

[481] $(8.23, 6.7, 6.11, 8.45, 8.48)$ Khyati Srigicherla.

[HW#3]

[8.23] Use THM 8.11 to show that for

random sample of size n from a normal pop.

w/ variance σ^2 , the sampling dist of S^2

has mean σ^2 & variance $\left(\frac{2\sigma^4}{n-1}\right)$



• (THM 8.11) IF \bar{X}, S^2 for $\begin{matrix} \text{mean} \\ \downarrow \\ \text{variance} \end{matrix}$ for $\begin{matrix} \text{RAND} \\ \text{SAMPLE} \\ \text{Size} \\ \underline{\underline{n}} \end{matrix} \sim \text{Norm } (\mu, \sigma^2)$

THEN \Rightarrow

① \bar{X}, S^2 are INDEPENDENT.

② rv $\left(\frac{(n-1)S^2}{\sigma^2}\right)$ has $\sim \chi^2$ dist w/ $v = n-1$

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

and

$$\bullet \text{Var}\left[\frac{(n-1)S^2}{\sigma^2}\right] = 2(n-1)$$

• Since $\left(\frac{(n-1)S^2}{\sigma^2}\right)$ follows a χ^2 dist w/ $v = n-1$ df,

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

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

w/ $(n-1)$ df.

we know for a χ^2 distribution that

$$M = v$$

$$\sigma^2 = 2v$$

$(v = n-1)$ df;

(6.7) Q: USE "integration by parts"
to show that:

Recursive
definition
of gamma
fn.

★ $\{ \Gamma(\alpha) = (\alpha-1) \Gamma(\alpha-1) \text{ for } \alpha > 1 \}$

"GAMMA Fn": $\Gamma(\alpha) = \int_0^\infty x^{\alpha-1} e^{-x} dx \text{ for } \alpha > 0.$

$$\text{uv} - \int v du \quad \left| \begin{array}{l} u = x^{\alpha-1} \\ du = (\alpha-1)x^{\alpha-2} dx \end{array} \right. \quad \begin{array}{l} dv = e^{-x} \\ v = -e^{-x} \end{array}$$

$$\Gamma(\alpha) = -x^{\alpha-1} e^{-x} \Big|_{0=x}^\infty + (\alpha-1) \left(\int_0^\infty x^{\alpha-2} e^{-x} dx \right)$$

$$(-0 + \cancel{e^{-\infty}}) = 0.$$

REMARK:

→ e decays faster to 0 than polynomial growth of $x^{\alpha-1}$.

$$(\Gamma(\alpha-1)) \quad \text{Thus we find:} \quad \boxed{\Gamma(\alpha) = \alpha-1 \Gamma(\alpha-1)}$$

As desired.

QED

(6.11) Q SHOW that a "Gamma dist" where $\alpha > 1$ has a relative maximum
at $x = \beta(\alpha-1)$.

Q What happens when $0 < \alpha < 1$ and when $\alpha = 1$.

(recall)

- $\Gamma(\alpha) = \int_0^\infty x^{\alpha-1} e^{-x} dx$ for $\alpha > 0$ | GAMMA FUNCTION.

- X has gamma dist. and it is referred to as a gamma rv. \Leftrightarrow pdf is given by:

$$g(x; \alpha, \beta) = \begin{cases} \frac{1}{\beta^\alpha \Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta} & \text{for } x > 0 \\ 0 & \text{elsewhere.} \end{cases}$$

WHERE $\alpha > 0$ $\beta > 0$.

- Let $X > 0$. Then, pdf is nonzero.

