

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

$$\text{Show } Y = cX \sim \text{Gamma}(\alpha, \frac{\beta}{c})$$

$$\text{where } c > 0$$

$$g(x) = cx$$

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

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

$$X \sim f_X(x) = \frac{\beta^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{-\beta x} \mathbb{1}_{x \geq 0}$$

$$f_Y(y) = f_X(g^{-1}(y)) \left| \frac{1}{c} \right|$$

$$f_Y(y) = f_X\left(\frac{y}{c}\right) \frac{1}{c}$$

$$f_Y(y) = \frac{\beta^\alpha}{\Gamma(\alpha)} \left(\frac{y}{c}\right)^{\alpha-1} e^{-\beta\left(\frac{y}{c}\right)} \cdot \frac{1}{c} \mathbb{1}_{\frac{y}{c} \geq 0}$$

$$f_Y(y) = \frac{\beta^\alpha}{\Gamma(\alpha)} \frac{y^{\alpha-1}}{c^{\alpha-1}} e^{-\frac{\beta y}{c}} \cdot \frac{1}{c} \mathbb{1}_{y \geq 0}$$

$$f_Y(y) = \frac{\beta^\alpha}{\Gamma(\alpha)} \frac{y^{\alpha-1} \cdot c}{c^\alpha} e^{-\frac{\beta}{c} y} \cdot \frac{1}{c} \mathbb{1}_{y \geq 0}$$

$$= \frac{\left(\frac{\beta}{c}\right)^\alpha}{\Gamma(\alpha)} y^{\alpha-1} e^{-\frac{\beta}{c} y} \mathbb{1}_{y \geq 0}$$

$$\sim \text{Gamma}(\alpha, \frac{\beta}{c})$$

CLT (central Limit Theorem)

$X_1, X_2, \dots, X_n \stackrel{\text{i.i.d.}}{\sim}$  with  $\mu, \sigma^2$  known

$$\Rightarrow \frac{\bar{X} - \mu}{\frac{\sigma}{\sqrt{n}}} \xrightarrow{d} Z \sim N(0, 1) := \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}}$$

$$X \sim \underset{\substack{\uparrow \\ \sigma > 0}}{\sigma} Z + \mu \sim N(\mu, \sigma^2)$$

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

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

$$Z_i^2 \sim \chi_1^2 := \text{Gamma}\left(\frac{1}{2}, \frac{1}{2}\right)$$

$\uparrow$   
"chi squared - 1 d.f."

$$Z_1^2 + \dots + Z_n^2 \sim \chi_n^2 = \text{Gamma}\left(\frac{n}{2}, \frac{1}{2}\right)$$

$\uparrow$   
"chi squared - n d.f."

d.f.  
degrees  
of  
freedom

so

$$\chi_m^2 + \chi_{n-m}^2 = \chi_n^2$$

$X \sim \chi_K^2$   
 Since: if  $X \sim \text{Gamma}(\alpha, \beta)$  and  $Y = cX$  then  $Y \sim \text{Gamma}(\alpha, \frac{\beta}{c})$   
 so  $Y = \frac{X}{K} \sim \text{Gamma}\left(\frac{K}{2}, \frac{K}{2}\right)$

$X_1 \sim \chi_{K_1}^2$  is indep of  $X_2 \sim \chi_{K_2}^2$

$R = \frac{X_1/K_1}{X_2/K_2} = \frac{U}{V}$

let  $U = \frac{X_1}{K_1} \sim \text{Gamma}\left(\frac{K_1}{2}, \frac{K_1}{2}\right) = \text{Gamma}(a, a)$  Let  $a = \frac{K_1}{2}$

$V = \frac{X_2}{K_2} \sim \text{Gamma}\left(\frac{K_2}{2}, \frac{K_2}{2}\right) = \text{Gamma}(b, b)$  Let  $b = \frac{K_2}{2}$

