

- Define the Jacobian

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

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

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

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

Then choose convenient definitions to fill out the transformation

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

- 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

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

Multivariate transformations

Multivariate continuous case: example 1

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

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

- Transformation: $\underline{Y_1 = X_1 + X_2}$ and $\underline{Y_2 = X_1/(X_1 + X_2)}$

Y_1 and Y_2 are functions of X_1 and X_2 .

- Inverse transformation:

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

$$J =$$

Multivariate transformations

Multivariate continuous case: example 1 (cont'd)

- Joint pdf of Y_1, Y_2

$$\begin{aligned} \underline{\underline{f_{Y_1, Y_2}(y_1, y_2)}} &= f_{X_1, X_2}(y_1 y_2, y_1(1-y_2)) |J| \\ &= f_{X_1}(y_1 y_2) \times f_{X_2}(y_1(1-y_2)) \times |J| \\ &= \frac{(y_1 y_2)^{\alpha_1-1} e^{-(y_1 y_2)/\beta}}{\Gamma(\alpha_1) \beta^{\alpha_1}} \times \frac{[y_1(1-y_2)]^{\alpha_2-1} e^{-[y_1(1-y_2)]/\beta}}{\Gamma(\alpha_2) \beta^{\alpha_2}} \times y_1 \end{aligned}$$

$$\begin{aligned} &= \frac{y_1^{\alpha_1+\alpha_2-1} e^{-y_1/\beta}}{\beta^{\alpha_1+\alpha_2}} \times y_2^{\alpha_1-1} (1-y_2)^{\alpha_2-1} \frac{1}{\Gamma(\alpha_1) \Gamma(\alpha_2)} \\ &\quad \xrightarrow{Y_1 \sim \text{Gamma}(\cdot, \cdot)} \quad \xrightarrow{Y_2 \sim \text{Beta}(\cdot, \cdot)} \\ &\Rightarrow Y_1 \text{ and } Y_2 \text{ are independent.} \end{aligned}$$

- (a) X_1 and X_2 are independent
- (b) Y_1 and Y_2 are function of $\begin{cases} Y_1 = h(X_1, X_2) = X_1 + X_2 \\ Y_2 = W(X_1, X_2) = \frac{X_1}{X_1 + X_2} \end{cases}$
 X_1 and X_2
- (c) Y_1 and Y_2 are independent.

Multivariate transformations

Multivariate continuous case: example 2

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



- Transformation: $\underline{Y_1 = \underline{X_1} + \underline{X_2}}$ and $\underline{Y_2 = X_2}$
add

- Inverse transformation:

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

- One-to-one transformation with

$$J =$$

Multivariate transformations

Multivariate continuous case: example 2 (cont'd)

- Joint pdf of Y_1, Y_2

$$\begin{aligned}
 f_{Y_1, Y_2}(y_1, y_2) &= f_{X_1, X_2}(y_1 - y_2, y_2) |J| = f_{X_1}(y_1 - y_2) \times f_{X_2}(y_2) \times 1 \\
 &= \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(y_1-y_2)^2} \times \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}y_2^2} \\
 &= \frac{1}{2\pi} e^{-\left(\frac{y_1^2}{2}-y_1y_2+y_2^2\right)} \\
 &= \left(\frac{1}{2\pi} e^{-\frac{y_1^2}{2}} \right) \left(\frac{1}{2\pi} e^{-\frac{y_2^2}{2}} \right) e^{-(y_1^2 - 2y_1y_2 + y_2^2)/2} e^{-\frac{y_1^2}{4} - \frac{y_2^2}{4}}
 \end{aligned}$$

- (a) X_1 and X_2 are independent
- (b) Y_1 and Y_2 are fractions of X_1 and X_2
- (c) Y_1 and Y_2 are NOT independent

Note: If X_1 and X_2 are independent then $h(X_1)$ and $W(X_2)$ are independent

If X_1 and X_2 are independent then $h(X_1, X_2)$ and $W(X_1, X_2)$ are not independent always.

