

Range of U & V : $\Rightarrow X_1 = \frac{U+V}{2}$ & $X_2 = \frac{U-V}{2}$.

$$U = X_1 + X_2, \quad V = X_1 - X_2, \quad \begin{aligned} X_1 &\geq 0 \\ X_2 &\geq 0 \end{aligned}$$

Unconditionally, $U \geq 0$ & $-\infty < V < \infty$.

Conditional Range:

$$0 < X_1 < \infty$$

$$\Leftrightarrow 0 < \frac{U+V}{2} < \infty$$

$$\Leftrightarrow -V < U < \infty / -U < V < \infty$$

Also, $0 < X_2 < \infty$

$$\Rightarrow 0 < \frac{U-V}{2} < \infty \Leftrightarrow V < U < \infty / -\infty < V < U$$

$$\textcircled{1} \& \textcircled{2} \Rightarrow \max(V, -V) < U < \infty \text{ --- } \textcircled{3}$$

$$\textcircled{3} \Rightarrow \text{if } -\infty < V < 0 \Rightarrow -V < U < \infty$$

$$\& \text{if } 0 < V < \infty \Rightarrow V < U < \infty$$

Hence, the joint density of U & V is

$$f_{U,V}(u,v) = \frac{1}{2} e^{-|u|} \text{ if } \begin{cases} -\infty < v < 0 & \& -v < u < \infty \\ 0 < v < \infty & \& v < u < \infty \end{cases}$$

Let f_V be the p.d.f. of V .

Then $f_V(v) = \frac{1}{2} \int_{-v}^{\infty} e^{-u} du$ if $-\infty < v < 0$

$$= \frac{1}{2} e^{-v} \text{ when } -\infty < v < 0 \quad \text{--- (4)}$$

And $f_V(v) = \frac{1}{2} \int_v^{\infty} e^{-u} du$ if $0 < v < \infty$

$$= \frac{1}{2} e^{-v} \text{ when } -\infty < v < 0 \quad \text{--- (5)}$$

Combining (4) & (5), we can write

$$f_V(v) = \frac{1}{2} e^{-|v|}, \quad v \in \mathbb{R}.$$

Remark !:- i) If $U = \{u_1, \dots, u_n\}$ are r.n. from std. exp.

$\& D = \{v_1, \dots, v_n\}$ will be the std. exp

(moreover, they are indep.)

$\Rightarrow \{u_1 - v_1, u_2 - v_2, \dots, u_n - v_n\}$ will be the r.n. from std. Laplace distⁿ.

ii) Note that $f(x) = \frac{1}{2} e^{-|x|}$ is ~~not~~ NOT diff. at $x=0$. Based on earlier result, we can avoid this issue very often.

Example:- If X_1, \dots, X_n are i.i.d. $N(0, 1)$, then

$\chi^2 = \sum_{i=1}^n X_i^2 \sim \chi_n^2$ [Chi-square distⁿ with n degrees of freedom]

Q:- What is the p.d.f. of χ^2 ??

Sol :-

$$x_i \sim N(0, 1) \quad \forall i = 1, \dots, n.$$

Consider the transformation :- (Multivariate extension of polar transformation)

$$x_1 = \sqrt{Y} \cos \theta_1$$

$$x_2 = \sqrt{Y} \sin \theta_1 \cos \theta_2$$

.

$$x_{n-1} = \sqrt{Y} \sin \theta_1 \dots \sin \theta_{n-2} \cos \theta_{n-1}$$

$$x_n = \sqrt{Y} \sin \theta_1 \dots \sin \theta_{n-2} \sin \theta_{n-1}$$

Transformation is $(x_1, \dots, x_n) \rightarrow (Y, \theta_1, \theta_2, \dots, \theta_{n-1})$.

Note that $x_1^2 + \dots + x_n^2 = \sum_{i=1}^n x_i^2 = Y$.

$$f_{x_1, \dots, x_n}(x_1, \dots, x_n) = C \times e^{-\sum_{i=1}^n x_i^2}$$

Hence, using Jacobian method, $f_{Y, \theta_1, \dots, \theta_{n-1}}(Y, \theta_1, \dots, \theta_{n-1}) = C \times e^{-\sum_{i=1}^n Y} |\mathcal{J}|$.

It is a known fact that

$$|J| = y^{\gamma_2 - 1} K(\theta), \text{ where } \theta = (\theta_1, \dots, \theta_{n-1})$$

\downarrow some f_i^n of θ .

