

## STAT 536:

Last class :

- Probability integral transform
- Transformation methods
- some properties of gamma dist.

Common transformations :

(1) Gamma dist.

$\alpha \rightarrow$  positive integer,  
 $\beta \rightarrow$  positive number.

if  $U_1, U_2, \dots, U_d \sim U(0, 1)$ .

then

$$Y = -\beta \sum_{j=1}^d \log(U_j)$$

$\sim Ga(\alpha, \beta)$

Recall

$$U \sim U(0, 1)$$

$$(1-U) \sim U(0, 1)$$

2) chi-sq dist:

$v \rightarrow \text{integer}(+)$

$$\text{if } \underbrace{U_1, U_2, \dots, U_{\alpha}}_{v} \sim U(0, 1).$$

$$\text{then } Y = -2 \sum_{j=1}^v \log(U_j) \\ \sim \chi^2_{2v}$$

3) Beta distribution  $(a, b)$ .

$a, b \rightarrow (+)$  integers.

$$\leftarrow \underbrace{U_1, U_2, \dots, U_{a+b}}_{;} \sim U(0, 1).$$

$$Y = \frac{\sum_{j=1}^a \log(U_j)}{\sum_{j=1}^{a+b} \log(U_j)} \sim \text{Beta}(a, b).$$

$$\underbrace{\sum_{j=1}^a \log(U_j)}_{\sum_{j=1}^a \log(v_i)} + \underbrace{\sum_{j=a+1}^{a+b} \log(U_j)}_{\sum_{j=a+1}^b \log(v_i)}$$

$$\underbrace{\sum_{j=1}^a \log v_i}_{\sim} + \underbrace{\sum_{j=a+1}^b \log v_i}_{\sim}$$

Generating normal r.v.'s :

Box Muller transformation :

Th: Suppose  $U_1$  and  $U_2$  are

independent  $U(0,1)$  r.v.'s

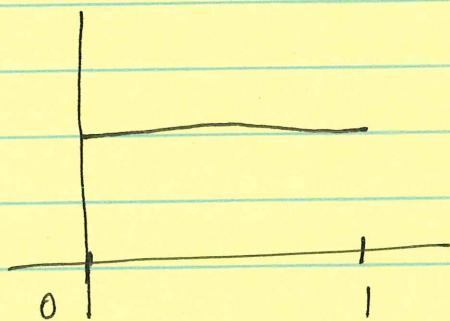
$$\text{Let } X_1 = \sqrt{-2 \log U_1} \cos(2\pi U_2)$$

$$X_2 = \sqrt{-2 \log U_1} \sin(2\pi U_2).$$

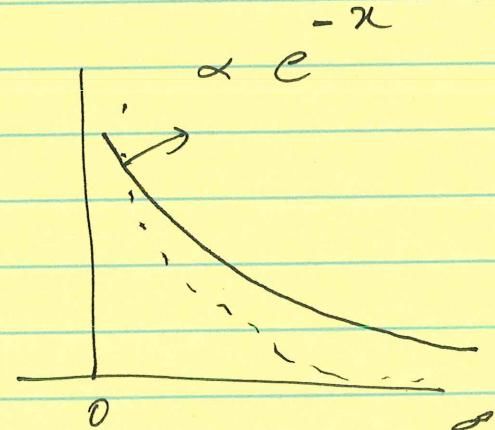
then  $(X_1, X_2)$  are independent r.v.'s.

with standard normal distribution.

