

$$\sum \binom{n}{r} p^r (1-p)^{n-r} = \int_0^p \frac{n!}{(i-1)!(n-i)!} t^{i-1} (1-t)^{n-i} dt$$

$0 < p < 1$

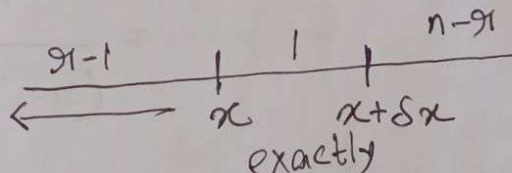
Order stat.

X_1, X_2, \dots, X_n are iid r.v.'s Y_r denote the r.v. of rank r

$$g_r(x) = \lim_{\delta x \rightarrow 0} \frac{P(x < Y_r < x + \delta x)}{\delta x}$$

Random variables of rank $\leq r-1$ takes values $\leq x$

• Random variable of rank $> r$ takes values $> x + \delta x$



Prob. that among n r.v.'s $r-1$ r.v.'s takes values $\leq x$. (event A)

$$= \binom{n}{r-1} [F(x)]^{r-1} [1-F(x)]^{n-r+1}$$

B: \exists exactly one r.v. that lies in $(x, x + \delta x]$

$$P(B) = \binom{n-r+1}{1} [F(x+\delta x) - F(x)]$$

$$P(B|A) = \frac{P(BA)}{P(A)} = \frac{\binom{n}{r-1} [F(x)]^{r-1} \binom{n-r+1}{1} [F(x+\delta x) - F(x)]}{\binom{n}{r-1} [F(x)]^{r-1} [1-F(x)]^{n-r+1}}$$

$$P(C|AB) = 1$$

exactly
 $C: n-1$ x_i 's are greater than $x + \delta x$
 $P(C) = \binom{n-1}{n-1} [1 - F(x + \delta x)]^{n-1}$

$$\begin{aligned} P(x < Y_{n-1} \leq x + \delta x) &= P(A \cap B \cap C) \\ &= P(A) P(B) P(C) \\ &= \binom{n}{n-1} \binom{n-1}{1} \binom{n-1}{n-1} \cdot \\ &\quad [F(x)]^{n-1} [F(x + \delta x) - F(x)] \\ &\quad [1 - F(x + \delta x)]^{n-1} \end{aligned}$$

$$\begin{aligned} \lim_{\delta x \rightarrow 0} \frac{P(x < Y_{n-1} \leq x + \delta x)}{\delta x} &= \frac{n!}{(n-1)! (n-1)!} \frac{[F(x)]^{n-1}}{[1 - F(x)]} f(x) \\ &= \frac{n!}{(n-1)! (n-1)!} [F(x)]^{n-1} f(x) \end{aligned}$$

density fun of $\min(X_1, X_2, \dots, X_n)$

$$g_1(x) = n [1 - F(x)]^{n-1} f(x)$$

$$\begin{aligned} G_1(x) &= \sum_{k=1}^{n-1} \binom{n}{k} [F(x)]^k [1 - F(x)]^{n-k} \\ &\quad + [F(x)]^n \end{aligned}$$

?

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

$$P\{\min(x_1, x_2, \dots, x_n) \leq y\}^c$$

$$= P\{\tau \leq y\}^c = P\{\tau > y\}$$

$$= P\{\{x_1 > y\} \cap \{x_2 > y\} \cap \dots \cap \{x_n > y\}\}$$

$$= [1 - F(y)]^n$$

$$G_1(y) = P(\tau \leq y)$$

$$= 1 - [1 - F(y)]^n$$

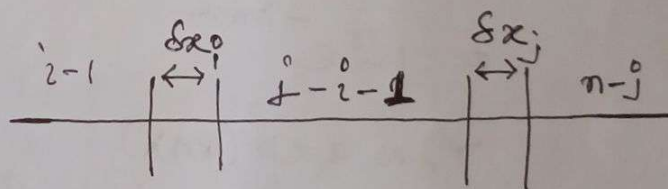
$$G_n(x) = P\{\tau_n \leq x\}$$

$$= P\{x_1 \leq x, x_2 \leq x, \dots, x_n \leq x\}$$

$$= [F(x)]^n \quad [\max(x_1, x_2, \dots, x_n) \leq x]$$

Joint density of $\tau_i, \tau_j, i < j$

$$g_{i,j}(x_i, x_j)$$



$$\frac{n!}{(i-1)! 1! (j-i-1)! 1! (n-j)!}$$

$$[F(x_i)]^{i-1} f(x_i)$$

$$[F(x_j) - F(x_i)]^{j-i-1} f(x_j)$$

$$[1 - F(x_j)]^{n-j}$$

$\mathcal{C} = \{(S_A, S_B, S_C) \mid A \subseteq [n], |A| = n-1, B \subseteq [n], B = 1, C \subseteq [n], |C| = n-n, A \cup B \cup C = [n]\}$
let S denote partition $= (S_A, S_B, S_C)$

Joint density of T_1, T_2, \dots, T_n

$$f(x_1, x_2, \dots, x_n) = n! f(x_1) f(x_2) \dots f(x_n)$$
$$-\infty < x_1 < x_2 < \dots < x_n < \infty.$$

Problem.

