

Let x_1, x_2, \dots, x_n be n independent and identically distributed variables, each with cumulative distn function $F(x)$. If these variables are arranged in ascending order of magnitude and they written as

$x_{(1)} \leq x_{(2)} \leq \dots \leq x_{(n)}$, we call $x_{(r)}$ as the r th order statistic, $r=1, 2, \dots, n$.

The $x_{(r)}$'s because of the inequality relation among them are necessarily dependent.

Note:- If we write these ordered values as

$$y_1 \leq y_2 \leq \dots \leq y_n \text{ then}$$

$$y_1 = x_{(1)} = \min(x_1, x_2, \dots, x_n)$$

$$y_r = x_{(r)} = r^{\text{th}} \text{ smallest of } x_1, x_2, \dots, x_n.$$

$$y_n = x_{(n)} = \max(x_1, x_2, \dots, x_n)$$

Cumulative Distribution Function of a single order statistic:-

Let $F_r(x)$, $r=1, 2, \dots, n$ denote the cdf of the r th order statistic $x_{(r)}$.

The cdf of the largest-order statistic $x_{(n)}$ is given by

$$F_n(x) = P(x_{(n)} \leq x) = P(x_i \leq x; i=1, 2, \dots, n)$$

$$= P(x_1 \leq x \cap x_2 \leq x \cap \dots \cap x_n \leq x)$$

$$= P(x_1 \leq x) \cdot P(x_2 \leq x) \cdot \dots \cdot P(x_n \leq x)$$

$$= [F(x)]^n$$

$\because x_i$'s are i.i.d.

Since x_1, x_2, \dots, x_n are i.i.d.

The cdf of the smallest order statistic $x_{(1)}$ is given by. (2)

$$\begin{aligned}
 F_1(x) &= P(x_{(1)} \leq x) \\
 &= 1 - P(x_{(1)} > x) \\
 &= 1 - P(x_i > x, i=1, 2, \dots, n) \\
 &= 1 - \prod_{i=1}^n P(x_i > x) \\
 &= 1 - \prod_{i=1}^n (1 - P(x_i \leq x)) \\
 &= 1 - (1 - F(x))^n.
 \end{aligned}$$

Since x_1, x_2, \dots, x_n are i.i.d. r.v.s.

In general, the cdf of the r th order statistic is given by.

$$\begin{aligned}
 F_r(x) &= P(x_{(r)} \leq x) \\
 &= P(\text{At least } r \text{ of the } x_i\text{'s are } \leq x) \\
 &= \sum_{j=r}^n P(\text{Exactly } j \text{ of the } n \text{ } x_i\text{'s are } \leq x) \\
 F_r(x) &= \sum_{j=r}^n \binom{n}{j} [F(x)]^j [1 - F(x)]^{n-j} \rightarrow (*)
 \end{aligned}$$

by using Binomial probability model.

Note: The above expression (*) can also be written as

$$F_r(x) = I_{F(x)}(r, n-r+1)$$

$$\text{where } I_p(a, b) = \frac{1}{B(p, b)} \int_0^p t^{a-1} (1-t)^{b-1} dt$$

is the incomplete Beta function.

*) Taking $r=1$, we get the smallest-order statistic $F_1(x)$ follows.

$$F_1(x) = \sum_{j=1}^n \binom{n}{j} [F(x)]^j [1 - F(x)]^{n-j}$$

$$F_r(n) = \sum_{j=0}^n \binom{n}{j} (F(n))^j (1-F(n))^{n-j} - \binom{n}{j} (F(n))^j (1-F(n))^{n-j} \Big|_{j=0} \quad (2)$$

$$= 1 - (1-F(n))^n$$

i.e. $F_r(n) = 1 - (1-F(n))^n \Rightarrow f_r(n) = n(1-F(n))^{n-1} f(n)$.

Substitute $r=n$, in (2), we get the cdf of largest order statistic $F_n(n)$ as follows,

$$F_n(n) = \sum_{j=n}^n \binom{n}{j} (F(n))^j (1-F(n))^{n-j}$$

$$= \binom{n}{n} (F(n))^n (1-F(n))^{n-n}$$

$\therefore F_n(n) = (F(n))^n \Rightarrow f_n(n) = n(F(n))^{n-1} f(n)$.