$R = \frac{U}{V} \sim \int_{\text{Supp}[U]} f_U(rt) f_V(t) \mathbb{1}_{t \in \text{Supp}[V]} |t| dt$

$= \int_0^\infty \left( \frac{a^a}{\Gamma(a)} (rt)^{a-1} e^{-art} \right) \left( \frac{b^b}{\Gamma(b)} t^{b-1} e^{-bt} \right) t dt$

$= \frac{a^a b^b}{\Gamma(a) \Gamma(b)} r^{a-1} \int_0^\infty t^{a+b-1} e^{-(b+ar)t} dt$

$= \frac{a^a b^b}{B(a, b)} r^{a-1} (b+ar)^{-(a+b)} \frac{\Gamma(a+b)}{(b+ar)^{a+b}}$

$= \frac{a^a b^b}{B(a, b)} r^{a-1} \left( b \left( 1 + \frac{a}{b} r \right) \right)^{-(a+b)}$

$= \frac{a^a b^b}{B(a, b)} r^{a-1} \frac{\left( 1 + \frac{a}{b} r \right)^{-(a+b)}}{b^a b^b}$

$= \frac{\left( \frac{a}{b} \right)^a}{B(a, b)} r^{a-1} \left( 1 + \frac{a}{b} r \right)^{-(a+b)}$

randomized  
 experiments  
 invented  
 by  
 Fisher

rand

$$= \frac{\left(\frac{a}{b}\right)^a}{B(a,b)} r^{a-1} \left(1 + \frac{a}{b}r\right)^{-(a+b)}$$

$$= \frac{\left(\frac{K_1}{K_2}\right)^{\frac{K_1}{2}}}{B\left(\frac{K_1}{2}, \frac{K_2}{2}\right)} r^{\frac{K_1}{2}-1} \left(1 + \frac{K_1}{K_2}r\right)^{-\frac{K_1+K_2}{2}} \quad \uparrow_{r=0}$$

$$= F_{K_1, K_2}$$

"F distribution with  $K_1$  and  $K_2$  degrees of freedom"

numerator  
denominator

"Fisher-Snedecor dist."

$Z \sim N(0,1)$  indep. of  $X \sim \chi_K^2$

$$W = \frac{Z}{\sqrt{X/K}} \sim f_W(w) = ?$$

$$W^2 = \frac{Z^2}{X/K} = \frac{Z^2/1}{X/K} \sim \frac{\chi_1^2}{\chi_K^2} \sim F_{1,K}$$

F dist

Note:  $f_W(w) = f_W(-w)$  ← F dist. is symmetric (pdf is even funct.)

← cdf of  $W^2$

$$F_{W^2}(w^2) = P(W \leq w^2) = P(W \in [-w, w])$$

$$= P(-w \leq W \leq w)$$

$$\overset{\text{cdf of } w^2}{F_{w^2}(w^2)} = P(W \in [-w, w]) = \overset{\text{cdf of } w}{F_w(w)} - F_w(-w)$$

$$F_{w^2}(w^2) = F_w(w) - F_w(-w)$$

Take  $\frac{d}{dw}$  of both sides

$$2w f_{w^2}(w^2) = f_w(w) - - f_w(-w)$$

$$2w f_{w^2}(w^2) = 2f_w(w)$$

$$w f_{w^2}(w^2) = f_w(w)$$

$$f_w(w) = w f_{w^2}(w^2)$$

$$f_w(w) = w \frac{\left(\frac{1}{k}\right)^{\frac{1}{2}}}{B\left(\frac{1}{2}, \frac{k}{2}\right)} (w^2)^{\frac{1}{2}-1} \left(1 + \frac{1}{k} w^2\right)^{-\frac{1+k}{2}}$$

