

$$\leq P\left(\frac{Z_n}{2n-1} \geq \frac{1}{2}\right).$$

$$\leq P\left(\left|\frac{Z_n}{2n-1} - p\right| \geq \frac{1}{2} - p\right)$$

Chebyshev.

$$\leq \frac{1}{\left(\frac{1}{2} - p\right)^2} \text{Var} \left(\frac{Z_n}{2n-1}\right).$$

$$= \frac{1}{\left(\frac{1}{2} - p\right)^2} \cdot \frac{p(1-p)}{(2n-1)} \rightarrow 0 \text{ as } n \rightarrow \infty.$$

Example:- Suppose that  $X$  follows Double Exponential distribution that is, its density is.

$$f(x) = \frac{1}{2} e^{-|x|}, x \in \mathbb{R}.$$

Calculate the CHF of  $X$ .

$$\begin{aligned} & \int_{-\infty}^{\infty} \cos tx \cdot \frac{1}{2} \cdot e^{-|x|} dx \\ &= \int_0^{\infty} \cos tx e^{-x} dx. \end{aligned}$$

$$\int_{-\infty}^{\infty} e^{itx} f(x) dx.$$

$$= \frac{1}{2} \left[ \int_{-\infty}^0 e^{(it+1)x} dx + \int_0^{\infty} e^{(it-1)x} dx \right]$$

$$= \frac{1}{2} \left( \frac{1}{1+it} + \frac{1}{1-it} \right).$$

$$= \frac{1}{1+t^2}.$$

## Inversion Theorem:-

Suppose that the CDF  $\phi$  of  $X$  is integrable on  $\mathbb{R}$ , that is,

$$\int_{-\infty}^{\infty} |\phi(t)| dt < \infty$$

Then, for  $x \in \mathbb{R}$ ,

$$f(x) = \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{-itx} \phi(t) dt \quad (\text{is density of } X)$$

Proof: Since, the last part of above result, all

$$\int_{-\infty}^{\infty} |\phi(t)| dt < \infty \text{ helps in finding out}$$

it holds that for every  $x$ , the integral diff.

$$\int_{-\infty}^{\infty} e^{-itx} \phi(t) dt \text{ exists.}$$

If  $a < b$  are such that  $P(X \in [a, b]) = 0$ , then uniqueness theorem tells us that

$$P(a \leq X \leq b) = \frac{1}{2\pi} \lim_{T \rightarrow \infty} \int_{-T}^T \frac{e^{-ita} - e^{-itb}}{it} \phi(t) dt$$

$$\left| \int_{-\infty}^{\infty} \frac{e^{-ita} - e^{-itb}}{it} \phi(t) dt \right| \leq (b-a) \int_{-\infty}^{\infty} |\phi(t)| dt < \infty.$$

Hence,

$$P(a \leq X \leq b) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \frac{e^{-ita} - e^{-itb}}{it} \phi(t) dt.$$

$$= \frac{1}{2\pi} \int_{-\infty}^{\infty} \int_a^b e^{-itx} dx \phi(t) dt.$$

$$= \frac{1}{2\pi} \int_{-\infty}^{\infty} \int_a^b e^{-itx} \phi(t) dx dt.$$

$$\begin{aligned}
 (\text{Fubini}) &= \frac{1}{2\pi} \cdot \int_a^b \int_{-\infty}^{\infty} e^{-itx} \phi(t) dt dx \\
 &= \int_a^b \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{-itx} \phi(t) dt dx \\
 &= \int_a^b f(x) dx.
 \end{aligned}$$

The above holds for  $a, b$  s.t.  $P(X \in \{a, b\}) = 0$ .

In order to complete the proof, it suffices to show that  $X$  is continuous, fix  $x \in \mathbb{R}$ .

$\exists a_n, b_n$  such that  $a_n \uparrow x$ ,  $b_n \downarrow x$  and

$$P(X \in \{a_n, b_n, a_{n+1}, b_{n+1}, \dots\}) = 0.$$

$$P(X=x) \leq P(a_n \leq X \leq b_n) = \int_{a_n}^{b_n} f(t) dt.$$

Letting  $n \rightarrow \infty$ , we get

$$P(X=x) = 0.$$

Example:- Suppose  $X \sim \text{Double exp.}$

$$\int_{-\infty}^{\infty} e^{itx} \frac{1}{2} e^{-|x|} dx = \frac{1}{1+t^2}, \quad t \in \mathbb{R}.$$

Since  $\int_{-\infty}^{\infty} \frac{dt}{1+t^2} < \infty$ , inversion thm applies

this gives us

$$f(x) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \frac{e^{-itx}}{1+t^2} dt \quad \text{is density of } X.$$

Note:- If a R.V. has two continuous densities, then they are identical.

$$g(x) = 2f(-x) = E[e^{ixZ}] \text{ where } Z \sim \text{Cauchy}.$$

Hence  $f$  is continuous & density of  $X$ .

$$\text{Thus, } f(x) = \frac{1}{2} e^{-|x|}, x \in \mathbb{R}.$$

$$\text{i.e. } \int_{-\infty}^{\infty} \frac{e^{-itx}}{\pi(1+t^2)} dt = e^{-|x|}, x \in \mathbb{R}.$$

Replacing  $(-x)$  by  $y$  we get,

$$E[e^{iyZ}] = e^{-|y|}, y \in \mathbb{R}.$$

$Z \sim \text{Cauchy}$ .

Suppose,  $Z_1$  &  $Z_2$  are i.i.d. from Cauchy.

$$\text{Define } Y = \frac{Z_1+Z_2}{2}.$$

$$E(e^{iyZ}) = E(e^{iyZ_1}) \cdot E(e^{iyZ_2}).$$

$$\phi_Y(t) = E(e^{itY}) = E\left[e^{\frac{1}{2}(e^{itZ_1} + e^{itZ_2})}\right] \\ = e^{\frac{1}{2}} E[e^{itZ_1}] E[e^{itZ_2}]$$

$$= e^{\frac{1}{2}} e^{-|t|} e^{-|t|} = e^{-|t|}.$$

$$= e^{-|t|}.$$

Invoking uniqueness theorem  $\frac{Z_1+Z_2}{2}$  also follows Cauchy.

Theorem:

If  $X$  &  $Y$  are such that

$$E[e^{tX}] = E[e^{tY}] < \infty \text{ for } |t| < \varepsilon.$$

for some  $\varepsilon > 0$ , then  $X \stackrel{d}{=} Y$ .

Pf:- Let,  $\phi_X$  &  $\phi_Y$  denote the respective CHF of  $X$  &  $Y$ . In view of the uniqueness theorem it suffices to show that

$$\phi_X(t) = \phi_Y(t) \text{ for every } t \in \mathbb{R}.$$

the hypothesis imply that all the moments of  $X$  &  $Y$  exists and are finite and match.

Further, Since  $E[e^{\pm \varepsilon X}] < \infty$ , we get,

$$\phi_X(t) = \sum_{n=0}^{\infty} \frac{(it)^n}{n!} E(X^n), \quad |t| \leq \varepsilon,$$

and likewise for  $Y$ .

$$\text{Hence, } \phi_X(t) = \phi_Y(t), \quad |t| \leq \varepsilon.$$

Our next claim is that for any  $t_0 \in \mathbb{R}$  and  $t \in \mathbb{R}$  such that  $|t-t_0| \leq \varepsilon$ , it holds that,

$$\phi_X(t) = \sum_{n=0}^{\infty} \frac{(t-t_0)^n}{n!} \phi_X^{(n)}(t_0), \quad (*)$$

and likewise for  $Y$ .

