightarrow \boxed{\mu}$$

$$V(\bar{X}) = V\left(\frac{\sum X_i}{n}\right) = \frac{1}{n^2} V(\sum X_i) = \frac{1}{n^2} \sum V(X_i) = \frac{n\sigma^2}{n^2}$$

$$\Rightarrow \boxed{\frac{\sigma^2}{n}}$$

ii) To show $\rightarrow E(S^2) = \sigma^2 \quad X_i \sim \text{Norm.}$

$$\frac{(n-1)S^2}{\sigma^2} \sim \chi^2$$

$$E(S^2) = E\left[\frac{1}{n-1} (\sum X_i^2 - n\bar{X}^2)\right] = \frac{1}{n-1} [E(\sum X_i^2) - nE(\bar{X}^2)]$$

$$= \frac{1}{n-1} [\sum E(X_i^2) - nE(\bar{X}^2)]$$

$$\text{Now, } \text{Var}(X_i) = E(X_i^2) - [E(X)]^2$$

$$E(X_i^2) = \mu^2 + \sigma^2$$

$$\text{Var}(\bar{X}) = E(\bar{X}^2) - [E(\bar{X})]^2$$

$$E(\bar{X}^2) = \mu^2 + \frac{\sigma^2}{n}$$

$$E(S^2) = \frac{1}{n-1} \left[\sum (\mu^2 + \sigma^2) - n\left(\mu^2 + \frac{\sigma^2}{n}\right) \right]$$

$$= \frac{1}{n-1} (n\mu^2 + n\sigma^2 - n\mu^2 - \sigma^2) = \frac{1}{n-1} \times \sigma^2 (n-1)$$

$$E(S^2) = \boxed{\sigma^2}$$

iii) To show $S^2 = \frac{2\sigma^4}{n-1}$

$$X \sim N(\mu, \sigma^2)$$

Then, $\frac{(n-1)S^2}{\sigma^2} \sim \chi^2_{n-1}$

$$V\left[\frac{(n-1)S^2}{\sigma^2}\right] = \frac{(n-1)^2}{\sigma^4} V(S^2)$$

$$V(\chi^2_{n-1}) = \frac{(n-1)^2}{\sigma^4} V(S^2)$$

$$2(n-1) = \frac{(n-1)(n-1)}{\sigma^4} V(S^2)$$

$$V(S^2) = \frac{2\sigma^4}{n-1}$$

iv) $P(0.5\sigma^2 < S^2 < 1.5\sigma^2)$
 $= P(S^2 < 1.5\sigma^2) - P(S^2 < 0.5\sigma^2)$
 $n=10$
 $\sigma^2 = 100$

$$P(S^2 < 1.5\sigma^2) = P(S^2 < 150) = P\left(\frac{9S^2}{\sigma^2} < \frac{150 \times 9}{100}\right)$$

$$= P(\chi^2_9 < 13.5) = 0.8587$$

$$P(S^2 < 0.5\sigma^2) = P(S^2 < 50)$$

$$= P\left(\frac{9S^2}{\sigma^2} < \frac{50 \times 9}{100}\right) = P(\chi^2_9 < 4.5)$$

$$= 0.1245$$

$$P(50 < S^2 < 150) = 0.8587 - 0.1245$$

$$= 0.7342$$

3. i) The likelihood function is :

$$\begin{aligned}
 L(p) &= C \frac{[(1-p)^4]^{86}}{[4p^3(1-p)]^2} \frac{[4p(1-p)^3]^{75}}{[p^4]^1} [6p^2(1-p)^2]^{16} \\
 &= C [(1-p)^{344}] [p^{75}(1-p)^{225}] [p^{32}(1-p)^{32}] [p^6(1-p)^2] [p^4] \\
 &= C (1-p)^{603} p^{117}, \text{ where } C \text{ is constant.}
 \end{aligned}$$

