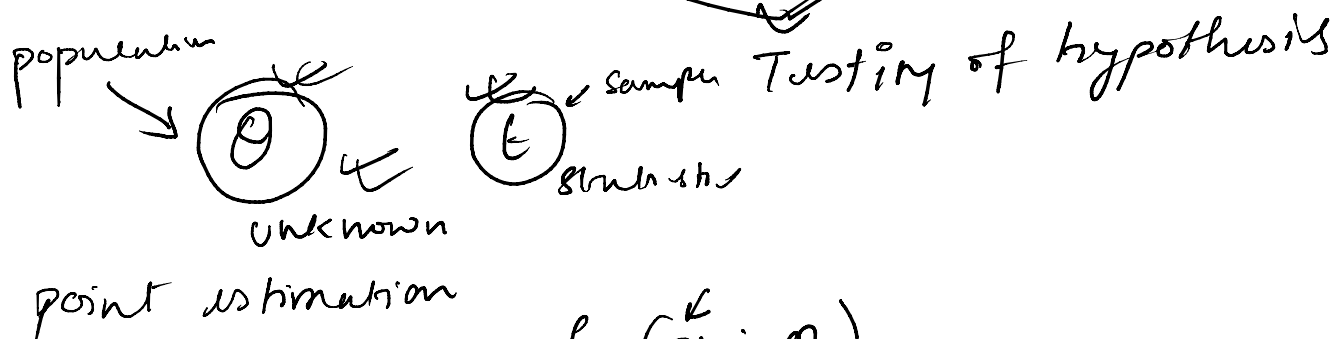
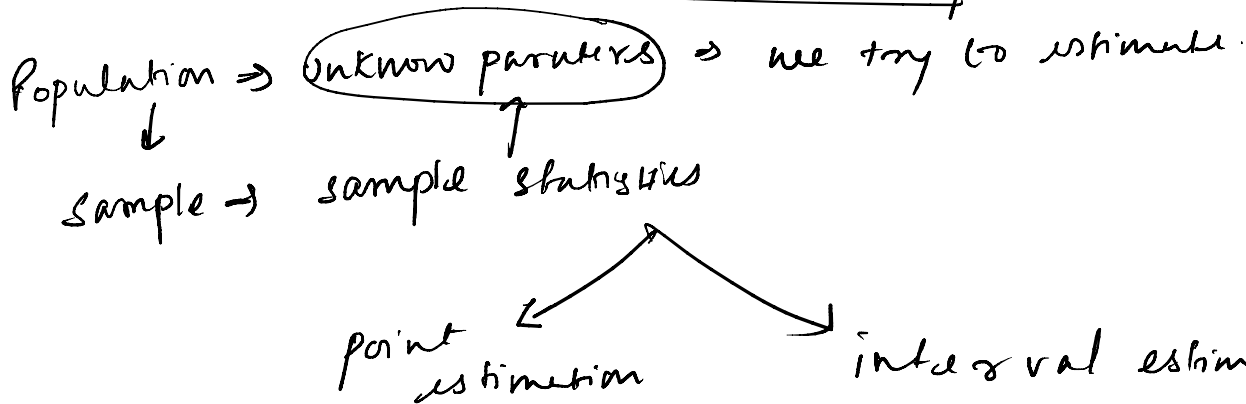


Statistical Inference



$$f(x; \theta)$$

\uparrow sample \uparrow trying to estimate.

x_1, x_2, \dots, x_n sample $\Rightarrow t$

t is an estimator of θ

when can you say t is satisfactory

\Rightarrow if $|t - \theta|$ is as small as possible

Properties of a good estimator.

- ① unbiasedness $E(t) = \theta$

(1) Unbiasedness

$$E(t) = \theta$$

$$\text{or } E(t) - \theta = 0$$

if $E(t) \neq \theta$

$$\frac{E(t) - \theta \neq 0}{\text{(then } t \text{ is biased)}} \times$$

for example

Normal population

θ is μ

t is \bar{x}

population mean

sample mean

You can say that \bar{x} is an unbiased estimator of μ if

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

(2) min variance

two sample ests

t_1 \rightarrow t_2 θ

if t_1 and t_2 both are unbiased then we will check $\text{var}(t_1)$ and $\text{var}(t_2)$

if $v(t_1) < v(t_2)$ then t_1 is a better estimator of θ .

