

4.3 Bivariate transformation

- Let (X, Y) be a bivariate Random vector
 $g: \mathbb{R}^2 \rightarrow \mathbb{R}^2$
 $g(x, y) := (g_1(x, y), g_2(x, y)) \in \mathbb{R}^2$

Then $(U, V) := g(X, Y)$ is a Random bivariate vector

$$\forall A \in \mathbb{R}^2 \quad P((U, V) \in A) = P((X, Y) \in g^{-1}(A))$$

Discrete Case

- if (X, Y) is discrete, then so is (U, V)

$$f_{UV}(u, v) = \sum_{\substack{x, y: \\ g_1(x, y) = u \\ g_2(x, y) = v}} f_{XY}(x, y) \quad (*)$$

Example

Let $X \sim \text{Poisson}(\theta)$

$Y \sim \text{Poisson}(\lambda)$

$X \perp\!\!\!\perp Y$

First way

We know

$$\begin{aligned} M_X(t) &= \mathbb{E} e^{tX} \\ &= \sum_{x=0}^{\infty} e^{tx} \frac{e^{-\theta} \theta^x}{x!} \\ &= \sum_{x=0}^{\infty} e^{-\theta} \frac{(e^t)^x}{x!} \\ &= e^{\theta(e^t - 1)} \end{aligned}$$

$$\text{Hence } M_{X+Y}(t) = M_X(t) M_Y(t) \quad (\text{since } X \perp\!\!\!\perp Y)$$

$$\begin{aligned} &= e^{\lambda(e^t - 1)} e^{\theta(e^t - 1)} \\ &= e^{(\lambda + \theta)(e^t - 1)}, \end{aligned}$$

which is the MGF for $\text{Poisson}(\lambda + \theta)$.

Second way

• Write $\begin{pmatrix} u \\ v \end{pmatrix} = g\left(\begin{pmatrix} x \\ y \end{pmatrix}\right) := \begin{pmatrix} x+y \\ y \end{pmatrix}$

Then, for $u \geq v$

•
$$f_{uv}(u, v) = \sum_{\substack{x, y \\ y=v \\ x+y=u}} f_{xy}(x, y)$$

$$= f_{xy}(u-v, v)$$

$$= f_x(u-v) f_y(v)$$

Since $x \perp y$

$$= e^{-\theta} \frac{\theta^{u-v}}{(u-v)!} e^{-\lambda} \frac{\lambda^v}{v!}$$

- Obtain $f_u(u)$ by marginalization:

$$\begin{aligned} f_u(u) &= \sum_v f_{uv}(u,v) \quad , \text{ since } f_{uv}(u,v)=0 \text{ if } v > u \\ &= e^{-(\theta+\lambda)} \sum_{v=0}^u \theta^{u-v} \lambda^v \frac{1}{(u-v)! v!} \\ &= e^{-(\theta+\lambda)} \frac{1}{u!} \underbrace{\sum_{v=0}^u \theta^{u-v} \lambda^v \binom{u}{v}}_{(\theta+\lambda)^u} \\ &= e^{-(\theta+\lambda)} \frac{1}{u!} (\theta+\lambda)^u \quad (\text{binomial formula}) \end{aligned}$$

Hence $U = X+Y \sim \text{Poisson}(\theta+\lambda)$.

Continuous Case

Change of variable formula

Let (X, Y) be a continuous bivariate vector

$$(X, Y) \sim f_{XY}$$

Let $g: \mathbb{R}^2 \rightarrow \mathbb{R}^2$ be a one-to-one mapping
i.e. $g^{-1}(\{u, v\})$ has at most one element.

Define $(U, V) = g(X, Y)$, what is $f_{UV}(u, v)$?