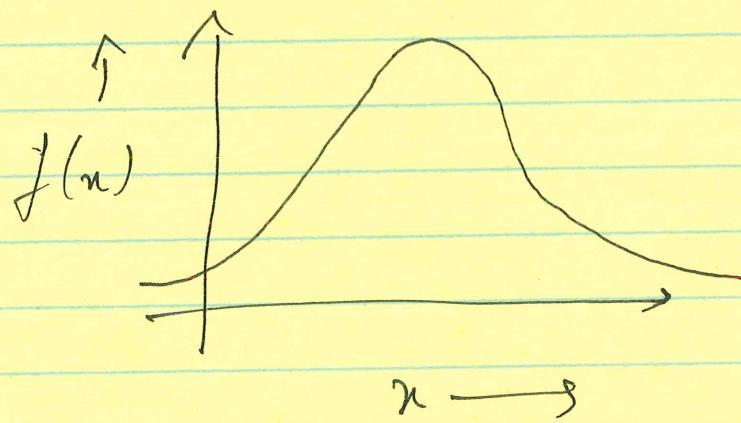
Intuition :



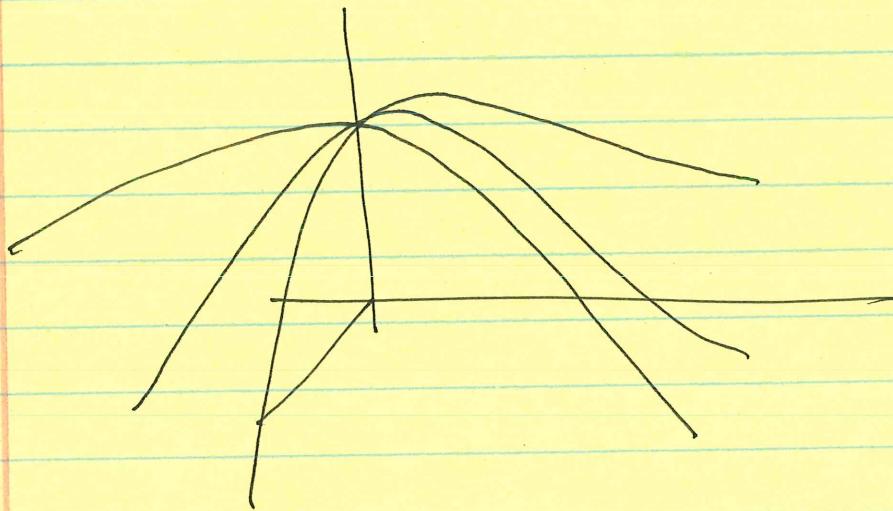
$\xrightarrow{\log}$



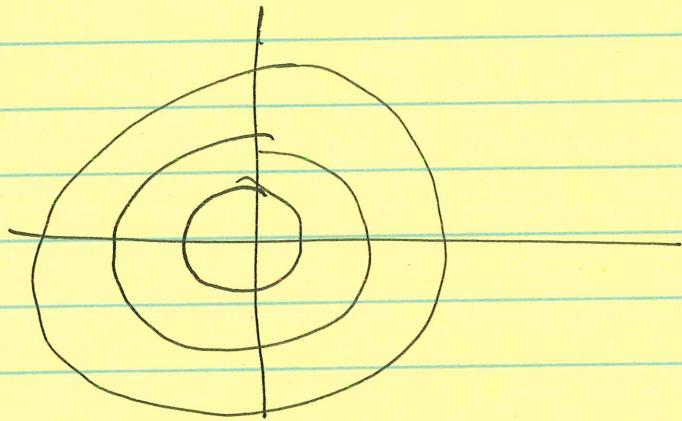
Normal dist (1d)  $N(0, 1)$ .



(2d) :  $N_2(0, I_{2 \times 2})$



Contour plot (under independent)

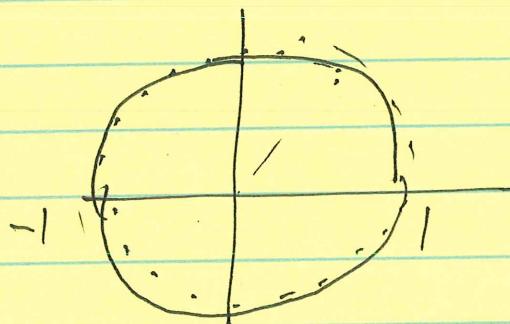


Now,

$$0 < \alpha_1 < \alpha_2 \dots \alpha_n < 1.$$

$$x_i = \log(2\pi\alpha_i) \quad y_i = \sin(2\pi\alpha_i).$$

Plot  $(x_i, y_i)$ .



