

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

## Normal Distribution stuff

### Properties of Characteristic Functions

$$(P0) \phi_X(0) = 1 \quad (P2) \phi_{aX+b}(t) = e^{itb} \phi_X(at)$$

$$(P1) \phi_X(t) = \phi_Y(t) \iff X \stackrel{d}{=} Y$$

$$(P3) \text{ If } X_1, X_2 \text{ are i.i.d then } \phi_{X_1+X_2}(t) = (\phi_X(t))^2$$

$$(P4) E[X^n] = \frac{\phi_X^{(n)}(0)}{i^n}$$

$$(P6) \text{ If } \phi_X(t) \in L^1 \Rightarrow f(x) = \frac{1}{2\pi} \int_{\mathbb{R}} e^{-itx} \phi_X(t) dt$$

$$(P8) \lim_{n \rightarrow \infty} \phi_{X_n}(t) = \phi_X(t) \Rightarrow X_n \xrightarrow{d} X$$

$X_1, X_2, \dots, X_n$  are i.i.d

with finite mean  $E[X] = \mu$

with finite variance  $\text{Var}[X] = \sigma^2$

$$\text{let } T_n = X_1 + X_2 + \dots + X_n \Rightarrow \phi_{T_n}(t) = (\phi_X(t))^n \quad (P3)$$

$$\text{let } \bar{X}_n = \frac{X_1 + X_2 + \dots + X_n}{n} = \frac{T_n}{n}$$

$$\Rightarrow \phi_{\bar{X}_n}(t) = \left( \phi_X\left(\frac{t}{n}\right) \right)^n \quad (P2)$$

$$\text{let } Z_n = \frac{\bar{X}_n - \mu}{\sigma/\sqrt{n}} = \frac{\sqrt{n}}{\sigma} \bar{X}_n + \frac{-\sqrt{n}}{\sigma} \mu$$

$$\text{Note } E[\bar{X}] = \mu \quad E[Z_n] = 0$$

$$\text{Var}[\bar{X}] = \frac{\sigma^2}{n} \quad \text{Var}[Z_n] = 1$$

$$\begin{aligned}
 \phi_{Z_n}(t) &\stackrel{(P2)}{=} e^{-it \frac{\sqrt{n}}{\sigma} \mu} \left( \phi_x \left( \frac{\sqrt{n}}{\sigma} \cdot \frac{t}{n} \right) \right)^n \\
 &= e^{\frac{-it\mu}{\sigma\sqrt{n}} \cdot n} \left( \phi_x \left( \frac{t}{\sigma\sqrt{n}} \right) \right)^n \\
 &= e^{\frac{-it\mu}{\sigma\sqrt{n}} n} \ln \left( \phi_x \left( \frac{t}{\sigma\sqrt{n}} \right) \right)^n \\
 &= e^{n \left( \ln \left( \phi_x \left( \frac{t}{\sigma\sqrt{n}} \right) \right) - \frac{itn}{\sigma\sqrt{n}} \right)} \\
 &= e^{\frac{\ln \left( \phi_x \left( \frac{t}{\sigma\sqrt{n}} \right) \right) - \frac{itn}{\sigma\sqrt{n}}}{\frac{1}{n}} \cdot \frac{\frac{t^2}{\sigma^2}}{\frac{t^2}{\sigma^2}}} \\
 &= e^{\frac{t^2}{\sigma^2} \left( \frac{\ln \left( \phi_x \left( \frac{t}{\sigma\sqrt{n}} \right) \right) - \frac{itn}{\sigma\sqrt{n}}}{\frac{t^2}{\sigma^2 n}} \right)} \\
 &= e^{\frac{t^2}{\sigma^2} \left( \frac{\ln \left( \phi_x \left( \frac{t}{\sigma\sqrt{n}} \right) \right) - \frac{itn}{\sigma\sqrt{n}}}{\frac{t^2}{\sigma^2 n}} \right)}
 \end{aligned}$$