Taking logs and differentiating with respect to p and setting equal to zero gives :

$$\begin{aligned}
 \frac{d}{dp} \ln L &= \frac{-603}{(1-p)} + \frac{117}{p} = 0 \\
 p &= \frac{117}{(603+117)} = \frac{117}{720} = 0.1625
 \end{aligned}$$

Checking for maximum :

$$\frac{d^2}{dp^2} \ln L = \frac{-603}{(1-p)^2} - \frac{117}{p^2} < 0$$

Hence, maximum value for $\ln L$ is at $p = 0.1625$.

ii) Goodness of fit test :

Testing hypotheses using χ^2 goodness of fit test :

H_0 the prob. conform to a $\text{Bin}(4, p)$ dist.

H_1 the prob. do not conform to a $\text{Bin}(4, p)$ dist.

using $\hat{p} = 0.1625$ from part (2),
 the prob. for Binomial dist. are :

$$\begin{aligned} P(X=0) &= (1-p)^4 = 0.49197 \\ P(X=1) &= 4p(1-p)^3 = 0.38183 \\ P(X=2) &= 6p^2(1-p)^2 = 0.11113 \\ P(X=3) &= 4p^3(1-p) = 0.01437 \\ P(X=4) &= p^4 = 0.00070 \end{aligned}$$

Expected values $\rightarrow$ 88.55, 68.73, 20.00, 2.59, 0.13
Combining Expected values < 5 to third group,

No. of claims	0	1	2 or more
Observed O_i	86	75	19
Expected E_i	88.55	68.73	22.72

$$\text{Degrees of freedom} = 3 - 1 - 1 = 1$$

$$\begin{aligned} \chi^2 &= \sum \frac{(O_i - E_i)^2}{E_i} \\ &= \frac{(86 - 88.55)^2}{88.55} + \frac{(75 - 68.73)^2}{68.73} + \frac{(19 - 22.72)^2}{22.72} \\ &= 0.079 + 0.572 + 0.608 \\ &= 1.254 \end{aligned}$$

This is less than the 5% critical value of 3.84.
We have insufficient evidence at 5% level to reject H_0 .

Hence, the model is a good fit.

4. $f(x) = \frac{c\beta^2}{(x+\beta)^4}$; $x > 0, \beta > 0$
where c is constant and β is a parameter.

i) Using 2 parameter version of Pareto distribution

PDF = $\frac{\alpha \lambda^\alpha}{(\lambda+x)^{\alpha+1}}$ Hence, β corresponds to α .

Thus, $c=3$ (as c corresponds to α here)

$E(X) = \frac{\lambda}{\alpha-1}$ $E(X) = \frac{\beta}{2}$

$V(X) = \frac{\alpha \lambda^2}{(\alpha-1)^2(\alpha-2)} = \frac{3\beta^2}{4}$

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

$\hat{\beta} = 2\bar{X}$

Bias = $E(\hat{\beta}) - \beta = E(2\bar{X}) - \beta = 2E(\bar{X}) - \beta$
 $= \frac{2}{n} \sum E(X_i) - \beta = \frac{2}{n} \times \frac{n\beta}{2} - \beta$

Bias = 0, hence unbiased.

MSE = $V(\hat{\beta}) + (\text{Bias})^2 = V(\hat{\beta}) = V(2\bar{X}) = 4V(\bar{X})$
 $= 4V\left(\frac{\sum X_i}{n}\right) = \frac{4}{n^2} \sum V(X_i) = \frac{4}{n^2} \times \frac{3\beta^2 n}{4}$

MSE = $\frac{3\beta^2}{n}$

As n increases, MSE tends to 0.