The RHTS of  $(*)$

$$\text{for } n \geq 0, \quad \phi^{(n)}(t_0) = E[(ix)^n e^{it_0 X}].$$

Define for  $n \geq 0$ ,

$$Z_n = \sum_{k=0}^n \frac{(t-t_0)^k}{k!} (ix)^k e^{it_0 x}.$$

as  $n \rightarrow \infty$ ;  $Z_n \rightarrow e^{itx}$  a.s.

$$|Z_n| \leq \sum_{k=0}^n \frac{|t-t_0|^k}{k!} |x|^k \leq e^{|(t-t_0)x|} \leq e^{\epsilon|x|}.$$

Since,  $E(e^{\epsilon|x|}) < \infty$ , DCT implies that

$$\begin{aligned} E[e^{itx}] &= \lim_{n \rightarrow \infty} E(Z_n) \\ &= \lim_{n \rightarrow \infty} \sum_{k=0}^n \frac{(t-t_0)^k}{k!} E[(ix)^k e^{it_0 x}] \\ &= \sum_{k=0}^{\infty} \frac{(t-t_0)^k}{k!} E[(ix)^k e^{it_0 x}]. \end{aligned}$$

Since,  $\phi_X$  and  $\phi_Y$  match in  $[-\epsilon, \epsilon]$ , it follows that

$$\phi_X^{(n)}(\epsilon) = \phi_Y^{(n)}(\epsilon), n \geq 1.$$

Applying (\*) with  $t_0 = \epsilon$ , we get that,

$$\phi_X(t) = \phi_Y(t) \quad \forall t \in [\epsilon, 2\epsilon].$$

Proceeding inductively, it can be shown that

$$\phi_X(t) = \phi_Y(t) \quad \forall t \geq 0.$$

similar argument works for  $t < 0$  and hence,  $\phi_X(t) = \phi_Y(t)$   $\square$

Example:-

Suppose that  $X$  has density

$$f(x) = \frac{1}{2^{3/2} \sqrt{\pi} |x|} \exp\left(-\frac{1}{2} (\ln|x|)^2\right) I(x \neq 0), x \in \mathbb{R}.$$

to show  $f(x) =$

$\rightarrow$

$$g(x) = \begin{cases} (1 + \sin(2\pi \ln x))f(x), & x > 0, \\ f(x), & x \leq 0. \end{cases}$$

Fix  $n \geq 0$ ,

$$\int_0^\infty x^n \sin(2\pi \ln x) f(x) dx = \int_0^\infty x^n \sin(2\pi y) f(e^y) e^{-\frac{1}{2}(2\pi y)^2} dy.$$

$$= c \int_{-\infty}^\infty e^{n(y+n)} e^{-(y+n)^2/2} \sin(2\pi(n+y)) dy.$$

$$dy = \frac{dx}{x}.$$

$$= c \int_{-\infty}^\infty e^{n(n+y)} e^{-(y+n)^2/2} \sin(2\pi(n+y)) dy.$$

$$= c \int_{-\infty}^\infty e^{(n-y)(n+\frac{y^2}{2})} e^{(y+n)(n-\frac{y^2}{2})} \sin(2\pi(n+y)) dy.$$

$$= c \int_{-\infty}^\infty e^{\frac{n^2-y^2}{2}} \sin(2\pi y) dy.$$

$$= c \cdot e^{\frac{n^2}{2}} \int_{-\infty}^\infty e^{-\frac{y^2}{2}} \sin(2\pi y) dy = 0. [\because \text{odd function}]$$

$$\text{i.e. } \int_{-\infty}^{\infty} g(x^n)g(x)dx = \int_{-\infty}^{\infty} x^n f(x)dx, n \geq 0.$$

for  $n=0$ , the above implies  $g$  is a density. If  $Y$  is a random variable with density  $g$  then all moments of  $X$  &  $Y$  are finite and match, even though their distribution are not same.

## Conditional Distribution & Expectation

Definition:- Suppose that  $f$  is the joint density of  $(X, Y)$  and

$$f_X(x) = \int_{-\infty}^{\infty} f(x,y)dy, x \in \mathbb{R}.$$

is the marginal density of  $X$ : The conditional density of  $Y$  given  $X=x$ , for any  $x$  such that  $f_X(x) > 0$ , is defined by,

$$f_{Y|X}(y) = \frac{f(x,y)}{f_X(x)}, y \in \mathbb{R}.$$

In this chapter unless mentioned otherwise,  $X$  and  $Y$  are R.V.s. with joint density  $f$  &  $f_X = \int_{-\infty}^{\infty} f(x,y)dy, x \in \mathbb{R}$ .

Thm:- If  $E|Y| < \infty$  then for almost all  $x$  such that  $f_X(x) > 0$ , it holds that

$$\int_{-\infty}^{\infty} |y| f_{Y|X}(y) dy < \infty.$$

Pf: Define  $g: \mathbb{R} \rightarrow \mathbb{R}$  by

$$g(x) = \begin{cases} \int_{-\infty}^{\infty} |y| f_p(y) dy, & \text{if } f_x(x) > 0, \\ 0, & \text{otherwise.} \end{cases}$$

and  $h: \mathbb{R}^2 \rightarrow \mathbb{R}$  by

$$h(x,y) = \begin{cases} f_{|x|}(y), & \text{if } f_x(x) > 0, \\ 0, & \text{otherwise.} \end{cases}$$

$$E(|Y|) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} |y| f(x,y) dx dy.$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} |y| h(x,y) f_x(x) dx dy.$$

$$= \int_{-\infty}^{\infty} f_x(x) \int_{-\infty}^{\infty} |y| h(x,y) dy dx.$$

$$= \int_{-\infty}^{\infty} f_x(x) g(x) dx.$$

This completes the proof of part I.  $\square$

Since, the above integral is finite, it follows that  $\{x \in \mathbb{R} : f_x(x) g(x) = \infty\}$  is a set of measure zero.

$$\begin{aligned} & \left\{ x \in \mathbb{R} : f_X(x) > 0 \text{ and } g(x) = \infty \right\} \\ & \subseteq \left\{ x \in \mathbb{R} : f_X(x)g(x) = \infty \right\} \end{aligned}$$

Definition:- Suppose that  $E(Y|X=x) < \infty$ .  
 The conditional expectation of  $Y$  given  $X=x$ , for any  $x$  s.t.  $f_X(x) > 0$  is defined by

$$E(Y|X=x) = \int_{-\infty}^{\infty} y f_{Y|X}(y) dy := g(x).$$

The following NOTATION is commonly used:  
 $E(Y|X) = g(X)$ .

Example:-

Suppose that  $(X, Y)$  follows  $\sim \text{BVN}$  with  $E(X) = E(Y) = 0$ ,  $\text{Var}(X) = \text{Var}(Y) = 1$  and correlation  $\text{corr}(X, Y) = \rho \in (-1, 1)$ .