$$\ln(a^b) = b \ln(a)$$

$$\exp(x) = e^x$$

Examine  $\lim_{n \rightarrow \infty} \phi_{Z_n}(t)$  with the hope

of it converging so we can get  $Z_n \xrightarrow{d} Z$

Using (P8) and find the densit with (P6)

$$\lim_{n \rightarrow \infty} \phi_{Z_n}(t) = e^{\frac{t^2}{\sigma^2} \left( \frac{\ln \left( \phi_x \left( \frac{t}{\sigma\sqrt{n}} \right) \right) - \frac{itn}{\sigma\sqrt{n}}}{\frac{t^2}{\sigma^2 n}} \right)}$$

$$\text{let } u = \frac{t}{\sigma\sqrt{n}} \quad \text{so as } n \rightarrow \infty, u \rightarrow 0$$

$$= e^{\frac{t^2}{\sigma^2} \lim_{u \rightarrow 0} \frac{\ln(\phi_x(u)) - iu\mu}{u^2}}$$

by L'Hôpital's Rule:

$$= e^{\frac{t^2}{\sigma^2} \lim_{u \rightarrow 0} \frac{\frac{\phi'_x(u)}{\phi_x(u)} - i\mu}{2u}}$$

The  
Gaussian  
Integral

$$\int e^{-\frac{t^2}{2}} dx = \sqrt{2\pi}$$

$$= e^{\frac{t^2}{\sigma^2} \lim_{u \rightarrow 0} \frac{\phi'_x(u)}{\phi_x(u)} - iu \over 2u}$$

by L'Hopital's Rule:

$$= e^{\frac{t^2}{\sigma^2} \lim_{u \rightarrow 0} \frac{\frac{d}{du} [\frac{\phi'_x(u)}{\phi_x(u)}]}{2}}$$

$[\frac{f}{g}]' = \frac{f'g + fg'}{g^2}$   
Quotient Rule

$$= e^{\frac{t^2}{2\sigma^2} \lim_{u \rightarrow 0} \frac{\phi_x(u) \phi''_x(u) - (\phi'_x(u))^2}{(\phi_x(u))^2}}$$

Use  $u = 0$  since doing  $\lim_{u \rightarrow 0}$

$$= e^{\frac{t^2}{2\sigma^2} \left( \frac{\phi_x(0) \phi''_x(0) - (\phi'_x(0))^2}{(\phi_x(0))^2} \right)}$$

by  
(P0)

(P0) says  
 $\phi_x(0) = 1$

$$= e^{\frac{t^2}{2\sigma^2} \left( \frac{(1)(\phi''_x(0)) - (\phi'_x(0))^2}{1^2} \right)}$$

(P4)

$$= e^{\frac{t^2}{2\sigma^2} (\phi''_x(0) - (\phi'_x(0))^2)}$$

$$= e^{\frac{t^2}{2\sigma^2} (i^2 E[X^2] - (i E[X])^2)}$$

$$= e^{\frac{t^2}{2\sigma^2} (i^2 E[X^2] - i^2 (E[X])^2)} = e^{\frac{t^2}{2\sigma^2} i^2 \overbrace{(E[X^2] - (E[X])^2)}^{\text{Var}[X]}}$$

$$= e^{\frac{t^2}{2\sigma^2} (-1) \text{Var}[X]} = e^{-\frac{t^2}{2\sigma^2} \cdot \sigma^2} = e^{-\frac{t^2}{2}} = \phi_Z(t)$$

$\lim_{n \rightarrow \infty} \phi_{Z_n}(t) = \phi_Z(t)$  so...

$$i^2 = -1$$

$$\text{Var}[X] = \sigma^2$$

$$\phi_z(t) = e^{-\frac{t^2}{2}}$$

Is  $\phi_z(t) \in L^1$ ?

$$\int_{\mathbb{R}} |e^{-\frac{t^2}{2}}| dt = \int_{\mathbb{R}} e^{-\frac{t^2}{2}} dt = \sqrt{2\pi} < \infty$$