\star we call it a Min variance Unbiased Estimator (MVUE)

(3) Consistency: $P \left\{ \left| t_n - \theta \right| > \epsilon \right\} \Rightarrow 0$

③ Consistency: $P\{ |t_n - \theta| > \epsilon \} \Rightarrow 0$
as $n \rightarrow \infty$

and $\epsilon > 0$



value of t_n converges to θ
as $n \rightarrow \infty$.

④ Efficiency:
• $E(t_n) \rightarrow \theta$ ✓
• $\text{var}(t_n) \rightarrow 0$ ✓
as $n \rightarrow \infty$

then the statistic t is called the efficient estimator of θ if t is asymptotically normally distributed and $\text{avar}(t_1) \leq \text{avar}(t_2)$
↑ efficient.
this is ~~sufficient~~ estimator.

⑤ Sufficiency: X_1, X_2, \dots, X_N with unknown θ .
↓
 x_1, x_2, \dots, x_n sample in size n

then if you can write,

$$f(x_1, x_2, \dots, x_n; \theta) = g(\mathcal{T}; \theta) h(x_1, x_2, \dots, x_n)$$

$$f(x_1, x_2, \dots, x_n, \theta) = f_1(x_1) f_2(x_2) \dots f_n(x_n)$$

Numerical

if the variance of independent and unbiased estimators T_1, T_2, T_3 of θ are in the ratio 2:3:5, which of the following estimators of θ would you prefer most?

$$t_1 = \frac{(2T_1 + T_2 + T_3)}{4}, \quad t_2 = \frac{(T_1 + T_2 + 2T_3)}{4}$$

$$t_3 = \frac{(T_1 + 2T_2 + T_3)}{4}$$

T_1, T_2, T_3 of θ

$$E(T_1) = E(T_2) = E(T_3) = \theta$$

$$\frac{V(T_1)}{2} = \frac{V(T_2)}{3} = \frac{V(T_3)}{5} = k$$

$$E\left(\frac{2T_1 + T_2 + T_3}{4}\right) = \frac{2E(T_1)}{4} + \frac{E(T_2)}{4} + \frac{E(T_3)}{4}$$

$$= 2\theta + \theta + \theta$$

$$= \frac{2\theta}{2} + \frac{\theta}{4} + \frac{\theta}{4}$$

$$= \theta/2 + 2\theta/4 = \frac{\theta}{2} + \frac{\theta}{2} = \theta$$

$$E\left(\frac{T_1 + T_2 + 2T_3}{4}\right) = \frac{\theta}{4} + \frac{\theta}{4} + \frac{2\theta}{4} = \theta$$

$$E\left(\frac{T_1 + 2T_2 + T_3}{4}\right) = \frac{\theta}{4} + \frac{2\theta}{4} + \frac{\theta}{4} = \theta$$

Thus all three estimators are unbiased for θ .

$$V\left(\frac{2T_1 + T_2 + T_3}{4}\right) = \frac{1}{16} \left[4V(T_1) + V(T_2) + V(T_3) \right]$$

$$= \frac{1}{16} \left[4 \times 2k + 3k + 5k \right]$$

$$= k$$

$$V\left(\frac{T_1 + T_2 + 2T_3}{4}\right) = \frac{2k + 3k + 4 \times 5k}{16}$$

$$= \frac{25k}{16} > k$$

$$V\left(\frac{T_1 + 2T_2 + T_3}{4}\right) = \frac{2k + 4 \times 3k + 5k}{16}$$

$$= \frac{19}{16} k$$

$$k < \frac{19}{16} k < \frac{25}{4} k$$

$\sqrt{(2T_1 + T_2 + T_3) / 4}$ is min

\therefore the estimator $\frac{2T_1 + T_2 + T_3}{4}$ is the preferred statistic among the given three.

Maximum likelihood method / estimation (MLE).

\downarrow
maximization of a log likelihood fn.

$$x_1, x_2, \dots, x_N \rightarrow \theta$$

$$x_1, x_2, \dots, x_n \rightarrow \theta$$

Likelihood fn, $L = f(x_1, x_2, \dots, x_n; \theta)$

f.o.c

$$\frac{\partial L(\theta)}{\partial \theta} \Big|_{\theta = \hat{\theta}} = 0$$

$$= \prod_{i=1}^n f(x_i; \theta)$$

f.o.c

$$\frac{\partial L}{\partial \theta} \Big|_{\theta = \hat{\theta}} = 0$$

$\theta = 1$

$$\frac{\partial^2 L(\theta)}{\partial \theta^2} \Big|_{\theta = \hat{\theta}} < 0 \quad \text{for maximisation}$$

