

Sec 3.5 - Multivariate Normal Dist.

def \rightarrow Multivariate Normal with mean $\vec{0}$ and covariance I_n

\uparrow vector of 0's \uparrow identity

$$\begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}_{n \times 1}$$

Recall $Z \sim N(0, 1)$ $f(z) = \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}}$

$z \in \mathbb{R}$

Suppose $Z_1, \dots, Z_n \stackrel{iid}{\sim} N(0, 1)$

Then $\vec{Z} = \begin{bmatrix} Z_1 \\ \vdots \\ Z_n \end{bmatrix}_{n \times 1} = (Z_1, \dots, Z_n) \uparrow$

random vector. transpose

is jointly normal.

Joint pdf is:

$$f_{\vec{Z}}(z_1, \dots, z_n) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi}} e^{-\frac{z_i^2}{2}}$$

$$= (2\pi)^{-n/2} e^{-\frac{1}{2} \sum_{i=1}^n z_i^2}$$

$$= (2\pi)^{-n/2} e^{-\frac{1}{2} \vec{z}' \vec{z}}$$

$$\vec{z}' \vec{z} = (z_1, \dots, z_n) \begin{pmatrix} z_1 \\ \vdots \\ z_n \end{pmatrix} = z_1^2 + z_2^2 + \dots + z_n^2$$

$$E[\vec{Z}] = \vec{0}$$

$$\text{Cov}(Z_i, Z_i) = \text{Var}(Z_i) = 1$$

$$E \begin{bmatrix} Z_1 \\ \vdots \\ Z_n \end{bmatrix} = \begin{bmatrix} E(Z_1) \\ \vdots \\ E(Z_n) \end{bmatrix} = \begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix}$$

$$\text{Cov}(\vec{Z}) = \begin{pmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1 \end{pmatrix} = I_n$$

$\text{Cov}(Z_1, Z_2) = 0$

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We say $\vec{Z} \sim N_n(\vec{0}, I_n)$
of RVs

MGF of \vec{Z} is

$$M_{\vec{Z}}(\vec{t}) = \mathbb{E}\left[e^{\vec{t}'\vec{Z}}\right]$$

$$= \mathbb{E}\left[e^{(t_1, t_2, \dots, t_n) \begin{bmatrix} z_1 \\ \vdots \\ z_n \end{bmatrix}}\right]$$

$$= e^{\frac{1}{2}\vec{t}'\vec{t}}$$

ex) Bivariate Normal

$$\vec{Z} = \begin{bmatrix} z_1 \\ z_2 \end{bmatrix} \sim N_2(\vec{0}, I_2)$$

$$\begin{pmatrix} \text{Var}(z_1) & \text{Cov}(z_1, z_2) \\ \text{Cov}(z_2, z_1) & \text{Var}(z_2) \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

~~def~~ def) We say $\vec{X} = (X_1, X_2)'$ is bivariate normal if

$$\vec{X}_{2 \times 1} = \vec{A}_{2 \times 2} \vec{Z}_{2 \times 1} + \vec{\mu}_{2 \times 1}$$

i.e.

$$\begin{pmatrix} X_1 \\ X_2 \end{pmatrix} = \begin{pmatrix} a & b \\ c & d \end{pmatrix} \begin{pmatrix} Z_1 \\ Z_2 \end{pmatrix} + \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix}$$

$$\Rightarrow X_1 = aZ_1 + bZ_2 + \mu_1$$

$$X_2 = cZ_1 + dZ_2 + \mu_2$$

Remarks

$$\textcircled{1} \mathbb{E}[\vec{X}] = \begin{pmatrix} \mathbb{E}[X_1] \\ \mathbb{E}[X_2] \end{pmatrix} = \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix}$$

$$\textcircled{2a} \text{Var}[X_1] = a^2 + b^2$$

proof) $\text{Var}[X_1] = \text{Var}[aZ_1 + bZ_2 + \mu_1]$

$$= \text{Var}[aZ_1 + bZ_2]$$

indep
 $= a^2 \text{Var}[Z_1] + b^2 \text{Var}[Z_2]$
 $= a^2 + b^2$

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$$(2b) \text{ var}[X_2] = c^2 + d^2$$

$$(2c) \text{ Cov}(X_1, X_2)$$

$$\begin{aligned} &= \text{Cov}(az_1 + bz_2, cz_1 + dz_2) \\ &= E[(az_1 + bz_2)(cz_1 + dz_2)] \\ &= ac + bd \end{aligned}$$