Hence, the joint density of $y, \theta_1, \dots, \theta_{n-1}$ is

$$f_{Y, \theta_1, \dots, \theta_{n-1}}(y, \theta_1, \dots, \theta_{n-1}) = c \times e^{-\frac{1}{2}y} \times y^{\gamma_2 - 1} K(\theta).$$

Let f_Y be the b.d.f. of Y .

\downarrow It is clear that $y, (\theta_1, \dots, \theta_{n-1})$ are indep

$$\begin{aligned} \text{Then } f_Y(y) &= \iiint_{\theta_1, \dots, \theta_{n-1}} c \cdot e^{-\frac{1}{2}y} y^{\gamma_2 - 1} K(\theta) d\theta \\ &= c \cdot e^{-\frac{1}{2}y} y^{\gamma_2 - 1}, \quad y \geq 0. \end{aligned}$$

This is the b.d.f. of $Y = \sum_{i=1}^n x_i^2 \sim \chi_n^2$.

Remark :-

If $x_1, \dots, x_n \sim N(\mu, \sigma^2)$,

then $\sum_{i=1}^n \left(\frac{x_i - \mu}{\sigma} \right)^2 \sim \chi_n^2$. (directly follows from the result $\frac{x_i - \mu}{\sigma} \sim N(0, 1)$)

Approach 3:-

$$\underline{x} = (x_1, \dots, x_n)$$

Q1 Intervetel to know the distⁿ of $U = U(x_1, \dots, x_n)$.

Procedure :- i) Devve the MGF of U .

ii) Check that $M_U(t)$ is coinciding with the MGF of any other distⁿ or not.
(Random Variable)

Example:-

Suppose $x_1, \dots, x_n \sim \text{Pois}(\lambda_i)$.

Want to know the distⁿ of $\sum_{i=1}^n x_i$.

Let

$$\gamma = \sum_{i=1}^n x_i$$

$$\begin{aligned} MGF \text{ of } \gamma &\leftarrow M_\gamma(t) \\ &= E[e^{t\gamma}] = E\left[e^{t \sum_{i=1}^n x_i}\right] = \prod_{i=1}^n M_{x_i}(t) \\ &= \prod_{i=1}^n \left\{ e^{\lambda_i(e^t - 1)} \right\} \\ &= e^{\sum_{i=1}^n \lambda_i (e^t - 1)}. \end{aligned}$$

Since
 x_i 's are
indep.

\hookrightarrow MGF of Poisson $(\sum_{i=1}^n \lambda_i)$.

Hence, $\gamma \sim \text{Poisson}(\sum_{i=1}^n \lambda_i)$.

Example:-

$$X_i \sim N(\mu_i, \sigma_i^2), \quad i = 1, \dots, n.$$

X_i 's are indep.

Want to know the distⁿ of $\gamma = a + \sum_{i=1}^n k_i X_i$.

$$M_\gamma(t) = E[e^{t\gamma}] = E\left[e^{t\left(\sum_{i=1}^n k_i X_i + a\right)}\right]$$

$$= e^{at} E\left[e^{t\sum_{i=1}^n k_i X_i}\right]$$

[Now, $e^{t\sum_{i=1}^n k_i X_i} = \prod_{i=1}^n e^{t k_i X_i} = \prod_{i=1}^n e^{t l_i X_i}$, where $l_i = t k_i$.]

$$= e^{at} E\left[e^{t\sum_{i=1}^n k_i X_i}\right]$$

$$= e^{at} \prod_{i=1}^n E\left[e^{t l_i X_i}\right]$$

because X_i 's are indep.

$$= e^{at} \prod_{i=1}^n \left(e^{t \mu_i l_i + \frac{1}{2} l_i^2 \sigma_i^2}\right)$$

(Using the MGF of $N(\mu, \sigma^2)$: $M_X(t) = e^{\mu t + \frac{1}{2} t^2 \sigma^2}$)

$$= e^{at} \times \left[e^{\sum_{i=1}^n t \mu_i l_i + \frac{1}{2} \sum_{i=1}^n l_i^2 \sigma_i^2}\right]$$

Put $U_i = K_i \sigma_i t_i$, we will have

$$M_Y(t) = e^{t(a + \sum_{i=1}^n K_i U_i) + \frac{1}{2} t^2 \sum_{i=1}^n K_i \sigma_i^2}.$$

↙
This is the MGF of

$$\mathcal{N}\left(a + \sum_{i=1}^n K_i U_i, \sum_{i=1}^n K_i^2 \sigma_i^2\right).$$