



# THE MULTIVARIATE NORMAL DISTRIBUTION

数学与统计学院 杨炜明



- Suppose  $X_1, X_2, ..., X_p$  are random variables.
- An p-dimensional random vector is a function

$$\boldsymbol{X} = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_p \end{bmatrix} = [X_1, X_2, \cdots, X_p]'$$



Multivariate distribution function

$$F(x_1, x_2, \dots x_p) = P(X_1 \le x_1, X_2 \le x_2, \dots, X_p \le x_p)$$

• Multivariate density function

$$f(x_1, \dots, x_p) = \frac{\partial^p}{\partial x_1 \dots \partial x_p} F(x_1, \dots, x_p) \qquad f(x_1, \dots, x_p) \ge 0$$

We have 
$$\int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} f(x_1, \dots, x_p) dx_1 \cdots dx_p = 1$$



If X, Y are random vector, A, B are constant matrices, then we have

$$E(X) = [E(X_1), E(X_2), \dots, E(X_p)]'$$

$$E(AX) = AE(X)$$

$$E(AXB) = AE(X)B$$

$$E(AX + BY) = AE(X) + BE(Y)$$



#### 随机向量X的协方差矩阵

$$D(X) = E\left[\left(X - E(X)\right)\left(X - E(X)\right)'\right]$$

$$= \begin{pmatrix} Cov\left(X_{1}, X_{1}\right) & Cov\left(X_{1}, X_{2}\right) & \cdots & Cov\left(X_{1}, X_{p}\right) \\ Cov\left(X_{2}, X_{1}\right) & Cov\left(X_{2}, X_{2}\right) & \cdots & Cov\left(X_{2}, X_{p}\right) \\ \vdots & \vdots & & \vdots \\ Cov\left(X_{p}, X_{1}\right) & Cov\left(X_{p}, X_{2}\right) & \cdots & Cov\left(X_{p}, X_{p}\right) \end{pmatrix}$$

$$= \left(\sigma_{ij}\right)_{p \times p} \stackrel{def}{=} \sum$$



If a is a constant vector, A, B are constant matrices, then we have

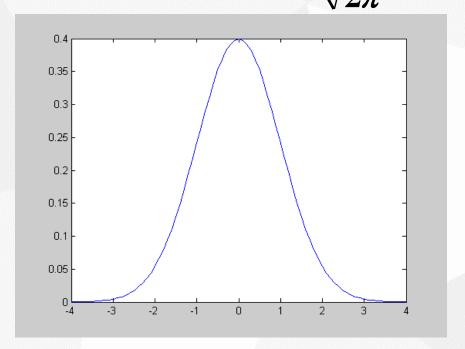
$$D(X+a) = D(X)$$

$$D(AX) = AD(X)A'$$

$$Cov(AX, BY) = ACov(X, Y)B'$$



If 
$$X \sim N(0,1)$$
,  $\varphi(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}$   $(-\infty < x < +\infty)$ 



$$P\{|x| \le 1\} = 0.6826, P\{|x| \le 2\} = 0.9545, P\{|x| \le 3\} = 0.9973$$



 $\mu - 3\sigma$ 

 $\mu-2\sigma$ 

If 
$$X \sim N(\mu, \sigma^2)$$
,  $f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{\frac{(x-\mu)^2}{2\sigma^2}}$   $(-\infty < x < +\infty)$ 

$$p(x)$$

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

$$P\{|x-\mu| \le \sigma\} = 0.6826$$

$$P\{|x-\mu| \le 2\sigma\} = 0.9545$$

$$P\{|x-\mu| \le 3\sigma\} = 0.9973$$

 $\mu + 2\sigma$ 

 $\mu + 3\sigma$ 

## The density function

$$f(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \qquad (-\infty < x < +\infty)$$

#### can be rewritten as

$$f(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{1}{2}(x-\mu)'(\sigma^2)^{-1}(x-\mu)} \quad (-\infty < x < +\infty)$$



