

Lec 16 Prob 241 11/2/17

Final π
Midterm 2 \downarrow

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$$X \sim N(0,1) := \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}, \quad \phi_X(t) = e^{-\frac{t^2}{2}}$$

$$E(X) = 0, SE(X) = 1 \quad \text{why?}$$

Recall proof of
Central Limit Thm.

$$\lim_{n \rightarrow \infty} Z_n \stackrel{d}{=} X \quad \text{where } Z_n = \frac{\bar{X} - \mu}{\frac{\sigma}{\sqrt{n}}}$$

$$E(Z_n) = 0, SE(Z_n) = 1 \quad \forall n$$

CLT
option

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

$$\textcircled{1} \sum_{i=1}^n X_i \stackrel{d}{\sim} N(n\mu, n\sigma^2) \quad \text{if } n \text{ large enough}$$

$$\textcircled{2} \bar{X} \stackrel{d}{\sim} N(\mu, \frac{\sigma^2}{n})$$

let $Y = \mu + \sigma X$ assume $\sigma \in (0, \infty)$

$$f_Y(y) = \underbrace{\frac{1}{|\sigma|}}_{\uparrow \sigma} f_X\left(\frac{y-\mu}{\sigma}\right) = \frac{1}{\sigma} \frac{1}{\sqrt{2\pi}} e^{-\frac{\left(\frac{y-\mu}{\sigma}\right)^2}{2}} = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2\sigma^2}(y-\mu)^2}$$

$$= N(\mu, \sigma^2)$$

general Normal r.v.

$$E(Y) = \mu + \sigma E(X) = \mu$$

$$SE(Y) = \underbrace{|\sigma|}_{\sigma} SE(X) = \underbrace{\sigma}_{1}$$

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

$X_1 \sim N(\mu_1, \sigma_1^2)$ ind. of $X_2 \sim N(\mu_2, \sigma_2^2)$, $Y = X_1 + X_2 \sim ?$

$$\begin{aligned}\phi_Y(t) &= \phi_{X_1}(t) \phi_{X_2}(t) = e^{it\mu_1 - \frac{\sigma_1^2 t^2}{2}} e^{it\mu_2 - \frac{\sigma_2^2 t^2}{2}} \\ &= e^{it(\mu_1 + \mu_2) - \left(\frac{\sigma_1^2 t^2}{2} + \frac{\sigma_2^2 t^2}{2}\right)} \\ &= e^{it(\mu_1 + \mu_2) - \frac{t^2}{2}(\sigma_1^2 + \sigma_2^2)} \Rightarrow Y \sim N(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2)\end{aligned}$$

$$Y = X_1 + X_2 \sim \int_{X_1} f_{X_1}(x) * \int_{X_2} f_{X_2}(t-x) dx$$

$$= \int_{\mathbb{R}} \frac{1}{\sqrt{2\pi\sigma_1^2}} e^{-\frac{1}{2\sigma_1^2}(x-\mu_1)^2} \frac{1}{\sqrt{2\pi\sigma_2^2}} e^{-\frac{1}{2\sigma_2^2}(t-x-\mu_2)^2} dx$$

↑
No indicator function!

∴ lots of work

$$N(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2)$$

$X \sim N(\mu, \sigma^2)$, $Y = e^X = g(X)$, $g^{-1}(y) = \ln(y) \Rightarrow |g'(y)| = \frac{1}{y}$ $\text{supp}(Y) = (0, \infty)$

$$f_Y(y) = f_X(g^{-1}(y)) \left| \frac{d}{dy} g^{-1}(y) \right| = \frac{1}{\sqrt{2\pi\sigma^2}} \frac{1}{y} e^{-\frac{1}{2\sigma^2}(\ln(y)-\mu)^2} = \text{Log Normal}(\mu, \sigma^2)$$

$X \sim \text{Log N}(\mu, \sigma^2)$, $Y = \ln(X) \sim N(\mu, \sigma^2)$

Change in Y reflects change in X, so if Y change $\sim N(\dots) \Rightarrow$
 X change $\sim \text{Log N}(\dots)$

The LogN dist is really cool. Consider the following

Situation. You have an amount of money/investment Y_0 .