- Let us now find relative maxima for the gamma dist by taking $\left\{ \frac{\partial}{\partial x} g(x; \alpha, \beta) = 0 \right\}$

SET

...
cont.

$$\Rightarrow \frac{\partial}{\partial x} g(x; \alpha, \beta) = \frac{\partial}{\partial x} \left(\frac{1}{B^\alpha \Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta} \right) = 0$$

$$k := \frac{1}{\beta^\alpha \Gamma(\alpha)} \text{ which is a CONSTANT}$$

$$\Rightarrow k \left[x^{\alpha-1} \left(-\frac{1}{\beta} e^{-x/\beta} \right) + e^{-x/\beta} ((\alpha-1)x^{\alpha-2}) \right] = 0$$

$$\Rightarrow k \left[\underbrace{(x^{\alpha-2})}_{=: f_1} \underbrace{(e^{-x/\beta})}_{=: f_2} \underbrace{\left(-\frac{x}{\beta} + \alpha - 1 \right)}_{=: f_3} \right] = 0$$

• $(x > 1)$; $k = \frac{1}{\beta^\alpha \Gamma(\alpha)}$ which is nonzero so we can divide both sides by k

\Rightarrow we recovered that the product of 3 factors is zero.

\Rightarrow That is, as f_i defined $\prod_{i=1}^3 f_i = (f_1)(f_2)(f_3) = 0$.

\Rightarrow This is true i.f.f. at least one of the three factors is zero.

• for $x > 0$ and $\alpha > 1$ and $\beta > 0$,

\rightarrow the exponential function $e^{-x/\beta} = f_2$ can never be 0.

\rightarrow the polynomial fn $x^{\alpha-2} = f_1$ can't be 0.

• Setting $f_3 = 0 \Rightarrow \frac{x}{\beta} = \alpha - 1 \Rightarrow \{x = \beta(\alpha-1)\}^*$

Therefore the gamma dist. achieves a relative max as desired.
when $x = \beta(\alpha-1)$.

- Next let us consider the CASE when $0 < \alpha < 1$. (8.)

$$\Rightarrow x^{-C_1} e^{-x/\beta} \left(-\frac{x}{\beta} - C_2 \right) \quad (C_2 > 0)$$

- Observe, as $x \rightarrow \infty$, the dominant term $e^{-x/\beta} \rightarrow 0$

That is the behavior in the limit, of the expression obtained previously.

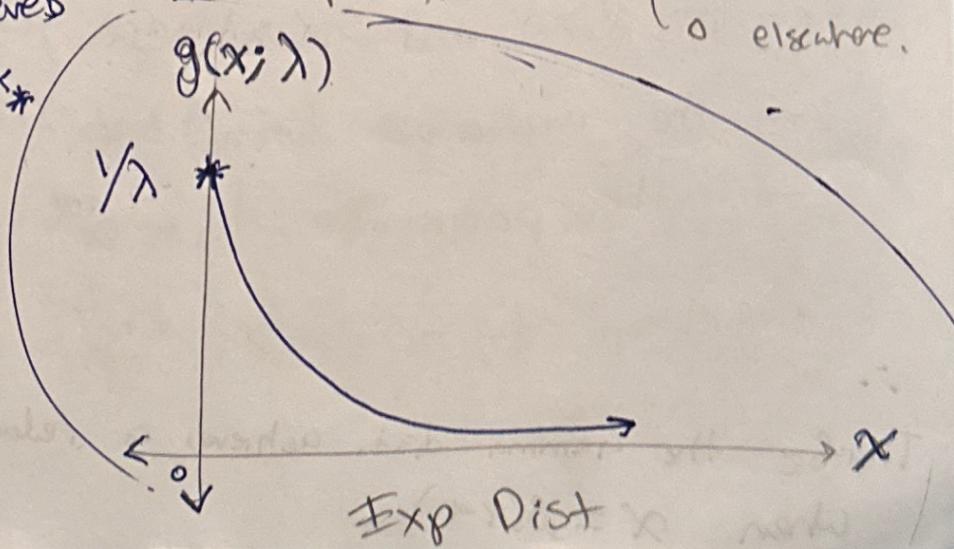
- Primarily, notice that the gamma fn: $\frac{1}{\beta^\alpha \Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta}$ tends $\rightarrow \infty$ as $x \rightarrow 0$ for the range of values $0 < \alpha < 1$ $(e^{-0/\beta})$ factor becomes 1, and polynomial growth is unbounded.
- Suppose instead we consider the CASE $\alpha = 1$.

- Then the gamma distribution is given by the exponential distribution (which belongs to the gamma family).

- That is, $\text{gamma}(\alpha=1, \beta) = \text{Exp}(X=\beta)$

- Observe, function $\xrightarrow{\text{gamma}}$ when $\alpha=1$ achieves an absolute max* at $x=0$.