Recall that; the joint density of  $(X, Y)$  is.

$$f(x, y) = \frac{1}{2\pi\sqrt{1-\rho^2}} \exp\left(-\frac{1}{2(1-\rho^2)}(x^2 - 2\rho xy + y^2)\right), x, y \in \mathbb{R}.$$

and the marginal density of  $X$  is.

$$f_X(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2}, x \in \mathbb{R}.$$

$\therefore$  the conditional density of  $Y$  given  $X=x$  is.

$$f_{Y|X}(y) = \frac{1}{\sqrt{2\pi(1-\rho^2)}} e^{-\frac{1}{2(1-\rho^2)}(y-\rho x)^2}, y \in \mathbb{R}.$$

i.e. given  $X=x$ , the conditional distribution of  $Y$  is  $N(\rho x, 1-\rho^2)$ .

$$E(Y|X=x) = \rho x.$$

$$\text{i.e. } E(Y|X) = \rho X.$$

$X \sim N(0, 1)$ $Z \sim N(0, 1)$ indep. $Y = \rho X + \sqrt{1-\rho^2} Z$ given $X=x$ $Y = \rho x + \sqrt{1-\rho^2} Z$ $Z \sim N(0, 1)$ $Y \sim N(\rho x, 1-\rho^2)$
---

Theorem, If  $E|Y| < \infty$ , then.

$$E(E(Y|x)) = E(Y) \quad [\text{formula of double expectation}]$$

Pf: For  $x \in \mathbb{R}$ , define.

$$g(x) = \begin{cases} \int_{-\infty}^{\infty} y f_{Y|x}(y) dy, & \text{if } f_x(x) > 0 \text{ and} \\ & \text{the integral exists} \\ 0, & \text{otherwise.} \end{cases}$$

$$E(Y) = \iint_{-\infty}^{\infty} y f(x,y) dx dy.$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} y f_{Y|x}(y) f_x(x) dx dy.$$

[Tonelli]

$$\begin{aligned} &= \int_{-\infty}^{\infty} f_x(x) \int_{-\infty}^{\infty} y f_{Y|x}(y) dy dx \\ &= \int_{-\infty}^{\infty} f_x(x) g(x) dx \\ &= E \left[ \int_{-\infty}^{\infty} g(x) dx \right] \\ &= E(E(Y|x)). \end{aligned}$$

Ex: Suppose that  $X$  and  $Y$  are as in the previous ex. Calculate.

$$E(X^2 Y^2).$$

FACT: If  $Y$  and  $Z$  have finite expectation then,  
 $E(Y+Z|X) = E[Y|X] + E[Z|X]$ .

FACT: If  $E|Y| < \infty$  and  $E[f(Y)] < \infty$ , where  $f: \mathbb{R} \rightarrow \mathbb{R}$  is such that  
 $E(f(X)|X) = f(X)E(Y|X)$ .

Corollary:  $E|Y| < \infty$  and  $E|Z| < \infty$ , for  $\alpha, \beta \in \mathbb{R}$ ,  
 $E(\alpha Y + \beta Z | X) = \alpha E(Y|X) + \beta E(Z|X)$ .

Soln:

$$\begin{aligned} E(X^8 Y^2) &= E(E(X^8 Y^2 | X)) \\ &= E[X^8 E(Y^2 | X)] \\ &= E[X^8 \cdot (\rho^2 X^2 + 1 - \rho^2)] \\ &= E[(\cancel{\rho}(1-\rho^2)X^8 + \rho^2 X^{10})] \\ &= (1-\rho^2) E(X^8) + \rho^2 E(X^{10}). \\ &= \rho^2 \cdot \frac{8! 10!}{5! 2^5} + (1-\rho^2) \frac{8!}{4! 2^4} \\ &= (1.3.5.7.9) \rho^2 + (1.3.5.7) (1-\rho^2). \\ &= (3.5.7) (8\rho^2 + 1) \end{aligned}$$

Ex: Suppose that  $X$  and  $Y$  have finite second moment and  $E(X|Y) = Y$  (i.e.)  $E(Y|X) = X$ .

Show that  $X = Y$  a.s.

Soln:

$$\begin{aligned} E[(X-Y)^2] &= E[X^2 - XY] + E[Y^2 - XY] \\ E[Y^2 - XY] &= E(E(Y^2 - XY | Y)) \\ &= E[Y^2 - YE(X|Y)] = 0 \end{aligned}$$

Similarly,  $E(X^2 - XY) = 0$ . Thus  $E(X-Y)^2 = 0$

i.e.  $X = Y$  a.s.

Ex: Suppose that  $(X, Y) \sim \text{BVN}$  as before.

Calculate  $E(X|X+Y)$

$$\text{Cov}(X, X+Y) = \text{Var}(X) + \text{Cov}(XX) = 1 + p.$$

Soln: Define  $Z = X+Y$ .

The Distribution of  $(X, Z)$  is BVNT with

$$E(X) = 0, E(Z) = 1, \text{Var}(X) = 1, \text{Var}(Z) = 2(1+p), \text{Cov}(X, Z) = 1+p.$$

The dist<sup>n</sup> of  $(Y, Z)$  is

$$(X, Z) \stackrel{d}{=} (Y, Z).$$

$$E(X|Z) = E(Y|Z) = U$$

$$\Rightarrow 2U = E(Z|Z) = Z.$$

$$U = \frac{Z}{2} \rightarrow U \sim N(0, 1)$$

Ex: Suppose the  $(X, Y)$  has joint density.

$$f(x, y) = \frac{1}{\sqrt{2\pi}} \frac{1}{y} e^{-\frac{x^2}{2y^2}} I(y > 0), (x, y) \in \mathbb{R}^2.$$

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

Soln:-

$$f_Y(y) = \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} \frac{1}{y} e^{-\frac{x^2}{2y^2}} dx.$$

$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-y^2/2} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi} y} e^{-\frac{x^2}{2y^2}} dx.$$

$$= e^{-y^2/2} \text{ for } y > 0 \text{ and } 0 \text{ elsewhere}$$

$$\mathbb{E}(XY) = \mathbb{E}(X\mathbb{E}(Y|X)) = \mathbb{E}(X)\mathbb{E}(Y|X)$$

$$\mathbb{E}(X) = 0, \mathbb{E}(Y|X)$$

$$f_{X|Y=y}(x) = \frac{1}{\sqrt{2\pi}} \frac{1}{y} \exp\left(-\frac{x^2}{2y^2}\right), x \in \mathbb{R}.$$

$$X|Y \sim N(0, y^2)$$

$$\mathbb{E}(XY) = \mathbb{E}(Y\mathbb{E}(X|Y)) = 0.$$

$$\text{Also, } \mathbb{E}(X) = 0.$$

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

$$\text{and Corr}(X, Y) = 0.$$

Ex: If  $X$  and  $Y$  are independent and  $E(Y|X) = E(Y)$ , then show that  $E(Y) < \infty$ .

Example: Suppose the conditional density of  $Y$  given  $X=x$  is  $h(y)$  for all  $x$ . Show that the marginal density of  $Y$  is  $h$  and it is independent of  $X$ .