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

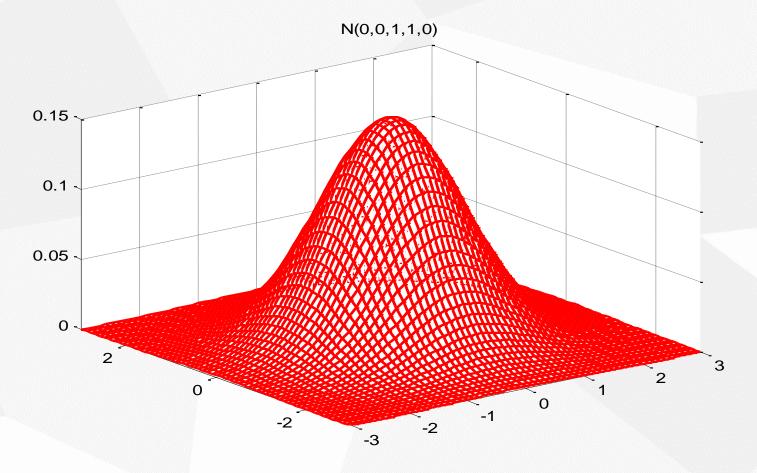
$$(X_1, X_2) \sim N_2(\mu_1, \mu_2, \sigma_1^2, \sigma_2^2, \rho)$$

$$EX_1 = \mu_1, DX_1 = \sigma_1^2,$$

$$EX_2 = \mu_2, DX_2 = \sigma_2^2$$

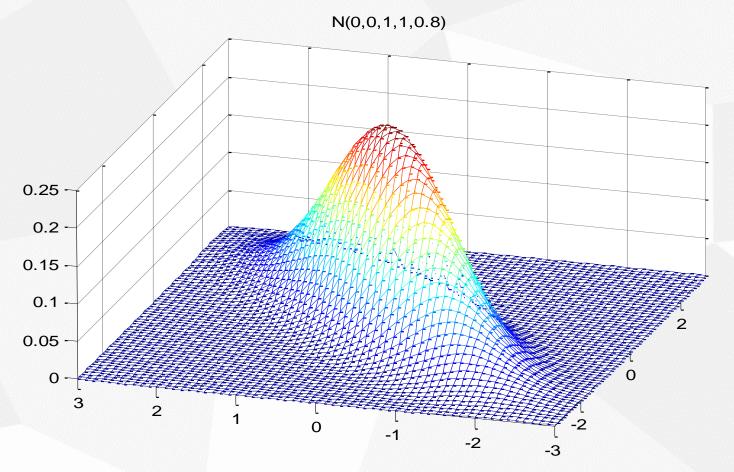
$$\rho\left(X_1 \ X_2\right) = \frac{Cov(X_1 \ X_2)}{\sqrt{D(X_1)D(X_2)}} = \frac{Cov(X_1 \ X_2)}{\sigma_1 \sigma_2}, \quad Cov(X_1 \ X_2) = \rho \ \sigma_1 \sigma_2$$

$$(X_1, X_2) \sim N_2(0, 0, 1, 1, 0), \quad f(x_1, x_2) = \frac{1}{2\pi} \cdot e^{-\frac{1}{2}(x_1^2 + x_2^2)}$$





$$(X_1, X_2) \sim N_2(0, 0, 1, 1, 0.8), p(x_1, x_2) = \frac{1}{2\pi \cdot 0.6} \cdot e^{-\frac{1}{0.72}(x_1^2 - 1.6x_1x_2 + x_2^2)}$$





$$X = \begin{pmatrix} X_1 \\ X_2 \end{pmatrix},$$

$$\mu = EX = \begin{pmatrix} EX_1 \\ EX_2 \end{pmatrix} = \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix}, \qquad X_1 和 X_2$$
 的均值向量
$$\Sigma = \text{cov}(X) = \begin{pmatrix} DX_1 & \text{cov}(X_1, X_2) \\ \text{cov}(X_2, X_1) & DX_2 \end{pmatrix} = \begin{pmatrix} \sigma_1^2 & \rho \sigma_1 \sigma_2 \\ \rho \sigma \sigma & \sigma & \sigma^2 \end{pmatrix} \qquad X_1 和 X_2$$
 的协方差矩阵

$$|\Sigma| = \sigma_1^2 \sigma_2^2 \left( 1 - \rho^2 \right)$$

$$\Sigma^{-1} = \begin{bmatrix} \frac{1}{\sigma_1^2 (1 - \rho^2)} & \frac{-\rho}{\sigma_1 \sigma_2 (1 - \rho^2)} \\ \frac{-\rho}{\sigma_1 \sigma_2 (1 - \rho^2)} & \frac{1}{\sigma_2^2 (1 - \rho^2)} \end{bmatrix}$$



