

Lec 17 Math 621 11/10/19

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CLT: $X_1, \dots, X_n \stackrel{iid}{\sim} w/\sigma^2 \Rightarrow \frac{\bar{X} - \mu}{\frac{\sigma}{\sqrt{n}}} \xrightarrow{d} N(0,1) = \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}}, X = \sigma Z + \mu \sim N(\mu, \sigma^2)$
 $Z_1, \dots, Z_n \stackrel{iid}{\sim} N(0,1)$
 $Z_1^2 + \dots + Z_n^2 \sim \chi_n^2 = \text{Gamma}(\frac{n}{2}, \frac{1}{2}), R = \frac{Z_1}{Z_2} \sim \text{Cauchy}(0,1) = \frac{1}{\pi} \frac{1}{r^2+1}$

$X_1 \sim \chi_{k_1}^2$ indep of $X_2 \sim \chi_{k_2}^2 \Rightarrow X_1 + X_2 \sim \chi_{k_1+k_2}^2 = \text{Gamma}(\frac{k_1+k_2}{2}, \frac{1}{2})$

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

already proved that we don't conv. of Gamma's.

$Y = cX \sim ?$ where $c > 0$

$f_Y(y) = \frac{1}{c} f_X(\frac{y}{c}) = \frac{1}{c} \frac{\beta^\alpha}{\Gamma(\alpha)} (\frac{y}{c})^{\alpha-1} e^{-\beta \frac{y}{c}}$

$= \frac{1}{c} \frac{\beta^\alpha}{\Gamma(\alpha)} \frac{y^{\alpha-1}}{c^{\alpha-1}} e^{-\frac{\beta}{c} y}$

$= \frac{(\frac{\beta}{c})^\alpha}{\Gamma(\alpha)} y^{\alpha-1} e^{-\frac{\beta}{c} y} = \text{Gamma}(\alpha, \frac{\beta}{c})$

If $X \sim \chi_k^2 = \text{Gamma}(\frac{k}{2}, \frac{1}{2})$

$Y = \frac{X}{k} \sim \text{Gamma}(\frac{k}{2}, \frac{k}{2})$

Let $X_1 \sim \chi_{k_1}^2$ ind. of $X_2 \sim \chi_{k_2}^2 \Rightarrow U = \frac{X_1}{k_1} \sim \text{Gamma}(\frac{k_1}{2}, \frac{k_1}{2})$, let $a := \frac{k_1}{2}$

let $V = \frac{X_2/k_2}{X_1/k_1} = \frac{U}{V}$ We've done something similar before...
 $V = \frac{X_2}{k_2} \sim \text{Gamma}(\frac{k_2}{2}, \frac{k_2}{2})$, let $b := \frac{k_2}{2}$

this looks like from a previous lecture

$Y \sim \int_0^\infty t |t| f_U(rt) f_V(t) dt = \int_0^\infty t \frac{a^a}{\Gamma(a)} (rt)^{a-1} e^{-art} \frac{b^b}{\Gamma(b)} t^{b-1} e^{-bt} dt$ $\uparrow t \in (0, \infty)$

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

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

$$\Rightarrow \frac{X_1/k_1}{X_2/k_2} \sim \frac{\left(\frac{k_1}{k_2}\right)^{\frac{k_1}{2}}}{\Gamma\left(\frac{k_1}{2}, \frac{k_2}{2}\right)} r^{\frac{k_1}{2}-1} \left(1 + \frac{k_1}{k_2}r\right)^{-\left(\frac{k_1+k_2}{2}\right)} \quad \mathbb{1}_{r \geq 0} = F(k_1, k_2)$$

Param Space

$$k_1, k_2 \in \mathbb{N}$$

the 'F-distribution' or 'Fisher-Snedecor' distr. this distr. comes up a lot, esp. in linear regression.

let $Z \sim N(0,1)$ indep of $X \sim \chi^2_k$. let $w = \frac{Z^2}{\frac{X}{k}} \sim T_k = ?$ Gaussian's T-distr. with k d.f.