Ex: Suppose that  $X_1, \dots, X_n$  are i.i.d. with finite mean calculated as follows:

$$E(X_1 + \dots + X_n) = \frac{(n-1)}{(n+1)} \mu$$

$$\text{Ans: } \frac{1}{n} (X_1 + \dots + X_n)$$

Example: Suppose that  $X, Y$  are i.i.d. from  $U(0, 1)$ , find the conditional distribution of  $X$  given  $X+Y$ .

$$f_{X|X+Y}(x) = \frac{1}{(1-x)^2}$$

$$f_{X+Y}(x) = \frac{1}{2} x$$

The joint density of  $X$  and  $Y$  is

$$f(x,y) = \mathbb{1}(0 \leq x, y \leq 1) \cdot (x, y \in \mathbb{R})$$

$$U := X$$

$$V := X+Y$$

$$\psi(u,v) = (u, v-u)$$

$$|\dot{\psi}(u,v)| = \left| \det \begin{pmatrix} 1 & -1 \\ 0 & 1 \end{pmatrix} \right| = 1.$$

the function  $\phi : (0,1) \times (0,1) \rightarrow \{(uv) \in \mathbb{R}^2 : 0 < u < 1, 0 < v < 1\}$

$$g(x,z) = \mathbb{1}(0 < x < z < 1+x < 2).$$

H.W. 7 (b)

① a.  $(pe^t + q)^n$ ,  $q = 1-p$

b.  $\exp(\lambda(e^t - 1))$

c.  $\frac{pe^t}{1-qe^t}$ ,  $t < -\ln q$

d.  $\left(\frac{pe^t}{1-qe^t}\right)^k$ ,  $t < -\ln q$

e.  $\frac{e^t(1-e^{nt})}{n(1-e^t)}$

f.  $\frac{e^{bt} - e^{at}}{t(b-a)}$

g.  $e^{let + \frac{1}{2}a^2t^2}$

h.  $\frac{\lambda}{\lambda-t}$ ,  $t < \lambda$

i.  $(1-2t)^{-\frac{n}{2}}$ ,  $t < \frac{1}{2}$

j.  $(1-\frac{t}{\lambda})^{-\alpha}$ ,  $t < \lambda$

$$2. \textcircled{a} \quad 2k\text{th moment} = \frac{\sigma^{2k} (2k)!}{2^k k!}$$

$$\textcircled{b} \quad k\text{th moment} = \frac{\alpha(\alpha+1)\dots(\alpha+k-1)}{\lambda^k}$$

$$\textcircled{c} \quad E(Y^{2k}) = (2k)! \cdot \binom{n+k-1}{k}.$$

$$\textcircled{d} \quad \text{2kth moment} \\ = \alpha(\alpha+1)\dots(\alpha+2k-1).$$

$$\textcircled{e} \quad (2k)\text{th moment}$$

$$= \frac{1}{(k+1)(2k+1)}.$$

$$3. \textcircled{a}, \textcircled{b} \quad \alpha = \frac{1}{\int_1^\infty e^{-x} x^2 dx} < \infty.$$

\textcircled{b} finite for  $|t| \leq 1$ .

$$4. \textcircled{a} \quad E(X^k) = \frac{(2k)!}{2^k k!}$$

$$\textcircled{b} \quad M(t) = \sum_{k=0}^{\infty} \frac{t^k}{k!} \cdot \frac{(2k)!}{2^n n!}.$$

$$t = \frac{1}{2}.$$

$$\sum_{k=0}^{\infty} \frac{(2k)!}{(k!)^2} \cancel{4^k}$$

by Stirling,

$$n! \sim \sqrt{2\pi n} \left(\frac{n}{e}\right)^n.$$

$$\frac{(2n)!}{n!} \sim \frac{\sqrt{4\pi n} \left(\frac{2n}{e}\right)^{2n}}{2\pi n \left(\frac{n}{e}\right)^{2n}} = \frac{4^n}{\sqrt{\pi n}},$$

$$\Rightarrow \frac{(2n)!}{(n!)4^n} \sim \frac{1}{\sqrt{\pi n}} \text{ as } n \rightarrow \infty.$$

ratio test gives us.  $\sum_{n=0}^{\infty} \frac{(2n)!}{(n!)^2 4^n} = \infty$ .

5.

① ( $\Rightarrow$ ) .

$Y \sim \text{Poisson}(\lambda)$ .

$$E[e^{tY}] = \exp[\lambda(e^t - 1)], \forall t \in \mathbb{R}.$$

$$= (E[e^{tx_1}])^n \Rightarrow$$

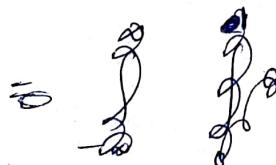
$$\Rightarrow E(e^{tx_1}) = \exp\left[\frac{\lambda}{n}(e^t - 1)\right] \forall t \in \mathbb{R}.$$

$$\Rightarrow X_i \sim \text{Poisson}\left(\frac{\lambda}{n}\right).$$

\* \*

the marginal density of  $Z$  is:

$$g_Z(z) = \int_{-\infty}^{\infty} g(x, z) dx.$$



Case 1  $0 < z \leq 1$ .

$$f(x) = g_Z(z) = \int_0^z 1 dx = z.$$

Case II  $1 < z < 2$ .

$$g_z(z) = \int_{z-1}^z 1 dx = 2-z.$$

$$\therefore g_z(z) = \begin{cases} z & ; z \in [0, 1] \\ 2-z & ; z \in (1, 2] \\ 0 & ; \text{o.w.} \end{cases}$$

The conditional distribution density of  $X$  given  $Z=z$  is.

$$g_{X|Z=z}(x) = \begin{cases} \frac{1(0 < x < z)}{z}, & 0 < z \leq 1. \\ \frac{1(z-1 < x < 1)}{2-z}, & 1 \leq z < 2. \end{cases}$$

Fix,  $0 \leq z \leq 1$ .

$$\begin{aligned} E(X|Z=z) &= \int_{-\infty}^{\infty} x g_{X|Z=z}(x) dx \\ &= \int_0^z \frac{1}{z} x dx = \frac{z}{2}. \end{aligned}$$

Fix  $1 < z < 2$ ,

$$E(X|Z=z) = \frac{1}{2-z} \int_{z-1}^1 x dx = \frac{z}{2}.$$

Fact: If  $\lim_{n \rightarrow \infty} \frac{a_n}{b_n} = 1$  ( $b_n \neq 0$ ) and  $\sum a_n$  converges, then so does  $\sum b_n$ .

"this is not true."

Counter example

$$a_n = (-1)^n / n, \text{ and } b_n = \begin{cases} -\frac{1}{n} & \text{if } n \text{ odd}, \\ \frac{1}{n}(1 + \ln 2n) & \text{if } n \text{ even.} \end{cases}$$

$$\lim_{n \rightarrow \infty} \frac{a_n}{b_n} \rightarrow 1.$$

$$\sum a_n \text{ conv.} \Leftrightarrow \sum_{n=1}^{2N} b_n = \sum_{n=1}^{2N} (b_n - a_n) + \sum_{n=1}^{2N} a_n.$$

$$= \sum_{n=1}^N \frac{1}{2N \ln 2N} + \sum_{n=1}^{2N} a_n.$$

$$\sum b_n \rightarrow \infty.$$

Fact: If  $a_n \downarrow 0$ , then  $\sum_{n=1}^{\infty} (-1)^n a_n$  converges.