$$\frac{1}{(1-\rho^{2})} \left[ \frac{(x_{1}-\mu_{1})^{2}}{\sigma_{1}^{2}} - \frac{2\rho(x_{1}-\mu_{1})(x_{2}-\mu_{2})}{\sigma_{1}\sigma_{2}} + \frac{(x_{2}-\mu_{2})^{2}}{\sigma_{2}^{2}} \right] \\
= (x_{1}-\mu_{1} \quad x_{2}-\mu_{2}) \left( \frac{1}{\sigma_{1}^{2}(1-\rho^{2})} \quad \frac{-\rho}{\sigma_{1}\sigma_{2}(1-\rho^{2})} \right) \left( \frac{x_{1}-\mu_{1}}{x_{2}-\mu_{2}} \right) \\
= (x-\mu)' \sum_{j=1}^{n-1} (x-\mu) \\
\frac{1}{2\pi\sigma_{1}\sigma_{2}} e^{-\frac{1}{2}(x-\mu)} \left[ \frac{(x_{1}-\mu_{1})^{2}}{\sigma_{1}^{2}} - \frac{2\rho(x_{1}-\mu_{1})(x_{2}-\mu_{2})}{\sigma_{1}\sigma_{2}} + \frac{(x_{2}-\mu_{2})^{2}}{\sigma_{2}^{2}} \right] \\
= \frac{1}{2\pi |\Sigma|^{\frac{1}{2}}} e^{-\frac{1}{2}(x-\mu)' \sum_{j=1}^{n-1} (x-\mu)}$$

$$X = \begin{pmatrix} X_1 \\ X_2 \end{pmatrix}, \quad \mu = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \quad \Sigma = \begin{pmatrix} 1 & 0.8 \\ 0.8 & 1 \end{pmatrix}$$

$$|\Sigma|^{\frac{1}{2}} = 0.6, \quad \Sigma^{-1} = \begin{pmatrix} \frac{1}{\sigma_1^2 (1 - \rho^2)} & \frac{-\rho}{\sigma_1 \sigma_2 (1 - \rho^2)} \\ \frac{-\rho}{\sigma_1 \sigma_2 (1 - \rho^2)} & \frac{1}{\sigma_2^2 (1 - \rho^2)} \end{pmatrix} = \begin{pmatrix} \frac{1}{0.36} & \frac{-0.8}{0.36} \\ \frac{-0.8}{0.36} & \frac{1}{0.36} \end{pmatrix}$$

$$\frac{1}{2\pi |\Sigma|^{\frac{1}{2}}} e^{-\frac{1}{2}(x-\mu)'\Sigma^{-1}(x-\mu)} = \frac{1}{2\pi \cdot 0.6} \cdot e^{-\frac{1}{0.72}(x_1^2 - 1.6x_1x_2 + x_2^2)}$$

$$X \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & 0.8 \\ 0.8 & 1 \end{pmatrix}\right).$$



$$(X_1, X_2) \sim N_2(0, 0, 1, 1, 0.8),$$
 
$$\begin{cases} Y_1 = 2X_1 + X_2 \\ Y_2 = 2X_1 - X_2 \end{cases}$$

$$EY_1 = 2EX_1 + EX_2 = 0,$$
  
 $DY_1 = 4DX_1 + DX_2 + 2\operatorname{cov}(2X_1, X_2) = 5 + 4 \times 0.8 = 8.2$ 

$$EY_2 = 2EX_1 - EX_2 = 0,$$
  
 $DY_2 = 4DX_1 + DX_2 - 2\cos(2X_1, X_2) = 5 - 4 \times 0.8 = 1.8$ 

$$cov(Y_1, Y_2) = cov(2X_1 + X_2, 2X_1 - X_2)$$

$$= cov(2X_1, 2X_1) + cov(X_2, 2X_1) + cov(2X_1, -X_2) + cov(X_2, -X_2) = 3$$



$$X = \begin{pmatrix} X_1 \\ X_2 \end{pmatrix}, \quad \mu_X = \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \quad \Sigma_X = \begin{pmatrix} 1 & 0.8 \\ 0.8 & 1 \end{pmatrix}$$

