

Multivariate transformations

Multivariate continuous case

The final technique for determining distributions of transformed random variables:
if we transform continuous random variables, using a one-to-one continuously differentiable transformation, we can *directly* find the pdf of the new random variables

Set-up

- Suppose continuous (X_1, \dots, X_n) has joint pdf $f_{X_1, \dots, X_n}(x_1, \dots, x_n)$ with support $\mathcal{A} = \{(x_1, \dots, x_n) : \underline{f_{X_1, \dots, X_n}(x_1, \dots, x_n)} > 0\}$

- Transformation:

$$Y = \begin{pmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{pmatrix}_{n \times 1} \quad Y = u(X) \quad \text{or} \quad \begin{matrix} Y_1 & = & u_1(X_1, \dots, X_n) \\ Y_2 & = & u_2(X_1, \dots, X_n) \\ \vdots & & \vdots \\ Y_n & = & u_n(X_1, \dots, X_n) \end{matrix}$$

$$u(\cdot) = \begin{pmatrix} u_1(\cdot) \\ u_2(\cdot) \\ \vdots \\ u_n(\cdot) \end{pmatrix}_{n \times 1}$$

with \mathcal{B} = support of $\underline{f_{Y_1, \dots, Y_n}(y_1, \dots, y_n)}$

$$\mathcal{B} = \{(y_1, \dots, y_n) : \int_{Y_1, Y_2, \dots, Y_n} (y_1, \dots, y_n) > 0\}$$

- Assume transformation is one-to-one with inverse functions

$$x_i = u_i^{-1}(y_1, \dots, y_n), \quad i = 1, \dots, n$$

- Define the Jacobian

$$J = \det \begin{pmatrix} \frac{\partial x_1}{\partial y_1} & \frac{\partial x_1}{\partial y_2} & \dots & \frac{\partial x_1}{\partial y_n} \\ \frac{\partial x_2}{\partial y_1} & \frac{\partial x_2}{\partial y_2} & \dots & \frac{\partial x_2}{\partial y_n} \\ \vdots & \vdots & \dots & \vdots \\ \frac{\partial x_n}{\partial y_1} & \frac{\partial x_n}{\partial y_2} & \dots & \frac{\partial x_n}{\partial y_n} \end{pmatrix} = \det \begin{pmatrix} \frac{\partial u_1^{-1}(y_1, \dots, y_n)}{\partial y_1} & \frac{\partial u_1^{-1}(y_1, \dots, y_n)}{\partial y_2} & \dots & \frac{\partial u_1^{-1}(y_1, \dots, y_n)}{\partial y_n} \\ \frac{\partial u_2^{-1}(y_1, \dots, y_n)}{\partial y_1} & \frac{\partial u_2^{-1}(y_1, \dots, y_n)}{\partial y_2} & \dots & \frac{\partial u_2^{-1}(y_1, \dots, y_n)}{\partial y_n} \\ \vdots & \vdots & \dots & \vdots \\ \frac{\partial u_n^{-1}(y_1, \dots, y_n)}{\partial y_1} & \frac{\partial u_n^{-1}(y_1, \dots, y_n)}{\partial y_2} & \dots & \frac{\partial u_n^{-1}(y_1, \dots, y_n)}{\partial y_n} \end{pmatrix}$$

number

- If J is continuous and $\underline{J \neq 0}$ over \mathcal{B} (except possibly on a set with probability zero),

$$f_{Y_1, \dots, Y_n}(y_1, \dots, y_n) = f_{X_1, \dots, X_n}(\underline{u}^{-1}(y_1, \dots, y_n)) |J| \quad (y_1, \dots, y_n) \in \mathcal{B}$$

$$= f_{X_1, X_2, \dots, X_n} \left(u_1^{-1}(y_1, \dots, y_n), \dots, u_n^{-1}(y_1, \dots, y_n) \right)$$

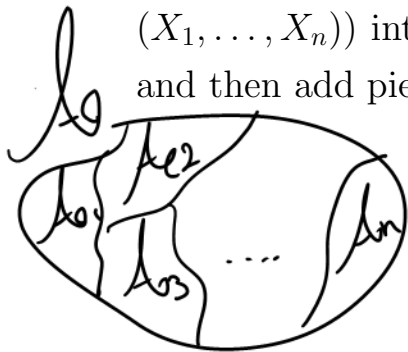
- Often only interested in one transformation $\underline{Y_1 = u_1(X_1, \dots, X_n)}$