Let $A = \{ (x, y) \mid f_{XY}(x, y) > 0 \}$
support of f_{XY}

and

$$B = g(A) := \{ g(x, y) \mid (x, y) \in A \}$$

$$\text{Write } \begin{pmatrix} u \\ v \end{pmatrix} := g(x, y) := \begin{pmatrix} g_1(x, y) \\ g_2(x, y) \end{pmatrix}$$

which has the inverse function

$$\begin{pmatrix} x \\ y \end{pmatrix} = h(u, v) := g^{-1}(u, v) := \begin{pmatrix} h_1(u, v) \\ h_2(u, v) \end{pmatrix}$$

Then the pdf $f_{uv}(u, v)$ is given by the "change of variable" formula

$$f_{uv}(u, v) = f_{xy}(h_1(u, v), h_2(u, v)) |J|$$

where J is the determinant of the Jacobian matrix

$$\begin{aligned} J &= \begin{vmatrix} \frac{\partial x}{\partial u} & \frac{\partial x}{\partial v} \\ \frac{\partial y}{\partial u} & \frac{\partial y}{\partial v} \end{vmatrix} = \begin{vmatrix} \frac{\partial h_1}{\partial u} & \frac{\partial h_1}{\partial v} \\ \frac{\partial h_2}{\partial u} & \frac{\partial h_2}{\partial v} \end{vmatrix} \\ &= \frac{\partial h_1}{\partial u} \frac{\partial h_2}{\partial v} - \frac{\partial h_1}{\partial v} \frac{\partial h_2}{\partial u} . \end{aligned}$$

Example

$$\begin{aligned} \text{Let } X &\sim N(0,1) \\ Y &\sim N(0,1) \quad , \quad X \perp\!\!\!\perp Y \end{aligned}$$

First way, via MGF

we already proved from Sec 4.2:

$$X+Y \sim N(0,2)$$

$$X-Y \sim N(0,2)$$

Second way, via change of variable formula

$$\text{Let } \begin{cases} U = X+Y \\ V = X-Y \end{cases}$$

$$\text{the mapping } \begin{cases} u = g_1(x,y) := x+y \\ v = g_2(x,y) := x-y \end{cases}$$

is one-to-one, and admits the inverse:

$$\begin{cases} x = h_1(u,v) = \frac{1}{2}(u+v) \\ y = h_2(u,v) = \frac{1}{2}(u-v) \end{cases}$$

The Jacobian of the transformation h :

$$J = \begin{vmatrix} \frac{\partial x}{\partial u} & \frac{\partial x}{\partial v} \\ \frac{\partial y}{\partial u} & \frac{\partial y}{\partial v} \end{vmatrix} = \begin{vmatrix} \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & -\frac{1}{2} \end{vmatrix} = -\frac{1}{4} - \frac{1}{4} = -\frac{1}{2}$$

$$\begin{vmatrix} \frac{\partial x}{\partial u} & \frac{\partial x}{\partial v} \\ \frac{\partial y}{\partial u} & \frac{\partial y}{\partial v} \end{vmatrix} = \begin{vmatrix} 1 & 1 \\ 1 & -1 \end{vmatrix} = -2$$

Hence

$$f_{uv}(u, v) = f_{xy}\left(\frac{1}{2}(u+v), \frac{1}{2}(u-v)\right) \cdot \frac{1}{2}$$

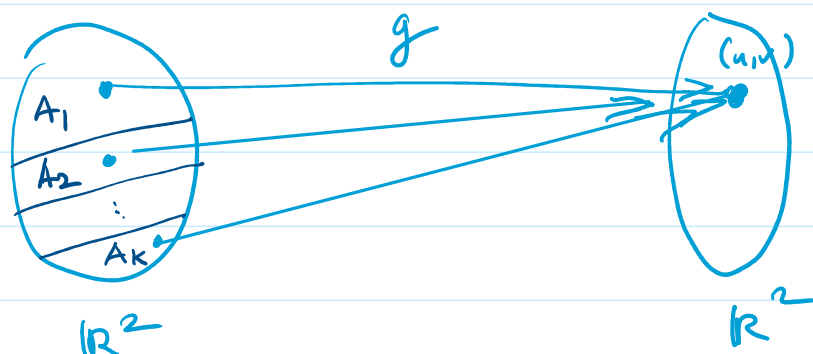
$$\begin{aligned} \times 1 \quad \rightarrow &= f_x\left(\frac{1}{2}(u+v)\right) f_y\left(\frac{1}{2}(u-v)\right) \cdot \frac{1}{2} \\ &= \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{1}{2}(u+v)\right)^2} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{1}{2}(u-v)\right)^2} \cdot \frac{1}{2} \\ &= \frac{1}{\sqrt{2\pi} \sqrt{2}} e^{-\frac{1}{4}u^2} \cdot \frac{1}{\sqrt{2\pi} \sqrt{2}} e^{-\frac{1}{4}v^2} \end{aligned}$$