$$Y = \begin{pmatrix} Y_1 \\ Y_2 \end{pmatrix} = \begin{pmatrix} 2 & 1 \\ 2 & -1 \end{pmatrix} \begin{pmatrix} X_1 \\ X_2 \end{pmatrix}$$

$$EY = \begin{pmatrix} 2 & 1 \\ 2 & -1 \end{pmatrix} EX = \begin{pmatrix} 2 & 1 \\ 2 & -1 \end{pmatrix} \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \quad \Sigma_{Y} = \begin{pmatrix} 2 & 1 \\ 2 & -1 \end{pmatrix} \begin{pmatrix} 1 & 0.8 \\ 0.8 & 1 \end{pmatrix} \begin{pmatrix} 2 & 1 \\ 2 & -1 \end{pmatrix} = \begin{pmatrix} 8.2 & 3 \\ 3 & 1.8 \end{pmatrix}$$

$$Y \sim N_2 \left( \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 8.2 & 3 \\ 3 & 1.8 \end{pmatrix} \right)$$



$$X = \begin{pmatrix} X_1 \\ X_2 \end{pmatrix}, \quad EX = \begin{pmatrix} EX_1 \\ EX_2 \end{pmatrix}, \quad DX = \begin{pmatrix} DX_1 & \operatorname{cov}(X_1, X_2) \\ \operatorname{cov}(X_1, X_2) & DX_2 \end{pmatrix}$$

$$Y = \begin{pmatrix} Y_1 \\ Y_2 \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \begin{pmatrix} X_1 \\ X_2 \end{pmatrix} + \begin{pmatrix} b_1 \\ b_2 \end{pmatrix}$$

$$EY = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} EX + \begin{pmatrix} b_1 \\ b_2 \end{pmatrix}, \quad \Sigma_Y = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \begin{pmatrix} DX_1 & \cos(X_1, X_2) \\ \cos(X_1, X_2) & DX_2 \end{pmatrix} \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}$$

$$Y \sim N_2 \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} EX + \begin{pmatrix} b_1 \\ b_2 \end{pmatrix}, \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \begin{pmatrix} DX_1 & \cos(X_1, X_2) \\ \cos(X_1, X_2) & DX_2 \end{pmatrix} \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}^{'}$$



#### p元正态分布的密度函数

$$p(x) = \frac{1}{(2\pi)^{\frac{p}{2}} |\Sigma|^{\frac{1}{2}}} \exp\left(-\frac{1}{2}(x-\mu)' \Sigma^{-1}(x-\mu)\right),$$

$$X = (X_1, \dots, X_p)', X \sim N_p(\mu, \Sigma).$$

$$X = \begin{pmatrix} X_1 \\ X_2 \\ X_3 \end{pmatrix}, \quad EX = \begin{pmatrix} 1 \\ 2 \\ 1 \end{pmatrix}, \quad DX = \begin{pmatrix} 2 & 0 & 0 \\ 0 & 3 & 0 \\ 0 & 0 & 3 \end{pmatrix}$$

$$X \sim N_3 \begin{pmatrix} 1 \\ 2 \\ 1 \end{pmatrix}, \begin{pmatrix} 2 & 0 & 0 \\ 0 & 3 & 0 \\ 0 & 0 & 3 \end{pmatrix}$$



$$Y = \begin{pmatrix} Y_1 \\ Y_2 \\ Y_3 \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \begin{pmatrix} X_1 \\ X_2 \\ X_3 \end{pmatrix} + \begin{pmatrix} b_1 \\ b_2 \\ b_3 \end{pmatrix} = AX + B$$

$$EY = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} EX + \begin{pmatrix} b_1 \\ b_2 \\ b_3 \end{pmatrix}, \quad \Sigma_Y = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \begin{pmatrix} DX_1 & cov(X_1, X_2) & cov(X_1, X_3) \\ cov(X_2, X_1) & DX_2 & cov(X_2, X_3) \\ cov(X_3, X_1) & cov(X_3, X_2) & DX_3 \end{pmatrix} \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix}$$

$$Y \sim N_2 \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} EX + \begin{pmatrix} b_1 \\ b_2 \\ b_3 \end{pmatrix}, \quad \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \begin{pmatrix} DX_1 & cov(X_1, X_2) & cov(X_1, X_3) \\ cov(X_2, X_1) & DX_2 & cov(X_2, X_3) \\ cov(X_3, X_1) & cov(X_3, X_2) & DX_3 \end{pmatrix} \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix}$$