Then choose convenient definitions to fill out the transformation

e.g. $Y_2 = X_2, \dots, Y_n = X_n$

need n Variables Y_1, \dots, Y_n from n Variables X_1, \dots, X_n

- If transformation is not one-to-one, then we partition \mathcal{A} (the support of (X_1, \dots, X_n)) into sets \mathcal{A}_i where a transformation $\mathbf{Y} = \mathbf{u}_j(\mathbf{X})$ is one-to-one and then add pieces



$$f_{\mathbf{Y}}(\mathbf{y}) = \sum_{i=1}^k f_{\mathbf{X}}(\mathbf{u}_i^{-1}(\mathbf{y})) |J_i|$$

$(x_1, x_2) \in (0, \infty) \times (0, \infty)$ **Multivariate transformations**

Multivariate continuous case: example 1

- $X_1 \sim \text{Gamma}(\alpha_1, \beta)$ and $X_2 \sim \text{Gamma}(\alpha_2, \beta)$ are independent

$$f_{X_i}(x) = \frac{1}{\Gamma(\alpha_i)\beta^{\alpha_i}} x^{\alpha_i-1} e^{-x/\beta}, \quad x > 0$$

$$f_{X_1, X_2}(x_1, x_2) = f_{X_1}(x_1) f_{X_2}(x_2)$$

$$\begin{aligned} Y_1 &= U_1(X_1, X_2) \\ Y_2 &= U_2(X_1, X_2) \end{aligned}$$

Step 1:

- Transformation: $Y_1 = X_1 + X_2$ and $Y_2 = X_1 / (X_1 + X_2)$

$$\begin{cases} Y_1 = X_1 + X_2 \\ Y_2 = \frac{X_1}{X_1 + X_2} \end{cases} \Rightarrow \begin{cases} X_1 = Y_1 Y_2 \\ X_2 = Y_1 - Y_1 Y_2 \end{cases} \Rightarrow \begin{cases} X_1 = Y_1 Y_2 = u_1^{-1}(Y_1, Y_2) \\ X_2 = Y_1 - Y_1 Y_2 = u_2^{-1}(Y_1, Y_2) \end{cases}$$

- Inverse transformation:

Step 2:

- $\mathcal{A} = (0, \infty) \times (0, \infty)$ while $\mathcal{B} =$

$$\mathcal{B} = \{(y_1, y_2) : f_{Y_1, Y_2}(y_1, y_2) > 0\} = \{(y_1, y_2) \in (0, \infty) \times (0, 1) : f_{X_1, X_2}(y_1 y_2, y_1 - y_1 y_2) > 0\}$$

$$\mathcal{B} = (0, \infty) \times (0, 1)$$

Step 3:

- One-to-one transformation with

$$\begin{cases} X_1 = Y_1 Y_2 \\ X_2 = Y_1 - Y_1 Y_2 \end{cases} \quad J = \det \begin{pmatrix} \frac{\partial X_1}{\partial Y_1} & \frac{\partial X_1}{\partial Y_2} \\ \frac{\partial X_2}{\partial Y_1} & \frac{\partial X_2}{\partial Y_2} \end{pmatrix} = \det \begin{pmatrix} Y_2 & Y_1 \\ 1 - Y_2 & -Y_1 \end{pmatrix}$$

$$= -Y_2 Y_1 - Y_1 (1 - Y_2)$$

$$= -Y_2 Y_1 - Y_1 + Y_1 Y_2 = -Y_1$$

Multivariate transformations

Multivariate continuous case: example 1 (cont'd)