Every time period, Y changes based on a prop. change R_i . $\mu_R = \dots$, $\sigma_R = \dots$

e.g. $Y_1 = Y_0(1+R_1)$ if $R_1 = .30$, $Y_0 = 10 \Rightarrow Y_1 = 13$ i.e. an increase of 30%

$$Y_2 = Y_1(1+R_2) = Y_0(1+R_1)(1+R_2)$$

$$\vdots$$

$$Y_t = Y_0 \prod_{i=1}^t (1+R_i) = Y_0 e^{\ln\left(\prod_{i=1}^t (1+R_i)\right)} = Y_0 e^{\sum_{i=1}^t \ln(1+R_i)}$$

let $X_i = \ln(1+R_i) \Rightarrow Y_t = Y_0 e^{\sum_{i=1}^t X_i}$

if t is large... $X = \sum_{i=1}^t X_i \stackrel{d}{\approx} N(\mu_X, \sigma_X^2)$ by the C.L.T.

$$e^X \approx \text{LogN}(\mu_X, \sigma_X^2) \approx \text{LogN}(\mu_R, \sigma_R^2)$$

What is μ_X ? $R = .3 \quad \ln(1+.03) = .0296 \approx .03!$

$R = -.5 \quad \ln(1+-.05) = -.051 \approx -.05!$

$\ln(1+x) \approx x$ Why? Taylor Series...

$$\ln(1+x) = x - \frac{x^2}{2} + \frac{x^3}{3} - \frac{x^4}{4} + \dots$$

$\Rightarrow \mu_X \approx \mu_R, \sigma_X \approx \sigma_R$

if x is small... these are small!

e.g. Start off with \$1000. Assume Stock market is iid $N(10\%, 10\%^2)$

What is prob after 5 yr you have more than \$1,650?

$Y_t = Y_0 e^X$. We need to scale the LogN!

Assum $a \in (0, \infty)$

$$\begin{aligned}
 X &\sim \text{Log } N, \quad Y = aX \sim \frac{1}{a} f_X\left(\frac{Y}{a}\right) = \frac{1}{a} \frac{1}{\sqrt{2\pi\sigma^2}} \frac{1}{\left(\frac{Y}{a}\right)} e^{-\frac{1}{2\sigma^2} \left(\ln\left(\frac{Y}{a}\right) - \mu\right)^2} \\
 &= \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2} \left(\ln(Y) - (\mu + \ln(a))\right)^2} \\
 &= \text{Log } N(\mu + \ln(a), \sigma^2)
 \end{aligned}$$

$$Y_t = 11000 e^X \quad X \sim N(50\%, 5(10\%)^2), \quad \ln(11000) = 6.91$$

$$\Rightarrow Y_5 \sim \text{Log } N\left(\overset{7.41}{50\% + 6.91}, \overset{.52}{5(10\%)^2}\right)$$

$$P(Y_5 > 1650) = 1 - F_{Y_5}(1650) = 1 - \Phi_{\text{norm}}(1650, 7.41, 0.5) \approx 51.2\%$$

$$Z \sim N(0,1), Y = Z^2 \sim ? \quad \text{Supp}(Y) = [0, \infty]$$

Note: $g(Z)$ is not a 1:1 function

$$\begin{aligned} F_Y(y) &= P(Y \leq y) = P(Z^2 \leq y) = P(Z \in [-\sqrt{y}, \sqrt{y}]) = 2P(Z \in [0, \sqrt{y}]) \\ &= 2 \int_0^{\sqrt{y}} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} dx = 2 \left(\Phi(\sqrt{y}) - \frac{1}{2} \right) = 2\Phi(\sqrt{y}) - 1 \end{aligned}$$

$$\begin{aligned} f_Y(y) &= F'_Y(y) = \frac{d}{dy} [2\Phi(\sqrt{y}) - 1] = 2 \frac{d}{dy} [\Phi(\sqrt{y})] = 2 \cdot \frac{1}{2} y^{-\frac{1}{2}} \Phi'(\sqrt{y}) = \frac{1}{\sqrt{y}} \frac{1}{\sqrt{2\pi}} e^{-\frac{(\sqrt{y})^2}{2}} \\ &= \frac{1}{\sqrt{2\pi y}} e^{-\frac{y}{2}} \sim \chi^2_1 \quad \text{"Chi-Square dist. w/ one d.o.f."} \end{aligned}$$

