

PROBABILITY AND STATISTICS - 2
UNIT 1 AND 2

2.

$$x_i = 1, 2, \dots, n$$

$$\bar{x} = \frac{\sum_{i=1}^n x_i}{n}$$

$$s^2 = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2$$

i) $\bar{x} = \frac{\sum x_i}{n}$

$$E(\bar{x}) = \frac{E(\sum x_i)}{n} = \frac{\sum E(x_i)}{n}$$

$$= \frac{\sum \mu}{n} = \frac{n\mu}{n}$$

$$\boxed{E(\bar{x}) = \mu}$$

$$V(\bar{x}) = V\left(\frac{\sum x_i}{n}\right)$$

$$= \frac{1}{n^2} V(\sum x_i) = \frac{1}{n^2} \sum V(x_i)$$

$$= \frac{1}{n^2} \sum \sigma^2 = \frac{n\sigma^2}{n^2}$$

$$V(\bar{x}) = \frac{\sigma^2}{n}$$

$$iii) (n-1) \frac{s^2}{\sigma^2} \sim \chi_{n-1}^2$$

$$V \left[(n-1) \frac{s^2}{\sigma^2} \right] = \chi_{n-1}^2 \quad V \left[\chi_{n-1}^2 \right]$$

$$(n-1) \frac{s^2}{\sigma^2} \sim \chi_{n-1}^2 \quad (200-1)$$

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

$$iv) n=10, \sigma^2=100$$

$$P(0.5 < s^2 < 0.5) = P(s^2 < 0.5) - P(s^2 < -0.5)$$

$$P\left(\frac{(n-1)s^2}{\sigma^2} < \frac{(n-1)0.5}{\sigma^2}\right) = P\left(\frac{(n-1)s^2}{\sigma^2} < \frac{(n-1)(-0.5)}{\sigma^2}\right)$$

$$P(\chi_{n-1}^2 < 0.045) = P(\chi_{n-1}^2 < -0.045)$$

$$P(\chi_{n-1}^2 < 0.045) = P(\chi_{n-1}^2 > 0.045)$$

$$P(\chi_{n-1}^2 < 0.045) = [1 - P(\chi_{n-1}^2 < 0.045)]$$

$$= 0.315$$

s.	No. of claims	0	1	2	3	4
	No. of policies	80	70	16	2	1

$$pdf = {}^nC_r p^r q^{n-r}$$

$$L = \prod_{i=1}^4 f(x_i)$$

$$= \prod_{i=1}^4 {}^nC_{x_i} p^{x_i} q^{n-x_i}$$

$$= \sum {}^nC_{x_i} \cdot p^{\sum x_i} q^{\sum (n-x_i)}$$

$$\ln L = \ln \sum x_i \ln(p) + \sum (n-x_i) \ln(q) + \text{const.}$$

$$= \sum x_i \ln(p) + \sum (n-x_i) \ln(1-p) + \text{const.}$$

$$\frac{d \ln L}{dp} = \frac{\sum x_i}{p} - \frac{\sum (n-x_i)}{1-p} = 0$$

$$= \sum (x_i) \cdot (1-p) - [\sum (n-x_i)] p$$

$$= \sum x_i - p \sum x_i = p \sum (n-x_i)$$

$$\sum x_i - p \sum x_i = p \sum (n-x_i)$$

iii) ~~From the above mention~~

5] $U(a, b)$
 i) To prove: $\hat{a} = \bar{x} - \sqrt{3}s$

Using MOM

Sample mean = Population mean

$$\bar{x} = \frac{1}{2}(a+b)$$

$$\hat{a} = 2\bar{x} - b$$

$$b = 2\bar{x} - a$$

$$s^2 = \frac{1}{12}(b-a)^2$$

$$12s^2 = (b-a)^2$$

$$s\sqrt{12} = b-a$$

$$a = b - s\sqrt{12}$$

$$= (2\bar{x} - a) - s\sqrt{12}$$

$$2s\sqrt{3} = (2\bar{x} - a) - a$$

$$2s\sqrt{3} = 2\bar{x} - 2a$$

$$2s\sqrt{3} = 2(\bar{x} - a)$$

$$s\sqrt{3} = \bar{x} - a$$

$$\hat{a} = \bar{x} - \sqrt{3}s$$

Hence Proved

ii) $\bar{x} = \frac{1}{2}(a+b)$

$$a = 2\bar{x} - b$$

$$s^2 = \frac{1}{12}(b-a)^2$$

$$12s^2 = (b-a)^2$$

$$2s\sqrt{3} = b-a$$

$$2s\sqrt{3} = b - (2\bar{x} - b)$$

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

$$= 2b - 2\bar{x}$$

$$= 2(b - \bar{x})$$

$$S\sqrt{3} = b - \bar{x}$$

$$\therefore b = \bar{x} + \sqrt{3}S$$

iii) The above mentioned estimators can't be used as the mean for a uniform distⁿ is always 0.

iv) $U(0, b)$

$$f(x_i) = \frac{1}{b-0} = \frac{1}{b}$$

$$L = \prod_{i=1}^n f(x_i) = \prod_{i=1}^n \frac{1}{b} = \frac{1}{b^n}$$

$$\ln L = -n \ln b$$

$$\frac{d \ln L}{d b} = \frac{-n}{b} = 0$$

$$b \neq \infty \therefore \hat{b} = \infty$$

$$\frac{d^2 \ln L}{d b^2} = \frac{n}{b^2} > 0$$

$\therefore$ It's minimum

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

8] i) unbiased estimator is an estimator such that it is equal to the true value of the parameter

ii) Bias is the difference between the expectation of the estimator and true value.

$$\text{Bias} = E(g(x)) - \theta$$

iii) MSE is the variance of the estimator wrt the true parameter value

$$\text{MSE} = \text{Var} + \text{Bias}^2$$

iv) $\tilde{\theta}$ with a positive bias is preferred over the other as MSE rules over biasedness. Even though it has a positive bias it would more accurately represent the data.

v) When both the parameters have a lower MSE they will be termed as consistency

vi) θ can be estimated by either Method of Moments method or by Most Likelihood method.