Ex let us consider a set of n Bernoullian

trials with p as probability of success in a trial

with the i th trial we associate a variable x_i such that,

$$p^{x_1} p^{x_2} \dots p^{x_n} = p^{\sum x_i}$$

$$x_i = \begin{cases} 1 & \text{if there is success} \\ 0 & \text{otherwise} \end{cases}$$

then the pmf of x_i is

$$f(x_i; p) = p^{x_i} (1-p)^{1-x_i} \quad \text{for } x_i = 0, 1$$

$$L(p) = \prod_{i=1}^n f(x_i; p) = p^{\sum x_i} \cdot (1-p)^{\sum (1-x_i)}$$

$$= p^{\sum x_i} (1-p)^{n - \sum x_i}$$

$$\log_e L(p) = \left(\sum x_i \right) \log_e p - (n - \sum x_i) \log_e (1-p)$$

f.o.c

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

$$= \frac{(1-p) \sum x_i - p(n - \sum x_i)}{p(1-p)}$$

$$= \frac{\sum x_i - p \sum x_i - np + p \sum x_i}{p(1-p)}$$

$$= \frac{\sum x_i - np}{p(1-p)}$$

f.o.c

$$\frac{d \log L(p)}{dp} = 0$$

$$\frac{\sum x_i - np}{p(1-p)} = 0$$

$$\therefore \sum x_i - np = 0 \Rightarrow p = \frac{\sum x_i}{n}$$

\therefore m.l.e of \hat{p} is \bar{x} .

$\hat{p} = \bar{x}$
 ↑
 sample proportion of sum

HW : TRY to find out the m.l.e in a distribution

HW: TRY to find out the mid in
 case of normal distribution
 and Poisson distribution

Topic: Interval estimation

x_1, x_2, \dots, x_n if \bar{x} is sample mean
 for a normal population
 with population mean
 μ and σ .

Case 1: estimate μ , σ is known.

test statistic

$$Z = \frac{\bar{x} - \mu}{\sigma / \sqrt{n}}$$

Z is a standard normal variable (distribution)

What is a
 standard normal
 distribution?

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

is a linear fun

$$Z \sim \frac{X - \mu}{\sigma}$$

is a standard normal variable.

$$P \left[Z_{1-\frac{\alpha}{2}} \leq \frac{\bar{x} - \mu}{\sigma / \sqrt{n}} \leq Z_{\alpha/2} \right] = 1 - \alpha$$

α is called the level of
 significance

probability of
 lying in rejection
 region

$Z \sim N(0, 1)$
 ↳ std normal variable

Question

$\sum Z^2 \sim \chi^2(n)$

$$P \left[\bar{x} - \frac{\sigma}{\sqrt{n}} \leq \mu \leq \bar{x} + \frac{\sigma}{\sqrt{n}} \right] = 1 - \alpha$$
 upper limit
 lower limit

$X \sim \chi^2(m)$
 $Y \sim \chi^2(n)$
 $\frac{X}{m} \sim \chi^2(m)$
 $\frac{Y}{n} \sim \chi^2(n)$
 $\sim F$ statistics

$\frac{X/m}{Y/n}$ where $X \sim \chi^2(m)$
 $Y \sim \chi^2(n)$
 then $\frac{X/m}{Y/n} \sim F(m, n)$

Case 2: Confidence limit to μ
 when σ is also unknown

\bar{x}

$$S^2 = \frac{1}{n} \sum (x_i - \bar{x})^2$$
 or $S'^2 = \frac{1}{(n-1)} \sum (x_i - \bar{x})^2$
 sample variance

(1) μ - with σ known $\rightarrow Z$
 with σ unknown $\rightarrow t$

test statistics is

$$\frac{\bar{x} - \mu}{S'/\sqrt{n}} \sim t_{(n-1)}$$

$$P \left[t_{1-\frac{\alpha}{2}, n-1} \leq \frac{\bar{x} - \mu}{s'/\sqrt{n}} \leq t_{\frac{\alpha}{2}, n-1} \right] = 1-\alpha$$

$$P \left[\bar{x} - \frac{s'}{\sqrt{n}} t_{\frac{\alpha}{2}, n-1} \leq \mu \leq \bar{x} + \frac{s'}{\sqrt{n}} t_{\frac{\alpha}{2}, n-1} \right] = 1-\alpha$$