$$f(u) = \begin{cases} 1 & u \in (0, 1) \\ 0 & \text{otherwise} \end{cases}$$

Proof:  $U_1 \sim U(0, 1)$ ,  $U_2 \sim U(0, 1)$ .  
 $U_1, U_2$  are independent.

$$f_{U_1, U_2}(u_1, u_2) = 1, \quad u_1, u_2 \in (0, 1)$$

Jacobian method: (method that allows us to compute density of a transformed s.v.)

$$f_{X_1, X_2}(x_1, x_2) = |\mathcal{J}| f_{U_1, U_2}\left(g_1^{-1}(x_1, x_2), g_2^{-1}(x_1, x_2)\right)$$

where

$$\rightarrow J = \begin{bmatrix} \frac{\partial u_1}{\partial x_1} & \frac{\partial u_1}{\partial x_2} \\ \frac{\partial u_2}{\partial x_1} & \frac{\partial u_2}{\partial x_2} \end{bmatrix}.$$

$$\text{and } u_1 = g_1^{-1}(x_1, x_2)$$

$$u_2 = g_2^{-1}(x_1, x_2).$$

$$x_1 = \sqrt{-2 \log u_1} \cdot \cos(2\pi v_2)$$

$$x_2 = \sqrt{-2 \log u_1} \cdot \sin(2\pi v_2).$$

$$x_1^2 + x_2^2 = -2 \log u_1$$

$$u_1 = \exp \left[ -\frac{(x_1^2 + x_2^2)}{2} \right]$$

$$x_1^2 = -2 \log u_1 \cos^2(2\pi v_2) \quad x_2^2 = -2 \log u_1 \sin^2(2\pi v_2) \\ = -2 \log u_1 [\cos^2(1) + \sin^2(1)]$$

and

$$\frac{x_2}{x_1} \frac{\cancel{x_2}}{\cancel{x_1}} = \tan(2\pi v_2)$$

$$v_2 = \underbrace{\frac{1}{2\pi} \tan^{-1} \left( \frac{x_2}{x_1} \right)}_{[1]}$$

Upon computing derivatives :

$$J = \begin{bmatrix} -n_1 \exp \left[ -\frac{(n_1^2 + n_2^2)}{2} \right], & -n_2 \exp \left[ \cancel{-\frac{(n_1^2 + n_2^2)}{2}} \right] \\ -\frac{1}{2\pi} \frac{n_2}{n_1^2 + n_2^2}, & \frac{1}{2\pi} \frac{n_1}{n_1^2 + n_2^2} \end{bmatrix}$$

$$|J| = \frac{1}{2\pi} \left( \frac{\pi_1^2 + \pi_2^2}{\pi_1^2 + \pi_2^2} \right) \exp \left[ - \frac{(\pi_1^2 + \pi_2^2)}{2} \right]$$

$$f_{x_1, x_2}(x_1, x_2) = \frac{1}{2\pi} \exp \left[ - \frac{(\pi_1^2 + \pi_2^2)}{2} \right]$$

$$= \frac{1}{\sqrt{2\pi}} \exp \left[ - \frac{x_1^2}{2} \right] \frac{1}{\sqrt{2\pi}} \exp \left[ - \frac{x_2^2}{2} \right]$$

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

→ Joint density of ind. std.

normal r.v.'s.

~~(X)~~

$$Y = \underline{\cancel{f(x)}}$$

↓

use

$$X \sim f(x)$$

$$Y = g(X).$$

use Jacobian

method to compute  
density of Y from

the density of X ( $f(x)$ ).