Gamma

since  $|e^{-\frac{t^2}{2}}| = e^{-\frac{t^2}{2}}$   
since  $e^{-\frac{t^2}{2}} > 0$

$$\int |\phi_z(t)| dt = \sqrt{2\pi} < \infty$$

$$\text{so } \phi_z(t) \in L^1$$

so can use (PG) on  $\phi_z(t) = e^{-\frac{t^2}{2}}$  to get density  
(PDF of Z)

$$\stackrel{(PG)}{\Rightarrow} f_z(z) = \int_{\mathbb{R}} e^{-itz} e^{-\frac{t^2}{2}} dt$$

can use  
(P6)  
since  
 $\phi_2(t) \in L^1$

$$(P6) \Rightarrow f_z(z) = \frac{1}{\pi} \int_{\mathbb{R}} e^{-itz} e^{-\frac{t^2}{2}} dt$$

$$= \frac{1}{2\pi} \int_{\mathbb{R}} e^{-(itz + \frac{t^2}{2})} dt$$

$$\int_{\mathbb{R}} e^{-\frac{t^2}{2}} dt = \sqrt{2\pi}$$

this is Gamma Function  
 $= \sqrt{2\pi} < \infty$  so is  $\in L^1$

completing the square:

$$ax^2 + bx + c \iff d(x+e)^2 + f$$

$$\frac{t^2}{2} + itz = \left( \frac{t}{\sqrt{2}} + \frac{\sqrt{2}iz}{2} \right)^2 - \left( \frac{\sqrt{2}iz}{2} \right)^2$$

$$\frac{t^2}{2} + itz = \left( \frac{t}{\sqrt{2}} + \frac{\sqrt{2}iz}{2} \right)^2 - \left( \frac{2i^2 z^2}{4} \right)$$

$$\frac{t^2}{2} + itz = \left( \frac{t}{\sqrt{2}} + \frac{\sqrt{2}iz}{2} \right)^2 - \left( -\frac{z^2}{2} \right)$$

$$f_z(z) = \frac{1}{2\pi} \int_{\mathbb{R}} e^{-\left( \left( \frac{t}{\sqrt{2}} \right) + \frac{\sqrt{2}iz}{2} \right)^2 - \frac{z^2}{2}} dt$$

$$= \frac{1}{2\pi} \int_{\mathbb{R}} e^{-\left( \left( \frac{t}{\sqrt{2}} \right)^2 + \frac{\sqrt{2}iz}{2} \right)^2 - \frac{z^2}{2}} dt$$

$$= \frac{1}{2\pi} e^{-\frac{z^2}{2}} \int_{\mathbb{R}} e^{-\left( \frac{t}{\sqrt{2}} + \frac{\sqrt{2}iz}{2} \right)^2} dt$$

let  $y = \frac{t}{\sqrt{2}} + \frac{\sqrt{2}iz}{2}$

$$\frac{dy}{dt} = \frac{1}{\sqrt{2}}$$

$$dt = \sqrt{2} dy$$

$$= \frac{1}{2\pi} e^{-\frac{z^2}{2}} \int_{\mathbb{R}} e^{-y^2} \sqrt{2} dy$$

$$= \frac{1}{\sqrt{2}\pi} e^{-\frac{z^2}{2}} \int_{\mathbb{R}} e^{-y^2} dy = \frac{1}{\sqrt{2}\pi} e^{-\frac{z^2}{2}} \sqrt{\pi}$$

$$f_z(z) = \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} = N(0,1)$$



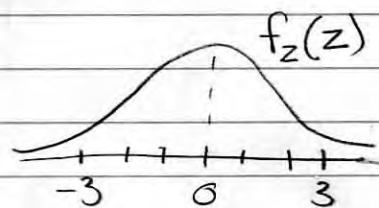
$$f_z(z) = \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} = N(\overset{\mu}{0}, \overset{\sigma^2}{1})$$

Normal

"Standard Normal Distribution"