$$Y \sim N_2 (AEX + B, ADXA')$$



$$X \sim N_3(\mu, 2I_3)$$

$$\mu = \begin{bmatrix} 2 \\ 0 \\ 0 \end{bmatrix}, \quad A = \begin{bmatrix} 0.5 & -1 & 0.5 \\ -0.5 & 0 & -0.5 \end{bmatrix}, \quad B = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$$

$$Y = AX + B$$

$$\sim N_2 \left[ \begin{bmatrix} 0.5 & -1 & 0.5 \\ -0.5 & 0 & -0.5 \end{bmatrix} \begin{bmatrix} 2 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 1 \\ 2 \end{bmatrix}, \begin{bmatrix} 0.5 & -1 & 0.5 \\ -0.5 & 0 & -0.5 \end{bmatrix} \begin{bmatrix} 2 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 2 \end{bmatrix} \begin{bmatrix} 0.5 & -1 & 0.5 \\ -0.5 & 0 & -0.5 \end{bmatrix} \right]$$

$$Y \sim N_2 \begin{bmatrix} 2 \\ 1 \end{bmatrix}, \begin{bmatrix} 3 & -1 \\ -1 & 1 \end{bmatrix}$$



设
$$X = \begin{pmatrix} X^{(1)} \\ X^{(2)} \end{pmatrix} p - r \sim N_p(\mu, \Sigma), 将 \mu, \Sigma 分为$$

$$\mu = \begin{pmatrix} \mu^{(1)} \\ \mu^{(2)} \end{pmatrix} \begin{matrix} r \\ p-r \end{matrix}, \quad \Sigma = \begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix} \begin{matrix} r \\ p-r \end{matrix},$$
 
$$\iiint X^{(1)} \sim N_r \left( \mu^{(1)}, \Sigma_{11} \right), X^{(2)} \sim N_{p-r} \left( \mu^{(2)}, \Sigma_{22} \right).$$



$$\begin{pmatrix} X_1 \\ X_2 \\ X_3 \\ X_4 \end{pmatrix} \sim N_4 \begin{pmatrix} 2 \\ 3 \\ 6 \\ 7 \end{pmatrix}, \begin{pmatrix} 8 & 2 & 0 & 0 \\ 2 & 10 & 0 & 0 \\ 0 & 0 & 9 & 3 \\ 0 & 0 & 3 & 7 \end{pmatrix}$$

$$\begin{pmatrix} X_1 \\ X_2 \end{pmatrix} \sim N_2 \begin{pmatrix} 2 \\ 3 \end{pmatrix}, \begin{pmatrix} 8 & 2 \\ 2 & 10 \end{pmatrix}$$

$$\begin{pmatrix} X_3 \\ X_4 \end{pmatrix} \sim N_2 \begin{pmatrix} 6 \\ 7 \end{pmatrix}, \begin{pmatrix} 9 & 3 \\ 3 & 7 \end{pmatrix}$$



随机向量X和Y的协方差矩阵

$$Cov(X,Y) = E\left[\left(X - EX\right)\left(Y - EY\right)'\right]$$

$$= \begin{bmatrix} Cov(X_1, Y_1) & Cov(X_1, Y_2) & \cdots & Cov(X_1, Y_q) \\ Cov(X_2, Y_1) & Cov(X_2, Y_2) & \cdots & Cov(X_2, Y_q) \\ \vdots & \vdots & \ddots & \vdots \\ Cov(X_p, Y_1) & Cov(X_p, Y_2) & \cdots & Cov(X_p, Y_q) \end{bmatrix}$$

为随机向量X和Y的协方差矩阵。若Cov(X,Y) = O, (其中O表示零矩阵),则称随机向量X和Y不相关。

设正态随机向量X和Y相互独立  $\Leftrightarrow Cov(X,Y) = O_{p \times q}$ ;



#### 随机向量X的相关矩阵

$$R = (r_{ij})_{p \times p}$$
 为 $X$ 的相关矩阵, 其中

$$r_{ij} = \frac{Cov(X_i, X_j)}{\sqrt{Var(X_i)}\sqrt{Var(X_j)}} = \frac{\sigma_{ij}}{\sqrt{\sigma_{ii}\sigma_{jj}}}, (i, j = 1, 2, \dots, p)$$