HW-9

$$7. f(x,y) = e^{-y} \mathbb{1}(0 < y < x < y+1), x, y \in \mathbb{R}.$$

Fix  $y > 0$ .  $(x,y) \mapsto (x-y, X)$

Claim:  $f_{X|Y}(x|y) = \frac{f(x,y)}{f_Y(y)} = \frac{e^{-y}}{\int_y^{y+1} e^{-x} dx} = \frac{e^{-y}}{e^{-y+1} - e^{-y}} = \frac{1}{e^y - e^{y-1}}$

$$f_{X|Y}(x|y) = \frac{f(x,y)}{f_Y(y)} = \int_0^\infty f(x,y) dx$$

~~0~~

~~y+1~~

~~y~~

<

8.

$$\Delta \sim \text{Std. Exp.}$$

$$(X | \Delta = \lambda) \sim N(\lambda, 1).$$

Conditional density of  $X$  given  $\Delta = \lambda$  is.

$$f_{X|\Delta}(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(x-\lambda)^2}, \quad x \in \mathbb{R}.$$

marginal of  $\Delta$  is,

$$f_\Delta(\lambda) = e^{-\lambda}.$$

$$f(x, \lambda) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(x^2 - 2\lambda x + \lambda^2 + 2\lambda)} \cdot 1(\lambda > 0).$$

$$= \cancel{\frac{1}{\sqrt{2\pi}}} e^{-\frac{1}{2}(x^2 + \lambda^2)} \cdot 1(\lambda > 0).$$

$\forall x, \lambda \in \mathbb{R}$ .

$$\begin{aligned} f_x(x) &= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(x^2 + \lambda^2)} 1(\lambda > 0) d\lambda. \\ &\stackrel{\cancel{\text{if } x > 0}}{=} e^{-\frac{x^2}{2}} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}\lambda^2} d\lambda. \\ &= \frac{e^{-\frac{x^2}{2}}}{((\gamma(x))^2)} \cdot (\gamma(x)) \end{aligned}$$

$$\begin{aligned} f_{X|\Delta}(x) &= \int_0^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(\lambda^2 - 2\lambda(x-1) + (x-1)^2 + x^2 - (x-1)^2)} \\ &\stackrel{\cancel{\text{if } x > 0}}{=} \frac{1}{\sqrt{2\pi}} \int_0^{\infty} \frac{1}{\sqrt{2\pi}} e^{\frac{1}{2}(\lambda - (x-1))^2} \cdot e^{-(\gamma(x))^2} d\lambda. \end{aligned}$$

$$\begin{aligned}
 &= e^{-\frac{1}{2}(2x-1)} \int_0^\infty \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(x-(x-1))^2} dx \\
 &= e^{-x+\frac{1}{2}} \int_0^\infty \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(x-(x-1))^2} dx \\
 &= e^{-x+\frac{1}{2}} [1 - \Phi(1-x)] \\
 &= e^{-x+\frac{1}{2}} \Phi(x-1).
 \end{aligned}$$

the marginal density of  $X$  is.

$$f_X(x) = e^{-x+\frac{1}{2}} \Phi(x-1), \quad x \in \mathbb{R}.$$

$$E(X) = E\mathbb{E}(X|\lambda) = E(\Delta) = 1.$$

$$\begin{aligned}
 13. \quad E(X\Phi(Y)) &= E\mathbb{E}[X\Phi(Y)|Y] \\
 &= E\mathbb{E}(X\Phi(Y)|X) = E[\Phi(Y) E(X|Y)] \\
 &= E(X E[\Phi(Y)|X]) = E[e^Y Y \Phi(Y)] \\
 &= e \cdot E[Y \Phi(Y)] \\
 &= e \int_{-\infty}^{\infty} y \Phi(y) \phi(y) dy.
 \end{aligned}$$

$$= e \int_{-\infty}^{\infty} y \phi(y) \int_{-\infty}^y \phi(z) dz dy.$$

$$= e \int_{-\infty}^{\infty} \int_{-\infty}^y y \phi(y) \phi(z) dz dy.$$

so



$$\int_{y=-\infty}^{\infty} \int_{z=-\infty}^y |\phi(y) \phi(z)| dz dy.$$

$$= \int_{y=-\infty}^{\infty} |y| \phi(y) \int_{z=-\infty}^y \phi(z) dz dy.$$

$$\leq \int_{y=-\infty}^{\infty} |y| \phi(y) dy. < \infty$$

$\because E(y) \text{ exist}$

By Fubini,

$$= P \int_{z=-\infty}^{\infty} \int_{y=z}^{\infty} |y| \phi(y) \phi(z) dy dz.$$

$$= P \int_{z=-\infty}^{\infty} \phi(z) \left( \int_{y=z}^{\infty} |y| \phi(y) dy \right) dz.$$

$$= P \int_{z=-\infty}^{\infty} \phi(z) \cdot \int_{y=z}^{\infty} \frac{y \cdot e^{-y^2/2}}{\sqrt{2\pi}} dy dz.$$

$$= P \int_{z=-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-z^2/2} \cdot \left[ -\frac{e^{-y^2/2}}{\sqrt{2\pi}} \right]_z^{\infty} dz.$$

$$= P \int_{z=-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-z^2/2} dz.$$

$$= \frac{P}{2\pi\sqrt{2}} \int_{z=-\infty}^{\infty} e^{-\frac{1}{2}(\sqrt{2}z)^2} dz.$$

$$= \frac{P}{2\pi\sqrt{2}} , \sqrt{2\pi}$$

$$= \frac{P}{\sqrt{4\pi}} = \frac{P}{2\sqrt{\pi}}$$

$$14. E(X^2 Y^2)$$

$$= E(E(X^2 Y^2 | Y))$$

$$= E(Y^2 E(X^2 | Y))$$

$$= E(Y^2 (1 - P^2 + P^2 Y^2))$$

$$= E(Y^2) - P^2 E(Y^2) + P^2 E(Y^4)$$

$$\Rightarrow E(Y^2) - P^2 (E(Y^4))$$

$$= 1 - P^2 + 3P^2$$

$$= 2P^2 + 1.$$

$$\text{cov}(X^2, Y^2) = |E(X^2 Y^2)| - E(X^2) E(Y^2)$$

$$= (2P^2 + 1) - 1.$$

$$= 2P^2.$$

$$\text{Var}(X^2) = E(X^4) - E(X^2) = 3 - 1 = 2.$$

$$\text{Var}(Y^2) = 2.$$

$$\therefore \text{corr}(X^2, Y^2) = \frac{2P^2}{\sqrt{2 \times 2}} = P^2.$$

Hw-8 ①  $X$  has CHF  $\phi_X$ .

$$Y = a + X.$$

$$\phi_Y(t) = E \left[ e^{itY} \right].$$

$$= E \left[ e^{it(a+X)} \right].$$

$$= e^{ita} E \left[ e^{itX} \right] e^{ita} \phi_X(t)$$

2.  $X$  has CHF  $\phi$ . (TFAE of  $\phi$ )

①  $\phi$  is real.  $\Rightarrow \phi(t) = \phi(-t)$   $\forall t \in \mathbb{R}$

②  $\phi(-t) = \phi(t)$   $\forall t \in \mathbb{R}$

③  $X \stackrel{d}{=} -X$

$$\phi(it) = E[\cos itX] + i E[\sin itX].$$

$$\begin{aligned} \phi(-t) &= E[\cos(-t)X] = E[i\cos tX] \\ &= \overline{E[i\cos tX]} = \overline{\phi(it)} \\ &= \overline{\phi(t)} \end{aligned}$$

①  $\Rightarrow$  ②  $\Rightarrow \phi(t) = \phi(-t) \quad \forall t \in \mathbb{R}$

$\phi(t)$  real

$$\Rightarrow \phi(t) = \overline{\phi(t)} = \phi(-t).$$

②  $\Rightarrow$  ③ Since  $\phi(-t)$  is CHF of  $-X$ ,  
uniqueness tells us  $X \stackrel{d}{=} -X$ .

