

Computational Statistics

Transformation of r.v.s

$$X \sim f_X(x)$$

$$Z = g(X)$$

Q: What is the density of Z ??

$$\begin{aligned} F_Z(z) &= \text{Prob}(Z \leq z) \\ &= \text{Prob}(g(X) \leq z) \\ &= \text{Prob}(X \leq g^{-1}(z)) \\ &= F_X(g^{-1}(z)) \end{aligned}$$

$$\frac{d}{dz} F_Z(z) = \frac{d}{dz} F_X(g^{-1}(z)) \quad \leftarrow \text{Apply chain rule.}$$

Examples: $g(x) = a + bx$

for $b \neq 0$

Example: Order statistics:

Let $X_1, \dots, X_n \stackrel{\text{iid}}{\sim} f_X(x)$

order statistics: $X_{(1)}, X_{(2)}, \dots, X_{(n)}$

$$X_{(1)} = \min_{1 \leq i \leq n} X_i \quad X_{(n)} = \max_{1 \leq i \leq n} X_i$$

$\forall x \in \mathbb{R},$

$$\begin{aligned} F_{X_{(n)}}(x) &= \text{Prob}(X_{(n)} \leq x) = \text{Prob}(X_1 \leq x, X_2 \leq x, \dots, X_n \leq x) \\ &= \text{Prob}(X_1 \leq x) \cdot \text{Prob}(X_2 \leq x) \cdot \dots \cdot \text{Prob}(X_n \leq x) \\ &= [F_X(x)]^n \end{aligned}$$

$$f_{X_{(n)}}(x) = \frac{d}{dx} F_{X_{(n)}}(x) = \frac{d}{dx} [F_X(x)]^n = n [F_X(x)]^{n-1} \cdot f_X(x)$$

$$\forall x \in \mathbb{R}$$

$$1 - F_{X_{(1)}}(x) = \text{Prob}(X_{(1)} \geq x) = \text{Prob}(x_1 \geq x, x_2 \geq x, \dots, x_n \geq x) \\ = (1 - F_X(x))^n$$

Quick review (Joint densities)

r-variable $(\Omega \rightarrow \mathbb{R})$

random vectors $(\Omega \rightarrow \mathbb{R}^d)$

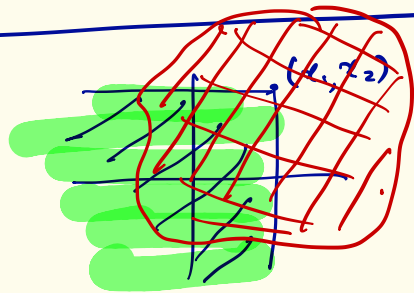
$$X = \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix}$$

$$F_{x_1, \dots, x_n}(x_1, \dots, x_n) = \text{Prob}(x_1 \leq x_1, x_2 \leq x_2, \dots, x_n \leq x_n)$$

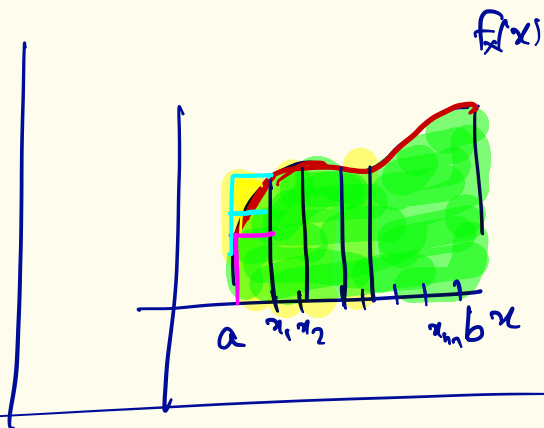
$$f_{x_1, x_2}(x_1, x_2) = \frac{1}{2\pi} e^{-\frac{x_1^2 + x_2^2}{2}}$$

$$-\infty < x_1 < \infty$$

$$-\infty < x_2 < \infty$$



$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{1}{2\pi} e^{-\frac{x_1^2 + x_2^2}{2}} dx_1 dx_2$$



discrete:

x_1	x_1	x_2	x_3
$P(x_1=x)$	P_1	P_2	P_3

x_1, x_2 : 2 discrete random variables.

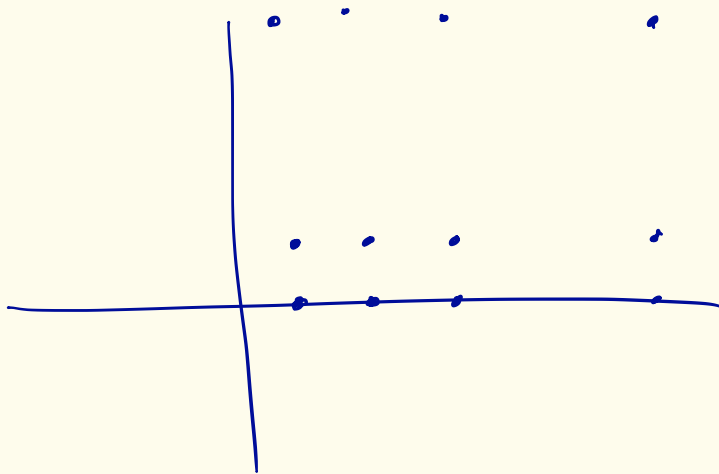
x_1	x_{11}	x_{12}	x_{13}	\dots
x_2				
x_{21}	★	★		
x_{22}		★	★	

$$\int_a^b f(x) dx$$

x_1, x_2

$x_1 \in \{1, \dots, 10\}$

$x_2 \in \{1, \dots, 10\}$



$$f_{x_1}(x_1) = \int_{x_2} f_{x_1, x_2}(x_1, x_2) dx_2$$

↓

marginal density of x_1

Conditional density:

$$f_{x_2|x_1=x_1} = \frac{f(x_1, x_2)}{f_{x_1}(x_1)} \quad \forall x_2$$

Independence of r.v.s.