PDF of a single order statistic:-

Let us assume that x_i 's are iid continuous r.v.s with pdf $f(x) = \frac{d}{dx} F(x)$. If $f_r(x)$ denotes the pdf of $x_{(r)}$ then

$$f_r(x) = \frac{d}{dx} (F_r(x))$$

$$= \frac{d}{dx} \left[I_{F(x)}(r, n-r+1) \right]$$

$$= \frac{d}{dx} \left[\frac{1}{B(r, n-r+1)} \int_0^{F(x)} t^{r-1} (1-t)^{n-r} dt \right] \rightarrow (1)$$

Let us write,

$$g(t) = \int t^{r-1} (1-t)^{n-r} dt$$

$$\rightarrow g'(t) = t^{r-1} (1-t)^{n-r} \rightarrow (2)$$

Consider, $\int_0^{F(x)} t^{r-1} (1-t)^{n-r} dt$

$$= g(t) \Big|_0^{F(x)}$$

$$= g(F(x)) - g(0) \rightarrow (3)$$

since $g(0)$ is a constant.

Again consider $\frac{d}{dn} \int_0^{F(n)} t^{r-1} (1-t)^{n-r} dt$

Using (3), the above expression can be rewritten as

$$\frac{d}{dn} \int_0^{F(n)} t^{r-1} (1-t)^{n-r} dt = g'(F(n))$$

$$= \frac{d}{dn} [g(F(n)) - g(0)]$$

$$= g'(F(n)) \cdot f(n) \rightarrow (4)$$

$$= (F(n))^{r-1} (1-F(n))^{n-r} f(n) \quad (\because \text{Using (3)})$$

Therefore, the pdf of the r th order statistic $f_r(n)$ can be written as

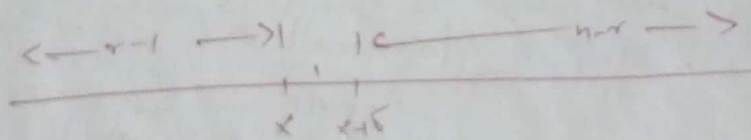
$$f_r(n) = \frac{1}{r(n-r+1)} (F(n))^{r-1} (1-F(n))^{n-r} f(n) \rightarrow (5)$$

Alternate proof:

By definition of pdf, we have

$$f_r(n) = \lim_{\delta n \rightarrow 0} \frac{P(x < x_{(r)} \leq x + \delta n)}{\delta n} \rightarrow (6)$$

The event $E: x < x_{(r)} \leq x + \delta n$ can be materialise as follows



$x_i \leq x$ for $(r-1)$ of the x_i 's.

$x < x_i \leq x + \delta n$ for one x_i .

$x_i \geq x + \delta n$ for the remaining $(n-r)$ of the x_i 's.

Hence, by the multinomial probability law, we have

$$P(x < x_{(r)} \leq x + \delta n) = \frac{n!}{(r-1)! 1! (n-r)!} p_1^{r-1} p_2^1 p_3^{n-r} \rightarrow (7)$$

where $p_1 = P(X_i \leq x) = F(x)$

$p_2 = P(x < X_i \leq x + \delta n) = F(x + \delta n) - F(x)$

$p_3 = P(X_i \geq x + \delta n) = 1 - P(X_i \leq x + \delta n) = 1 - F(x + \delta n)$

Substituting etc above in (7), we get

(5)

$$f_r(n) = \lim_{\delta n \rightarrow 0} \frac{n!}{(\sigma-1)! 1! (n-r)!} \cdot (F(n))^{\sigma-1} \cdot \left(\frac{F(n+\delta n) - F(n)}{\delta n} \right) (1-F(n+\delta n))^{n-r}$$

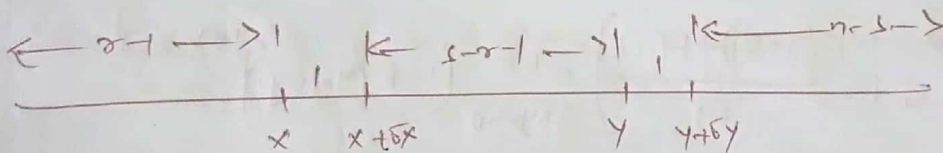
$$\therefore f_r(n) = \frac{1}{\beta(\sigma, n-r+1)} (F(n))^{\sigma-1} f(n) \cdot (1-F(n))^{n-r} \rightarrow (8)$$

Joint pdf of two order statistics:-

Let us denote the joint pdf of $X_{(r)}$ and $X_{(s)}$, where $1 \leq r \leq s \leq n$ by $f_{rs}(x, y)$. Then

$$f_{rs}(x, y) = \lim_{\delta x \rightarrow 0} \lim_{\delta y \rightarrow 0} \frac{P(x \leq X_{(r)} \leq x + \delta x \cap y \leq X_{(s)} \leq y + \delta y)}{\delta x \cdot \delta y} \rightarrow (9)$$

The event $E = x \leq X_{(r)} \leq x + \delta x \cap y \leq X_{(s)} \leq y + \delta y$ can be made clear as follows,



$x_i \leq x$ for $r-1$ of the x_i 's.