③  $\Rightarrow$  ①  $X \stackrel{d}{=} -X$ .

$$\phi(t) = \phi(-t) = \overline{\phi(t)}$$

$\therefore \phi$  is real.

4.

$$\textcircled{a} \text{ Binomial } (n, p) \quad \phi(t) = (q + pe^{it})^n$$

$$\textcircled{b} \text{ Poisson } (\lambda) \quad \phi(t) = \exp(\lambda(e^{it} - 1))$$

$$\textcircled{c} \text{ Negative Binomial } (k, p) \rightarrow \left( \frac{pe^{it}}{1+qe^{it}} \right)^k$$

$$\textcircled{d} \text{ Uniform } (a, b)$$

$$\phi(t) = \begin{cases} \frac{e^{ibt} - e^{iat}}{it(b-a)}, & t \neq 0. \\ 1, & t = 0. \end{cases}$$

$$\textcircled{e} \text{ Triangular}$$

$$\phi(t) = E[\cos(tx)]$$

$$= 2 \int_0^1 (1-x) \cos(tx) dx$$

$$= 2 \left[ \int_0^1 \cos(tx) dx - \int_0^1 x \cos(tx) dx \right]$$

$$\phi(t) = \begin{cases} \frac{2(1-\cos t)}{t^2}, & t \neq 0. \\ 1, & t = 0. \end{cases}$$

$\textcircled{f}$

$$\textcircled{f} \text{ Normal } (\mu, \sigma^2) \quad \phi(t) = e^{i\mu t - \frac{1}{2}\sigma^2 t^2}$$

$$\textcircled{g} \text{ Exp } (\lambda) \rightarrow \frac{\lambda}{\lambda - it}$$

(h)

$\chi^2_2 \sim \text{Exp}(\frac{1}{2})$

$$\chi^2_2 \sim \text{Exp}(\frac{1}{2})$$

(a) Ans. A

Let,  $X_1, \dots, X_n$  be i.i.d. from  $\chi^2_2$ . using H(3)

$Y = X_1 + \dots + X_n$  then  $Y \sim \chi^2_{2n}$  Ans. (b)

$$\text{CHf of } Y \text{ is, } \phi_Y(t) = E[e^{itX_1}]^n$$

$$= \left( \frac{1/2}{1/2 - it} \right)^n$$

$$= (1 - 2it)^{-n}$$

(i) Double Exponential.  $\phi(t) = \frac{1}{1+t^2}$

(f) Cauchy's CHf.  $\phi(t) = e^{-|t|}$ .

(5)  $X$  has density

$$f(x) = \frac{1}{2^{3/2} \pi^{1/2}} |x|^{-1} \exp\left(-\frac{1}{2} (\ln|x|)^2\right) \mathbf{1}(x \neq 0), \quad x \in \mathbb{R}.$$

(b)

$$\sum_{n=0}^{\infty} \frac{\phi^{(n)}(0) t^n}{n!}$$

$$= \sum_{n=0}^{\infty} \frac{E[(ix)^n] t^n}{n!}$$

$$= \sum_{n=0}^{\infty} \frac{E[(ix)^{2n}] t^{2n}}{(2n)!}$$

$$= \sum_{n=0}^{\infty} (-1)^n \frac{t^{2n}}{(2n)!} E(X^{2n})$$

$E[e^{2n \ln|X|}]$   
 $\& \ln|X| \sim N(0,1)$   
 $= \int_0^\infty e^{-\frac{(2n)^2}{2}} e^{-2n^2}$   
 $= e^{-2n^2}$

$$= \sum_{n=0}^{\infty} t^n (-1)^n \frac{t^{2n}}{(2n)!} e^{-2n^2}.$$

c) Show that, for  $t \neq 0$ ,

$$\lim_{n \rightarrow \infty} \left| \frac{(-1)^n t^{2n}}{(2n)!} e^{2n^2} \right| = \infty$$

Stirling:  $n! \sim \sqrt{2\pi n} \left(\frac{n}{e}\right)^n$  as  $n \rightarrow \infty$ .

$$\frac{n!}{\sqrt{2\pi n} \left(\frac{n}{e}\right)^n} \leq C \quad \forall n \in \mathbb{N}.$$

$$n! \leq C \sqrt{2\pi n} \left(\frac{n}{e}\right)^n. \quad \forall n \in \mathbb{N}.$$

$$\begin{aligned}
 |\ln|t|| &= 2n \ln|t| + 2n^2 - \ln(2n)! \\
 &\geq 2n \ln|t| + 2n^2 - \ln(e^{\sqrt{4\pi n}} \left(\frac{2n}{e}\right)^{2n}) \\
 &= 2n \ln|t| + 2n^2 - \ln e - \frac{1}{2} \ln(4\pi n) \\
 &\quad - 2n(\ln 2n - 1)
 \end{aligned}$$

$$\begin{aligned}
 &\approx 2n \left[ \frac{\ln|t|}{n} + 1 - \frac{\ln e}{n} + \frac{\ln(4\pi n)}{2n^2} \right] \\
 &\quad \downarrow \quad \downarrow \quad \downarrow \quad \downarrow \\
 &\quad 0 \quad 0 \quad \frac{1}{n} \quad \frac{n}{2n^2} \\
 &\approx \frac{\ln|t|}{n} + 1 - \frac{1}{n} + \frac{\ln(4\pi n)}{2n^2}
 \end{aligned}$$

$$\Rightarrow 2n^2$$

hence,  $\lim_{n \rightarrow \infty} \left| \frac{(-1)^n t^{2n} e^{-2n^2}}{(2n)!} \right| = \infty$ .

and hence, the Taylor series diverges for every  $t \neq 0$ .

Qn

6. If  $X$  has CHF  $\phi$ , then:

$$P(a \leq X \leq b) = \lim_{T \rightarrow \infty} \frac{1}{2\pi} \int_{-T}^T \frac{e^{-iat} - e^{-ibt}}{it} \phi(t) dt.$$

$\forall a, b$  such that  $P(X \in \{a, b\}) = 0$ .

Suppose  $X$  and  $Y$  have the same CHF.

Then  $P(a \leq X \leq b) = P(a \leq Y \leq b)$ .  $(*)$

$\forall a, b$  s.t.  $P(X \in \{a, b\}) = P(Y \in \{a, b\}) = 0$ .

The set  $\mathcal{S} = \{x \in \mathbb{R}, P(X=x) > 0 \text{ or } P(Y=x) > 0\}$  is countable.

Let  $\{a_n\}_{n=1}^{\infty} \subseteq \mathcal{S}$  and  $\{b_n\}_{n=1}^{\infty} \subseteq \mathcal{S}$  s.t.

$b_n > a_n \downarrow -\infty$  as  $n \rightarrow \infty$ .

using  $n \rightarrow \infty$ , we get

$$P(X \leq b) = P(Y \leq b). \quad (**)$$

Fix any  $x \in \mathbb{R}$  and let  $b_n \in \mathcal{S}$  s.t.  $b_n \downarrow x$ .

using  $(*)$   $(**)$ .

we get.

$$P(X \leq b_n) = P(Y \leq b_n).$$

Letting  $n \rightarrow \infty$  & using right continuity of CDF we get,

$$P(X \leq x) = P(Y \leq x).$$

7.