x_1 & x_2 are r.v.s with the joint density

$$f_{x_1, x_2}(x_1, x_2)$$

Let $f_{x_1}(x_1)$ & $f_{x_2}(x_2)$ be the marginal densities

of x_1 and x_2 resp.

Then x_1 & x_2 are called as independent r.v.s.

if

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

$$E(h(x_1, \dots, x_n)) = \int \int \dots \int h(x_1, \dots, x_n) f_{x_1, \dots, x_n}(x_1, \dots, x_n) dx_1 \dots dx_n$$

For any random vector x

$$x = \begin{pmatrix} x_1 \\ \vdots \\ x_d \end{pmatrix}$$

$$\mu_i = E(x_i)$$

$$E(x) = \begin{pmatrix} \mu_1 \\ \vdots \\ \mu_d \end{pmatrix} = \mu$$

Σ = covariance matrix

$$\Sigma = E[x - \mu][x - \mu]^T$$

$$\Sigma_{ij} = E(x_i - \mu_i)(x_j - \mu_j)$$

Linear transformation of random vectors.

$$x = \begin{pmatrix} x_1 \\ \vdots \\ x_d \end{pmatrix}, \quad y = \begin{pmatrix} y_1 \\ \vdots \\ y_d \end{pmatrix}$$

$$y = Ax \quad \text{where} \quad A \in \mathbb{R}^{d \times d}$$

$$\mu_x = E(X), \quad \mu_y = E(Y)$$

$$\mu_y = E(Y) = E(AX) = A E(X) = A\mu_x$$

$$\Sigma_y = E(Y - \mu_y)(Y - \mu_y)^T, \quad \Sigma_x = E(X - \mu_x)(X - \mu_x)^T$$
$$= E[A(X - \mu_x)] [A(X - \mu_x)]^T$$

$$= E[A(X - \mu_x)(X - \mu_x)^T A^T]$$

$$= A[E(X - \mu_x)(X - \mu_x)^T] A^T$$

$$\Sigma_y = A \Sigma_x A^T$$

$$d=2$$

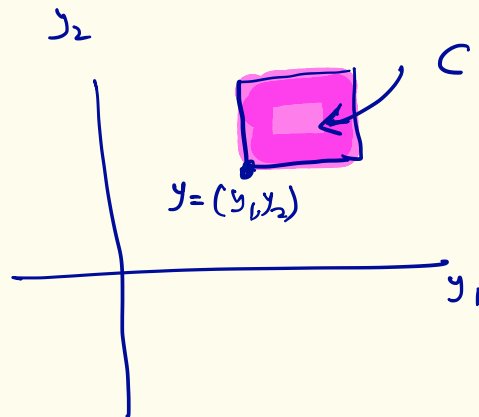
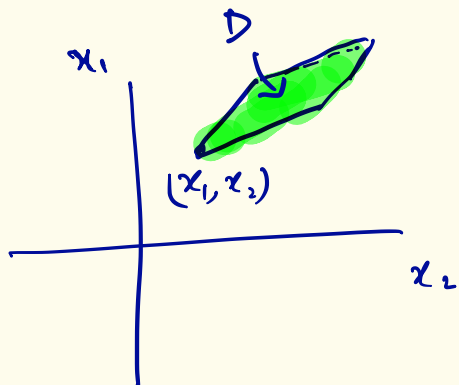
$$x = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}, \quad y = \begin{pmatrix} y_1 \\ y_2 \end{pmatrix}$$

$$Y = AX$$

Suppose A^{-1} exists.

Consider the area $C = [y_1, y_1+h] \times [y_2, y_2+h]$

in $y_1 \times y_2$ plane.



$$f_Y(y) h^2 \approx \text{Prob}(Y \in C)$$

where $Y = \begin{pmatrix} y_1 \\ y_2 \end{pmatrix}$ and $y = \begin{pmatrix} y_1 \\ y_2 \end{pmatrix}$

$$\begin{aligned}
 \text{Prob}(Y \in C) &= \text{Prob}(X \in D) \approx h^2 f_Y(y) \\
 &= h^2 |A^{-1}| f_X(x) \\
 &= h^2 |A|^{-1} f_X(x)
 \end{aligned}$$

$$\text{Prob}(Y \in C) \approx h^2 \frac{f_X(A^T y)}{|A|}$$

$$f_Y(y) = \frac{f_X(A^T(y))}{|A|}$$

taking $h \rightarrow 0$

$$y \in \mathbb{R}^2$$

$X_1, \dots, X_n \stackrel{\text{iid}}{\sim} U[0,1]$

Find the densities of $X_{(1)}$ and $X_{(n)}$