若记 
$$V^{\frac{1}{2}} = diag\left(\sqrt{\sigma_{11}}, \sqrt{\sigma_{22}}, \dots, \sqrt{\sigma_{pp}}\right)$$
为标准差矩阵,

则记 
$$\Sigma = V^{\frac{1}{2}}RV^{\frac{1}{2}}$$
,或 $R = \left(V^{\frac{1}{2}}\right)^{-1}\Sigma\left(V^{\frac{1}{2}}\right)^{-1}$ .



$$R = \begin{pmatrix} X_1 \\ X_2 \\ X_3 \\ X_4 \end{pmatrix} \sim N_4 \begin{pmatrix} 2 \\ 3 \\ 6 \\ 7 \end{pmatrix}, \begin{pmatrix} 8 & 2 & 0 & 0 \\ 2 & 10 & 0 & 0 \\ 0 & 0 & 9 & 3 \\ 0 & 0 & 3 & 7 \end{pmatrix}$$

$$R = \begin{pmatrix} \frac{1}{\sqrt{8}} & 0 & 0 & 0 \\ 0 & \frac{1}{\sqrt{10}} & 0 & 0 \\ 0 & 0 & \frac{1}{\sqrt{9}} & 0 \\ 0 & 0 & 0 & \frac{1}{\sqrt{7}} \end{pmatrix} \begin{pmatrix} 8 & 2 & 0 & 0 \\ 2 & 10 & 0 & 0 \\ 0 & 0 & 9 & 3 \\ 0 & 0 & 3 & 7 \end{pmatrix} \begin{pmatrix} \frac{1}{\sqrt{8}} & 0 & 0 & 0 \\ 0 & \frac{1}{\sqrt{10}} & 0 & 0 \\ 0 & 0 & 9 & 3 \\ 0 & 0 & 3 & 7 \end{pmatrix}$$



$$X = \begin{pmatrix} X_1 \\ X_2 \end{pmatrix}, \quad \mu_X = \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix}, \quad \Sigma_X = \begin{pmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{pmatrix}$$

$$Z = \begin{pmatrix} Z_1 \\ Z_2 \end{pmatrix} = \begin{pmatrix} 1 & -1 \\ 1 & 1 \end{pmatrix} \begin{pmatrix} X_1 \\ X_2 \end{pmatrix}$$

$$EZ =$$

$$\Sigma_z =$$



$$EX = \begin{pmatrix} 2\\4\\-1\\3\\0 \end{pmatrix}, DX = \begin{pmatrix} 4&-1&\frac{1}{2}&-\frac{1}{2}&0\\-1&3&1&-1&0\\\frac{1}{2}&1&6&1&-1\\-\frac{1}{2}&-1&1&4&0\\0&0&-1&0&2 \end{pmatrix}$$

$$A = \begin{pmatrix} 1 & -1 \\ 1 & 1 \end{pmatrix}, B = \begin{pmatrix} 1 & 1 & 1 \\ 1 & 1 & -2 \end{pmatrix}$$

$$E(AX^{(1)}), E(BX^{(2)})$$
 $Cov(X^{(1)}), Cov(AX^{(1)}), Cov(BX^{(2)})$ 



$$X_1 \sim N_p(\mu_1, \Sigma_{11}), \quad X_2 \sim N_q(\mu_2, \Sigma_{22})$$

$$\begin{pmatrix} X_1 \\ X_2 \end{pmatrix} \sim N_{p+q} \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix}, \begin{pmatrix} \Sigma_{11} & 0 \\ 0 & \Sigma_{22} \end{pmatrix}$$



# 样本统计量的特征

总体
$$X \sim N(\mu, \sigma^2)$$
容量为 $n$ 的随机样本 $\begin{pmatrix} X_1 \\ X_2 \\ \vdots \\ X_n \end{pmatrix}$ 

样本平均数 
$$\bar{X} = \frac{1}{n} \sum_{i=1}^{n} X_i$$
 样本方差  $S^2 = \frac{1}{n-1} \sum_{i=1}^{n} (X_i - \bar{X})^2$ 



#### 估计量的评价标准(样本均值和方差的性质)

#### 一、无偏性

若 $\hat{\theta} = \hat{\theta}(X_1, \dots, X_n)$ 的数学期望存在,且 $E\hat{\theta} = \theta$ ,

则称 $\hat{\theta}$ 是 $\theta$ 的无偏估计量.