$acz_1^2 + adz_1z_2 + bcz_1z_2 + bdz_2^2$

(2d) Define $\Sigma = AA'$ (variance-) = Covariance matrix.

$$A = \begin{pmatrix} a & b \\ c & d \end{pmatrix}$$

$$AA' = \begin{pmatrix} a & b \\ c & d \end{pmatrix} \begin{pmatrix} a & c \\ b & d \end{pmatrix}$$

$$= \begin{pmatrix} a^2 + b^2 & ac + bd \\ ca + db & c^2 + d^2 \end{pmatrix}$$

$$= \begin{pmatrix} \sigma_1^2 & \text{Cov}(X_1, X_2) \\ \text{Cov}(X_1, X_2) & \sigma_2^2 \end{pmatrix}$$

$$\rho = \frac{\text{Cov}(X_1, X_2)}{\sigma_1 \sigma_2}$$

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$$= \begin{pmatrix} \sigma_1^2 & \rho \sigma_1 \sigma_2 \\ \rho \sigma_1 \sigma_2 & \sigma_2^2 \end{pmatrix}$$

always symmetric

A positive semidefinite matrix.

- all eigenvalues are nonneg.
- $x' \Sigma x \geq 0 \quad \forall x \in \mathbb{R}^n$

(2e) The pdf of $\vec{X} = (X_1, X_2)'$ is given by.

$$f_{\vec{X}}(\vec{x}) = \frac{1}{2\pi |\Sigma|^{1/2}} \exp \left\{ -\frac{1}{2} (\vec{x} - \vec{\mu})' \Sigma^{-1} (\vec{x} - \vec{\mu}) \right\}$$

determinant

$$M_{\vec{X}}(\vec{t}) = e^{t' \vec{\mu} + \frac{1}{2} t' \Sigma t}$$

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$$f(x_1, x_2) = \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} \exp \left\{ -\frac{1}{2(1-\rho^2)} \left[\left(\frac{x_1-\mu_1}{\sigma_1} \right)^2 - 2\rho \left(\frac{x_1-\mu_1}{\sigma_1} \right) \left(\frac{x_2-\mu_2}{\sigma_2} \right) + \left(\frac{x_2-\mu_2}{\sigma_2} \right)^2 \right] \right\}$$

$$|\Sigma|^{1/2}$$

$$\begin{aligned} \det(\Sigma) &= \det \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix} \\ &= \sigma_1^2 \sigma_2^2 (1-\rho^2) \end{aligned}$$

We can say that

$$\vec{X} = (x_1, x_2)' \sim N_2(\vec{\mu}, \Sigma)$$

OR.

$$(x_1, x_2)' \sim N_2(\mu_1, \mu_2, \sigma_1^2, \sigma_2^2, \rho)$$

③ $\vec{\mu}, \Sigma$ uniquely determines the dist of \vec{X}

④ we could have defined

$$X_1 = a_1 Z_1 + a_2 Z_2 + a_3 Z_3 + \mu_1$$

$$X_2 = b_1 Z_1 + b_2 Z_2 + b_3 Z_3 + \mu_2$$

but using linear algebra,
equivalent to

$$X_1 = \vec{a}_1 \vec{Z}_1 + \vec{a}_2 \vec{Z}_2 + \mu_1$$

$$X_2 = \vec{b}_1 \vec{Z}_1 + \vec{b}_2 \vec{Z}_2 + \mu_2$$

⑤ Marginal Dist

$$X_1 \sim N(\mu_1, a^2 + b^2) = N(\mu_1, \sigma_1^2)$$

$$X_2 \sim N(\mu_2, c^2 + d^2) = N(\mu_2, \sigma_2^2)$$