Hence, $\hat{\beta}$ is consistent.

iii) $\hat{\beta} = b\bar{X}$
 $E(\hat{\beta}) = E(b\bar{X}) = bE\left(\frac{\sum X_i}{n}\right) = \frac{b}{n} \sum E(X_i)$

$$= \frac{b}{n} \times \frac{\beta \times n}{2} = \frac{b\beta}{2}$$

$$V(\hat{\beta}) = V(b\bar{X}) = b^2 V\left(\frac{\sum X_i}{n}\right) = \frac{b^2}{n^2} \sum V(X_i)$$

$$= \frac{b^2}{n^2} \times \frac{3\beta^2 \times n}{4} = \frac{3b^2\beta^2}{4n}$$

$$MSE = V(\beta_2) + \text{Bias}^2 = \frac{3b^2\beta^2}{4n} + \left(\frac{b\beta}{2} - \beta\right)^2$$

$$= \frac{3b^2\beta^2}{4n} + \left(\frac{b\beta - 2\beta}{2}\right)^2 = \frac{3b^2\beta^2}{4n} + \left(\frac{b^2\beta^2 + 4\beta^2 - 4b\beta^2}{4}\right)$$

$$= \frac{3b^2\beta^2 + nb^2\beta^2 + 4n\beta^2 - 4nb\beta^2}{4n}$$

$$M = \frac{\beta^2}{4n} (3b^2 + nb^2 + 4n - 4nb)$$

Diff. $\frac{dM}{db} = \frac{\beta^2}{4n} (6b + 2nb - 4n) = 0$

$$6b + 2nb - 4n = 0$$

$$3b + nb - 2n = 0$$

$$b(3+n) = 2n$$

$$b = \frac{2n}{3+n} = \frac{2}{\left(\frac{3+n}{n}\right)} \Rightarrow \boxed{\frac{2}{\left(1+\frac{3}{n}\right)}}$$

Checking maximum, $\frac{d^2M}{db^2} = \frac{\beta^2(6+2n)}{4n} > 0$

Hence d^2M/db^2 minimises is minimum

Thus, $b = \frac{2}{(1+3/n)}$ minimises the MSE.

$$iv) E(\hat{\beta}_2) = \frac{b\beta}{2} = \frac{2}{(1+3/n)} \times \frac{\beta}{2} = \frac{n\beta}{n+3}$$

$$\begin{aligned} \text{Bias} &= E(\hat{\beta}_2) - \beta \\ &= \frac{n\beta}{n+3} - \beta = \frac{n\beta - \beta(n+3)}{n+3} = \frac{n\beta - n\beta - 3\beta}{n+3} = \frac{-3\beta}{n+3} \end{aligned}$$

$\therefore$ we have (-ve) bias.

It underestimates true parameter of β .

$$\begin{aligned} \text{MSE} &= \frac{\beta^2}{4n} (3b^2 + nb^2 + 4n - 4nb) \\ &= \frac{\beta^2}{4n} (b^2(n+3) + 4n(1-b)) \\ &= \frac{\beta^2}{4n} \left[\frac{4n^2}{(n+3)^2} (n+3) + 4n \left[\frac{3+n-2n}{n+3} \right] \right] \\ &= \beta^2 \left[\frac{4n^2}{n+3} + \frac{4n(3-n)}{n+3} \right] \\ &= \beta^2 \left[\frac{4n^2 + 12n - 4n^2}{n+3} \right] \end{aligned}$$

$$\text{MSE} = \frac{12n\beta^2}{n+3}$$

As $n \rightarrow \infty$, MSE doesn't tend to 0.

Hence, it is inconsistent.

5. i) $X \sim U(a, b)$

$$E(X) = \frac{a+b}{2} \quad \bar{X} = \frac{a+b}{2} \quad \underline{a = 2\bar{X} - b} \quad \text{--- (1)}$$

$$V(X) = \frac{(b-a)^2}{12} \Rightarrow S^2 = \frac{(b-a)^2}{12}, 12S^2 = (b-a)^2, 2\sqrt{3}S = b-a$$