$x < x_i \leq x + \delta x$ for one x_i .

$x + \delta x < x_i \leq y$ for $(s-r-1)$ of x_i 's.

$y < x_i \leq y + \delta y$ for one x_i . and

$x_i > y + \delta y$ for $(n-s)$ of the x_i 's.

Hence, by using the multinomial probability law, we can get

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$$P(E) = P(x \leq X_{(r)} \leq x + \delta x \cap y \leq X_{(s)} \leq y + \delta y)$$

$$P(K) = \frac{n!}{(r-1)! 1! (s-r-1)! (n-s)!} \quad \begin{matrix} r-1 & s-r-1 & n-s \\ P_1 & P_2 & P_3 & P_4 & P_5 \end{matrix} \rightarrow \text{xxxx}$$

where $P_1 = P(X_i \leq n) = F(n)$

$$P_2 = P(n < X_i \leq n + \delta n) = F(n + \delta n) - F(n)$$

$$P_3 = P(n + \delta n \leq X_i \leq y) = F(y) - F(n + \delta n)$$

$$P_4 = P(y \leq X_i \leq y + \delta y) = F(y + \delta y) - F(y)$$

$$\rightarrow P_5 = P(X_i \geq y + \delta y) = 1 - P(X_i \leq y + \delta y) = 1 - F(y + \delta y)$$

Now, substituting like above in ~~xxxx~~ and ~~xxxx~~, we get =

$$f_{r,s}(n, y) = \lim_{\delta n \rightarrow 0} \lim_{\delta y \rightarrow 0} \frac{P(K)}{\delta n \cdot \delta y}$$

$$= \frac{n!}{(r-1)! (n-s)! (s-r-1)!} (F(n))^{r-1} \lim_{\delta n \rightarrow 0} \left(\frac{F(n + \delta n) - F(n)}{\delta n} \right)$$

$$\lim_{\delta y \rightarrow 0} \left(\frac{F(y + \delta y) - F(y)}{\delta y} \right) \cdot \lim_{\delta y \rightarrow 0} (1 - F(y + \delta y))^{n-s}$$

$$\lim_{\delta n \rightarrow 0} (F(y) - F(n + \delta n))^{s-r-1}$$

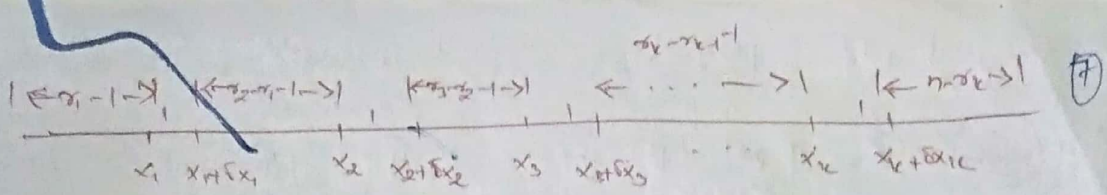
$$\therefore f_{r,s}(n, y) = \frac{n!}{(r-1)! (s-r-1)! (n-s)!} (F(n))^{r-1} f(n) (F(y) - F(n))^{s-r-1} f(y) (1 - F(y))^{n-s}$$

Joint pdf of k-order statistics:

The joint pdf of k-order statistics $X_{(r_1)}, X_{(r_2)}, \dots, X_{(r_k)}$

where $1 \leq r_1 < r_2 < \dots < r_k \leq n$ and $1 \leq k \leq n$ is $f(x_1, x_2, \dots, x_k)$

joint pdf (on using the following configuration and multinomial probability)



$$f_{x_1, x_2, \dots, x_k}(n_1, n_2, \dots, n_k) = \frac{n!}{(r_1-1)! (r_2-r_1-1)! \dots (r_k-r_{k-1}-1)! (n-r_k)!}$$