Central Limit Theorem

$$\frac{\bar{X} - \mu}{\frac{\sigma}{\sqrt{n}}} \xrightarrow{d} N(0, 1)$$



(P4)

$$E[Z] = \frac{\phi'_z(0)}{i} = 0$$

$$\phi_z(t) = e^{-\frac{t^2}{2}}$$

since  $\phi'_z(t) = -t e^{-\frac{t^2}{2}}$

$$\phi'_z(0) = -0 e^{-\frac{0^2}{2}} = 0(1) = 0$$

$$\begin{aligned} \text{Var}[Z] &= E[Z^2] - (E[Z])^2 = E[Z^2] - 0 = E[Z^2] \\ &= E[Z^2] \stackrel{(P4)}{=} \frac{\phi''_z(0)}{i^2} = \frac{-0^2 e^{-\frac{0^2}{2}} - e^{-\frac{0^2}{2}}}{-1} = 1 \end{aligned}$$

$$\text{Var}[Z] = 1$$

since

$$\phi''_z(t) = -(-t^2 e^{-\frac{t^2}{2}} + e^{-\frac{t^2}{2}})$$

If  $Z \sim N(0, 1)$  then  $\phi_z(t) = e^{-\frac{t^2}{2}}$

$$X = \overset{\sigma > 0}{\sigma} Z + \mu \sim \frac{1}{\sigma} f_Z\left(\frac{X - \mu}{\sigma}\right)$$

$$E[X] = \mu$$

$$\overset{\text{PDF}}{f_X(x)} = \frac{1}{\sigma} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2} \left(\frac{x - \mu}{\sigma}\right)^2}$$

$$\text{Var}[X] = \sigma^2$$

$$f_X(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2} (x - \mu)^2}$$

"Normal Distribution"

pdf of "Normal r.v."

$$\phi_X(t) = e^{it\mu} \phi_Z(\sigma t)$$

$$= e^{it\mu} e^{-\frac{\sigma^2 t^2}{2}}$$

remember:

$$\phi_Z(z) = e^{-\frac{z^2}{2}}$$

$$\phi_X(t) = \phi_{\sigma Z + \mu}(t)$$

$$\textcircled{P2} \left( = \phi_{\mu}(t) \phi_Z(\sigma t) \right)$$

$$= e^{it\mu} \phi_Z(\sigma t)$$

$$= e^{it\mu} e^{-\frac{(\sigma t)^2}{2}} = e^{it\mu} e^{-\frac{\sigma^2 t^2}{2}}$$

$\textcircled{P2}$

$$\phi_{ax+b}(t)$$

$$= e^{itb} \phi_X(at)$$

$$\phi_C = e^{itc}$$

constant

Characteristic  
function  
for  
 $X \sim N(\mu, \sigma)$

$$\phi_X(t) = e^{it\mu - \frac{\sigma^2 t^2}{2}} = e^{t\left(\mu - \frac{\sigma^2 t}{2}\right)}$$

## "Normal Density"

If  $X \sim N(\mu, \sigma^2)$  then PDF is  $f_X(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$

$\mu$  is mean

$\sigma^2$  is variance  $\sigma$  is std. dev. (SE)

$X_1 \sim N(\mu_1, \sigma_1^2)$   
 $X_2 \sim N(\mu_2, \sigma_2^2)$   $\rightarrow X_1, X_2$  are indep.

$$T = X_1 + X_2$$

$\leftarrow$  does not work well using convolution formulas, so use

characteristic functions

$$\phi_T(t) = \phi_{X_1+X_2}(t)$$

$$\stackrel{(P2)}{=} \phi_{X_1}(t) + \phi_{X_2}(t)$$

$$= e^{it\mu_1 - \frac{\sigma_1^2 t^2}{2}} \cdot e^{it\mu_2 - \frac{\sigma_2^2 t^2}{2}}$$

$$= e^{it\mu_1 + it\mu_2 - \left(\frac{\sigma_1^2 t^2}{2} + \frac{\sigma_2^2 t^2}{2}\right)}$$

$$= e^{it(\mu_1 + \mu_2) - \frac{(\sigma_1^2 + \sigma_2^2)t^2}{2}}$$

matches  $\phi_X(t)$  for  $X \sim N$   
for  $X \sim N(\mu = \mu_1 + \mu_2, \sigma^2 = \sigma_1^2 + \sigma_2^2)$