First note that $W^2 = \frac{Z^2/1}{\frac{X}{k}} \sim F(1, k)$ since $Z^2 \sim \chi^2_1$ indep $X \sim \chi^2_k$

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

Take d/dw of both sides

$$\begin{aligned} \frac{d}{dw} f_{W^2}(w^2) &= f_W(w) - f_W(-w) = 2f_W(w) \Rightarrow f_W(w) = \frac{1}{2} f_{W^2}(w^2) \\ &= \frac{1}{2} \frac{\left(\frac{1}{k}\right)^{\frac{k}{2}}}{\Gamma\left(\frac{k}{2}\right)} (w^2)^{\frac{k}{2}-1} \left(1 + \frac{w^2}{k}\right)^{-\left(\frac{k+1}{2}\right)} = \frac{\Gamma\left(\frac{k+1}{2}\right)}{\sqrt{k} \Gamma\left(\frac{k}{2}\right) \Gamma\left(\frac{k}{2}\right)} \left(1 + \frac{w^2}{k}\right)^{-\left(\frac{k+1}{2}\right)} \end{aligned}$$

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

On the way, you will prove this differently...

HW...

$$\lim_{k \rightarrow \infty} T_k = N(0,1)$$

$$\text{Supp}(R) = \mathbb{R}$$

$$Z_1, Z_2 \stackrel{iid}{\sim} N(0,1), R = \frac{Z_1}{Z_2} \sim \int_{\mathbb{R}} f(u) f(u) |u| du = \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{r^2 u^2}{2}} \frac{1}{\sqrt{2\pi}} e^{-\frac{u^2}{2}} |u| du$$

$$= \frac{1}{2\pi} \left(\int_0^{\infty} e^{-\left(\frac{1+r^2}{2}\right) u^2} u du + \int_{-\infty}^0 e^{-\left(\frac{1+r^2}{2}\right) u^2} u du \right) = \frac{1}{\pi} \int_0^{\infty} e^{-\left(\frac{1+r^2}{2}\right) u^2} u du$$

let $t = u^2 \Rightarrow \frac{dt}{du} = 2u \Rightarrow du = \frac{1}{2} \frac{1}{u} dt$, $u=0 \Rightarrow t=0$, $u=\infty \Rightarrow t=\infty$

$$= \frac{1}{\pi} \int_0^{\infty} e^{-\left(\frac{1+r^2}{2}\right) t} \frac{1}{2} \frac{1}{u} du = \frac{1}{2\pi} \frac{1}{\left(\frac{1+r^2}{2}\right)} = \frac{1}{\pi} \frac{1}{1+r^2} = \text{Cauchy}(0,1)$$

st $\sigma > 0$

$$X = \sigma R + c \sim \text{Cauchy}(c, \sigma) = \frac{1}{\sigma \pi} \frac{1}{1 + \left(\frac{r-c}{\sigma}\right)^2} \quad \text{HW}$$

Note $\text{Cauchy}(0,1) = T_1 = \frac{\left[\frac{(1+1)}{2}\right]}{\sqrt{(1)\pi} \left[\frac{(1)}{2}\right]} \left(1 + \frac{r^2}{1}\right)^{-\frac{(1+1)}{2}} = \frac{1}{\pi} \frac{1}{1+r^2}$ why?

$$\frac{Z_1}{Z_2} \stackrel{?}{=} \frac{Z_1}{\sqrt{Z_1^2 + Z_2^2}}$$

modulo a random sign but it doesn't matter...

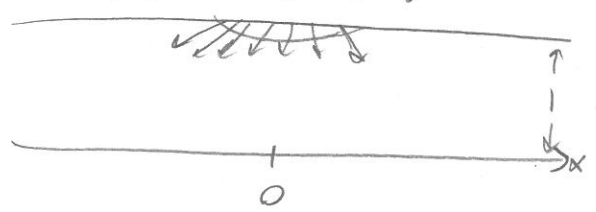
$$E[R] = \int_{\mathbb{R}} r \frac{1}{\pi} \frac{1}{1+r^2} dr = \infty. \text{ No expectation!}$$

$$M_R(t) = \int_{\mathbb{R}} e^{tr} \frac{1}{\pi} \frac{1}{1+r^2} dr = \infty \text{ No MGF! (HW)}$$

$$\phi_R(b) = \int_{\mathbb{R}} e^{itb} \frac{1}{\pi} \frac{1}{1+r^2} dr = \text{complex analysis} = e^{-|t|} \quad \phi'_R(b) = -\frac{\pm}{|t|} e^{-|t|}$$

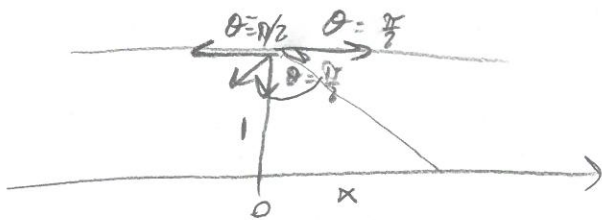
$\phi'_R(0)$ not defined $\Rightarrow E(R)$ d.n.e.