Note:  $k_1=1$ ,  $k_2=k$

$$f_w(w) = \cancel{w} w^{-1} \frac{\Gamma\left(\frac{k+1}{2}\right)}{\sqrt{k\pi} \Gamma\left(\frac{k}{2}\right)} \left(1 + \frac{w^2}{k}\right)^{-\frac{k+1}{2}}$$

is called the Student T distribution  
with  $k$  degrees of freedom

got this from

$$\frac{1}{B\left(\frac{1}{2}, \frac{k}{2}\right)} = \frac{\Gamma\left(\frac{k+1}{2}\right)}{\Gamma\left(\frac{1}{2}\right) \Gamma\left(\frac{k}{2}\right)} = \frac{\Gamma\left(\frac{k+1}{2}\right)}{\sqrt{\pi} \Gamma\left(\frac{k}{2}\right)}$$

$$\text{and } (w^2)^{\frac{1}{2}-1} = w^{2 \cdot (-\frac{1}{2})} = w^{-1}$$

William  
Gosset  
came up  
with  
Student's T  
dist.

Note:  $T_1 \stackrel{\text{T-dist, 1 d.f.}}{=} \frac{\Gamma(\frac{1+1}{2})}{\sqrt{\pi} \Gamma(\frac{1}{2})} (1+w^2)^{-1} = \frac{\Gamma(1)}{\sqrt{\pi} \sqrt{\pi}} (1+w^2)^{-1} = \frac{1}{\pi} \frac{1}{1+w^2} = \text{Cauchy}(0,1)$

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

$R = \frac{Z_1}{Z_2} \sim \text{Cauchy}(0,1) \stackrel{\text{PDF}}{:=} \frac{1}{\pi} \frac{1}{r^2+1}$

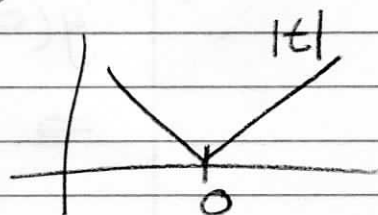
$X = c + \sigma R = \frac{1}{\sigma \pi} \frac{1}{(\frac{r-c}{\sigma})^2 + 1} = \text{Cauchy}(c, \sigma)$   
where  $\sigma > 0$

$\phi_R(t) = E[e^{itR}] = \frac{1}{\pi} \int_{\mathbb{R}} \frac{e^{itr}}{r^2+1} dr = \dots$

by complex analysis, get

$\phi_R(t) = e^{-|t|} = \begin{cases} e^{-t} & \text{if } t \geq 0 \\ e^t & \text{if } t \leq 0 \end{cases}$

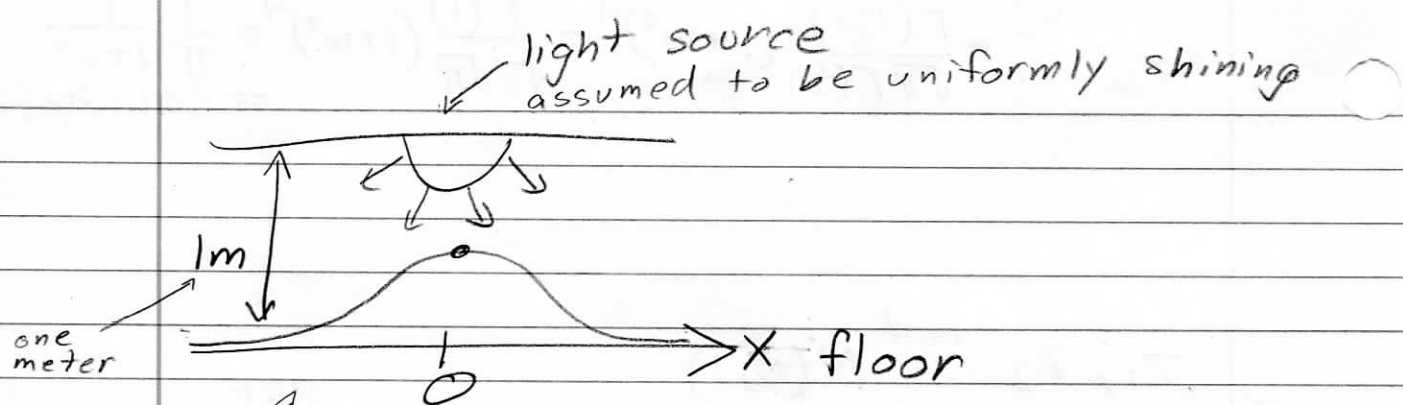
$\phi'_R(t) = \begin{cases} -e^{-t} & \text{if } t > 0 \\ e^t & \text{if } t < 0 \\ \text{undefined} & \text{if } t = 0 \end{cases}$



