

Recall - result:

$$X_n \xrightarrow{d} X \quad \text{iff} \quad E(f(X_n)) \rightarrow E(f(X)) \quad \forall f \in C_b(\mathbb{R})$$

↓  
bounded  
real  
fns.

This is a characterization of convergence of distributions.

Some standard notations:

- $X_n \xrightarrow{d} F$   
→ a cdf

this means,  $X_n$  converges to some r.v whose CDF is  $F$ .

- $F_n \xrightarrow{d} F$   
→  $F_n$ -cdf of  $X_n$ .  $\xrightarrow{d}$  cdf  $F$  (of some r.v).

## Complex Random Variables.

$Z$  is a complex valued r.v on  $(\Omega, \mathcal{A}, P)$   
if  $Z = X + iY$ , where  $X, Y$  are real valued r.v.s

Define expectation,

$$E(Z) := E(X) + i \cdot E(Y), \quad \text{if } E(X) \text{ & } E(Y) \text{ are both finite.}$$

## Properties:

(a)  $Z_1, Z_2$  - complex r.v.s.

$\alpha_1, \alpha_2$  - complex nos.

$E(Z_1)$  &  $E(Z_2)$  both exist.

$$\text{then, } \Rightarrow E(\alpha_1 Z_1 + \alpha_2 Z_2) = \alpha_1 \cdot E(Z_1) + \alpha_2 \cdot E(Z_2)$$

[easy to prove.]

$$\text{take } \alpha_1 = u_1 + i v_1, \alpha_2 = u_2 + i v_2$$

$$Z_1 = X_1 + i Y_1, Z_2 = X_2 + i Y_2$$

& do some algebra.

(b) For any complex r.v  $Z$ ,

$$|E(Z)| \leq E(|Z|). \rightarrow \text{looks analogous to}$$

! !

$|Ex| \leq E(|x|),$   
but it isn't !!

Proof of (b):

For every complex  $w$ ,  $\exists$  a complex no.  $\alpha$  with  $|\alpha|=1$

$$\text{s.t. } |w| = \alpha \cdot w.$$

if  $w=0$ , take any  $\alpha$ .

[easy to check]

$\therefore$  Applying with  $w=E(Z)$ ,

$\exists \alpha \in \mathbb{C}$  with  $|\alpha|=1$ .

$$\text{s.t., } |E(Z)| = \underbrace{\alpha \cdot E(Z)}_{\text{complex}}.$$

$\downarrow$  Real.

$$\begin{aligned}
 \Rightarrow |E(Z)| &= |\operatorname{Re}(\alpha E(Z))| \\
 &\stackrel{\text{easy to check !!}}{=} |\operatorname{Re} \cdot E(\alpha Z)| \\
 &\Rightarrow = |E(\operatorname{Re}(\alpha Z))| \\
 &\leq E \underbrace{|\operatorname{Re}(\alpha Z)|}_{\leq} \\
 &\leq E |\alpha Z| \\
 &= E |Z| \quad [\because |\alpha|=1]
 \end{aligned}$$

Suppose,  $Z = X+iY$ .

then,  $E(Z) := E(X) + iE(Y)$ .

$$\therefore |E(Z)| = \sqrt{(E(X))^2 + (E(Y))^2},$$

whereas,

$$E|Z| = E\left(\sqrt{X^2+Y^2}\right)$$

$\therefore$  for real r.v.s  $X, Y$ ,

we're saying:

$$\sqrt{(E(X))^2 + (E(Y))^2} \leq E(\sqrt{X^2+Y^2})$$

This is not a L<sub>1</sub> ineq.

This is stronger.

Consequence of (b):

DCT holds for complex r.v.s as well !!

$Z_n, n \geq 1$  is a sequence of complex r.v.s &

$Z$  is a complex r.v.,

$\dots \rightarrow a.s \rightarrow \dots$

$Z$  is a complex r.v,

and if  $Z_n \xrightarrow{a.s} Z$ , & if

$\exists Y$  with  $E(Y) < \infty$  s.t,

$$|Z_n| \leq |Y| \quad \forall n,$$

then  $E|Z_n - Z| \rightarrow 0$ . [the "real-DCT"]

in particular,

$$EZ_n \rightarrow EZ.$$

[using part (b)].