- Marginal distribution of Y_1

$$\begin{aligned}
 f_{Y_1}(y_1) &= \int_{-\infty}^{\infty} f_{Y_1, Y_2}(y_1, y_2) dy_2 = \frac{1}{\sqrt{2\pi}} e^{-y_1^2/4} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-(y_2 - \frac{y_1}{2})^2} dy_2 \\
 &\stackrel{\text{the density}}{\sim} \frac{1}{\sqrt{2\pi}} e^{-y_1^2/4} \stackrel{\text{of normal } (\frac{y_1}{2}, \frac{1}{2})}{\sim} \stackrel{\text{Variance}}{=} 1
 \end{aligned}$$

Recall: $X \sim N(\mu, \sigma^2)$

$$f_X(x) = \frac{1}{\sqrt{2\pi}\sigma^2} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

$$\mu = \frac{y_1}{2}, \sigma^2 = \frac{1}{2}$$

$$f_{Y_1}(y_1) = \frac{1}{\sqrt{2\pi(\frac{1}{2})^2}} e^{-\frac{(y_2 - \frac{y_1}{2})^2}{2(\frac{1}{2})}} = \frac{1}{\sqrt{2}} \left[\frac{1}{\sqrt{2\pi(\frac{1}{2})}} e^{-\frac{(y_2 - \frac{y_1}{2})^2}{2(\frac{1}{2})}} \right]$$

Multivariate transformations

Multivariate continuous case: example 3 - convolutions

- Previous example (sum of two continuous r.v.s) is often of interest

- $\underbrace{(X_1, X_2)} \sim \underbrace{f_{X_1, X_2}(x_1, x_2)}$

- Transformation: $\underline{S = X_1 + X_2}$ and $\underline{T = X_2}$

- Inverse transformation: $\underline{\underline{X_1 = S - T}}$ and $\underline{\underline{X_2 = T}}$

- one-to-one transformation with

$$\longrightarrow J = \det \begin{pmatrix} 1 & -1 \\ 0 & 1 \end{pmatrix} = 1$$

- Derive pdf of S

$$f_{S,T}(s,t) = \underbrace{f_{X_1, X_2}(s-t, t)}_{x_1 \quad x_2} \quad f_S(s) = \int_{-\infty}^{\infty} \underbrace{f_{X_1, X_2}(s-t, t)}_{\text{pdf}} dt \quad \leftarrow$$

- If X_1, X_2 are independent then

$$f_{X_1} * f_{X_2} \xrightarrow{\text{Convolution}} f_S(s) = \int_{-\infty}^{\infty} f_{X_1}(s-t) f_{X_2}(t) dt$$

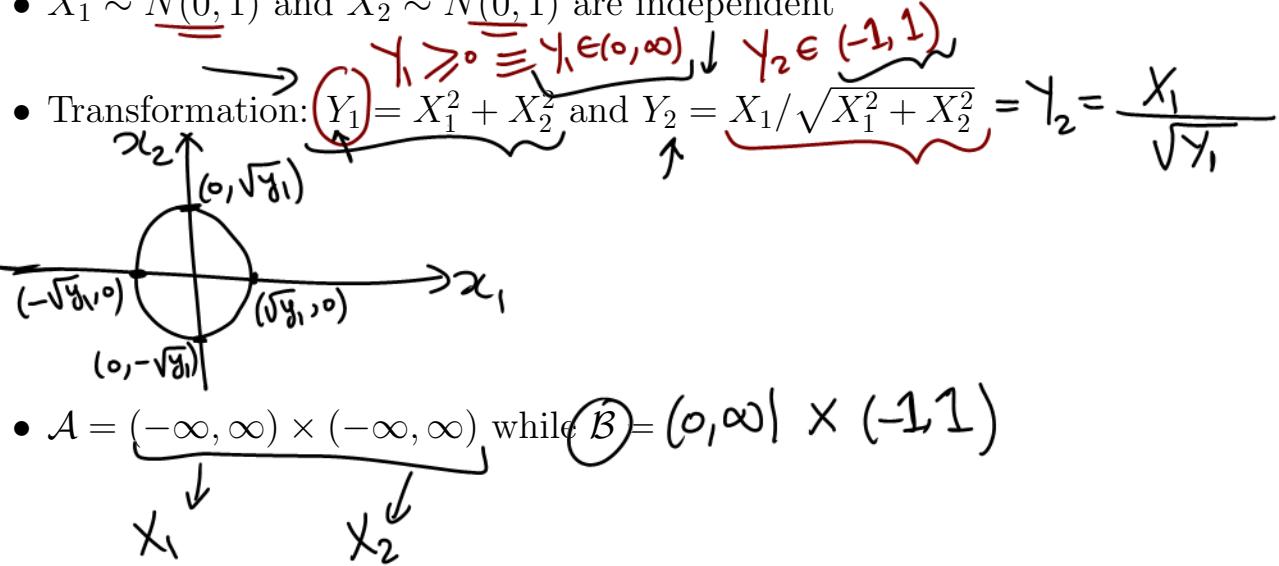
which is called the convolution formula

Multivariate transformations

Multivariate continuous case: example 4 (not one-to-one)