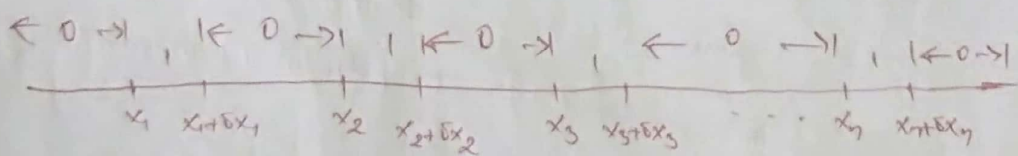
$$\begin{aligned} & (F(x_1))^{r_1-1} f(x_1) \cdot (F(x_2)-F(x_1))^{r_2-r_1-1} f(x_2) \cdot (F(x_3)-F(x_2))^{r_3-r_2-1} f(x_3) \\ & \dots \cdot (1-F(x_k))^{n-r_k} f(x_k). \end{aligned} \rightarrow \textcircled{a}$$

Joint pdf of all n-order statistics :-

In particular the joint pdf of all the n-order statistics is obtained on taking $k=n$ in \textcircled{a} . This implies that $r_i = i$, for $i = 1, 2, \dots, n$. Hence the joint pdf of $x_{(1)}, x_{(2)}, \dots, x_{(n)}$ is given by

$$f_{1, 2, \dots, n}(n_1, n_2, \dots, n_n) = n! f(x_{(1)}) f(x_{(2)}) \dots f(x_{(n)}). \rightarrow \textcircled{b}$$

We can easily obtain \textcircled{b} by using the following configuration



Dist'n of Range :-

Let w_{rs} be the pdf of the dist'n of $w_{rs} = x_{(s)} - x_{(r)}$, $s < r$.

We have the joint pdf of $x_{(r)}$ and $x_{(s)}$ as,

$$f_{rs}(u, v) = \frac{n!}{(r-1)! (s-r-1)! (n-s)!} (F(u))^{r-1} f(u) (F(v)-F(u))^{s-r-1} f(v) (1-F(v))^{n-s}$$

Transform $(x_{(r)}, x_{(s)})$ to the new variables w_{rs} & $x_{(r)}$ as

$$w_{rs} = y - u \Rightarrow v \text{ and } u = u$$

$$\Rightarrow y = u + w_{rs} \text{ and } v = u$$

$$\therefore J = \frac{\partial(x, y)}{\partial(u, w)} = \begin{vmatrix} 1 & 1 \\ 0 & 1 \end{vmatrix} = 1 \Rightarrow |J| = 1$$



The joint pdf $f_{r,s}(m, y)$ transforms to the joint pdf of x_r and $w_{r,s}$ as

$$g(m, w_{r,s}) = C_{r,s} \bar{F}(m)^{r-1} f(m) [\bar{F}(m+w_{r,s}) - \bar{F}(m)]^{s-r-1} f(m+w_{r,s}) (1 - \bar{F}(m+w_{r,s}))^{n-s}$$

where $C_{r,s} = \frac{n!}{(r-1)!(s-r-1)!(n-s)!}$

Integrating the above w.r. to m from $-\infty$ to ∞ , we get the pdf of $w_{r,s}$ as

$$g(w_{r,s}) = C_{r,s} \int_{-\infty}^{\infty} \bar{F}(m)^{r-1} f(m) [\bar{F}(m+w_{r,s}) - \bar{F}(m)]^{s-r-1} f(m+w_{r,s}) (1 - \bar{F}(m+w_{r,s}))^{n-s} dm \rightarrow (*)$$

Width of Range: $(w = x_{(r)} - x_{(1)})$

Taking $r=1$ and $s=n$ in $(*)$, we obtain the pdf of the range $w = x_{(n)} - x_{(1)}$ as

$$g(w) = n(n-1) \int_{-\infty}^{\infty} f(m) [\bar{F}(m+w) - \bar{F}(m)]^{n-2} f(m+w) dm \rightarrow \text{①}$$

The cdf of w is given by,

$$G(w) = P(W \leq w) = \int_0^w g(u) du$$

$$G(w) = \int_0^w n(n-1) \int_{-\infty}^{\infty} f(m) [\bar{F}(m+u) - \bar{F}(m)]^{n-2} f(m+u) dm du$$

$$= n \int_{-\infty}^{\infty} f(m) \int_0^w (n-1) f(m+u) [\bar{F}(m+u) - \bar{F}(m)]^{n-2} du dm$$

$$\therefore G(w) = n \int_{-\infty}^{\infty} f(m) \cdot [\bar{F}(m+w) - \bar{F}(m)]^{n-1} dm \rightarrow \text{②}$$