Ex 1: let x_1, x_2, \dots, x_n be a random ~~variable~~ sample from a population with continuous density show that $T_1 = \min(x_1, \dots, x_n)$ is exponential with parameter $n\lambda$ if & only if each x_i is exponential with parameter λ .

→

Distribution funⁿ of T_1

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

$$= 1 - (1 - (1 - e^{-\lambda x}))^n$$

$$= 1 - e^{-\lambda n x}$$

$$T_1 \sim \exp(n\lambda)$$

$$X_i \sim \exp(\lambda) \Rightarrow T_1 \sim \exp(n\lambda).$$

~~✗~~

Now, $T_1 \sim \exp(n\lambda).$

$$\Rightarrow P(T_1 \leq x) = 1 - e^{-\lambda n x}$$

$$\Rightarrow P(T_1 > x) = e^{-\lambda n x}$$

$$\Rightarrow P(\{x_1 > x\} \cap \{x_2 > x\} \cap \dots \cap \{x_n > x\})$$
$$= e^{-\lambda n x}$$

$$\Rightarrow \prod_{i=1}^n P(X_i > x) = e^{-\lambda n x}$$

$$\Rightarrow [P(X_1 > x)]^n = e^{-\lambda n x}$$

$$\Rightarrow P(X_1 > x) = e^{-\lambda x}$$

$$\Rightarrow P(X_1 < x) = 1 - e^{-\lambda x}$$

Ex 2: Suppose $X \sim \exp(1)$. Given x_1, x_2, \dots, x_n
 suppose x_1, x_2, \dots, x_n are iid and $x_i \sim \exp(1)$
 compute cdf $\gamma_n - \log n$ as $n \rightarrow \infty$. (p-708) G. Karpoori

$$\Rightarrow X_i \sim \exp(1)$$

$$\boxed{\begin{aligned} &1 - e^{-x} \\ &\lim_{n \rightarrow \infty} \left(1 + \frac{m}{n}\right)^n = e^m \end{aligned}}$$

$$G_n(x) = P(\gamma_n \leq x)$$

$$P(\gamma_n - \log n \leq y) = P(\gamma_n \leq y + \log n)$$

$$\Rightarrow P(\gamma_n \leq y + \log n)$$

$$\Rightarrow G_n(y + \log n) = \left[P(X_1 \leq y + \log n) \right]^n$$

$$= \left(1 - e^{-(y + \log n)}\right)^n = \left(1 - \frac{e^{-y}}{e^{\log n}}\right)^n$$

$$\lim_{n \rightarrow \infty} \left(1 - \frac{e^{-y}}{e^{\log n}}\right)^n = e^{-e^{-y}} = \exp(-e^{-y})$$

Q

Ex 3: Show that for a random sample of size 2 from $N(0, \sigma^2)$ population

$$E(Y_1) = -\sigma/\sqrt{\pi}$$

$$\rightarrow \text{pdf } f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{x^2}{2\sigma^2}} \quad -\infty < x < \infty$$

$$E[Y_1] = \int_{-\infty}^{\infty} x g_1(x) dx$$

$$g_1(x) = \frac{2}{1! 1!} (1-F(x))^{2-1} f(x)$$

$$= 2(1-F(x))f(x)$$

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

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

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

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

$$f'(x) = f(x) \cdot \left(-\frac{x}{\sigma^2}\right)$$

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

$$= \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{x^2}{2\sigma^2}} \cdot \left(-\frac{x}{\sigma^2}\right)$$

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

$$\therefore E[Y_1] = \int_{-\infty}^{\infty} x \cdot 2(1-F(x)) - f'(x) \frac{\sigma^2}{x} dx$$

$$\int_{-\infty}^{\infty} e^{-\frac{x^2}{2\sigma^2}} dx = \frac{\sqrt{\pi}}{\sigma} \quad \text{Ans.}$$

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

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

$$= -2 \sigma^2 \left[\int_{-\infty}^{\infty} (1-F(x)) f'(x) dx - \int_{-\infty}^{\infty} (-F'(x)) f'(x) dx \right]$$

$$= -2 \sigma^2 \left[(1-F(x)) f(x) - \int_{-\infty}^{\infty} \right]$$

$$E[Y_1] = (1-F(x)) \int_{-\infty}^{\infty} x f(x) dx$$

$$- \int_{-\infty}^{\infty} \left(\frac{d}{dx} (1-F(x)) \right) \int_{-\infty}^{\infty} x f(x) dx dx$$

$$= (1-F(x)) \int_{-\infty}^{\infty} -f'(x) \frac{\sigma^2}{x} dx - \int_{-\infty}^{\infty} \left(\frac{d}{dx} (1-F(x)) \right) \int_{-\infty}^{\infty} x \left(-f'(x) \frac{\sigma^2}{x} \right) dx dx$$

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

$$- \int_{-\infty}^{\infty} + f(x) \int_{-\infty}^{\infty} (\sigma^2 f'(x) dx) dx$$

complete it !!