(P1)

$$\rightarrow T = X_1 + X_2 \sim N(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2)$$



$X \sim N(\mu, \sigma^2)$ ,  $Y = e^X \sim ?$  Find density (PDF).

$$g(x) = e^x$$

$$g^{-1}(y) = \ln(y)$$

$$X = \ln(y) = g^{-1}$$

$$\frac{d}{dy}[g^{-1}(y)] = \frac{1}{y}$$

$$f_Y(y) = f_X(g^{-1}(y)) \left| \frac{d}{dy}[g^{-1}(y)] \right|$$

$$= \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(\ln(y)-\mu)^2}{2\sigma^2}} \mathbb{1}_{\ln y \in (-\infty, \infty)} \cdot \frac{1}{y}$$

$$= \frac{1}{\sqrt{2\pi\sigma^2}} \cdot \frac{1}{y} e^{-\frac{1}{2\sigma^2}(\ln(y)-\mu)^2} \mathbb{1}_{y \geq 0}$$

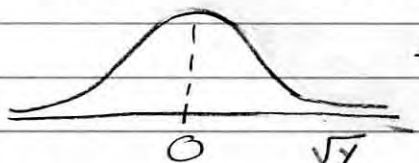
$$= \frac{1}{\sqrt{2\pi\sigma^2 y^2}} e^{-\frac{1}{2\sigma^2}(\ln(y)-\mu)^2} \mathbb{1}_{y \geq 0}$$

this density is called  $\text{LogN}(\mu, \sigma^2)$  dist.  
"Log-Normal"

$$Z \sim N(0,1), \text{ and } Y = Z^2 = g(Z)$$

but now  $g$  is not one-to-one

$$F_Y(y) = P(Y \leq y) = P(Z^2 \leq y) = P(Z \in [-\sqrt{y}, \sqrt{y}])$$



$$f_Z(z) = \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} \leftarrow \begin{array}{l} \text{even function} \\ \text{so symmetric} \\ \text{around } z=0 \end{array}$$

$$\text{so } F_Y(y) = \int_{-\sqrt{y}}^{\sqrt{y}} f_Z(z) dz = 2 \int_0^{\sqrt{y}} f_Z(z) dz$$

$$= 2 \left( \overset{\text{cdf}}{F_Z(\sqrt{y})} - F_Z(0) \right) = 2(F_Z(\sqrt{y}) - 0.5)$$

$$F_Y(y) = 2F_Z(\sqrt{y}) - 1$$

$$\Rightarrow f_Y(y) = 2 \left( \frac{1}{2} y^{-\frac{1}{2}} \right) F_Z(\sqrt{y})$$

$$= y^{-\frac{1}{2}} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(\sqrt{y})^2}$$

$$\propto y^{\frac{1}{2}-1} e^{-\frac{1}{2}y} = y^{\alpha-1} e^{\beta y}$$

$$\propto \text{Gamma}\left(\frac{1}{2}, \frac{1}{2}\right) = \chi^2$$

$\chi^2$  "Chi-Squared distribution  
with 1 degrees of freedom"

$$Z_1, Z_2, \dots, Z_K \stackrel{\text{i.i.d.}}{\sim} N(0, 1)$$

$$X_K = Z_1^2 + Z_2^2 + \dots + Z_K^2 \sim \chi_K^2$$

If

$X_1, X_2, \dots, X_K$

are i.i.d

$\text{Gamma}(\alpha, \beta)$

then

$T = X_1 + X_2 + \dots + X_K$   
is

$\text{Gamma}(K\alpha, \beta)$

defines Chi-squared with  
K degrees of freedom  $\chi_K^2$

$$\chi^2 := \text{Gamma}\left(\frac{K}{2}, \frac{1}{2}\right)$$

pdf

$$f(x) = \frac{1}{2^{K/2} \Gamma(\frac{K}{2})} x^{\frac{K}{2}-1} e^{-\frac{1}{2}x} \mathbb{1}_{x \geq 0}$$