Pdf. $g(x; \lambda) = \begin{cases} \frac{1}{\lambda} e^{-x/\lambda} & \text{for } x > 0 \\ 0 & \text{elsewhere.} \end{cases}$

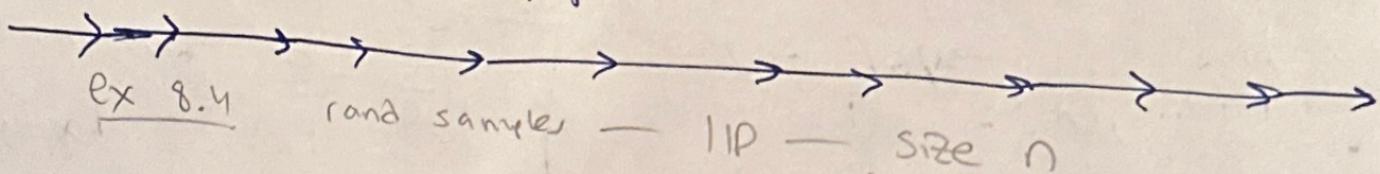


< SAMPLING DIST >

(8.45) Verify the results of EX 8.4

that is, the Sampling distributions

of Y_1, Y_n , and X shown there
for random samples from an
exp pop.



VERIFY!

- Sampling dist Y_1, Y_n are given by param θ from exp pop w/

$$\rightarrow g_1(y_1) = \begin{cases} \frac{n}{\theta} \cdot e^{-ny_1/\theta} & \text{for } y_1 > 0 \\ 0 & \text{elsewhere} \end{cases}$$

and

$$\rightarrow g_n(y_n) = \begin{cases} \frac{n}{\theta} e^{-y_n/\theta} (1 - e^{-y_n/\theta})^{n-1} & \text{for } y_n > 0 \\ 0 & \text{elsewhere} \end{cases}$$

and

- for RAND SAMPLE size $n = 2m+1$. . .
the sampling dist of the median given by,

$$\rightarrow f(\tilde{x}) = \begin{cases} \frac{(2m+1)!}{m!m!\theta} e^{-\tilde{x}(m+1)/\theta} (1 - e^{-\tilde{x}/\theta})^m & \text{for } \tilde{x} > 0 \\ 0 & \text{elsewhere} \end{cases}$$

(THM 8.16)

- For rand samples size n from infinite pop.
- PDF of r th ORDER STAT Y_r is given by:

$$g_r(y_r) = \left(\frac{n!}{(r-1)!(n-r)!} \right) \left[\int_{-\infty}^{y_r} f(x) dx \right]^{r-1} \frac{f(y_r)}{f(y_r)}$$

for $-\infty < y_r < \infty$

$$\left[\int_{y_r}^{\infty} f(x) dx \right]^{n-r}$$

* CASE 1: Y_1

POF
for EXP
exp PdF

$$f(x) = \begin{cases} \frac{1}{\theta} e^{-x/\theta} & \text{for } x > 0 \\ 0 & \text{elsewhere.} \end{cases}$$

$$g_1(y_1) = \left(\frac{n!}{\theta^n (n-1)!} \right) \cdot \left(\sum_{k=1}^{y_1} \frac{1}{\theta} e^{-x/\theta} dx \right)$$

$\text{for } 0 < y_1 < \infty$

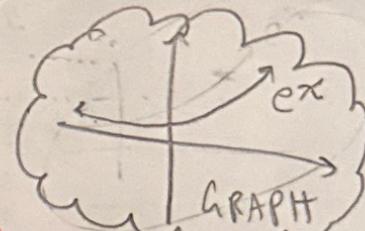
$$\Rightarrow g_1(y_1) = \frac{n}{\theta} e^{-y_1/\theta} \left(+ e^{-y_1/\theta} \right)^{n-1}$$