B integral. (Beta)

$$B(z_1, z_2) = \int_0^1 t^{z_1-1} (1-t)^{z_2-1} dt$$

$z_1 > 0, z_2 > 0$

Beta
function

Gamma integrals:

$$\Gamma(z) = \int_0^{\infty} e^{-u} u^{z-1} du$$

$$\Gamma(z) = (z-1) \Gamma(z-1)$$

If z is a positive integer

$$\Gamma(z) = (z-1)!$$

Relation between Beta & Gamma

$$B(z_1, z_2) = \frac{\Gamma(z_1) \Gamma(z_2)}{\Gamma(z_1 + z_2)}$$

$$B(m, n) = \frac{(m-1)! (n-1)!}{(m+n-1)!}$$

$$g_{\pi}(x) = \frac{n!}{(\pi-1)! (n-\pi)!} [F(x)]^{\pi-1} [1-F(x)]^{n-\pi} f(x)$$

$$= \frac{1}{B(\pi, n-\pi+1)} [F(x)]^{\pi-1} [1-F(x)]^{n-\pi} f(x).$$

Ex 4: Show that in odd samples of size n from $U[0,1]$ population, the mean and variance of the distribution of median are $1/2$ and $\frac{1}{4(n+2)}$ respectively.

→

$$n = 2m+1$$

$(m+1)^{\text{th}}$ order statistics is the median.

$E[Y_{m+1}]$ ← to compute

$$g_{m+1}(x) = \frac{1}{B(m+1, m+1)} [F(x)]^m [1-F(x)]^m f(x)$$

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

$$E[Y_{m+1}] = \frac{1}{B(m+1, m+1)} \int_0^1 x \cdot x^m (1-x)^m dx$$

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

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

$$\begin{aligned}
&= \frac{B(m+2, m+1)}{B(m+1, m+1)} \\
&= \frac{\Gamma(m+2) \Gamma(m+1)}{\Gamma(2m+3)} \cdot \frac{\Gamma(2m+2)}{\Gamma(m+1) \Gamma(m+1)} \\
&= \frac{\Gamma(m+2) \Gamma(2m+2)}{\Gamma(2m+3) \Gamma(m+1)} = \frac{\cancel{\Gamma(m+2)} \Gamma(m+1) \Gamma(2m+2)}{\Gamma(2m+2) (2m+2) \Gamma(m+1)} \\
&= \frac{m+1}{2m+2} = \frac{1}{2}
\end{aligned}$$

$$E[Y_{m+1}^2] = \frac{1}{B(m+1, m+1)} \int_0^1 x^2 x^m (1-x)^m dx$$

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

$$= \frac{1}{B(m+1, m+1)} \int_0^1 x^{(m+3)-1} (1-x)^{(m+1)-1} dx$$

$$= \frac{B(m+3, m+1)}{B(m+1, m+1)} = \frac{\Gamma(m+3) \Gamma(m+1) \Gamma(2m+2)}{\Gamma(m+1) \Gamma(m+1) \Gamma(2m+4)}$$

$$= \frac{\Gamma(m+3) \Gamma(2m+2)}{\Gamma(m+1) \Gamma(2m+4)} = \frac{(m+2) \Gamma(m+2) \Gamma(2m+2)}{\Gamma(m+1) (2m+3) \Gamma(2m+3)}$$

$$= \frac{(m+2) (m+1) \cancel{\Gamma(m+1)} \Gamma(2m+2)}{\Gamma(m+1) (2m+3) (2m+2) \Gamma(2m+2)} = \frac{m+2}{2(2m+3)}$$

variance =

$$\begin{aligned}
 & E(Y_{m+1}^2) - [E(Y_{m+1})]^2 \\
 &= \frac{m+2}{2(2m+3)} - \left(\frac{1}{2}\right)^2 \\
 &= \frac{1}{4(n+2)}
 \end{aligned}$$