- Joint pdf of Y_1, Y_2

Step 4:

$$\begin{cases} X_1 = Y_1 Y_2 \\ X_2 = Y_1(1 - Y_2) \end{cases} \Rightarrow f_{X_1, X_2}(x_1, x_2) \equiv f_{X_1, X_2}(y_1 y_2, y_1(1 - y_2))$$

$$f_{Y_1, Y_2}(y_1, y_2) = f_{X_1, X_2}(y_1 y_2, y_1(1 - y_2)) |J|$$

X_1 and X_2 are ind.
 $X_1 \sim \text{Gamma}(\alpha_1, \beta)$

$$= \underbrace{f_{X_1}(y_1 y_2)}_{\alpha_1} \times \underbrace{f_{X_2}(y_1(1 - y_2))}_{\alpha_2} \times |J|$$

$$= \frac{(y_1 y_2)^{\alpha_1 - 1} e^{-(y_1 y_2)/\beta}}{\Gamma(\alpha_1) \beta^{\alpha_1}} \times \frac{[y_1(1 - y_2)]^{\alpha_2 - 1} e^{-[y_1(1 - y_2)]/\beta}}{\Gamma(\alpha_2) \beta^{\alpha_2}} \times y_1$$

Note:

$$= \frac{y_1^{\alpha_1 + \alpha_2 - 1} e^{-y_1/\beta}}{\Gamma(\alpha_1 + \alpha_2) \beta^{\alpha_1 + \alpha_2}} \times y_2^{\alpha_1 - 1} (1 - y_2)^{\alpha_2 - 1} \frac{1}{\Gamma(\alpha_1) \Gamma(\alpha_2)} \frac{\Gamma(\alpha_1 + \alpha_2)}{1}$$

① $Y_1 \sim \text{Gamma}(\alpha_1 + \alpha_2, \beta)$

② $Y_2 \sim \text{Beta}(\alpha_1, \alpha_2)$

$\mathcal{B} = \underbrace{(0, \infty)}_{y_1} \times (0, 1)$

③ $f_{Y_1, Y_2}(y_1, y_2) = f_{Y_1}(y_1) f_{Y_2}(y_2)$ Y_1 and Y_2 are independent

Multivariate transformations

Multivariate continuous case: example 2

- $X_1 \sim N(0, 1)$ and $X_2 \sim N(0, 1)$ are independent

- Transformation: $Y_1 = X_1 + X_2$ and $Y_2 = X_2$

Step 1

- Inverse transformation:

$$Y_1 = X_1 + X_2 \implies X_1 = Y_1 - Y_2$$

$$Y_2 = X_2 \implies X_2 = Y_2$$

Step 2

- $\mathcal{A} = (-\infty, \infty) \times (-\infty, \infty)$ while $\mathcal{B} = (-\infty, \infty) \times (-\infty, \infty)$

Step 3:

- One-to-one transformation with

$$J = \det \begin{pmatrix} \frac{\partial X_1}{\partial Y_1} & \frac{\partial X_1}{\partial Y_2} \\ \frac{\partial X_2}{\partial Y_1} & \frac{\partial X_2}{\partial Y_2} \end{pmatrix} = \det \begin{pmatrix} 1 & -1 \\ 0 & 1 \end{pmatrix} = 1 - 0 = 1$$

Multivariate transformations

Multivariate continuous case: example 2 (cont'd)

- Joint pdf of Y_1, Y_2

$$\begin{aligned}
 \underbrace{f_{Y_1, Y_2}(y_1, y_2)} &= f_{X_1, X_2}(\underbrace{y_1 - y_2}_{x_1}, \underbrace{y_2}_{x_2}) \underbrace{|J|}_{=1} = \underbrace{f_{X_1}(y_1 - y_2)} \times \underbrace{f_{X_2}(y_2)} \times 1 \\
 &= \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(y_1 - y_2)^2} \times \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}y_2^2} \\
 &= \frac{1}{2\pi} e^{-\left(\frac{y_1^2}{2} - y_1 y_2 + y_2^2\right)} \\
 &= \frac{1}{2\pi} e^{-\frac{y_1^2}{2}} e^{y_2^2 + 2(y_1/2)y_2}
 \end{aligned}$$

- Marginal distribution of Y_1

$$f_{Y_1}(y_1) = \int_{-\infty}^{\infty} f_{Y_1, Y_2}(y_1, y_2) dy_2 = \frac{1}{\sqrt{2\pi}} e^{-y_1^2/4} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-(y_2 - \frac{y_1}{2})^2} dy_2$$