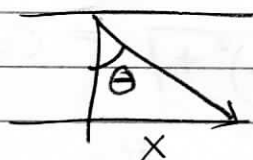
so

$\phi'_R(0)$  undefined  $\Rightarrow E[R]$  is undefined

"Cauchy dist. has no mean"



what is the dist. of light  
brightness on the floor?



$\leftarrow x = \tan \theta$  where

uniform

$$\theta \sim U\left(-\frac{\pi}{2}, \frac{\pi}{2}\right) = \frac{1}{\pi} \mathbb{1}_{\theta \in \left[-\frac{\pi}{2}, \frac{\pi}{2}\right]}$$

$$g(\theta) = \tan \theta = \frac{x}{1} = x$$

$$\Rightarrow \theta = \arctan(x) = g^{-1}(x)$$

Cauchy  
dist.

also  
known  
as  
Lorenz-  
dist.

late 1800s

$$g^{-1}(x) = \tan^{-1}(x)$$

$$\frac{d}{dx} [g^{-1}(x)] = \frac{1}{1+x^2}$$

$$f_x(x) = f_{\theta}(g^{-1}(x)) \left| \frac{d}{dx} [g^{-1}(x)] \right|$$

$$= \frac{1}{\pi} \mathbb{1}_{\arctan(x) \in \left[-\frac{\pi}{2}, \frac{\pi}{2}\right]} \cdot \frac{1}{1+x^2}$$

same as  $x \in [\tan(-\frac{\pi}{2}), \tan(\frac{\pi}{2})]$   
 $x \in (-\infty, \infty)$

$$= \frac{1}{\pi} \frac{1}{1+x^2} = \text{Cauchy}(0, 1)$$



## Applications to Statistics

### Applications of $Z, T, \chi^2, F$ to Statistics

Let  $X_1, X_2, \dots, X_n \stackrel{i.i.d.}{\sim} N(\mu, \sigma^2)$

$$T = X_1 + X_2 + \dots + X_n \sim N(n\mu, n\sigma^2)$$

estimator for  $\mu$   $\bar{X} \sim N(\mu, \frac{\sigma^2}{n})$   $\leftarrow$  estimator is r.v.

$\bar{X}$  is

estimate for  $\mu$

estimate for  $\mu$   $\bar{X} = \frac{1}{n} \sum x_i$   $\leftarrow$  estimate is a specific realization

$\nwarrow$  estimator for  $\sigma^2$

$$S_n^2 = \frac{1}{n-1} \sum (X_i - \bar{X}_n)^2$$

$$s_n^2 = \frac{1}{n-1} \sum (x_i - \bar{x})^2$$

$\nwarrow$  estimate for  $\sigma$

### Want to know

- ①  $S_n^2 \sim ?$  Find dist.
- ② Relationship between  $\bar{X}_n$  and  $S_n^2$



$$Z_1, \dots, Z_n \stackrel{i.i.d.}{\sim} N(0, 1) \quad \text{Let } \vec{Z} = \begin{bmatrix} Z_1 \\ Z_2 \\ \vdots \\ Z_n \end{bmatrix}$$

$$\underbrace{\vec{Z}^T \vec{Z}}_{\text{dot product}} = \sum Z_i^2 \sim \chi_n^2$$