Let $\bar{F}(m+u) - \bar{F}(m) = v$

$\bar{F}(m+u) = v + \bar{F}(m)$

$m+u = F^{-1}(v + \bar{F}(m))$

$u = F^{-1}(v + \bar{F}(m)) - m$

$$\begin{aligned} & \frac{d}{du} [\bar{F}(m+u) - \bar{F}(m)] = -f(m+u) \\ & \frac{d}{du} [F^{-1}(v + \bar{F}(m)) - m] = \frac{1}{f(m+u)} \end{aligned}$$

$$n(n-1) \int_{-\infty}^{\infty} f(m) \int_0^w [\bar{F}(m+u) - \bar{F}(m)]^{n-2} f(m+u) du dm$$

$$= \int_{-\infty}^{\infty} f(m) \int_0^w [\bar{F}(m+u) - \bar{F}(m)]^{n-1} \frac{d}{du} [\bar{F}(m+u) - \bar{F}(m)] \cdot \frac{d}{du} [F^{-1}(v + \bar{F}(m)) - m] du dm$$

$$= \int_{-\infty}^{\infty} f(m) \int_0^w [\bar{F}(m+u) - \bar{F}(m)]^{n-1} (-1) \cdot \frac{1}{f(m+u)} du dm$$

$$= - \int_{-\infty}^{\infty} f(m) \int_0^w [\bar{F}(m+u) - \bar{F}(m)]^{n-1} du dm$$



Ex: Show that for a random sample of size 2 from $N(0, \sigma^2)$ population, $E(\bar{x}_{(1)}) = -\sigma/\sqrt{\pi}$.

Sol:

For $n=2$, the pdf $f_1(x)$ of $x_{(1)}$ is given by,

$$f_1(x) = \frac{1}{\beta(1,2)} (1-F(x)) f(x)$$

$$= 2 \cdot (1-F(x)) f(x) \quad ; \quad -\infty < x < \infty$$

where $f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-x^2/2\sigma^2}$ ($\because X \sim N(0, \sigma^2)$)

$$\therefore E(\bar{x}_{(1)}) = \int_{-\infty}^{\infty} x \cdot f_1(x) dx$$

$$= 2 \int_{-\infty}^{\infty} x (1-F(x)) f(x) dx \quad \rightarrow (1)$$

$$= 2 \left(\int_{-\infty}^0 (1-F(x)) f(x) dx + \int_0^{\infty} F(x) f(x) dx \right)$$

We have, $\log f(x) = \log\left(\frac{1}{\sigma\sqrt{2\pi}}\right) - \frac{x^2}{2\sigma^2}$

Differentiating above w.r. to x we get,

$$\frac{f'(x)}{f(x)} = -\frac{x}{\sigma^2} \Rightarrow -\sigma^2 \frac{f'(x)}{f(x)} = x f(x)$$

Integrate w.r. to x , we get,

$$-\sigma^2 \int \frac{f'(x)}{f(x)} dx = \int x f(x) dx$$

$$\therefore \int x f(x) dx = -\sigma^2 \int \frac{1}{f(x)} f'(x) dx$$

$$= -\sigma^2 f(x) \quad \rightarrow (2)$$

Integrating (1) by parts and using (2), we get-

$$E(\bar{x}_{(1)}) = 2 \left((1-F(x)) (-\sigma^2 f(x)) \Big|_{-\infty}^0 - 2 \int_{-\infty}^0 (-\sigma^2 f(x)) f'(x) dx \right)$$



Ex: Show that in odd samples of size n from $U(0,1)$ popn, the mean and variance of the distn of median are $\frac{1}{2}$ and $\frac{1}{4(n+2)}$ resp.

Sol: we have, $f(x) = 1$; $0 \leq x \leq 1$

$$F(x) = P(X \leq x) = \int_0^x f(u) du \\ = \int_0^x 1 \cdot du = x.$$

Let $n = 2m+1$ (odd), where m is a positive integer ≥ 1 .

