

# The multivariate normal distribution

Stat 571  
10-17-13

(1)

Univariate case,  $f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$   
 $-\infty < x < \infty$

Multivariate case:

$$f(\vec{x}) = \frac{1}{(2\pi)^{p/2} |\Sigma|^{1/2}} e^{-\frac{1}{2}(\vec{x}-\vec{\mu})' \Sigma^{-1} (\vec{x}-\vec{\mu})}$$

$-\infty < x_i < \infty$   
 for  $i=1, \dots, p$

Special case:

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Bivariate normal ( $p=2$ )

$$\vec{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \quad \vec{\mu} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} \quad \Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{12} & \sigma_{22} \end{bmatrix}$$

$$\Sigma^{-1} = \frac{1}{\sigma_{11}\sigma_{22} - \sigma_{12}^2} \begin{bmatrix} \sigma_{22} & -\sigma_{12} \\ -\sigma_{12} & \sigma_{11} \end{bmatrix}$$

$$(\vec{x}-\vec{\mu})' \Sigma^{-1} (\vec{x}-\vec{\mu})$$

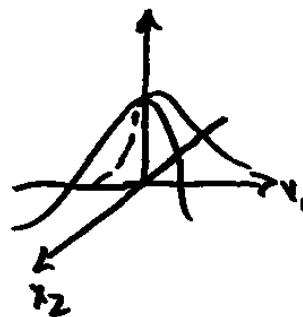
$$= [(x_1 - \mu_1), (x_2 - \mu_2)] \frac{1}{\sigma_{11}\sigma_{22} - \sigma_{12}^2} \begin{bmatrix} \sigma_{22} & -\sigma_{12} \\ -\sigma_{12} & \sigma_{11} \end{bmatrix} \begin{bmatrix} x_1 - \mu_1 \\ x_2 - \mu_2 \end{bmatrix}$$

$$\begin{aligned}
 &= \frac{\sigma_{12}(x_1 - \mu_1)^2 - 2\sigma_{12}(x_1 - \mu_1)(x_2 - \mu_2) + \sigma_{11}(x_2 - \mu_2)^2}{\sigma_{11}\sigma_{22} - \sigma_{12}^2} \quad (3) \\
 &= \frac{\left(\frac{x_1 - \mu_1}{\sigma_1}\right)^2 - 2\sigma_{12} \left(\frac{x_1 - \mu_1}{\sigma_1}\right) \left(\frac{x_2 - \mu_2}{\sigma_{22}}\right) + \left(\frac{x_2 - \mu_2}{\sigma_{22}}\right)^2}{1 - \frac{\sigma_{12}^2}{\sigma_{11}\sigma_{22}}} \\
 &= \frac{1}{1-p^2} \left[ \left(\frac{x_1 - \mu_1}{\sigma_1}\right)^2 - 2p \left(\frac{x_1 - \mu_1}{\sigma_1}\right) \left(\frac{x_2 - \mu_2}{\sigma_{22}}\right) + \left(\frac{x_2 - \mu_2}{\sigma_{22}}\right)^2 \right] \\
 &= Q
 \end{aligned}$$

$$f(x_1, x_2) = \frac{1}{2\pi|\Delta|^{1/2}} e^{-\frac{1}{2}Q} \quad (4)$$

$$\begin{aligned}
 |\Delta|^{1/2} &= \sqrt{\sigma_{11}\sigma_{22} - \sigma_{12}^2} \\
 &= \sqrt{(\sigma_{11}\sigma_{22})(1 - \frac{\sigma_{12}^2}{\sigma_{11}\sigma_{22}})} \\
 &= \sigma_1\sigma_2\sqrt{1-p^2}
 \end{aligned}$$

$$f(x_1, x_2) = \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-p^2}} e^{-\frac{1}{2}Q}$$



The contours of the graph are found

by setting  $f(x_1, x_2) = k$ ,

which is equivalent to setting  $Q = \text{constant}$

$$(\bar{x} - \bar{\mu})' \Sigma^{-1} (\bar{x} - \bar{\mu}) = c^2$$

These are ellipses centered at  $\bar{\mu}$ ,

and whose axes are the eigenvectors

of  $\Sigma$ , with lengths  $c\sqrt{\lambda_1}$  and  $c\sqrt{\lambda_2}$ ,

where  $\lambda_1 < \lambda_2$  are the eigenvalues of  $\Sigma$ .

