

Lecture 22

Ex $X \sim \text{Gamma}(\alpha, \lambda)$ $Y \sim \text{Gamma}(\beta, \lambda)$ $X \perp Y$

$$U = X + Y \quad \text{and} \quad V = \frac{X}{X + Y}$$

What's the dist of U and V ?

$$f(u, v) = f_{X, Y}(g_1^{-1}(u, v), g_2^{-1}(u, v)) |\det J|$$

① Get Inverses

$$u = g_1(x, y) = x + y$$

$$v = g_2(x, y) = x / (x + y)$$

$$uv = (x + y) \left(\frac{x}{x + y} \right) = x$$

$$\text{so } \boxed{x = g_1^{-1}(u, v) = uv}$$

$$u - uv = x + y - x = y$$

$$\text{so } y = g_2^{-1}(u, v) = u(1-v)$$

② Get $f_{X,Y}$

Since $X \perp Y$ then

$$f_{X,Y}(x,y) = f_X(x) f_Y(y)$$

$$= \frac{\lambda e^{-\lambda x} (\lambda x)^{\alpha-1}}{\Gamma(\alpha)} \frac{x e^{-xy} (xy)^{\beta-1}}{\Gamma(\beta)}$$

③ Get $|\det J|$

$$J = \begin{bmatrix} \frac{\partial g_1^{-1}}{\partial u} & \frac{\partial g_1^{-1}}{\partial v} \\ \frac{\partial g_2^{-1}}{\partial u} & \frac{\partial g_2^{-1}}{\partial v} \end{bmatrix} = \begin{bmatrix} v & u \\ 1-v & -u \end{bmatrix}$$

$$\begin{aligned} \det J &= (v)(-u) - (u)(1-v) \\ &= -uv - u + uv = -u \end{aligned}$$

$$|\det J| = |-u| = u$$

④ Plug-in

$$f(u,v) = f_{X,Y}(uv, u(1-v)) u$$

$$= \frac{\lambda e^{-\lambda uv} (\lambda uv)^{\alpha-1}}{\Gamma(\alpha)} \frac{\lambda e^{-\lambda u(1-v)} (\lambda u(1-v))^{\beta-1}}{\Gamma(\beta)} u$$

for $u > 0$ and $0 < v < 1$

= ... algebra

$$f(u,v) = \underbrace{\frac{\lambda^{\alpha+\beta}}{\Gamma(\alpha)\Gamma(\beta)}}_{\text{const}} \underbrace{u^{\alpha+\beta-1} e^{-\lambda u}}_{\text{only } u} \underbrace{v^{\alpha-1} (1-v)^{\beta-1}}_{\text{only } v}$$

$u \perp v$

Claim:

$$U \sim \text{Gamma}(\alpha + \beta, \lambda)$$

$$V \sim \text{Beta}(\alpha, \beta)$$

Theorem: Transf. and Independence

If $X \perp Y$ and

$$U = g(X)$$

← no Y

$$V = h(Y)$$

← no X

Then $U \perp V$.

Ex.

$$U = X^2 \text{ and } V = \log Y \dots$$

Ex.

← assume $X, Y > 0$

$$U = XY \text{ and } V = X$$

What's the dist of U and V ?

① Get Inverses

$$u = g_1(x, y) = xy$$

$$v = g_2(x, y) = x \rightarrow x = v = g_1^{-1}(u, v)$$

$$\frac{u}{v} = \frac{xy}{x} = y$$

$$\text{so } y = g_2^{-1}(u, v) = \frac{u}{v}$$

② Get $\det J$

$$J = \begin{bmatrix} \frac{\partial g_1^{-1}}{\partial u} & \frac{\partial g_1^{-1}}{\partial v} \\ \frac{\partial g_2^{-1}}{\partial u} & \frac{\partial g_2^{-1}}{\partial v} \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 1/v & -u/v^2 \end{bmatrix}$$

$$\begin{aligned} \det J &= (0)\left(-\frac{u}{v^2}\right) - \left(\frac{1}{v}\right)(1) \\ &= -1/v \end{aligned}$$

$$|\det J| = 1/v$$

③ Plug-in

$$f(u, v) = f_{X, Y}(v, u/v) \frac{1}{v}$$

Multivariate RVs

If X_1, \dots, X_n are RVs then

$$\underline{X} = \begin{bmatrix} X_1 \\ \vdots \\ X_n \end{bmatrix}$$

is called a multivariate RV or
a random vector.