Recall if the transformation is not one-to-one, break the support of \mathbf{X} into subsets where the transformation is one-to-one (i.e., apply transformation on each piece and add the resulting density pieces)

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



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

- Inverse transformation:

$$Y_1 = X_1^2 + X_2^2$$

$$Y_2 = \frac{X_1}{\sqrt{X_1^2 + X_2^2}}$$

$$X_1 = Y_2 \sqrt{Y_1}$$

$$X_2 = \pm \sqrt{Y_1 - Y_2^2}$$

$$= \pm \sqrt{Y_1 - Y_2^2 Y_1}$$

$$= \pm \sqrt{Y_1(1 - Y_2^2)}$$

- Piece I: $X_1 = \sqrt{Y_1} Y_2$, $X_2 = \sqrt{Y_1(1 - Y_2^2)}$
- Piece II: $X_1 = \sqrt{Y_1} Y_2$, $X_2 = -\sqrt{Y_1(1 - Y_2^2)}$

- Each transformation piece with

$$\rightarrow J_1 = \det \begin{pmatrix} \frac{y_2}{2\sqrt{y_1}} & \sqrt{y_1} \\ \frac{\sqrt{1-y_2^2}}{2\sqrt{y_1}} & \frac{\sqrt{y_1}}{2\sqrt{(1-y_2^2)}}(-2y_2) \end{pmatrix} = -\frac{y_2^2}{2\sqrt{1-y_2^2}} - \frac{\sqrt{1-y_2^2}}{2} = \frac{-1}{2\sqrt{1-y_2^2}}$$

$$\rightarrow J_2 = \det \begin{pmatrix} \frac{y_2}{2\sqrt{y_1}} & \sqrt{y_1} \\ -\frac{\sqrt{1-y_2^2}}{2\sqrt{y_1}} & -\frac{\sqrt{y_1}}{2\sqrt{(1-y_2^2)}}(-2y_2) \end{pmatrix} = \frac{\sqrt{1-y_2^2}}{2} + \frac{y_2^2}{2\sqrt{1-y_2^2}} = \frac{1}{2\sqrt{1-y_2^2}}$$

Multivariate transformations

Multivariate continuous case: example 4 (cont'd)

- Joint pdf of Y_1, Y_2

$$\begin{aligned}
 & f_{Y_1, Y_2}(y_1, y_2) \\
 &= f_{X_1, X_2} \left(\sqrt{y_1} y_2, \sqrt{y_1(1-y_2^2)} \right) |J_1| + f_{X_1, X_2} \left(\sqrt{y_1} y_2, -\sqrt{y_1(1-y_2^2)} \right) |J_2| \\
 &= 2 \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}y_1 y_2^2} \times \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}y_1(1-y_2^2)} \times \frac{1}{2\sqrt{1-y_2^2}} \\
 &= \frac{1}{2\pi} \frac{1}{\sqrt{1-y_2^2}} e^{-\frac{1}{2}y_1} , \quad y_1 > 0, \quad y_2 \in (-1, 1)
 \end{aligned}$$

- Marginal distribution of Y_1

$$\begin{aligned}
 f_{Y_1}(y_1) &= \int_{-\infty}^{\infty} f_{Y_1, Y_2}(y_1, y_2) dy_2 = \frac{1}{2\pi} e^{-\frac{1}{2}y_1} \int_{-1}^1 \frac{1}{\sqrt{1-y_2^2}} dy_2 \\
 &= \frac{1}{2\pi} e^{-\frac{1}{2}y_1} \times \text{arcsin } y_2 \Big|_{-1}^1 \\
 &= \frac{1}{2\pi} e^{-\frac{1}{2}y_1} \left(\frac{\pi}{2} - \left(-\frac{\pi}{2} \right) \right) \\
 &\Rightarrow Y_1 \sim \text{Exp}(2)
 \end{aligned}$$