(a)  $f(x) = \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{-itx} \phi(t) dt, x \in \mathbb{R}.$

$$\begin{aligned} |f(x)| &= \frac{1}{2\pi} \left| \int_{-\infty}^{\infty} e^{-itx} \phi(t) dt \right| \\ &\leq \frac{1}{2\pi} \int_{-\infty}^{\infty} |\phi(t)| dt. \end{aligned}$$

Claim: Suppose  $g: \mathbb{R} \rightarrow [0, \infty)$  is such that  $\int_{-\infty}^{\infty} g(t) dt < \infty$ .

then,  $h(x) = \int_{-\infty}^{\infty} e^{-itx} g(t) dt, x \in \mathbb{R}.$

Proof of the claim:

Let,  $x = \int_{-\infty}^{\infty} g(t) dt.$

if  $x = 0$ , then  $h(x) = 0 \forall x$  and hence nothing to prove. Assume WLOG that  $x > 0$ . Then  $x^{-1}g$  is a density.

Let,  $Z$  be a r.v with density  $x^{-1}g$

$$\text{then } h(x) = \int_{-\infty}^{\infty} e^{-itx} g(t) dt = x E[e^{-iz}]$$

Since, CHF is continuous so for  $h$ .

$$f(x) = \int_{-\infty}^{\infty} e^{-itx} \phi(t) dt.$$

write  $\phi$  as

$$\phi(t) = (\psi_1^+(t) - \psi_1^-(t)) + i(\psi_2^+(t) - \psi_2^-(t)).$$

$$\begin{aligned}
 \text{(b)} \quad Z &= X+Y \\
 \phi_Z(t) &= \phi_X(t)\phi_Y(t) \\
 |\phi_Z(t)| &\leq |\phi_X(t)| \\
 &\leq |\phi_{X^*}(t)|
 \end{aligned}$$

$$\begin{aligned}
 9. \quad \text{Define,} \quad g(x) &= \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{-itx} \phi(t) dt, \quad \forall x \in \mathbb{R}.
 \end{aligned}$$

problem 7  $\Rightarrow$   $g$  is continuous.

Inversion thm  $\Rightarrow$   $g$  is density of  $X$ .  
 $f$  is also continuous and density of  $X$ .

$$\therefore f = g.$$

$$\begin{aligned}
 10. \quad Y &= \beta \left( \sum_{j=1}^n |\alpha_j| \right)^{-1} \sum_{k=1}^n \alpha_k X_k, \quad \beta > 0, \quad 0 < \beta < \infty \\
 \phi_Y(t) &= E[e^{itY}] \\
 &= E \left[ \exp \left( it \beta \sum_{j=1}^n \alpha_j X_j \right) \right] \\
 &= E \left[ \exp \left( it \sum_{j=1}^n \beta \alpha_j X_j \right) \right] \\
 &= \prod_{j=1}^n E \left[ e^{it \beta \alpha_j X_j} \right]
 \end{aligned}$$

$$\begin{aligned}
 &= \prod_{j=1}^n e^{-\alpha_j t + \beta_j x_j} \\
 &= e^{-\beta t + \sum_{j=1}^n \alpha_j x_j} \\
 &= e^{-\beta t}.
 \end{aligned}$$

By uniqueness thm,  $Y \sim \text{Cauchy}$ .

(b)  $E [e^{it \sum_{j=1}^n \alpha_j X_j}]$

$$\begin{aligned}
 &= \prod_{j=1}^n E [e^{it \alpha_j X_j}] \\
 &= \prod_{j=1}^n e^{it \alpha_j + \frac{t^2 \alpha_j^2}{2}} \\
 &= e^{-\frac{t^2}{2} (\sum_{j=1}^n \alpha_j^2)}.
 \end{aligned}$$

12.  $M_x(t) < \infty$ ,  $|t| \leq \varepsilon$ . (for some  $\varepsilon > 0$ ).

and,

$$E(X^n) = 0 \quad \forall \text{ odd } n \in \mathbb{N}.$$

$$\begin{aligned}
 M_x(t) &= \sum_{n=0}^{\infty} \frac{t^n}{n!} E(X^n) \\
 &= \sum_{n=0}^{\infty} \frac{t^{2n}}{(2n)!} E(X^{2n}).
 \end{aligned}$$

$\forall |t| \leq \varepsilon$ .

$$M_{-X}(t) = \sum_{n=0}^{\infty} \frac{t^{2n}}{(2n)!} E((-x)^{2n}) = M_x(t).$$

$\therefore X \& -X \text{ has same MGF } \forall |t| \leq \varepsilon$ .

i.e.  $X$  and  $-X$  have the same MGF  
in  $[-\varepsilon, \varepsilon]$ , which is also finite  
hence,  $X \stackrel{d}{=} -X$ .

13.

$$f(x) = \begin{cases} \frac{1}{\pi} \cdot \frac{1 - \cos x}{x^2}, & x \neq 0, \\ \frac{1}{2\pi}, & x = 0. \end{cases}$$

V ~ Triangular dist.

CHF of V is.

$$g(x) = (1 - |x|) \cdot \mathbb{1}(|x| \leq 1).$$

$$h_v(x) = \int_{-\infty}^{\infty} e^{-itx} f(t) dt$$

$$g \equiv h_v.$$

~~$$\text{for } E[e^{-itX}] = (1 - |t|) \mathbb{1}(|t| \leq 1).$$~~

$$\Rightarrow E[e^{-itz}] = (1 - |t|) \mathbb{1}(|t| \leq 1).$$

$$\phi_z(t) = E[e^{-itz}] = (1 - |t|)^2 \mathbb{1}(|t| \leq 1).$$

Inversion formula implies that density of Z is,

$$f_Z(z) = \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{itz} \phi_z(t) dt$$

Integrating with respect to t.

$$\text{where } i = \frac{1}{\pi} \int_0^{\infty} (1-t)^2 \cos(tz) dt$$

$$= \frac{2}{\pi} \cdot \frac{z - \sin z}{z^3}$$

14. ( $\Rightarrow$ )

$Y \sim \text{Cauchy}$ .

Let,  $\phi$  be the CDF of  $X_1$ .

Then, for all  $t \in \mathbb{R}$ ,

$$\phi_{X_1}\left(\frac{t}{n}\right)^n = E[e^{itY}] = e^{-|t|}.$$

$$\Rightarrow \phi_{X_1}\left(\frac{t}{n}\right) = e^{-\frac{|t|}{n}}.$$

Suppose,  $n = 2$ .

$$\phi\left(\frac{t}{2}\right)^2 = e^{-|t|}.$$

$$\phi\left(\frac{t}{2}\right) = \pm e^{-\frac{|t|}{2}}$$

Suppose that,

$$\phi\left(\frac{t}{2}\right) = -e^{-|t|/2} \quad \text{for some } t.$$

$$\phi(0) = 1.$$

then  $\phi(\xi) = 0$  ~~for some~~ for some  $\xi$ .

$$e^{-|2\xi|} = \phi(\xi)^2 = 0 \quad \text{which is a contradiction.}$$

$$\text{Hence, } \phi\left(\frac{t}{2}\right) = e^{-\frac{|t|}{2}}$$

$$\Rightarrow X_1 \sim \text{Cauchy}.$$

for general  $n$  it need complex analysis.

15.