### Definition:

Complex r.vs

$$Z_1 = X_1 + i \cdot Y_1$$

:

:

$$Z_n = X_n + i \cdot Y_n$$

are said to be independent if

$(X_1, Y_1), \dots, (X_n, Y_n)$  are independent random vectors.

### Consequence:

$Z_1, Z_2$  - complex independent r.vs,

$$\text{then } E(Z_1 \cdot Z_2) = E(Z_1) \cdot E(Z_2).$$

Proof: Write  $Z_1 = X_1 + i \cdot Y_1$

$$Z_2 = X_2 + i \cdot Y_2$$

, just do it !!

just do it !!

### Definition: Characteristic Function. (C.F.)

for a real r.v  $X$ , its characteristic fn

$\varphi_X$  is defined by

$$\varphi_X(t) = E(e^{itX}), \quad \varphi_X: \mathbb{R} \rightarrow \mathbb{C}.$$

$$\varphi_X(t) = E(\cos tX) + iE(\sin tX).$$

\* C.F. is a function

$$\varphi_X: \mathbb{R} \rightarrow \mathbb{C},$$

$\varphi_X(t)$  exists  $\forall t \in \mathbb{R}$ .  $\because E(\cos tX)$  &  $E(\sin tX)$

[Unlike MGF.]

are always bounded.  
within  $[-1, 1]$

### Properties:

(a)  $\varphi_X(0) = 1$

(b)  $|\varphi_X(t)| \leq 1$ .

Proof:

$$\begin{aligned} |\varphi_X(t)| &= |E(e^{itX})| \\ &\leq E|e^{itX}| = 1. \end{aligned}$$

(c)  $\varphi_X$  is a uniformly continuous fn on  $\mathbb{R} \rightarrow \mathbb{C}$ .

Proof:

$$\begin{aligned}
 |\varphi_{X(t+h)} - \varphi_X(t)| &= |E(e^{i(t+h)X}) - E(e^{itX})| \\
 &= |E(e^{itX}(e^{ihX} - 1))| \\
 &\leq E |e^{itX} \cdot (e^{ihX} - 1)| \\
 [\because E|e^{itX}| = 1] \hookrightarrow &= E |e^{ihX} - 1| \xrightarrow{(DCT)} 0 \\
 &\therefore |e^{ihX} - 1| \rightarrow 0, \\
 &\text{&} |e^{ihX} - 1| \leq 2 < \infty. \\
 &\quad \uparrow \text{constant r.v.} \quad \square
 \end{aligned}$$

(d)  $\varphi_{a+bx}(t) = e^{iat} \cdot \varphi_x(bt)$

Proof: easy to check.

$$\begin{aligned}
 \varphi_{a+bx}(t) &= E(e^{it(a+bx)}) \\
 &= E(e^{iat} \cdot e^{i(bt)-X}) = e^{iat} \cdot E(e^{i(bt)X}) \\
 &= e^{iat} \cdot \varphi_x(bt).
 \end{aligned}$$

(e)  $\varphi_{-X}(t) = \varphi_X(-t) = \overline{\varphi_X(t)}$

\* if 2 r.v.s have same CDF, they have same c.f.

(f) If  $X \stackrel{d}{=} -X$  [ie,  $X$  has symmetric dist<sup>"</sup>]  
 $\therefore X = N(0, 1)$

then  $\varphi_x(t) = \varphi_{-x}(t)$

$$\varphi_x(t) \stackrel{!!}{=} \overline{\varphi_x(t)}$$

$\therefore \varphi_x(t)$  is real-valued.

Is the converse true?

is if  $\varphi_x(t)$  is real-valued,  
 can we say:  $X$  has  
 symmetric dist<sup>"</sup>?

Not until we prove that  
 C.F. uniquely determines the  
 distribution.