$$2\sqrt{3}S = 2\bar{X} - a - a \quad \{ \text{as } b = 2\bar{X} - a \}$$

$$2\sqrt{3}S = 2\bar{X} - 2a$$

$$\sqrt{3} S = \bar{X} - a$$

$$\hat{a} = \bar{X} - \sqrt{3} S$$

ii) $b = 2\bar{X} - a$

$$b = 2\bar{X} - \bar{X} + \sqrt{3} S$$

$$\hat{b} = \bar{X} + \sqrt{3} S$$

iii) Sample of Observations : 1, 2, 8, 50, 150

$$\bar{X} = 42.2, S = 63.57$$

$$\hat{a} = \bar{X} - \sqrt{3} S$$

$$= -67.906$$

$$\hat{b} = \bar{X} + \sqrt{3} S$$

$$= 152.3064$$

Conclusion → • value of $\hat{b}$ is very close to sample value.
• value of $\hat{a}$ is very far from the true sample value,
So it is the potential weakness of MOM.

iv) $X \sim U(0, b)$

$$L = \prod_{x=1}^n f(x, b) = \left(\frac{1}{b}\right)^n$$

$$\log L = -n \log b$$

$$\frac{dL}{db} = \frac{-n}{b}$$

$$\frac{dL}{db} \Rightarrow 0 \Rightarrow \frac{-n}{b} = 0 \quad \text{gives } b = \infty \text{ } \{ \text{not possible} \}$$

$$\frac{d^2L}{db^2} = \frac{n}{b^2} > 0 \quad \text{minimum likelihood estimate,}$$

Hence, $\hat{b} = \max(x_i)$

6. $H_0: p = 0.1$
 $H_1: p > 0.1$

i) $P(\text{type I error}) = P(\text{rejecting } H_0 / H_0 \text{ is true})$
let X be the no. of hits in first 12 minute,
 Y be no. of hits in step 12 minutes.

$$\begin{aligned} P(\text{type I error}) &= P(X \geq 3 | p = 0.1) + P(X = 0 | p = 0.1) \\ &\quad P(Y \geq 5 | p = 0.1) + P(X = 1 | p = 0.1) \\ &\quad P(Y \geq 4 | p = 0.1) \\ &= (1 - 0.8891) + 0.2824(1 - 0.9957) + (0.6590 - 0.2824) \\ &\quad (1 - 0.9744) + (0.8891 - 0.6590)(1 - 0.8881) \\ &= 0.14727 \approx 15\% \end{aligned}$$

ii) Probability of regressing null hypotheses when $p = 0.3$

$$\begin{aligned} &= P(X \geq 3 | p = 0.3) + P(X = 0 | p = 0.3)P(X \geq 5 | p = 0.3) \\ &\quad + P(X = 1 | p = 0.3)P(X \geq 4 | p = 0.3) + P(X = 2 | p = 0.3) \\ &\quad P(X \geq 3 | p = 0.3) \\ &= (1 - 0.2528) + 0.0130(1 - 0.7237) + (0.0850 - 0.0138) \\ &\quad (1 - 0.4925) + (0.2528 - 0.0850)(1 - 0.2528) \\ &= 0.9125 \approx 91\% \end{aligned}$$

iii) Probability of type II error
Accepting H_0 when H_0 is false

$$\begin{aligned} &= 1 - 0.91253 \\ &= 0.08747 \approx 9\% \quad (\text{where } p = 0.3) \end{aligned}$$

iv) 10 space agencies in aggregate fired 120 missiles and recorded H_0 hits.

$$\frac{\bar{X} - \mu}{\sqrt{\frac{\sigma^2}{n}}} \sim N(0,1)$$

$$n = 120, \quad \mu = \mu_0$$

$$\hat{p} = \frac{H_0}{120} = \frac{1}{3} = 0.3333$$

$$Z_{10\%} = 1.2816$$

Lower bound of 90% right tailed confidence interval for 'p' is ÷

$$\hat{p} - 1.2816 \sqrt{\frac{\hat{p}(1-\hat{p})}{n}} = 0.3333 - 1.2816 \sqrt{\frac{0.3333(1-0.3333)}{120}} \\ = 0.2782$$

v) $p > 0.278$ at 10% LOS.