Distribution of the range

$$R = Y_{(n)} - Y_{(1)}$$

$$P(R \leq x) = P(Y_{(n)} - Y_{(1)} \leq x)$$

$$= \int \int_{x_n - x_1 \leq x} g_{1,n}(x_1, x_n) dx_1 dx_n$$

$$= \int \int_{x_n - x_1 \leq x} \frac{n!}{(n-2)! \cancel{(n-1)!} \cancel{(n-2)!}} f(x_1) f(x_n) [F(x_n) - F(x_1)]^{n-2} dx_1 dx_n$$

$$= \int_{-\infty}^{\infty} \int_{x_1}^{x_1+x} [F(x_n) - F(x_1)]^{n-2} f(x_n) dx_n f(x_1) dx_1$$

$$y = \underbrace{F(x_n) - F(x_1)}$$

$$dy = f(x_n) dx_n$$

$$\int_{x_1}^{x_1+x} [F(x_n) - F(x_1)]^{n-2} f(x_n) dx_n$$

$$= \int_0^{F(x_1+x) - F(x_1)} y^{n-2} dy = \frac{1}{n-1} y^{n-1} \Big|_0^{F(x_1+x) - F(x_1)}$$

$$= \frac{1}{n-1} [F(x_1+x) - F(x_1)]^{n-1}$$

CTSP

$$P(R \leq x)$$

$$= c \int_{-\infty}^{\infty} \frac{n!}{(n-2)!(n-1)} [F(x_1+x) - F(x_1)]^{n-1} f(x_1) dx_1$$

Joint Probability Distribution of Functions of random variable

Suppose $Y_1 = g_1(x_1, x_2)$, $Y_2 = g_2(x_1, x_2)$ where x_1, x_2 are jointly continuous.

We assume g_1, g_2 satisfies the following Equations

$y_1 = g_1(x_1, x_2)$, $y_2 = g_2(x_1, x_2)$ can be uniquely solved to give $x_1 = h_1(y_1, y_2)$, $x_2 = h_2(y_1, y_2)$

g_1, g_2 have continuous partial derivatives. $\forall x_1, x_2$

We can write

$$f_{Y_1, Y_2}(y_1, y_2) = f_{x_1, x_2}(h_1(y_1, y_2), h_2(y_1, y_2)) \times |J|^{-1}$$

$$J = \det \begin{bmatrix} \frac{\partial g_1}{\partial x_1} & \frac{\partial g_1}{\partial x_2} \\ \frac{\partial g_2}{\partial x_1} & \frac{\partial g_2}{\partial x_2} \end{bmatrix}$$

Ex 1: x_1, x_2 are two r.v's with joint pdf f_{x_1, x_2} . let $Y_1 = x_1 + x_2$, $Y_2 = x_1 - x_2$. we want to compute joint pdf of f_{Y_1, Y_2}

$$\begin{aligned} \rightarrow \quad Y_1 &= x_1 + x_2 & x_1 &= \frac{Y_1 + Y_2}{2} \\ Y_2 &= x_1 - x_2 & x_2 &= \frac{Y_1 - Y_2}{2} \end{aligned}$$

$$g_1(x_1, x_2) = x_1 + x_2$$

$$g_2(x_1, x_2) = x_1 - x_2$$

$$\begin{vmatrix} \frac{\partial \theta_1}{\partial x_1} & \frac{\partial \theta_1}{\partial x_2} \\ \frac{\partial \theta_2}{\partial x_1} & \frac{\partial \theta_2}{\partial x_2} \end{vmatrix} = \begin{vmatrix} 1 & 1 \\ +1 & -1 \end{vmatrix} = -2$$

$$|J|^{-1} = \frac{1}{2}$$

$$f_{Y_1, Y_2}(y_1, y_2)$$

$$= f_{X_1, X_2}\left(\frac{y_1 + y_2}{2}, \frac{y_1 - y_2}{2}\right) \times \frac{1}{2}$$

let x_1, x_2 are two r.v's s.t $x_1 \sim \exp(\lambda_1)$
 $x_2 \sim \exp(\lambda_2)$

$$y_1 = \lambda_1 e^{-\lambda_1 x_1}$$

$$y_2 = \lambda_2 e^{-\lambda_2 x_2}$$

$$\Rightarrow \frac{y_1}{\lambda_1} = e^{-\lambda_1 x_1} \Rightarrow -\lambda_1 x_1 = \log\left(\frac{y_1}{\lambda_1}\right)$$

$$\Rightarrow x_1 = -\frac{1}{\lambda_1} \log\left(\frac{y_1}{\lambda_1}\right)$$

$$f_{Y_1, Y_2} = \begin{cases} \frac{1}{2} \lambda_1 \lambda_2 \exp\left(-\frac{\lambda_1}{2}(y_1 + y_2)\right) \exp\left(-\frac{\lambda_2}{2}(y_1 - y_2)\right) & \begin{matrix} y_1 + y_2 \geq 0, \\ y_1 - y_2 \geq 0, \\ y_1 > |y_2| \end{matrix} \\ 0 & \text{otherwise} \end{cases}$$