Special case of the bivariate normal:  $\rho = 0$

$$\begin{aligned} f(x_1, x_2) &= \frac{1}{2\pi \sigma_1 \sigma_2} e^{-\frac{1}{2} \left[ \left( \frac{x_1 - \mu_1}{\sigma_1} \right)^2 + \left( \frac{x_2 - \mu_2}{\sigma_2} \right)^2 \right]} \\ &= \frac{1}{\sqrt{2\pi} \sigma_1} e^{-\frac{1}{2} \left( \frac{x_1 - \mu_1}{\sigma_1} \right)^2} \cdot \frac{1}{\sqrt{2\pi} \sigma_2} e^{-\frac{1}{2} \left( \frac{x_2 - \mu_2}{\sigma_2} \right)^2}, \end{aligned}$$

so  $x_1$  and  $x_2$  are independent.

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Back to the  $\rho \neq 0$  case:

Find the marginal density of  $X_1$ .

$$f(x_1) = \int_{-\infty}^{\infty} f(x_1, x_2) dx_2 \quad (7)$$

$$= \int_{-\infty}^{\infty} \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-p^2}} e^{-\frac{1}{2}\frac{1}{1-p^2}\left[\left(\frac{x_1-\mu_1}{\sigma_1}\right)^2 - 2p\left(\frac{x_1-\mu_1}{\sigma_1}\right)\left(\frac{x_2-\mu_2}{\sigma_2}\right) + \left(\frac{x_2-\mu_2}{\sigma_2}\right)^2\right]} dx_2$$

$$\text{Let } z_1 = \frac{x_1-\mu_1}{\sigma_1} \rightarrow z_2 = \frac{x_2-\mu_2}{\sigma_2}$$

$$\frac{dz_1}{dx_1} = \frac{1}{\sigma_1} \quad dx_1 = \sigma_1 dz_1$$

$$= \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-p^2}} \int_{-\infty}^{\infty} e^{-\frac{1}{2}\frac{1}{1-p^2}\left[z_1^2 - 2pz_1z_2 + z_2^2\right]} \sigma_2 dz_2$$

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$$z_2^2 - 2pz_1z_2 + z_1^2$$

$$= z_2^2 - 2pz_1z_2 + p^2z_1^2 + z_1^2 - p^2z_1^2$$

$$= (z_2 - pz_1)^2 + z_1^2(1-p^2)$$

$$\text{Now } f(x_1) = \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-p^2}} \int_{-\infty}^{\infty} e^{-\frac{1}{2}\frac{1}{1-p^2}\left[(z_2 - pz_1)^2 + z_1^2(1-p^2)\right]} \sigma_2 dz_2$$

$$= \frac{e^{-\frac{1}{2}z_1^2}}{2\pi\sigma_1\sqrt{1-p^2}} \int_{-\infty}^{\infty} e^{-\frac{1}{2}\frac{1}{1-p^2}(z_2 - pz_1)^2} dz_2$$

$$= \frac{e^{-\frac{1}{2} z_1^2}}{2\pi \sigma_1 \sqrt{1-p^2}} \underbrace{\int_{-\infty}^{\infty} \frac{e^{-\frac{1}{2} \left( \frac{z_2 - pz_1}{\sqrt{1-p^2}} \right)^2}}{\sqrt{2\pi} \sqrt{1-p^2}} dz_2}_1$$
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$$= \frac{e^{-\frac{1}{2} z_1^2}}{\sqrt{2\pi} \sigma_1}$$

General result: If  $\vec{X} \sim N_p(\vec{\mu}, \Sigma)$ ,

then  $X_i \sim N(\mu_i, \sigma_{ii})$

Theorem: If  $\vec{X} \sim N_p(\vec{\mu}, \Sigma)$ ,  
 then  $\vec{a}' \vec{X} \sim N(\vec{a}' \vec{\mu}, \vec{a}' \Sigma \vec{a})$

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Theorem: If  $\vec{a}' \vec{X} \sim N(\vec{a}' \vec{\mu}, \vec{a}' \Sigma \vec{a})$  if and only if  $\vec{a}$ ,  
 then  $\vec{X} \sim N_p(\vec{\mu}, \Sigma)$ .

Theorem: If  $\vec{X}$  is  $N_p(\vec{\mu}, \Sigma)$  and  
 A is a  $q \times p$  matrix of constants, then  
 $A \vec{X} \sim N_q(A \vec{\mu}, A \Sigma A')$

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Hw #3 due Oct 24

4. 1,3,4,6