$$H_0: p = 0.278 \quad \text{v/s} \quad H_1: p > 0.278$$

One sample Binomial Model

$$\frac{\bar{X} - np_0}{\sqrt{np_0q_0}} \sim N(0,1) \quad \text{With continuity correction.}$$

$$\frac{39.5 - 120(0.278)}{\sqrt{120 \times 0.278 \times 0.722}} = 1.2511$$

• We don't have sufficient evidence to reject H_0 , at 10% Level of Sig.

vi) Lower bound of Confidence Interval implies that is only a 10% chance of $p \leq 0.2782$ whereas from the Hypothesis test, 'p' could be less than or equal to 0.2780 with $p > 10\%$.

vii) $H_0: \mu_1 = \mu_2$ v/s $H_1: \mu_1 \neq \mu_2$

$$TS = \frac{(\bar{X}_1 - \bar{X}_2) - (\mu_1 - \mu_2)}{S_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \sim t_{n_1+n_2-2}$$

Given, $\bar{X}_1 = 65, \bar{X}_2 = 70, S_1 = 54, S_2 = 70, n_1 = 12, n_2 = 15$

$$S_p^2 = \frac{1}{25} [11(2916) + 14(4800)] = 4027.04$$

$$\frac{65 - 70}{65.45 \sqrt{\frac{1}{12} + \frac{1}{15}}} = -0.2034$$

There is ± 2.060 ($\approx t_{25, 2.5\%}$)

So we have insufficient evidences to reject H_0 at 5% level.

7. i) Public
 $\bar{X}_1 = 30$
 $S_1^2 = 64.3125$

Private
 $\bar{X}_2 = 35.0555$
 $S_2^2 = 67.4027$

ii) 2 sided t-test can be applied in case the samples come from populations with equal variances.

We are testing $H_0: \sigma_1^2 = \sigma_2^2$ v/s $H_1: \sigma_1^2 \neq \sigma_2^2$

Test Statistic is $\frac{S_1^2/\sigma_1^2}{S_2^2/\sigma_2^2} \sim F_{n_1+n_2-1}$

Value of statistics is $\frac{64.31}{67.42} = 0.9542$

$F_{8,8}$ values at 5% levels are 0.2256 & 4.433.
Since the value of test statistics b/w the above values we have insufficient evidences to reject the hypotheses and conclude that the population variances are equal.

iii) $H_0 = \mu_{B1} = \mu_{B2} ; H_1 = \mu_{B1} > \mu_{B2}$

$$T.S. = \frac{(\bar{X}_2 - \bar{X}_1) - (\mu_2 - \mu_1)}{S_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} = \frac{35.0555 - 30}{8.1152 \sqrt{\frac{2}{9}}}$$

T.S. = 1.32151

Tabulated Value = $t_{16, 5\%} = 1.746$

Since, $T.S_{cal} < \text{Tabulated value}$,
we have insufficient evidence to reject H_0 .

8. i) Unbiased estimator $\rightarrow$ It is an estimator where expected value is equal to the parameter.
Estimator is said to be unbiased if bias is equal to ~~the~~ zero for all values of parameter θ .

ii) Biased Estimator $\rightarrow$ It is an estimator which is consistently different from the parameter to be estimated.

iii) The mean square error of an estimator $\hat{\theta}$ is defined by $MSE(\hat{\theta}) = \text{var}(\hat{\theta}) + \text{Bias}^2$

iv) The estimator having less MSE is more consistent

v) They both would be considered to be consistent when MSE minimises such that when, $n \rightarrow \infty$, $MSE \rightarrow 0$.

vi) i) Method of Moments
ii) Maximum Likelihood estimate

9. i) Variable t_k is defined as $t_k \Rightarrow \frac{N(0,1)}{\sqrt{\sum x_k^2 / K}}$, where K denotes degrees of freedom.

and the two random variables $N(0,1)$ and $\sum x_k^2$ are independent.