Ex 2: x_1, x_2 are two r.v's with joint pdf

$$f_{X_1, X_2}(x_1, x_2) = \begin{cases} 4x_1 x_2 e^{-(x_1^2 + x_2^2)} & x_1 > 0, x_2 > 0 \\ 0 & \text{elsewhere} \end{cases}$$

We want to compute density of $Y_1 = \sqrt{x_1^2 + x_2^2}$

$$y_1 = \sqrt{x_1^2 + x_2^2}, \quad y_2 = x_1$$

$$y_1^2 = x_1^2 + x_2^2, \quad y_2^2 = x_1^2$$

$$x_2^2 = y_1^2 - y_2^2, \quad x_1^2 = y_2^2$$

we have $x_2^2 > 0 \Rightarrow y_1^2 > y_2^2$

as $x_1 > 0$, Then $y_1 > y_2 > 0$.

$$\begin{vmatrix} \frac{\partial y_1}{\partial x_1} & \frac{\partial y_1}{\partial x_2} \\ 1 & 0 \end{vmatrix} = \begin{vmatrix} \frac{x_1}{\sqrt{x_1^2 + x_2^2}} & \frac{x_2}{\sqrt{x_1^2 + x_2^2}} \\ 1 & 0 \end{vmatrix}$$

$$= \frac{-x_2}{\sqrt{x_1^2 + x_2^2}}$$

$$|J|^{-1} = \frac{\sqrt{x_1^2 + x_2^2}}{x_2}$$

$$f_{y_1, y_2} \mathbb{Q} = \begin{cases} \frac{\sqrt{x_1^2 + x_2^2}}{x_2} \cdot 4y_2 \sqrt{y_1^2 - y_2^2} e^{-\left(y_2^2 + y_1^2 - y_2^2\right)} & \text{where } y_1, y_2 > 0 \\ 0 & \text{otherwise} \end{cases}$$

where $y_1, y_2 > 0$

0, otherwise

$$= \begin{cases} \frac{\sqrt{x_1^2 + x_2^2}}{x_2} \cdot 4y_2 \sqrt{y_1^2 - y_2^2} e^{-y_1^2} & , y_1, y_2 > 0 \\ 0 & , \text{otherwise} \end{cases}$$

$$= \begin{cases} \frac{y_1}{\sqrt{y_1^2 - y_2^2}} \cdot 4y_2 \sqrt{y_1^2 - y_2^2} e^{-y_1^2} & \\ = 4y_1 y_2 e^{-y_1^2} & \end{cases}$$

$$\begin{aligned}
 f_{Y_1}(y_1) &= \int_0^{\infty} 4y_1 y_2 e^{-y_1^2} dy_2 \\
 &= \int_0^{y_1} 4y_1 y_2 e^{-y_1^2} dy_2 \\
 &= 4y_1 e^{-y_1^2} \int_0^{y_1} y_2 dy_2 = 2y_1 e^{-y_1^2} y_1^2 \\
 &= 2y_1^3 e^{-y_1^2}
 \end{aligned}$$

Ex 3: X_1, X_2 are two non-neg indep
 r.v.'s we want to compute
 density of $Y_1 = X_1 + X_2$

$$\rightarrow Y_1 = X_1 + X_2, \quad Y_2 = X_1, \quad X_1, X_2 > 0$$

$$X_2 = Y_1 - Y_2, \quad X_1 = Y_2$$

$$\begin{vmatrix} \frac{\partial y_1}{\partial x_1} & \frac{\partial y_1}{\partial x_2} \\ \frac{\partial y_2}{\partial x_1} & \frac{\partial y_2}{\partial x_2} \end{vmatrix} = \begin{vmatrix} 1 & 1 \\ 0 & 1 \end{vmatrix} = -1$$

$$|J|^{-1} = 1$$

$$\begin{aligned}
 f_{Y_1, Y_2} &= \begin{cases} f_{X_1, X_2}(y_2, y_1 - y_2) & y_1, y_2 > 0 \\ 0 & \text{otherwise} \end{cases} \\
 &= \begin{cases} f_{X_1}(y_2) \cdot f_{X_2}(y_1 - y_2) & y_1, y_2 > 0 \\ 0 & \text{otherwise} \end{cases}
 \end{aligned}$$

$$\int_0^{y_1} f_{x_1}(x_2) \cdot f_{x_2}(y_1 - y_2) dy_2.$$

$$f_{X_1, X_2}(x_1, x_2) = \begin{cases} \alpha^{-2} e^{-(x_1+x_2)/\alpha} & , x_1 > 0, x_2 > 0, \alpha > 0 \\ 0 & , \text{otherwise} . \end{cases}$$

compute pdf of $\frac{1}{2}(x_1 - x_2)$.