(g)  $X, Y$ -independent

$$\varphi_{x+y}(t) = \varphi_x(t) + \varphi_y(t).$$

- -

\* for a discrete distribution with values

$$x_1, x_2, \dots \text{ & pmf } p(x_1), p(x_2), \dots$$

$$\varphi_x(t) = \sum_i e^{itx_i} \cdot p(x_i)$$

For a random variables with density  $f$ ,

$$\varphi_x(t) = \int e^{itx} \cdot f(x) dx$$

Some examples.

(a)  $X \sim \text{Bin}(n, p)$ . write  $q = 1 - p$ .

$$\begin{aligned}\varphi_x(t) &= \sum_{k=0}^n \binom{n}{k} e^{itk} \cdot p^k \cdot q^{n-k} \\ &= \sum_{k=0}^n \binom{n}{k} \cdot (pe^{it})^k \cdot q^{n-k} \\ &= (pe^{it} + q)^n\end{aligned}$$

(b)  $X \sim \text{Poi}(\lambda)$ .

$$\begin{aligned}\varphi_x(t) &= e^{-\lambda} \cdot \sum_{k=0}^{\infty} e^{itk} \cdot \frac{\lambda^k}{k!} \\ &= e^{-\lambda} \cdot \sum_{k=0}^{\infty} \frac{(\lambda e^{it})^k}{k!} = e^{-\lambda} \cdot e^{\lambda e^{it}} \\ &= e^{-\lambda(1-e^{it})}\end{aligned}$$

(c)  $X \sim \text{exp}(\lambda)$ .

$$\begin{aligned}\varphi_x(t) &= \lambda \cdot \int_0^{\infty} e^{itx} \cdot e^{-\lambda x} \cdot dx \\ &= \lambda \cdot \int_0^{\infty} e^{-(\lambda - it)x} dx \stackrel{?}{=} \left( \frac{\lambda}{\lambda - it} \right)\end{aligned}$$

quick thinking  
assume  $\lambda - it = 0$ .  
 $\therefore \int_0^{\infty} e^{-0} = \frac{1}{0}$ .

that shortcut works!!

over. / n -> r .. 1

$$\text{work out: } = \left( \lambda \int \cos tx \cdot e^{-\lambda x} dx + i\lambda \int \sin tx \cdot e^{-\lambda x} dx \right)$$

(d)  $X \sim N(0, 1)$

→ symmetric.

$\therefore \varphi_x(t)$  should be real-valued.

$$\varphi_x(t) = \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} \cdot \cos tx \cdot e^{-x^2/2} dx$$

$$= \frac{2}{\sqrt{2\pi}} \cdot \int_0^{\infty} \cos tx \cdot e^{-x^2/2} dx.$$

$$\varphi'_x(t) = \frac{-2}{\sqrt{2\pi}} \cdot \int_0^{\infty} \sin tx \cdot x e^{-x^2/2} dx \quad \left[ * \int x e^{-x^2/2} dx = e^{-x^2/2} \right]$$

$$\begin{aligned} \text{Int. by parts.} &= \frac{-2}{\sqrt{2\pi}} \cdot \left[ \left( \sin tx (-e^{-x^2/2}) \right) \Big|_{x=0}^{x=\infty} + t \int_0^{\infty} \cos tx \cdot e^{-x^2/2} dx \right] \end{aligned}$$

$$\therefore \varphi'_x(t) = -t \cdot \varphi_x(t), \quad \varphi_x(0) = 1.$$

→ a simple differential eqn.

Soln:  $\boxed{\varphi_x(t) = e^{-t^2/2}}$

$$f \text{ density of } N(0, 1)$$

$$\hat{f}(t) = \sqrt{2\pi} \cdot f(t).$$

$\therefore$  for  $X \sim N(\mu, \sigma^2)$

$$\varphi_X(t) = e^{i\mu t} \cdot e^{-\sigma^2 t^2/2}.$$

Characteristic  $f^n$   $\xleftarrow[\text{correspondance}]{1-1}$  distribution.