$$\chi_1^2 = \frac{1}{2^{1/2} \Gamma(\frac{1}{2})} x^{-\frac{1}{2}} e^{-\frac{1}{2}x}$$

$$= \frac{1}{\sqrt{2} \sqrt{\pi}} x^{-\frac{1}{2}} e^{-\frac{1}{2}x}$$

$$= \frac{1}{\sqrt{2\pi}} x^{-\frac{1}{2}} e^{-\frac{1}{2}x}$$

Test wed

$$X \sim \chi_K^2$$

$$Y = \sqrt{X} \sim \chi_K = ? \quad \text{find pdf}$$

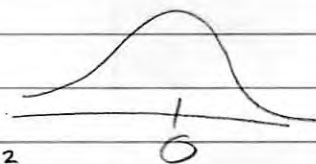
Y is a  
"chi r.v."  
 $\chi$

$$X = Y^2 = g^{-1}(Y)$$

$$f_Y(y) = f_X(y^2) 2y$$

$$= \frac{1}{2^{K/2} \Gamma(K/2)} (y^2)^{\frac{K}{2}-1} e^{-\frac{y^2}{2}} (2y) \mathbb{1}_{y \geq 0}$$

$$= \frac{1}{2^{K/2} \Gamma(K/2)} y^{K-1} e^{-\frac{y^2}{2}} \mathbb{1}_{y \geq 0} = \chi_K$$



$$Z \sim N(0,1) \quad |Z| \sim \underbrace{\frac{1}{\sqrt{2}}}_{\frac{1}{\sqrt{2}}} \underbrace{\frac{1}{\Gamma(\frac{1}{2})}}_{\sqrt{\pi}} e^{-\frac{z^2}{2}} \mathbb{1}_{z \geq 0}$$

$$|Z| = \sqrt{Z^2} = \sqrt{\chi_1^2} = \chi_1$$

$$= Z \left( \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} \mathbb{1}_{z \geq 0} \right)$$



$$z_1, z_2 \stackrel{i.i.d.}{\sim} N(0,1)$$

$$R = \frac{z_1}{z_2} \sim f_R(r) = \int_{\mathbb{R}} f(ru) f(u) |u| du$$

$$\text{Supp}[R] = \mathbb{R}$$

$$= \int_{\mathbb{R}} \frac{1}{\sqrt{2\pi}} e^{-\frac{r^2 u^2}{2}} \frac{1}{\sqrt{2\pi}} e^{-\frac{u^2}{2}} |u| du$$

$$= \frac{1}{2\pi} \int_{\mathbb{R}} e^{-\left(\frac{r^2+1}{2}\right)u^2} |u| du$$

even function  
symmetric around 0

$$= \frac{1}{2\pi} \cdot 2 \int_0^{\infty} e^{-\left(\frac{r^2+1}{2}\right)u^2} u du$$

Cauchy  
dist  
a.k.a.  
Lorenz  
dist.

$$\begin{aligned} \text{Let } t &= u^2 \\ \Rightarrow \frac{dt}{du} &= 2u \\ du &= \frac{1}{2u} dt \end{aligned}$$

$$= \frac{1}{\pi} \int_0^{\infty} e^{-\left(\frac{r^2+1}{2}\right)t} u \cdot \frac{1}{2u} dt$$

$$= \frac{1}{2\pi} \int_0^{\infty} e^{-\left(\frac{r^2+1}{2}\right)t} dt$$

$$\text{let } a = \frac{r^2+1}{2}$$

$$= \frac{1}{2\pi} \int_0^{\infty} e^{-at} dt = \frac{1}{2\pi} \cdot \frac{1}{a}$$

$$= \frac{1}{2\pi} \frac{1}{\frac{r^2+1}{2}} = \frac{1}{\pi} \cdot \frac{1}{r^2+1}$$

defines Cauchy(0,1) "Standard Cauchy"

Cauchy  
has  
no mean,  
no  
moments

$E[X^n]$   
is called  
nth moment