$$y_1 = \frac{1}{2}(x_1 - x_2) \quad , \quad y_2 = \frac{1}{2}(x_1 + x_2)$$

$$\therefore y_1 = \frac{1}{2}(x_1 - y_2)$$

$$2y_1 = x_1 - y_2 \Rightarrow x_1 = 2y_1 + y_2$$

$$x_2 = y_2.$$

$$x_2 > 0.$$

$$\Rightarrow y_2 > 0.$$

$$x_1 > 0 \Rightarrow 2y_1 + y_2 > 0$$

$$\Rightarrow y_2 > -2y_1$$

⊗ .

$$J = \begin{vmatrix} \frac{1}{2} & -\frac{1}{2} \\ 0 & 1 \end{vmatrix} = \frac{1}{2}$$

$$|J|^{-1} = 2$$

$$f_{Y_1, Y_2}(y_1, y_2) = 2 f_{X_1, X_2}(2y_1 + y_2, y_2)$$

$$= 2 \times \frac{1}{\alpha^2} e^{-\frac{2(y_1 + y_2)}{\alpha}}$$

$$y_1 > 0,$$

$$f_{Y_1}(y) = \int_0^{\infty} \frac{2}{\alpha^2} e^{-\frac{2(y_1 + y_2)}{\alpha}} dy_2$$

$$= \frac{2}{\alpha^2} \int_0^{\infty} e^{-\frac{2(y_1 + y_2)}{\alpha}} dy_2$$

$$-\infty < y_1 < \infty$$

$$-2y_1 < y_2 \text{ if } y_1 < 0$$

$$0 < y_2 < \infty \text{ if } y_1 \geq 0$$

$$= \frac{1}{\alpha} e^{-2y_1/\alpha}$$

$$y_1 < 0 \quad \int_{-2y_1}^{\infty} \frac{2}{\alpha^2} e^{-\frac{2(y_1+y_2)}{\alpha}} dy_2 = \frac{2}{\alpha^2} \int_{-2y_1}^{\infty} e^{-\frac{2(y_1+y_2)}{\alpha}} dy_2$$

$$= \frac{2}{\alpha^2} \left. \frac{e^{-\frac{2(y_1+y_2)}{\alpha}}}{-\frac{2}{\alpha}} \right|_{-2y_1}^{\infty}$$

$$= -\frac{1}{\alpha} \left. e^{-\frac{2(y_1+y_2)}{\alpha}} \right|_{-2y_1}^{\infty} = -\frac{1}{\alpha} (0 - e^{-\frac{2(y_1-2y_1)}{\alpha}}) = \frac{1}{\alpha} e^{+2y_1/\alpha} = \frac{1}{\alpha} e^{2y_1/\alpha}$$

$$\therefore f_{Y_1}(y) = \frac{1}{\alpha} e^{-\frac{2|y|}{\alpha}} \quad \text{where } -\infty < y < \infty$$

Ex 5: let X_1, X_2, \dots, X_n be iid exponentially distributed r.v's with parameter/rate λ

$$\text{let } Y_i = \sum_{j=1}^i X_j, \quad i=1, 2, \dots, n$$

a) Compute joint density Y_i 's.

b) Compute density Y_n using result of (a)

c) Compute conditional density of Y_1, Y_2, \dots, Y_{n-1} given $Y_n = t$

$$\Rightarrow X_i = \sum_{j=1}^i X_j - \sum_{j=1}^{i-1} X_j$$

$$Y_1 = X_1, \quad Y_2 = X_1 + X_2, \quad Y_3 = X_1 + X_2 + X_3, \dots$$

$$X_1 = Y_1, \quad X_2 = Y_2 - Y_1, \quad X_3 = Y_3 - Y_2, \dots$$

$$0 < y_1 < y_2 < \dots < y_n < \infty$$

$$J = \begin{vmatrix} 1 & 0 & 0 & \dots & 0 \\ 1 & 1 & 0 & \dots & 0 \\ & & \ddots & & \\ 1 & 1 & \dots & \dots & 1 \end{vmatrix} = 1.$$

$$|J|^{-1} = 1$$

$$f_{Y_1, Y_2, \dots, Y_n}(y_1, \dots, y_n)$$

$$= f_{X_1, X_2, \dots, X_n}(y_1, y_2 - y_1, y_3 - y_2, \dots, y_n - y_{n-1})$$

$$f_{X_1, X_2, \dots, X_n}(x_1, x_2, \dots, x_n) = \lambda^n e^{-\lambda \sum x_i}$$

$$= \lambda^n e^{-\lambda y_n}$$

$$(b) \quad f_{Y_2, \dots, Y_n}(y_2, \dots, y_n) = \int_0^{y_2} f_{Y_1, Y_2, \dots, Y_n}(y_1, y_2, \dots, y_n) dy_1$$

$$= \lambda^n y_2 e^{-\lambda y_n}$$

$$f_{Y_3, \dots, Y_n}(y_3, \dots, y_n) = \int_0^{y_3} f_{Y_1, Y_2, \dots, Y_n}(y_1, \dots, y_n) dy_2$$