$f_{uv}(u, v)$ factorizes, so $u \perp v$ and

$$u \sim N(0, 2)$$

$$v \sim N(0, 2).$$

when the transformation $(x,y) \mapsto g(x,y) \in \mathbb{R}^2$
is many-to-one



if we may partition the support of $f_{X,Y}$

$$A = \{ (x,y) \mid f_{X,Y}(x,y) > 0 \}$$

into disjoint subsets

$$A = A_1 \cup \dots \cup A_k$$

such that g is one-to-one from each A_i to $g(A_i)$, $i=1, \dots, k$.

Let $h_i = (h_{i1}, h_{i2})$ be the inverse function of g restricted to domains $A_i \rightarrow g(A_i)$
and J_i be the corresponding Jacobian
Then,

$$f_{U,V}(u,v) = \sum_{i=1}^k f_{X,Y}(h_{i1}(u,v), h_{i2}(u,v)) |J_i|$$

Example.

if $X, Y \sim N(0,1)$, $X \perp Y$
 what is the distribution of $\begin{cases} u = X/Y \\ v = |Y| \end{cases}$?

Note (x, y) and $(-x, -y)$ map to the same (u, v)
 as partition
 $A = \mathbb{R}^2 = \underbrace{\mathbb{R} \times \mathbb{R}_+}_{A_1} \cup \underbrace{\mathbb{R} \times \mathbb{R}_-}_{A_2} \cup \underbrace{\mathbb{R} \times \{0\}}_{A_3}$

if $(x, y) \in A_3$ $f_{X,Y}(x, y) = f_X(x) f_Y(y)$ but (u, v)
 is not defined. Not of concern,
 since $P((X, Y) \in A_3) = 0$.

For A_1 : $\begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} uv \\ v \end{pmatrix}$

$$J_1 = \begin{vmatrix} \frac{\partial x}{\partial u} & \frac{\partial x}{\partial v} \\ \frac{\partial y}{\partial u} & \frac{\partial y}{\partial v} \end{vmatrix} = \begin{vmatrix} v & u \\ 0 & 1 \end{vmatrix} = v$$

For A_2 : $\begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} -uv \\ -v \end{pmatrix} \Rightarrow J_2 = \begin{vmatrix} -v & -u \\ 0 & -1 \end{vmatrix} = v$.

hence

$$f_{uv}(u, v) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(uv)^2} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}v^2} |v| + \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(-uv)^2} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(-v)^2} |v|$$

$$f_{uv}(u,v) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}v^2(u^2+1)} |v| + \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}v^2(u^2+1)} |v|$$

$$= \frac{1}{\pi} e^{-\frac{1}{2}v^2(u^2+1)} v, \quad \text{for } v > 0.$$

$$f_{uv}(u,v) = 0 \quad \forall v < 0. \quad \text{Thus,}$$

$$f_u(u) = \int_0^{\infty} \frac{1}{\pi} e^{-\frac{1}{2}v^2(u^2+1)} v \, dv$$

$$= \frac{1}{\pi(u^2+1)} e^{-\frac{1}{2}v^2(u^2+1)} \Big|_0^{\infty}$$

$$= \frac{1}{\pi(u^2+1)} \quad \text{for all } u \in \mathbb{R}$$

$$\Rightarrow U = X/Y \sim \text{Cauchy}(1).$$