Q] In sampling distribution $\frac{\bar{X} - \mu}{S/\sqrt{n}} \sim t_k$ is used

$\bar{X}$ - Sample mean

μ - Population mean

S - Sample variance

n - size of sample

ii) For t_k with $k > 2$

Mean : 0

Variance : $\frac{k}{k-2}$

iii) $n = 10$,

$\bar{x} = 50$

$s^2 = 48.667$

$$99\% \text{ CI} = \bar{x} \pm t_{\alpha/2, n-1} (S/\sqrt{n})$$

$$= \bar{x} \pm t_{0.5\%, 9} (S/\sqrt{n})$$

$$= 50 \pm 3.250 (\sqrt{48.667/10})$$

$$= (42.8303, 57.1696)$$

iv) $\mu = 0, \sigma^2 = \frac{9}{9-2} = 1.2857$

$$99\% \text{ CI for } \mu \neq \mu_0 \text{ (} \sigma/\sqrt{n} \text{)}$$

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

$$99\% \text{ CI} = \bar{x} \pm z_{\alpha/2} (\sigma/\sqrt{n})$$

$$= 139.449 \pm z_{0.5\%} (\sqrt{1.2857/10})$$

$$= (139.441, 140.38)$$

11) $n = 12$

$$\sum x = 213200$$

$$\sum x^2 = 4919860000$$

$$\text{Sample mean} = 17767$$

$$\text{Sample S.d} = 10144$$

$$\begin{aligned} \text{Revised } \sum x &= 213200 - 11000 - 480000 + 27500 + 31500 \\ &= 213200 \end{aligned}$$

$$\text{Revised mean} = \frac{213200}{12} = 17767$$

New S.d

$$\begin{aligned} \sum x^2 &= 4919860000 - (11000)^2 - (480000)^2 + (27500)^2 + (31500)^2 \\ &= 4243360000 \end{aligned}$$

$$s^2 = \frac{1}{n-1} (\sum x_i^2 - n(\bar{x})^2)$$

$$= \frac{1}{11} (4243360000 - 12(17767)^2)$$

$$= 41396775.64$$

$$S = 6437.0326$$

12.) The CRLM results hold under very general conditions except where the range of distribution involves parameters such as the uniform distribution in this case

ii)

$$Y = \max X_i$$

$$P[Y < y] = P[\max X_i < y]$$

$$= P[n(X_i < y)]$$

$$= \prod_{i=1}^n P[X_i < y]$$

$$= \prod_{i=1}^n \int_0^y \frac{dx}{\theta} = \left(\frac{y}{\theta}\right)^n$$

$$PDF: \frac{n}{\theta^n} y^{n-1} \text{ for } 0 < y < \theta$$

$$E[Y^k] = \int_0^{\theta} y^k \frac{n}{\theta^n} y^{n-1} dy$$

$$= \frac{n}{n+1} \int_0^{\theta} \frac{n+1}{\theta^n} y^{n+1-1} dy$$

$$= \frac{n}{n+1} \frac{\theta^{n+1} - 0}{\theta^n}$$

$$= \frac{n\theta}{n+1}$$

$$\text{iii) Bias } [\hat{\theta}(n)] = E[\hat{\theta}(n) - \theta]$$

$$= E[cY - \theta]$$

$$= c E[Y] - \theta$$

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

$$= \left(\frac{cn}{n+1} - 1\right) \theta$$

$$MSE [\hat{\theta}(n)] = E[\hat{\theta}(n) - \theta]^2$$

$$= E[c^2 Y^2 - 2c\theta Y + \theta^2]$$

$$= c^2 E[Y^2] - 2c\theta E[Y] + \theta^2$$

$$= \frac{c^2 n \sigma^2}{n+2} - \frac{2cn\sigma^2}{n+1} + \sigma^2$$

iv) For $\hat{\theta}(c)$ to be an unbiased estimator we need Bias $[\hat{\theta}(c)] = 0$

$$\left(\frac{cn}{n+1} - 1\right)\sigma = 0$$

$$c = \frac{n+1}{n}$$

v) To minimize $MSE[\hat{\theta}(c)]$ we need

$$\frac{d}{dc} MSE[\hat{\theta}(c)]$$

$$= \frac{d}{dc} \left[\frac{c^2 n \sigma^2}{n+2} - \frac{2cn\sigma^2}{n+1} + \sigma^2 \right]$$

$$= 2c \frac{n\sigma^2}{n+2} - \frac{2n\sigma^2}{n+1}$$

Thus,

$$c_m = \frac{2n\sigma^2}{n+1} - \frac{n+2}{2n\sigma^2} - \frac{n+1}{n+1}$$

vi) In order to minimize error in estimation, it is preferred to opt for an estimator which has lower MSE, hence in this case $\hat{\theta}(c_m)$ will be preferred.

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

$$\hat{\lambda} = \frac{\sum x_i}{n} = 200$$

$$P(-1.96 < Z < 1.96) = 0.95$$

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

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

95% CI for λ when $\hat{\lambda} = 200, n = 1$

$$\left(200 - 1.96 \sqrt{200}, 200 + 1.96 \sqrt{200}\right)$$

$$(172.28191, 227.71809)$$