A physical interpretation:



Imagine a light at height = 1 shining randomly $U(-\frac{\pi}{2}, \frac{\pi}{2})$. What is the density of the

brightness on the ground below (x) if the light is being over $x=0$?



$$f_{\theta}(\theta) = \frac{1}{\pi} \mathbb{1}_{\theta \in (-\frac{\pi}{2}, \frac{\pi}{2})} \quad (4)$$

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

This is 1:1 if $\theta \in [-\frac{\pi}{2}, \frac{\pi}{2}]$ which it is in our case here.

$$f_x(x) = f_{\theta}(g^{-1}(x)) \left| \frac{d}{dx}(g^{-1}(x)) \right| = \frac{1}{\pi} \mathbb{1}_{\arctan(x) \in [-\frac{\pi}{2}, \frac{\pi}{2}]} \frac{1}{1+x^2} = \frac{1}{\pi} \frac{1}{1+x^2} = \text{Cauchy}(0,1)$$

$x \in \mathbb{R}$

We have all the tools to prove everything if an intro stats course!

$X_1, \dots, X_n \stackrel{iid}{\sim}$ something. \bar{X} estimates μ since $E(\bar{X}) = \mu$, $S^2 := \frac{1}{n-1} \sum (X_i - \bar{X})^2$ estimates σ^2 as $E(S^2) = \sigma^2$

Let $X_1, \dots, X_n \stackrel{iid}{\sim} N(\mu, \sigma^2) \Rightarrow T_n \sim N(\mu, \sigma^2/n)$ proven using ch.f.'s

Applications to Statistics: $\Rightarrow \bar{X}_n \sim N(\mu, \frac{\sigma^2}{n})$ because you scale T_n by $\frac{1}{n}$ (also proven using ch.f.'s)

$$S_n^2 = \frac{1}{n-1} \left((X_1 - \bar{X})^2 + (X_2 - \bar{X})^2 + \dots + (X_n - \bar{X})^2 \right) \sim ?$$

Let's begin with something easier...

$$Z_1, \dots, Z_n \stackrel{iid}{\sim} N(0,1) \quad \sum_{i=1}^n Z_i^2 \sim \chi_n^2 \quad \text{let } \vec{Z} = \begin{pmatrix} Z_1 \\ \vdots \\ Z_n \end{pmatrix} \Rightarrow \vec{Z}^T \vec{Z} \sim \chi_n^2$$

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

$$\begin{aligned} \text{Note, } X_i - \mu &= X_i - \bar{X} + \bar{X} - \mu \Rightarrow (X_i - \mu)^2 = (X_i - \bar{X} + \bar{X} - \mu)^2 = (X_i - \bar{X})^2 + 2(X_i - \bar{X})(\bar{X} - \mu) + (\bar{X} - \mu)^2 \\ \sum (X_i - \mu)^2 &= \sum (X_i - \bar{X})^2 + 2 \left(\sum X_i \bar{X} + \sum \bar{X}^2 - \sum X_i \mu + \sum \bar{X} \mu \right) + \sum (\bar{X} - \mu)^2 \\ &= \sum (X_i - \bar{X})^2 + 2 \left(n \bar{X}^2 - n \bar{X}^2 - n \bar{X} \mu + n \bar{X} \mu \right) + n (\bar{X} - \mu)^2 \\ &= \sum (X_i - \bar{X})^2 + n (\bar{X} - \mu)^2 \Rightarrow \frac{\sum (X_i - \mu)^2}{\sigma^2} = \frac{\sum (X_i - \bar{X})^2}{\sigma^2} + \frac{n (\bar{X} - \mu)^2}{\sigma^2} \sim \chi_{n-1}^2 + \chi_1^2 \sim \chi_n^2 \end{aligned}$$