Then median observation is $X_{(m+1)}$. Taking $r = (m+1)$ in pdf of $X_{(r)}$

$$f_r(x) = \frac{1}{\beta(r, n-r+1)} \cdot (F(x))^{r-1} (1-F(x))^{n-r} f(x).$$

The pdf of median $X_{(m+1)}$ is given by,

$$f_{m+1}(x) = \frac{1}{\beta(m+1, m+1)} \cdot x^m (1-x)^m \cdot 1.$$

$$\leftarrow E(X_{(m+1)}) = \frac{1}{\beta(m+1, m+1)} \int_0^1 x \cdot x^m (1-x)^m dx$$

$$= \frac{1}{\beta(m+1, m+1)} \int_0^1 x^{m+1} (1-x)^m dx.$$

$$= \frac{1}{\beta(m+1, m+1)} \int_0^1 x^{(m+2)-1} (1-x)^{(m+1)-1} dx$$

$$= \frac{\beta(m+2, m+1)}{\beta(m+1, m+1)} = \frac{\Gamma(m+2) \Gamma(m+1)}{\Gamma(2m+3)} \cdot \frac{\Gamma(2m+2)}{\Gamma(m+1) \Gamma(m+1)}$$

$$= \frac{(m+1) \cdot \Gamma(m+1) \cdot \Gamma(2m+2)}{(2m+2) \Gamma(2m+2) \Gamma(m+1)} = \frac{m+1}{2m+2} = \frac{1}{2}$$

$$E(X_{(m+1)}^2) = \int_0^1 x^2 f_{m+1}(x) dx = \int_0^1 x^2 x^m (1-x)^m dx = \int_0^1 x^{m+2} (1-x)^m dx \\ = \frac{\beta(m+3, m+1)}{\beta(m+1, m+1)} = \frac{m+2}{2(2m+3)}$$

$$f(x) = \frac{1}{\beta(k, \beta)} x^{k-1} (1-x)^{\beta-1} \\ \beta(k, \beta) = \frac{\Gamma(k) \Gamma(\beta)}{\Gamma(k+\beta)}$$



$$\begin{aligned} \therefore \text{Var}(X_{(n+1)}) &= E(X_{(n+1)}^2) - [E(X_{(n+1)})]^2 \\ &= \frac{n+2}{2(2n+3)} - \frac{1}{4} = \frac{1}{4(2n+3)} \\ &= \frac{1}{4(n+2)} \end{aligned}$$

eg:- Let $x_1, x_2, \text{ and } x_3$ be a random sample of size 3 from

$$f(x) = 2x; 0 < x < 1.$$

obtain the density of Y_1 , the first order statistic. Also find

$$P(Y_1 > \frac{1}{2}).$$

sol:-

$$n=3, f(x) = 2x; 0 < x < 1.$$

$$\begin{aligned} F(x) = P(X \leq x) &= \int_0^x f(u) du \\ &= \int_0^x 2u du = 2 \left(\frac{u^2}{2} \right)_0^x = x^2. \end{aligned}$$

The pdf of 1st order statistic Y_1 is,

$$\begin{aligned} f_1(y) &= n [1 - F(x)]^{n-1} f(x) \\ &= 3 (1 - x^2)^2 2x = 6x(1 - x^2)^2 \end{aligned}$$

$$G_1(y) = P(Y_1 \leq y) = 1 - P(Y_1 \geq y)$$

$$\begin{aligned} &= 1 - \int_y^1 6x(1 - x^2)^2 dx \\ &= 1 - 6y(1 - y^2)^2 \end{aligned}$$

$$\begin{aligned} 6u(1-u^2)^2 \\ 6u(1+u^4-2u^2) \\ 6(u+u^5-2u^3) \end{aligned}$$

$$P(Y_1 \leq \frac{1}{2}) = \int_0^{\frac{1}{2}} f(u) du = \int_0^{\frac{1}{2}} 6u(1-u^2)^2 du$$

$$= 6 \int_0^{\frac{1}{2}} (u+u^5-2u^3) du = 6 \left(\frac{u^2}{2} + \frac{u^6}{6} - 2 \frac{u^4}{4} \right)_0^{\frac{1}{2}}$$

$$= 6 \left(\frac{y^2}{2} + \frac{y^6}{6} - \frac{y^4}{2} \right) = 3y^2 + y^6 - 3y^4$$

$$P(Y_1 \geq \frac{1}{2}) = 1 - (3y^2 + y^6 - 3y^4) \Rightarrow P(Y_1 \geq \frac{1}{2}) = 1 - \left(3 \cdot \frac{1}{4} + \frac{1}{64} - 3 \cdot \frac{1}{16} \right) //$$

Ex. Let y_1, y_2, y_3 denote the order statistics of a random sample of size 3 from a distn having pdf.

$$f(x) = \begin{cases} 1 & ; 0 < x < 1 \\ 0 & ; \text{otherwise.} \end{cases}$$

Find the joint density of Range and Midrange.