ii) Mean of t_k for $K > 2 = 0$
Variance of t_k for $K > 2 = \frac{K}{K-2}$

iii) a) We know that for a sample from a normal population,

$$\frac{\bar{X} - \mu}{S/\sqrt{n}} \sim t_{n-1}$$

For the given confidence level $t_9 = 3.25$,

$$\text{Confidence Interval for } \mu \text{ is } \left(50 - 3.25 \times \sqrt{\frac{48.667}{10}}, 50 + 3.25 \times \sqrt{\frac{48.667}{10}} \right)$$

$$\text{i.e. } (42.83, 57.17)$$

b) From (ii) above, we know that $t_{n-1} \sim N\left(0, \sqrt{\frac{n-1}{n-3}}\right)$
 $t_{n-1} \sim N\left(0, \sqrt{\frac{9}{7}}\right)$

$$\frac{\bar{X} - \mu}{S/\sqrt{n}} \sim N\left(0, \sqrt{\frac{9}{7}}\right)$$

$$\frac{\bar{X} - \mu}{S/\sqrt{7n/9}} \sim N(0, 1)$$

Critical value for given level of confidence is 2.58.

Confidence interval for μ is $\left(50 - 2.58 \times \sqrt{\frac{48.667}{10} \times \frac{9}{7}}, 50 + 2.58 \times \sqrt{\frac{48.667}{10} \times \frac{9}{7}}\right)$

$\Rightarrow (43.54, 56.45)$

10. $n=1000$ $X \sim \text{Poi}(n\lambda)$
 $\lambda=3$ $\Rightarrow X \sim \text{Poi}(3000)$

i) $P(\text{type I error}) = P(\text{reject } H_0 \mid H_0 \text{ is true})$
 $= P(X > 3100 \mid X \sim \text{Poi}(3000))$

using normal approximation,

$$P(X > 3100) \approx P\left(Z > \frac{3100 - 3000}{\sqrt{3000}}\right) = 1 - P(Z < 1.825)$$

$\approx 3.39\%$

ii) Type II error = event of accepting the hypotheses when it is false.

iii) Power of test = $P(\text{rejecting } H_0 \mid H_0 \text{ is false})$
 $= P[X > 3100 \mid X \sim \text{Poi}(n\lambda) \sim N(n\lambda, n\lambda)]$
 $= 1 - P\left[Z < \frac{3100 - n\lambda}{\sqrt{n\lambda}}\right]$

The value of power of test will depend on the value of parameter under hypotheses testing.

iv) $\hat{\mu}$ is estimator of μ , $\hat{\mu}$ follows $N(\mu, \frac{\hat{\sigma}^2}{n})$

Hence, $\frac{\hat{\mu} - \mu}{\sqrt{\hat{\sigma}^2/n}} \sim N(0, 1)$, or

$$P(-2.5758 < \frac{2.9 - \mu}{\sqrt{2.9/1000}} < 2.5758) = 0.99$$

Hence, the confidence interval for μ is $(2.768, 3.032)$

11. $n=12$
 $\sum X = 213,200$
 $\sum X^2 = 4919,860,000$
 $\bar{X} = 17,767$
 $S = 10,144$

New Sample Mean

$$\sum X' = \sum X - 11000 - 48,000 + 27,500 + 31,500$$

$$= 213,200$$

$$\bar{X}' = \frac{213200}{12} = 17767$$

New Sample S.D.

$$\sum X'^2 = 4919860000 - (11000)^2 - (48000)^2 + (27500)^2 + (31500)^2$$

$$= 4243360,000$$

$$S'^2 = \frac{1}{n-1} (\sum X'^2 - n(\bar{X}')^2) = \frac{1}{11} (4243360000 - 12(17767)^2)$$

$$= 41396775.64$$

$$S' = 6434.032611$$

12. i) The Cramér-Rao lower bound result holds under very general conditions except where the range of dist^n under the parameter, such as the uniform dist^n in this case.

This is due to a discontinuity, to the derivative in the formula does not make sense.

ii) $Y = \max X_i$

Since, $0 < X_i < \theta$, support of X will be 0 and θ .