$$= \int_0^{y_3} \lambda^n y_2 e^{-\lambda y_n} dy_2$$

$$= \lambda^n \frac{y_3^2}{2} e^{-\lambda y_n}$$

$$= \lambda^n \frac{y_3^2}{2} e^{-\lambda y_n}$$

$$f_{Y_n}(y_n) = \int_0^{y_n} \lambda^n e^{-\lambda y_n} = \lambda^n \frac{y_n^{n-1}}{(n-1)!} e^{-\lambda y_n}$$

$$f_{U|V}(u|v) = \lim_{\substack{du \rightarrow 0 \\ dv \rightarrow 0}} \frac{f_{u,v}(u,v) du dv}{f_V(v) dv} = \frac{f_{u,v}(u,v)}{f_V(v)}$$

c)

$$(Y_1, Y_2, \dots, Y_{n-1} | Y_n) = \frac{f_{Y_1, Y_2, \dots, Y_{n-1}}(y_1, y_2, \dots, y_{n-1})}{f_{Y_n}(y_n)}$$

$$= \frac{\lambda^n e^{-\lambda y_n}}{\lambda^n \frac{y_n^{n-1}}{(n-1)!} e^{-\lambda y_n}} = \frac{y_n^{n-1}}{(n-1)!} \frac{(n-1)!}{y_n^{n-1}} = \frac{(n-1)!}{t^{n-1}}$$

~~$(-1)^{n-1} y_n = t$~~

Covariance.

The Covariance b/w X and Y denoted by $\text{COV}(X, Y)$ is defined by

$$\begin{aligned}\text{COV}(X, Y) &= E([X - E(X)][Y - E(Y)]) \\ &= E[\cancel{XY} - XE(Y) - YE(X) + E(X)E(Y)]\end{aligned}$$

$$\begin{aligned}&= E(XY) - E(X)E(Y) - E(Y)E(X) + E(X)E(Y) \\ &= \cancel{E[XY]} + E(X)E(Y) \\ &= \cancel{E[XY]} + E(X)E(Y) \\ &= E[XY] - 2E(X)E(Y) + E(X)E(Y) \\ &= E[XY] - E(X)E(Y).\end{aligned}$$

If X and Y are independent

Then $E[X] \cdot E[Y] = E[XY]$

Hence $\text{COV}(X, Y) = 0$.

But converse is not True.

$$P\{X=0\} = P\{X=1\} = P\{X=-1\} = \frac{1}{3}$$

$$Y = \begin{cases} 0 & X \neq 0 \\ 1 & X = 0 \end{cases}$$

$$E[X] = 0$$

$$XY = 0$$

$$E[XY] = 0$$

$$\text{COV}(X, Y)$$

$$= 0 - 0 = 0.$$

X and Y are independent? No.

$$P\{X \in A\} P\{Y \in B\} = P\{X \in A, Y \in B\}.$$

$$A = \{0\}, B = \{0\}$$

$$P\{X \in A, Y \in B\} = 0.$$

$$P\{X \in A\} = \frac{1}{3}, P\{Y \in B\} = \frac{2}{3}$$

$$P\{X \in A\} P\{Y \in B\} \neq P\{X \in A, Y \in B\}$$

\therefore Not independent.

P1. $\text{Cov}(X, Y) = \text{Cov}(Y, X)$

P2 $\text{Cov}(X, X) = \text{Var}(X)$

P3 $\text{Cov}(aX, Y) = a \text{Cov}(X, Y)$

P4 $\text{Cov}\left(\sum_{i=1}^n X_i, \sum_{j=1}^m Y_j\right) = \sum_{i=1}^n \sum_{j=1}^m \text{Cov}(X_i, Y_j)$

Proof:

P4 : $\text{Cov}\left(\sum_{i=1}^n X_i, \sum_{j=1}^m Y_j\right)$

$= E\left[\left(\sum_{i=1}^n X_i\right) \cdot \left(\sum_{j=1}^m Y_j\right)\right]$

$= E\left[\left(\sum_{i=1}^n X_i - E\left(\sum_{i=1}^n X_i\right)\right) \left(\sum_{j=1}^m Y_j - E\left(\sum_{j=1}^m Y_j\right)\right)\right]$

$= E\left[\left(\sum_{i=1}^n X_i - \sum_{i=1}^n E(X_i)\right) \left(\sum_{j=1}^m Y_j - \sum_{j=1}^m E(Y_j)\right)\right]$

$= E\left[\left(\sum_{i=1}^n (X_i - E(X_i))\right) \left(\sum_{j=1}^m (Y_j - E(Y_j))\right)\right]$