Inversion formula:

Let  $\varphi_X$  be the characteristic function of  $X$  &  
 $F_X$  be the CDF.

then, for any  $a < b$  in  $\mathbb{R}$ ,

$$P(a < X < b) + \frac{1}{2} (P(X=a) + P(X=b)) =$$

$$\frac{1}{2\pi} \cdot \lim_{T \rightarrow \infty} \int_{-\infty}^{\infty} \frac{e^{ita} - e^{itb}}{it} \cdot \varphi_X(t) dt.$$

In particular, for  $a, b \in C(F_X)$ ,  $F(b) - F(a) =$   
 $\downarrow$   
set of all  
continuity  
pts. of cdf of  $X$ .

\* fact to recall from Sem - 2:

Suppose, let  $X, Y$  - independent r.v.s.  
 $Y$  has a density  $f$ .

$X$  has a density  $f$ .

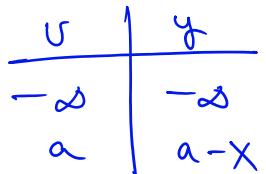
then,  $P(X+Y \leq a) = E(g(X))$ , where  $g(x) = P(Y \leq a-x)$

$$= \int_{-\infty}^{a-x} f(y) dy.$$

$= \int_{-\infty}^{a-x} f(y) dy$

↓ change of variable:

call  $v = y + x$ .



$$= E \left( \int_{-\infty}^a f(v-x) \cdot dv \right)$$

$$= \int_{-\infty}^a E(f(v-x)) \cdot dv$$

$\therefore X, Y$  - ind. rvs,

$Y$  has density  $f$ .

$\Rightarrow$

$X+Y$  has a density  $g$   
given by  $g(v) = E(f(v-x))$ .

Now, Feller's way of proving:

C.F  $\longleftrightarrow$  CDF  
1-1 correspondance.

Let  $X$  have a C.F  $\varphi_X$ .

$$\frac{1}{\sqrt{2\pi n}} \int_{\mathbb{R}} e^{-itv} \varphi_X(v) e^{-v^2/2n} \cdot dv, \quad t \in \mathbb{R}.$$

some real.

$$= \frac{1}{\sqrt{2\pi n}} \cdot \int_{\mathbb{R}} e^{-itv} \cdot E(e^{itv}) \cdot e^{-v^2/2n} dv$$

$$= \frac{1}{\sqrt{2\pi n}} \cdot \int_{\mathbb{R}} E(e^{-iv(t-x)}) \cdot e^{-v^2/2n} \cdot dv$$

$$= E \left( \frac{1}{\sqrt{2\pi n}} \cdot \int_{\mathbb{R}} e^{-iv(t-x)} \cdot e^{-v^2/2n} dv \right)$$

→ C.F. of  $N(0, 1)$  evaluated at  $(t-x)$

$$\sigma^2 = n .$$

$$= E \left( e^{-\frac{n}{2}(t-x)^2} \right)$$

$$= E \left( \frac{\sqrt{n}}{\sqrt{2\pi}\sqrt{n}} \cdot e^{-\frac{n}{2}(t-x)^2} \right)$$

|||

density of  $X + \frac{1}{\sqrt{n}} \cdot Z$ ,

$Z \sim N(0, 1)$

LHS  $\rightarrow$  a crazy integral  
using C.F. of  $X$

RHS  $\rightarrow$  density of  
 $X + \frac{1}{\sqrt{n}} \cdot Z$ .

So now, if

$$\varphi_x = \varphi_y ,$$

then,

$$\Rightarrow X + \frac{1}{\sqrt{n}} Z \xrightarrow{d} Y + \frac{1}{\sqrt{n}} Z .$$

Now, as  $n \rightarrow \infty$ ,  $\frac{1}{\sqrt{n}} \rightarrow 0$ .

∴ By Slutsky,  $\frac{1}{\sqrt{n}} Z \xrightarrow{d} 0$

$$\therefore \boxed{X \xrightarrow{d} Y} .$$