* $g_1(y_1) = \begin{cases} \frac{n}{\theta} e^{-ny_1/\theta} & \text{for } y_1 > 0 \\ 0 & \text{elsewhere.} \end{cases}$

$$\Rightarrow \left(\frac{1}{\theta} \cdot \frac{-\theta}{1} \right) e^{-y_1/\theta} \Big|_{x=y_1}^{\infty=0}$$

$$\Rightarrow -1 [e^{-\infty} - e^{-y_1/\theta}]$$

$$\Rightarrow +e^{-y_1/\theta}$$



* CASE 2: Y_n

$$g_n(y_n) = \left(\frac{n!}{(n-1)! \theta^n} \right) \cdot \left(\sum_{k=0}^{y_n} \frac{1}{\theta} e^{-x/\theta} dx \right)^{n-1} \cdot \left(\frac{1}{\theta} e^{-y_n/\theta} \right) \left(\sum_{x=y_n}^{\infty} f(x) dx \right)^{n-n}$$

$0 < y_n < \infty, y_n > 0 \text{ for pdf to be nonzero.}$

* $g_n(y_n) = \begin{cases} \frac{n}{\theta} e^{-y_n/\theta} (1 - e^{-y_n/\theta})^{n-1} & \text{for } y_n > 0 \\ 0 & \text{elsewhere} \end{cases}$

★ CASE 3: size ($n=2m+1$) from exp dist prop.

the sampling dist of MEDIAN:

$$\begin{aligned}
 f(\tilde{x}) &= \frac{(2m+1)!}{((m+1)!)^2 ((2m+1)-(m+1))!} \left(\frac{1}{\theta} e^{-\tilde{x}/\theta} \right)^m \frac{1}{\theta} e^{-\tilde{x}/\theta} \left(\int_{\tilde{x}}^{\infty} \frac{1}{\theta} e^{-dx/\theta} dx \right)^m \\
 &= \left(\frac{(-1(e^{-\tilde{x}/\theta}))|_{\tilde{x}}}{0} - \frac{(-1(e^{-\tilde{x}/\theta}) - e^{-\tilde{x}/\theta})}{1 - e^{-\tilde{x}/\theta}} \right) \left(\frac{(-1(e^{-\tilde{x}/\theta}))|_{\infty}}{\tilde{x}} - \frac{(-e^{-\infty} - e^{-\tilde{x}/\theta})}{0} + e^{-\tilde{x}/\theta} \right) \\
 &= \left(\frac{(2m+1)!}{m! m!} \right) \left(1 - e^{-\tilde{x}/\theta} \right)^m \frac{1}{\theta} e^{-\tilde{x}/\theta} \left(e^{-\tilde{x}/\theta} \right)^m
 \end{aligned}$$

* $\tilde{x} > 0$ for PDF to be non-zero.
* evaluate integrals.

$$\Rightarrow f(\tilde{x}) = \begin{cases} \left(\frac{(2m+1)!}{m! m! \theta} \right) (e^{-(m+1)\tilde{x}/\theta}) (1 - e^{-\tilde{x}/\theta})^m & \text{for } \tilde{x} > 0 \\ 0 & \text{elsewhere} \end{cases}$$

[8.48] find mean & variance

of the sampling distribution of \bar{Y}_1
for the random samples of size n
from

pop of exercise 8.46.

• \bar{Y}_1 - rv of interest. * $0 < y_1 < 1$

$$g_1(y_1) = \frac{(n!)}{0!(n-1)!} \left(\int_0^{y_1} 1 dx \right)^{n-1} \cdot 1 \cdot \left(\int_{y_1}^1 1 dx \right)^{n-1}$$

$$g_1(y_1) = \begin{cases} n (1-y_1)^{n-1} & \text{for } 0 < y_1 < 1 \\ 0 & \text{elsewhere.} \end{cases}$$

Sampling Dist
for continuous UNF
 $\alpha = 0$, $\beta = 1$,
pop.