Defn: PMF/PDF

If the X_i are discrete then the
joint PMF is the function

$$\underline{x} \in \mathbb{R}^n$$

$$f(\underline{x}) = f(x_1, x_2, \dots, x_n)$$

$$= P(X_1 = x_1, X_2 = x_2, \dots, X_n = x_n)$$

If the X_i 's are cts then the joint PDF is the function $f: \mathbb{R}^n \rightarrow \mathbb{R}$ so that for any $A \subset \mathbb{R}^n$

$$P(\underline{X} \in A) = \int_A f(\underline{x}) d\underline{x}$$

$$= \int_A \dots \int f(x_1, \dots, x_n) dx_1 \dots dx_n$$

Expectation: If $g: \mathbb{R}^n \rightarrow \mathbb{R}$ then discrete

$$E[g(\underline{X})] = \begin{cases} \sum_{x_1} \sum_{x_2} \dots \sum_{x_n} g(x_1, \dots, x_n) f(x_1, \dots, x_n) \\ \int \dots \int_{\mathbb{R}^n} g(x_1, \dots, x_n) f(x_1, \dots, x_n) dx_1 \dots dx_n \end{cases}$$

Defn: Marginal Dist

Discrete:

$$f(x_i) = \sum_{x_1} \sum_{x_2} \dots \sum_{x_{i-1}} \sum_{x_{i+1}} \dots \sum_{x_n} f(x_1, \dots, x_n)$$

skipped i

Cts:

$$f(x_i) = \int \dots \int f(x_1, \dots, x_n) dx_1 \dots dx_{i-1} dx_{i+1} \dots dx_n$$

We can get the marginal dist of
any seq

$$x_{i_1}, x_{i_2}, \dots, x_{i_m}$$

by summing/integrating out the other
Vars.

Ex.

$$f(x_2, x_4) = \int \dots \int f(x_1, \dots, x_n) dx_1 dx_3 dx_5 \dots dx_n$$

Defn: Conditional Dist

If I have two sets of vars:

X_1, \dots, X_n and Y_1, \dots, Y_m

the conditional of the X s given the Y s is:

$$f(\underline{x} | \underline{y}) = f(x_1, \dots, x_n | y_1, \dots, y_m)$$

$$= \frac{f(x_1, \dots, x_n, y_1, \dots, y_m)}{f(y_1, \dots, y_m)}$$

Ex. X_1, \dots, X_4 have the dist (PDF)

$$f(x_1, \dots, x_4) = \frac{3}{4} (x_1^2 + x_2^2 + x_3^2 + x_4^2)$$

for $0 < x_i < 1$.

$$a) P(X_1 < \frac{1}{2}, X_2 < \frac{3}{4}, X_4 > \frac{1}{2})$$

$$= \int_{\frac{1}{2}}^1 \int_0^1 \int_0^{\frac{3}{4}} \int_0^{\frac{1}{2}} \frac{3}{4} (x_1^2 + x_2^2 + x_3^2 + x_4^2) dx_1 dx_2 dx_3 dx_4$$

$$= \dots$$

$$= \frac{3}{256}$$

b) what's the dist of X_1 and X_2 ?

$$\underline{f(x_1, x_2)} = \iint f(x_1, \dots, x_4) dx_3 dx_4$$

$$= \int_0^1 \int_0^1 \frac{3}{4} (x_1^2 + x_2^2 + x_3^2 + x_4^2) dx_3 dx_4$$

$$= \dots$$

$$= \frac{1}{2} + \frac{3}{4} (x_1^2 + x_2^2)$$

$$\underline{\hspace{10cm}}$$

(c)

$$E[X_1 X_2] \quad g(x_1, \dots, x_4)$$

$$\begin{aligned} \textcircled{1} &= \int \dots \int x_1 x_2 f(x_1, \dots, x_4) dx_1 \dots dx_4 \\ &= \int_0^1 \int_0^1 \int_0^1 \int_0^1 x_1 x_2 \frac{3}{4} (x_1^2 + x_2^2 + x_3^2 + x_4^2) dx_1 \dots dx_4 \end{aligned}$$

$$\begin{aligned} \textcircled{2} &= \iint x_1 x_2 f(x_1, x_2) dx_1 dx_2 \\ &= \int_0^1 \int_0^1 x_1 x_2 \left(\frac{1}{2} + \frac{3}{4} (x_1^2 + x_2^2) \right) dx_1 dx_2 \end{aligned}$$

$$= \dots = 5/16$$

(d) Conditional Dist

$$f(x_3, x_4 | x_1, x_2) = \frac{f(x_1, \dots, x_4)}{f(x_1, x_2)}$$

$$= \frac{\frac{3}{4}(x_1^2 + x_2^2 + x_3^2 + x_4^2)}{\frac{1}{2} + \frac{3}{4}(x_1^2 + x_2^2)}$$