For, $0 < y < \theta$

$$\begin{aligned} P(Y < y) &= P(\max X_i < y) \\ &= P\left[\bigcap_{i=1}^n (X_i < y)\right] = \prod_{i=1}^n P(X_i < y) \quad [\because X_i \text{ are independent}] \\ &= \prod_{i=1}^n \left[\int_0^y \frac{dx}{\theta} \right] \end{aligned}$$

$$= \left(\frac{y}{\theta}\right)^n$$

PDF of Y will be,

$$g_Y(y) = \frac{d}{dy} P(Y < y) = \frac{n}{\theta^n} y^{n-1} \quad \text{For } 0 < y < \theta$$

Now, For any non-negative real no. k ,

$$\begin{aligned} E(Y^k) &= \int_0^\theta y^k \frac{n}{\theta^n} y^{n-1} dy \\ &= \frac{n}{n+k} \int_0^\theta \frac{n+k}{\theta^n} y^{n+k-1} dy = \frac{n}{n+k} \cdot \frac{\theta^{n+k} - 0}{n+k} \\ &= \frac{n\theta^k}{n+k} \end{aligned}$$

iii) Bias of estimator $\hat{\theta}(c)$ is given as :

$$\begin{aligned} \text{Bias}(\hat{\theta}(c)) &= E[\hat{\theta}(c) - \theta] = E[cY - \theta] = cE(Y) - \theta \\ &= c \frac{n\theta}{n+1} - \theta \quad (\text{using the results in (b) with } h=1) \\ &= \left(\frac{cn}{n+1} - 1\right) \theta \end{aligned}$$

Mean Square Error of the estimator $\hat{\theta}(c)$ is given as:

$$\begin{aligned} \text{MSE}[\hat{\theta}(c)] &= E[\{\hat{\theta}(c) - \theta\}^2] = E[\{cY - \theta\}^2] \\ &= E[c^2Y^2 - 2c\theta Y + \theta^2] \\ &= c^2E[Y^2] - 2c\theta E(Y) + \theta^2 \\ &= c^2 \frac{n\theta^2}{n+2} - c \frac{2n\theta^2}{n+1} + \theta^2 \quad [\text{using (ii) with } k=1, h=2] \end{aligned}$$

iv) For $\hat{\theta}(c)$ to be unbiased estimator of θ , we need,

$$\begin{aligned} \text{Bias}(\hat{\theta}(c)) &= 0 \\ \left(\frac{cn}{n+1} - 1\right) \theta &= 0 \\ c &= \frac{n+1}{n} \end{aligned}$$

v) In order to minimise $\text{MSE}[\hat{\theta}(c)]$, we need

$$\begin{aligned} 0 &= \frac{d}{dc} \text{MSE}[\hat{\theta}(c)] \\ &= \frac{d}{dc} \left[c^2 \frac{n\theta^2}{n+2} - \frac{c^2 n\theta^2}{n+1} + \theta^2 \right] = 2c \frac{n\theta^2}{n+2} - \frac{2n\theta^2}{n+1} \end{aligned}$$

$$c = \frac{2n\theta^2}{n+1} \cdot \frac{n+2}{2n\theta^2} = \frac{n+2}{n+1}$$

$$\text{Note: } \frac{d^2 \text{MSE}[\hat{\theta}(c)]}{dc^2} = \frac{d}{dc} \left[\frac{2cn\theta^2}{n+2} - \frac{2n\theta^2}{n+1} \right] = \frac{2n\theta^2}{n+2} > 0 \rightarrow \text{minimum}$$

vi) In order to minimise error in estimator, it is preferred to go for an estimator which has lower MSE among different competing estimators. So, here $\hat{\theta}(C_m)$ will be preferred over $\hat{\theta}(C_n)$.

As n becomes large, $\hat{\theta}(C_n) = \frac{n+1}{n} Y \rightarrow Y$

Similarly, $\hat{\theta}(C_m) = \frac{n+2}{n+1} Y \rightarrow Y$

Thus the two estimators become one and the same as $n \rightarrow \infty$.