$$\text{Note: } Z_i = \frac{X_i - \mu}{\sigma}$$

$$\Rightarrow \sum_{i=1}^n \left( \frac{X_i - \mu}{\sigma} \right)^2 \sim \chi_n^2$$

$$= \frac{1}{\sigma^2} \sum (X_i - \mu)^2 \quad \begin{array}{l} \text{because} \\ X_i - \mu \\ = X_i - \bar{X} + \bar{X} - \mu \end{array}$$

$$\begin{array}{l} \text{so} \\ (X_i - \mu)^2 \\ = ((X_i - \bar{X}) + (\bar{X} - \mu))^2 \\ = (X_i - \bar{X})^2 + 2(X_i - \bar{X})(\bar{X} - \mu) + (\bar{X} - \mu)^2 \end{array}$$

$$= \frac{1}{\sigma^2} \left( \sum (X_i - \bar{X})^2 + 2 \sum (X_i - \bar{X})(\bar{X} - \mu) + \sum (\bar{X} - \mu)^2 \right)$$

$$\begin{array}{l} \text{notice } \sum (X_i - \bar{X})(\bar{X} - \mu) \\ = \sum X_i \bar{X} - \bar{X}^2 - X_i \mu + \bar{X} \mu \quad \text{using } \sum X_i = n\bar{X} \\ = n\bar{X}^2 - n\bar{X}^2 - n\bar{X}\mu + n\bar{X}\mu \\ = 0 \end{array}$$

$$= \frac{\sum (X_i - \bar{X})^2}{\sigma^2} + \frac{n(\bar{X} - \mu)^2}{\sigma^2} \sim \chi_n^2$$

$$= \frac{(X_i - \bar{X})^2}{\sigma^2} + \left( \frac{\sqrt{n}(\bar{X} - \mu)}{\sigma} \right)^2$$

$$= \frac{(X_i - \bar{X})^2}{\sigma^2} + \left( \frac{\bar{X} - \mu}{\sigma/\sqrt{n}} \right)^2$$

$$= \frac{(n-1)S^2}{\sigma^2} + Z^2$$

Recall  $\bar{X} - \mu \sim N(0, \sigma^2/n)$   
 $\bar{X} \sim N(\mu, \sigma^2/n)$   
 $Z^2$  is same as  $\chi_1^2$

Conjecture

$$\frac{(n-1)S^2}{\sigma^2} \sim \chi_{n-1}^2$$

1) therefore:

$$\sum_{i=1}^n \left( \frac{X_i - \mu}{\sigma} \right)^2 = \frac{(X - \bar{X})^2}{\sigma^2} + \left( \frac{\bar{X} - \mu}{\sigma/\sqrt{n}} \right)^2$$

$X_i$  are r.v.'s  
 $\mu, \sigma$  are constants

using  $S_n^2 = \frac{1}{n-1} \sum (X_i - \bar{X}_n)^2$   
 $\Rightarrow \sum (X_i - \bar{X}_n)^2 = (n-1)S_n^2$

and  $\frac{\bar{X} - \mu}{\sigma/\sqrt{n}} = Z \sim N(0, 1)$   
because  $\bar{X} \sim N(\mu, \sigma^2)$

get that

$$\begin{aligned} \sum_{i=1}^n \left( \frac{X_i - \mu}{\sigma} \right)^2 &= \frac{(n-1)S_n^2}{\sigma^2} + Z^2 \\ &= \frac{(n-1)S_n^2}{\sigma^2} + \chi_1^2 \end{aligned}$$

$S_n^2, Z$  are r.v.'s  
since  $Z^2 = \chi_1^2$   
↑  
chi-squared  
d.f. = 1

Conjecture:

$$\frac{(n-1)S^2}{\sigma^2} \sim \chi_{n-1}^2$$

Using conjecture, get:

$$\begin{aligned} \sum_{i=1}^n \left( \frac{X_i - \mu}{\sigma} \right)^2 &= \chi_{n-1}^2 + \chi_1^2 = \chi_n^2 \end{aligned}$$