$= E\left(\sum_{i=1}^n \sum_{j=1}^m (X_i - E(X_i)) (Y_j - E(Y_j))\right)$

$= \sum_{i=1}^n \sum_{j=1}^m \text{Cov}(X_i, Y_j)$

P5. $\text{Var}\left(\sum X_i\right) = \sum \text{Var}(X_i) + 2 \sum_{i < j} \text{Cov}(X_i, X_j)$

If X_i and X_j are independent then

$\text{Var}\left(\sum X_i\right) = \sum \text{Var}(X_i)$

Proof:

$$\text{var}(\sum x_i) = \text{cov}\left(\sum_{i=1}^n x_i, \sum_{j=1}^n x_j\right) \text{ [by P2]}$$

$$= \sum_{i=1}^n \sum_{j=1}^n \text{cov}(x_i, x_j) \text{ [by P4]}$$

$$= \sum_{i=1}^n \text{var}(x_i) + \sum_{i \neq j} \text{cov}(x_i, x_j) \text{ [by P2]}$$

$$= \sum_{i=1}^n \text{var}(x_i) + 2 \sum_{i < j} \text{cov}(x_i, x_j) \text{ [By P1]}$$

Variance of Binomial Distribution.

$$Y = \sum x_i$$

$$Y \sim \text{Bin}(n, p), \quad x_i \sim \text{Bern}(p)$$

x_i 's are independent.

$$\text{var}(Y)$$

$$= \text{var}\left(\sum x_i\right)$$

$$= \sum_{i=1}^n \text{var}(x_i) = \sum_{i=1}^n p(1-p)$$

$$= np(1-p)$$

Correlation b/w two r.v's X & Y

denoted by $\rho(X, Y)$ is defined as long as $\text{var}(X) \text{var}(Y)$ is positive.

$$\text{var}(X) \cdot \text{var}(Y) \neq 0.$$

$$\rho(x, y) = \frac{\text{Cov}(x, y)}{\sqrt{\text{Var}(x) \text{Var}(y)}}$$

Proof: $-1 \leq \rho(x, y) \leq 1$

$$\text{Var}\left(\frac{x}{\sigma_x} + \frac{y}{\sigma_y}\right) \geq 0. \text{ where } \sigma_x^2 = \text{Var}(x)$$

$$\sigma_y^2 = \text{Var}(y)$$

$$\Rightarrow \frac{1}{\sigma_x^2} \text{Var}(x) + \frac{1}{\sigma_y^2} \text{Var}(y) + 2 \frac{\text{Cov}(x, y)}{\sigma_x \sigma_y} \geq 0$$

$$\Rightarrow \frac{1}{\sigma_x^2} \text{Var}(x) + \frac{1}{\sigma_y^2} \text{Var}(y) + 2 \rho(x, y) \geq 0$$

$$\Rightarrow \frac{1}{\sigma_x^2} \text{Var}(x) + \frac{1}{\sigma_y^2} \text{Var}(y) + 2 \rho(x, y) \geq 0$$

$$\Rightarrow \rho(x, y) \geq -1 \quad \text{--- (i)}$$

Now,

$$\Rightarrow \text{Var}\left(\frac{x}{\sigma_x} - \frac{y}{\sigma_y}\right) \geq 0$$

$$\Rightarrow \frac{1}{\sigma_x^2} \text{Var}(x) + \frac{1}{\sigma_y^2} \text{Var}(y) - 2 \frac{\text{Cov}(x, y)}{\sigma_x \sigma_y} \geq 0$$

$$\Rightarrow 2 \frac{\text{Cov}(x, y)}{\sigma_x \sigma_y} \leq 2$$

$$\Rightarrow \rho(x, y) \leq 1 \quad \text{--- (ii)}$$

From (i) & (ii)

$$-1 \leq \rho(x, y) \leq 1 \quad (\text{Proved}).$$

Ex 1
let X_1, X_2, \dots, X_n be iid r.v s.t.
 $E[X_i] = \mu$ and $\text{Var}(X_i) = \sigma^2$

let $\bar{X} = \frac{\sum_{i=1}^n X_i}{n}$ denote the sample mean.

The random variable

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

is called

sample variance.

Compute a) $\text{Var}(\bar{X})$. (b) $E[S^2]$

$$\begin{aligned} \rightarrow \text{a) } \text{Var}(\bar{X}) &= \text{Var}\left(\frac{\sum_{i=1}^n X_i}{n}\right) = \frac{1}{n^2} \left(\text{Var} \sum_{i=1}^n X_i \right) \\ &= \frac{\sum \text{Var}(X_i)}{n^2} = \frac{n\sigma^2}{n^2} = \frac{\sigma^2}{n}. \end{aligned}$$

$$\begin{aligned} \text{b) } (n-1)S^2 &= \sum (X_i - \bar{X})^2 \\ &= \sum (X_i - \mu + \mu - \bar{X})^2 \end{aligned}$$