REMARK:
uniform dist \equiv :

$$f(x) = \begin{cases} \frac{1}{\beta-\alpha} & \text{for } \alpha < x < \beta \\ 0 & \text{elsewhere} \end{cases}$$

when $\alpha = 0$
 $\beta = 1 \dots$

$$f(x) = \begin{cases} 1 & \text{for } 0 < x < 1 \\ 0 & \text{elsewhere} \end{cases}$$

$$E(\bar{y}_1) = n \int_0^1 y_1 (1-y_1)^{n-1} dy_1$$

$$E(x) = \int_{-\infty}^{\infty} x f(x) dx$$

$$\begin{aligned} u &= 1-y_1 \\ du &= -dy_1 \end{aligned}$$

$$= n \int_0^1 (1-u) u^{n-1} du$$

$$\begin{aligned} u &= u^n \\ du &= (n-1)u^{n-2} du \\ dv &= 1-u \\ v &= u - \frac{u^2}{2} \end{aligned}$$

$$= n \left[u^n - \frac{1}{2} u^{n+1} \Big|_{u=0}^{u=1} \right]$$

$$- (n-1) \left[u^{n-1} - \frac{u^n}{2} \Big|_0^1 \right]$$

$$+ n \left[\left(1 - \frac{1}{2} \right) - (n-1) \left[\frac{1}{n} u^n - \frac{1}{2(n+1)} u^{n+1} \Big|_0^1 \right] \right]$$

$$M = \frac{\alpha+\beta}{2} = \frac{1}{2}$$

$$\sigma^2 = \frac{1}{12} (\beta-\alpha)^2 = \frac{1}{12}$$

$$+n\left[+\frac{1}{2} + (n-1) \left(\left(\frac{1}{n} - \frac{1}{2(n+1)} \right) - (0) \right) \right]$$

$$n \left(+\frac{1}{2} + (n-1) \frac{2(n+1)-n}{2(n+1)(n)} \right)$$

$$n \left(\frac{(n+1) - (n-1)(n+2)}{2(n+1)(n)} \right)$$

$$n \left(\frac{2}{2(n+1)(n)} \right) = n \left(\frac{1}{(n+1)n} \right)$$

$$\frac{n^2 + n + n^2 + n + 2}{2n + 2 - 2}$$

$$+ 2 + n - 2$$

$$2n - 2$$

$$E(y_1) = \frac{1}{n+1} \star$$

$$E(y_1^2) = n \int_0^1 y_1^2 (1-y_1)^{n-1} dy_1 \quad | \quad u = 1-y_1$$

$$= n \int_0^1 (1-u)^2 u^{n-1} du$$

$$= n \left[-\frac{1}{3}(1-u)^3 u^{n-1} \Big|_0^1 + \frac{1}{3} \int_0^1 (1-u)^3 u^{n-1} du \right] \quad | \quad \begin{aligned} u &= (1-u)^3 & du &= (1-u)^2 du \\ du &= n-1 u^{n-2} du & v &= -\frac{1}{3}(1-u)^3 \end{aligned}$$

$$a = u^{n-1}$$

$$da = (n-1)u^{n-2} du$$

$$db = (1-u)^3 du$$

$$b = -\frac{1}{4}(1-u)^4$$

~~* Used mathematica *~~

$$= n \left[\frac{u^{n+2}}{n+2} - \frac{2u^{n+1}}{(n+1)} + \frac{u^n}{n} \Big|_0^1 \right]$$

$$\frac{1}{3} \cdot \frac{1}{2} \cdot \frac{1}{1}$$

$$\Rightarrow \frac{2n}{n^3 + 3n^2 + 2n} = \frac{2}{(n^2 + 3n + 2)} = \frac{2}{(n+2)(n+1)}$$

• Thus the second moment is,

$$\boxed{\mathbb{E}(y_1^2) = \frac{2}{(n+1)(n+2)}} \quad \star$$

• we found previously that the mean is,

$$\boxed{M = \mathbb{E}(y_1) = \frac{1}{n+1}} \quad \star$$

• We know the variance is the second moment minus the square of the first moment...

that is, $\text{Var}(y_1) = \mathbb{E}(y_1^2) - [\mathbb{E}(y_1)]^2$

$$\Rightarrow \text{Var}(y_1) = \frac{2}{(n+1)(n+2)} - \left(\frac{1}{n+1}\right)^2 = \frac{2(n+1) - (n+2)}{(n+1)^2(n+2)}$$

$$\boxed{\text{Var}(y_1) = \frac{n}{(n+1)^2(n+2)}} \quad \star$$

$$\begin{aligned} & 2n+2 - n-2 \\ & = n \end{aligned}$$