If  $X_n \xrightarrow{P} X$  as  $n \rightarrow \infty$ .

$$\lim_{n \rightarrow \infty} \phi_n(t) = \phi(t) \quad \forall t \in \mathbb{R}$$

(Q)  $\phi_n(t) = E[e^{itX_n}]$ .

$$\phi(t) = E[e^{itX}]$$

$$e^{itX_n} \xrightarrow{P} e^{itX}$$

$$|e^{itX_n}| \leq 1. \quad D.C.T.$$

(Qn):  $X_1, X_2$  are iid. from Std. uniform.  
Y follows triangular  $(C(1-|x|)1(|x| \leq 1))$ .

(a) Show that  $X_1 + X_2 \stackrel{d}{=} Y + 1$ .

(b) Verify using CHF.

(Q) If  $Z_1, Z_2$  are iid.  $\sim U(-\frac{1}{2}, \frac{1}{2})$ , show  
that  $Z_1 + Z_2 \stackrel{d}{=} Y$ .

6.  $(X, Y) \sim N_2(\mu, \Sigma)$ .

$$\mu = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} \quad \Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{12} & \sigma_{22} \end{bmatrix}$$

$$X' = \frac{X - \mu_1}{\sqrt{\sigma_{11}}} \quad Y' = \frac{Y - \mu_2}{\sqrt{\sigma_{22}}}$$

$\therefore X'$  &  $Y'$  follows bivariate normal with mean zero, variance 1, and correlation  $\rho$ .

$$\rho = \frac{\sigma_{12}}{\sqrt{\sigma_{11}\sigma_{22}}}$$

$$Z = \frac{X' - \rho Y'}{\sqrt{1-\rho^2}}$$

check that  $Y'$  and  $Z$  are independent.

$$\begin{aligned} X &= \mu_1 + \sqrt{\sigma_{11}} X' \\ &= \mu_1 + \sqrt{\sigma_{11}} (\rho Y' + \sqrt{1-\rho^2} Z) \\ &= \mu_1 + \rho \sqrt{\frac{\sigma_{11}}{\sigma_{22}}} (Y - \mu_2) + \sqrt{(1-\rho^2)\sigma_{11}} Z. \end{aligned}$$

Since,  $Z$  is independent of  $Y$ , it follows that the conditional distribution of  $X$  given  $Y$  is normal with mean  $\mu_1 + \rho \sqrt{\frac{\sigma_{11}}{\sigma_{22}}} (Y - \mu_2)$  and variance  $(1-\rho^2)\sigma_{11}$ .

10.  $(X, Y)$  have joint density.

$$f(x, y) = [(1+ax)(1+ay) - a] e^{-x-y-axy} \mathbf{1}(x, y > 0), x, y \in \mathbb{R}$$

The marginal density of  $Y$  is.

$$f_Y(y) = \int_0^\infty f(x,y) dx, \quad y > 0.$$

$$= (1+ay-a) e^{-y} \int_0^\infty e^{-x(1+ay)} dx.$$

$$+ a(1+ay) e^{-y} \int_0^\infty x e^{-x(1+ay)} dx.$$

$$= \frac{1+ay-a}{1+ay} \cdot e^{-y} + \frac{a e^{-y}}{1+ay}.$$

$$= \frac{1+ay}{1+ay} \cdot e^{-y}$$

$$= e^{-y}.$$

The conditional density of  $X$  given  $Y=y$  is.

$$f_{X|Y}(x) = [(1+ax)(1+ay)-a] e^{-x(1+ay)}$$

$$\therefore E(X|Y=y) = \int_0^\infty x [(1+ax)(1+ay)-a] e^{-x(1+ay)} dx.$$

$$= (1+ay-a) \int_0^\infty x e^{-x(1+ay)} dx,$$

$$+ a(1+ay) \int_0^\infty x^2 e^{-x(1+ay)} dx,$$

$$= \frac{1+a(y+1)}{(1+ay)^2}$$

$$E(X|Y) = \frac{1+a(1+Y)}{(1+aY)^2}$$

⑪  $X \sim \text{Gamma}(a, 1)$   $Y \sim \text{Gamma}(a + \frac{1}{2}, 1)$ .

Corollary Suppose  $U$  and  $V$  are R.V's.

s.t.  $\left. \begin{array}{l} E[e^{tU}] < \infty \\ E[e^{tV}] < \infty \end{array} \right\}$  for all  $|t| < \epsilon$ .  
 $(\epsilon > 0)$ .

and  $E(U^n) = E(V^n)$ ,  $n \geq 1$

then  $U \stackrel{d}{=} V$

Soln: Let  $Z = 2\sqrt{XY}$ .

$$E(Z^n) = 2^n E(X^{\frac{n}{2}}) E(Y^{\frac{n}{2}}).$$

$$= 2^n \cdot \frac{\Gamma(a+\frac{n}{2})}{\Gamma(a)} \cdot \frac{\Gamma(a+\frac{1}{2}+\frac{n}{2})}{\Gamma(a+\frac{1}{2})}$$

$$\text{Let } n=2m = 2^m \cdot \frac{\Gamma(a+m)}{\Gamma(a)} \cdot \frac{\Gamma(a+m+\frac{1}{2})}{\Gamma(a+\frac{1}{2})}$$

$$= 2^{2m} a(a+1)\dots(a+m-1)(a+\frac{1}{2})(a+\frac{3}{2})\dots(a+m-\frac{1}{2})$$

$$= 2a(2a+2)\dots(2a+2m-2)(2a+1)(2a+3)\dots(2a+2m-1)$$

$$= (2a)(2a+1)\dots(2a+2m-1)$$

$$= \frac{\Gamma(2a+n)}{\Gamma(2a)} = E(U^n).$$

where  $U \sim \text{Gamma}(2a)$ .

$$E(e^{tU}) < \infty$$

$$E(e^{tz}) = E(e^{2t\sqrt{XY}}) \leq E(e^{t(x+y)})$$

$$= E(e^{tx}) E(e^{ty}) < \infty$$

$$E[Z^n] = 2^n E(X^{\frac{n}{2}})E(Y^{\frac{n}{2}}).$$

$$= 2^n \frac{\Gamma(a+\frac{n}{2})}{\Gamma(a)} \cdot \frac{\Gamma(a+\frac{n+1}{2})}{\Gamma(a+\frac{1}{2})}$$

$$= 2^n \frac{\Gamma(a+\frac{n}{2})}{\Gamma(a+\frac{1}{2})} \cdot \frac{\Gamma(a+\frac{n+1}{2})}{\Gamma(a)}$$

14.

$$(X, Y) \sim \text{BVN}.$$

$$E[\Phi(x)\Phi(y)]$$

Now,  $\bullet$

$$E[\Phi(y)|x] = \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi(1-\rho^2)}} \phi(y) e^{-\frac{1}{2}(\frac{y-\rho x}{\sqrt{1-\rho^2}})^2} dy.$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{y} \frac{1}{\sqrt{1-\rho^2}} \phi(\frac{y-\rho x}{\sqrt{1-\rho^2}}) \phi(z) dz dy$$

$$Y \sim N(\rho x, 1-\rho^2)$$

$$Z \sim N(0, 1) \quad \text{indep of } Y$$

$$= P(Z < Y).$$

$$= P(Z - Y < 0).$$

$$= \Phi\left(\frac{\rho x}{\sqrt{1-\rho^2}}\right).$$

$$(Y|X) \sim Z \Rightarrow (Y|X) \sim Z$$

$$E[\Phi(x)\Phi(y)] = E\left[\Phi(x)\Phi\left(\frac{\rho x}{\sqrt{1-\rho^2}}\right)\right]$$