Recall $\Gamma(x) = \int_0^\infty t^{x-1} e^{-t} dt$, $\Gamma(\frac{1}{2}) = \int_0^\infty t^{-\frac{1}{2}} e^{-t} dt = \int_0^\infty \frac{1}{u} e^{-u^2} 2u du = 2 \int_0^\infty e^{-u^2} du$

$$f_Y(y) = \frac{\left(\frac{1}{2}\right)^{\frac{1}{2}} y^{-\frac{1}{2}} e^{-\frac{y}{2}}}{\Gamma(\frac{1}{2})} = \text{Gamma}\left(\frac{1}{2}, \frac{1}{2}\right)$$

$$\text{let } u = \sqrt{t} \Rightarrow \frac{du}{dt} = \frac{1}{2} \frac{1}{\sqrt{t}} \Rightarrow dt = 2\sqrt{t} du = 2u du$$

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

$$\frac{1}{\sqrt{2}} = \frac{1}{2^{\frac{1}{2}}} = 2^{-\frac{1}{2}} = (2^{-1})^{\frac{1}{2}} = \left(\frac{1}{2}\right)^{\frac{1}{2}}$$

$X_1 \sim \text{Gamma}\left(\frac{1}{2}, \frac{1}{2}\right)$, $X_2 \sim \text{Gamma}\left(\frac{1}{2}, \frac{1}{2}\right)$ when $X_i = Z_i^2$

$$X_1 + X_2 \sim \text{Gamma}\left(1, \frac{1}{2}\right)$$

$$X_1, \dots, X_k \stackrel{\text{i.i.d.}}{\sim} \text{Gamma}\left(\frac{1}{2}, \frac{1}{2}\right) \quad \sum_{i=1}^k X_i \sim \text{Gamma}\left(\frac{k}{2}, \frac{1}{2}\right) = \frac{\left(\frac{1}{2}\right)^{\frac{k}{2}} x^{\frac{k}{2}-1} e^{-\frac{x}{2}}}{\Gamma\left(\frac{k}{2}\right)}$$

Note $\chi^2_2 = \text{Exp}\left(\frac{1}{2}\right)$? Yes... How?

$$= \frac{1}{2^{\frac{k}{2}} \Gamma\left(\frac{k}{2}\right)} x^{\frac{k}{2}-1} e^{-\frac{x}{2}} = \chi^2_k$$

"Chi-Square w/ k degrees of freedom"

Put another way...

$$X_1, \dots, X_k \stackrel{iid}{\sim} N(0,1)$$

$$\sum_{i=1}^k X_i^2 \sim \chi_k^2$$

let $X \sim \chi_k^2$, $Y = \sqrt{X} \sim ?$ $\text{supp}(Y) = (0, \infty)$

$$g^{-1}(y) = y^2 \Rightarrow \frac{d}{dy} [g^{-1}(y)] = 2y$$

$$f_Y(y) = f_X(y^2) 2y = \frac{1}{2^{k/2} \Gamma(k/2)} (y^2)^{\frac{k}{2}-1} e^{-\frac{y^2}{2}} 2y$$

$$= \frac{1}{2^{k/2-1} \Gamma(k/2)} y^{k-1} e^{-\frac{y^2}{2}} \sim \chi_k$$

is precise
↓
Chi with k d.o.f.
↓
boundary will become clear later

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

$$|X| \sim ? \quad \text{well } X^2 \sim \chi_1^2, \quad \sqrt{X^2} \sim \chi_1 = \sqrt{\frac{2}{\pi}} e^{-\frac{x^2}{2}} = 2 \left(\frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} \right)$$

↑
makes sense?

$$X \sim \chi_k^2 \quad \text{let } Y = \frac{X}{k} \sim ?$$

Let's do scales of Gammas. $c \in (0, \infty)$

$$X \sim \text{Gamma}(\alpha, \beta), \quad Y = cX \sim \frac{1}{c} f_X\left(\frac{y}{c}\right) = \frac{\beta^\alpha \left(\frac{y}{c}\right)^{\alpha-1} e^{-\frac{\beta y}{c}}}{c \Gamma(\alpha)}$$

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