Sol:-

$$n = 3.$$

$$f(x) = 1.$$

$$F(x) = x.$$

The joint density of range and midrange is,

$$g(x, w) = \frac{n!}{(r-1)!(s-r)!(n-s)!} [F(x)]^{r-1} f(x) [F(x+w) - F(x)]^{s-r-1} f(x+w) [1 - F(x+w)]^{n-s}$$

$$= n(n-1) f(x) \cdot \frac{(F(x+w) - F(x))^{n-2}}{F(x) - F(x)} f(x+w)$$

$$= n(n-1) \cdot 1 \cdot (x+w-x)^{n-2} f(x+w)$$

$$= 6w f(x+w) \cdot = n(n-1) (y-x)^{n-2}$$

Ex. a) Find the pdf of $x_{(r)}$ in a random sample of size n from the exponential distn

$$f(x) = \alpha e^{-\alpha x} ; \alpha > 0, x > 0.$$

b) Show that $x_{(r)}$ and $w_{rs} = x_{(s)} - x_{(r)}$, $r < s$, are independently distd.

c) What is the distn of $w_1 = x_{(n)} - x_{(1)}$?

Sol:-

$$\text{Here } F(x) = P(X \leq x) = \int_0^x \alpha \cdot e^{-\alpha u} du = 1 - e^{-\alpha x}$$

The pdf of $x_{(r)}$ is given by

$$f_r(x) = \frac{1}{\beta(r, n-r+1)} [F(x)]^{r-1} [1-F(x)]^{n-r} f(x)$$

$$= \frac{1}{\beta(r, n-r+1)} \cdot (1 - e^{-\alpha x})^{r-1} e^{-\alpha x(n-r)} \alpha \cdot e^{-\alpha x}$$



Shot on realme 2

$$f_r(x) = \frac{1}{\beta(r, \eta-r+1)} \cdot \alpha \cdot e^{-\alpha x (\eta-r+1)} \cdot (1 - e^{-\alpha x})^{\eta-r} ; x > 0. \quad (12)$$

b) The joint pdf of $X_{(r)}$ and $W_{rs} = X_{(s)} - X_{(r)}$ is given by

$$g(x, w_{rs}) = \frac{\eta!}{(r-1)! (s-r-1)! (\eta-s)!} \left[F(x) \right]^{r-1} f(x) \left[F(x+w_{rs}) \right]^{s-r-1} f(x+w_{rs}) \left[1 - F(x+w_{rs}) \right]^{\eta-s}$$

$$= \frac{\eta!}{(r-1)! (\eta-s)!} \cdot \frac{(\eta-r)!}{(s-r-1)! (\eta-s)!} \left(1 - e^{-\alpha x} \right)^{\eta-r} \alpha e^{-\alpha x}$$

$$\left[e^{-\alpha x} - e^{-\alpha(x+w_{rs})} \right]^{s-r-1} \alpha e^{-\alpha(x+w_{rs})} \left(e^{-\alpha(x+w_{rs})} \right)^{\eta-s}$$

$$= \left[\frac{1}{\beta(r, \eta-r+1)} \cdot \alpha \cdot e^{-\alpha x (s-r-1 + r + 1 + \eta-s)} \left(1 - e^{-\alpha x} \right)^{\eta-r} \right]$$

$$\left[\frac{1}{\beta(s-r, \eta-s+1)} \cdot \alpha \cdot e^{-\alpha w_{rs} (\eta-s+1)} \left(1 - e^{-\alpha w_{rs}} \right)^{\eta-s-1} \right] \rightarrow (*)$$

$\therefore X_{(r)}$ and W_{rs} are independently distributed.