Case 3 confidence interval of σ , when μ is known

Test statistics is $\sum_{i=1}^n \frac{(x_i - \mu)^2}{\sigma^2}$

$\sim \chi^2_{(n)}$

$$P \left[\chi^2_{1-\alpha/2, n} \leq \frac{\sum (x_i - \mu)^2}{\sigma^2} \leq \chi^2_{\alpha/2, n} \right] = 1-\alpha$$

$$P \left[\frac{\sum (x_i - \mu)^2}{\chi^2_{\alpha/2, n}} \leq \sigma^2 \leq \frac{\sum (x_i - \mu)^2}{\chi^2_{1-\alpha/2, n}} \right] = 1-\alpha$$

Case 4 confidence limit to σ when μ is unknown

Test statistics is $\sum (x_i - \bar{x})^2$

test statistics is $\frac{\sum (x_i - \bar{x})^2}{\sigma^2}$

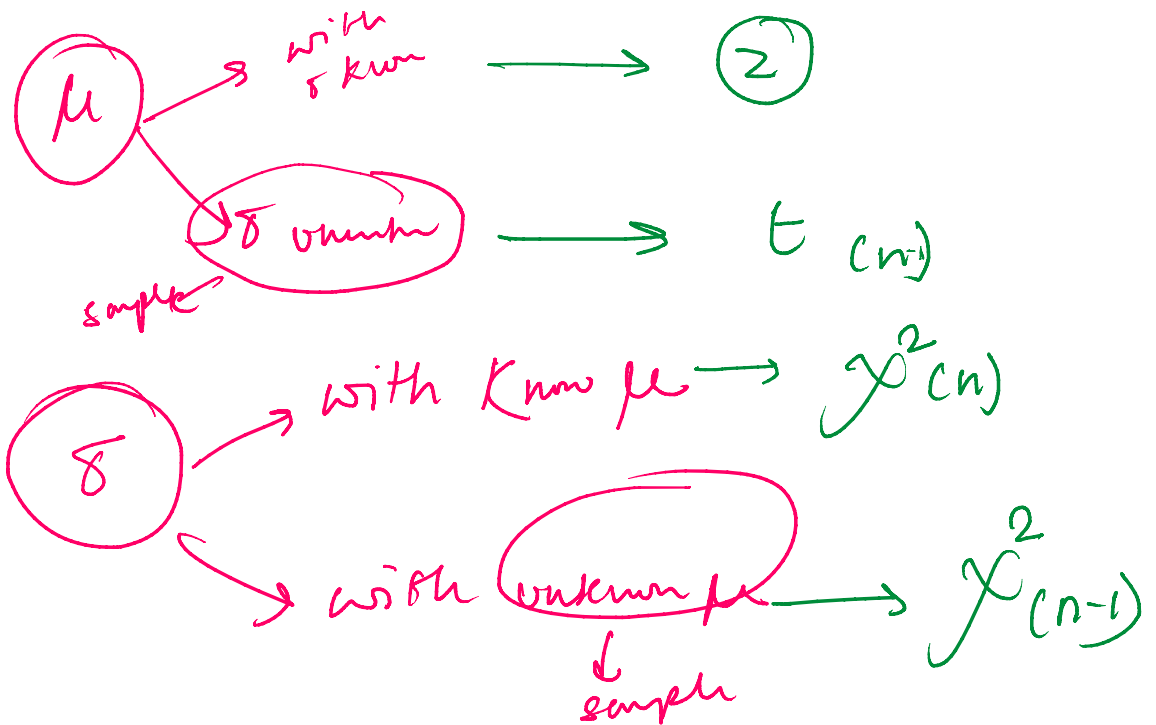
$$s'^2 = \frac{1}{n-1} \sum (x_i - \bar{x})^2$$

$$= (n-1) s'^2 / \sigma^2 \sim \chi^2_{(n-1)}$$

confidence limits are

$$\frac{(n-1) s'^2}{\chi^2_{\frac{\alpha}{2}, n-1}} \quad \text{and} \quad \frac{(n-1) s'^2}{\chi^2_{1-\frac{\alpha}{2}, n-1}}$$

summary!



Q

Suppose that a random variable of size 10, drawn from a normal population with mean $\mu = 200$ and sd 12. find

10, drawn

has mean 40 and sd 12. find 99% confidence limits

for the population mean.

(Given $t_{0.005, 9} = 3.25$, $t_{0.005, 10} = 2.21$)

$1 - \alpha$
 $\alpha = 100 - 99\%$
 $= 1\%$
 $\alpha = 0.01$

μ
confidence interval
for μ
 $\alpha = 0.01$

$n = 10$

$\bar{x} = 40, s = 12$

Which case?
and then calculate.