c) Taking $s=r+1$ in $(*)$, the pdf of $W_1 = X_{(r+1)} - X_{(r)}$ becomes,

$$g(w_1) = \frac{1}{\beta(1, \eta-r)} \cdot \alpha e^{-\alpha(\eta-r) \cdot w_1}$$

$$= (\eta-r) \cdot \alpha \cdot e^{-\alpha(\eta-r)w_1} ; w_1 > 0.$$

which shows that W_1 has an exponential distn with parameter

$$\underline{(\eta-r) \cdot \alpha.}$$

$$E^2(X_{(r)}) = -2\sigma^2 \int_{-\infty}^{\infty} [f(x)]^2 dx = -\frac{1}{\pi} \int_{-\infty}^{\infty} e^{-x^2/\sigma^2} dx.$$

$$= -\frac{1}{\pi} \frac{\sqrt{\pi}}{(\sigma/\sigma)} = -\frac{\sigma}{\sqrt{\pi}} \quad \left(\because \int_{-\infty}^{\infty} e^{-ax^2} dx = \frac{\sqrt{\pi}}{a} \right)$$



Ex: Let x_1, x_2, \dots, x_n be a random sample of size n from a common pdf

(14)

$$f(x) = \begin{cases} 1 & ; 0 < x < 1 \\ 0 & ; \text{otherwise.} \end{cases}$$

- i) Find the pdf, mean and variance of $X_{(1)}$.
- ii) Find the pdf, mean and variance of $X_{(n)}$.
- iii) Find $\text{Corr}(X_{(1)}, X_{(n)})$.

Sol:

Given $f(x) = 1 ; 0 < x < 1$

$$F(x) = x ; x \geq 0.$$

$$f_1(x) = n(1-F(x))^{n-1} f(x)$$

$$= n(1-x)^{n-1}$$

$$E(X_{(1)}) = \int_0^1 x f_1(x) dx$$

$$= \int_0^1 n \cdot x (1-x)^{n-1} dx$$

$$= n \cdot B(2, n) = n \cdot \frac{\Gamma(2) \Gamma(n)}{\Gamma(n+2)} = \frac{n \Gamma(2)}{(n+1) \Gamma(n)} = \frac{n}{n+1}$$

$$E(X_{(1)}^2) = \int_0^1 x^2 f_1(x) dx$$

$$= \int_0^1 n \cdot x^2 (1-x)^{n-1} dx$$

$$= n B(3, n) = n \frac{\Gamma(3) \Gamma(n)}{\Gamma(n+3)} = \frac{n \cdot 2 \cdot 1!}{(n+2)(n+1) \Gamma(n)}$$

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

$$\text{Var}(X_{(1)}) = E(X_{(1)}^2) - [E(X_{(1)})]^2$$

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

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

$$\text{Var}(X_{(1)}) = \frac{n}{(n+2)(n+1)^2}$$

$(n-1) (n-2) (n-3) \dots (n-3)$

$\frac{2 \cdot 1! \cdot (n-1)!}{(n+2)}$

$(n+3-1) (n+3-2) (n+3-3) \dots (n+3-3)$
 $(n+2)(n+1) \cdot n$

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

$$ii) f_n(n) = n^{n-1} ; 0 < n < 1.$$

(15)

$$E(x_{(1)}) = \frac{\gamma}{\gamma+1}$$

$$Var(x_{(1)}) = \frac{\gamma}{(\gamma+2)(\gamma+1)^2}$$

$$iii) Corr(x_{(1)}, x_{(2)}) = \frac{Cov(x_{(1)}, x_{(2)})}{\sqrt{Var(x_{(1)}) \cdot Var(x_{(2)})}}$$

$$E(x_{(1)}, x_{(2)}) = \int_0^1 \int_0^1 ny f_{(n)}(n, y) dx dy$$

$$= \gamma(\gamma-1) \int_0^1 \int_0^1 ny(y-x)^{\gamma-2} dx dy$$

$$\because f_{(n)}(n, y) = \gamma(\gamma-1) f^{(n)}(F(y)-F(x))^{\gamma-2} f(y) ; 0 < n < 1.$$

$$\therefore E(x_{(1)}, x_{(2)}) = \gamma(\gamma-1) \int_0^1 \int_0^1 n \cdot y^{\gamma-1} \left(1 - \frac{x}{y}\right)^{\gamma-2} dx \cdot dy$$

$$= \gamma(\gamma-1) \int_0^1 \int_0^1 y^{\gamma+1} t \cdot (1-t)^{\gamma-2} dt dy \quad \left(\because \frac{x}{y} = t\right)$$

$$= \frac{1}{\gamma+2}$$

$$Cov(x_{(1)}, x_{(2)}) = \frac{1}{(\gamma+1)^2(\gamma+2)} \quad \text{and}$$

$$Corr(x_{(1)}, x_{(2)}) = \frac{1}{\gamma}$$