X为任意总体  $X_1, ..., X_n$  为简单随机样本  $\hat{\mu} = \bar{X}$   $\mu$ 的矩估计量。

$$E(\bar{X}) = E\left(\frac{\sum_{i=1}^{n} X_{i}}{n}\right) = \frac{\sum_{i=1}^{n} E(X_{i})}{n} = \mu$$



# 样本的中心矩是否是总体中心矩的无偏估计?以*k*=2 为例证明

$$E(X) = \mu, \quad D(X) = \sigma^{2}$$

$$\Rightarrow E(X^{2}) = \sigma^{2} + \mu^{2}$$

$$E(\bar{X}) = \mu, \quad D(\bar{X}) = D\left(\frac{1}{n}\sum_{i=1}^{n}X_{i}\right) = \frac{1}{n^{2}}D\left(\sum_{i=1}^{n}X_{i}\right) = \frac{D(X)}{n} = \frac{\sigma^{2}}{n}$$

$$\Rightarrow E(\bar{X}^{2}) = \frac{\sigma^{2}}{n} + \mu^{2}$$



$$\sum_{i=1}^{n} (X_i - \bar{X})^2 = \sum_{i=1}^{n} X_i^2 - n\bar{X}^2$$

$$E\left\{\frac{1}{n}\sum_{i=1}^{n}\left(X_{i}-\bar{X}\right)^{2}\right\}=\frac{1}{n}\sum_{i=1}^{n}E\left(X_{i}^{2}\right)-E\left(\bar{X}^{2}\right)$$

$$= \mu^2 + \sigma^2 - \left(\mu^2 + \frac{\sigma^2}{n}\right) = \frac{(n-1)}{n}\sigma^2$$

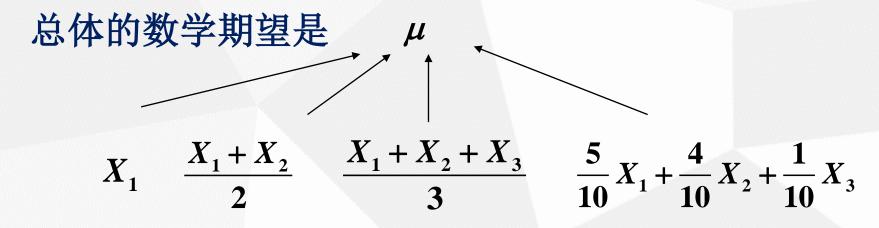
$$E(S^{2}) = E\left(\frac{\sum_{i=1}^{n} (X_{i} - \overline{X})^{2}}{n-1}\right) = \sigma^{2}$$



#### 二、有效性

若 $\hat{\theta}_1 = \hat{\theta}_1(X_1, \dots, X_n)$ , $\hat{\theta}_2 = \hat{\theta}_2(X_1, \dots, X_n)$ 都是 $\theta$ 的无偏估计量,且 $D(\hat{\theta}_1) \leq D(\hat{\theta}_2)$ ,则称 $\hat{\theta}_1$ 较 $\hat{\theta}_2$ 有效.

 $X_1, X_2, X_3$  是从该总体中抽取的一个样本.



都是未知参数 μ的无偏估计,并指出哪一个最有效?



解: 
$$E(X_1) = \mu$$
  $E(\frac{X_1 + X_2}{2}) = \mu$ 

$$E\left(\frac{1}{3}X_1 + \frac{1}{3}X_2 + \frac{1}{3}X_3\right) = \mu \qquad E\left(\frac{5}{10}X_1 + \frac{4}{10}X_2 + \frac{1}{10}X_3\right) = \mu$$

这表明都是未知参数 μ的无偏估计.

$$D(X_1) = \sigma^2 \qquad D\left(\frac{X_1 + X_2}{2}\right) = \frac{\sigma^2}{2}$$

$$D\left(\frac{1}{3}X_1 + \frac{1}{3}X_2 + \frac{1}{3}X_3\right) = \frac{\sigma^2}{3}$$

$$D\left(\frac{5}{10}X_1 + \frac{4}{10}X_2 + \frac{1}{10}X_3\right) = \left(\frac{25}{100} + \frac{16}{100} + \frac{1}{100}\right)\sigma^2$$



#### 三、一致性

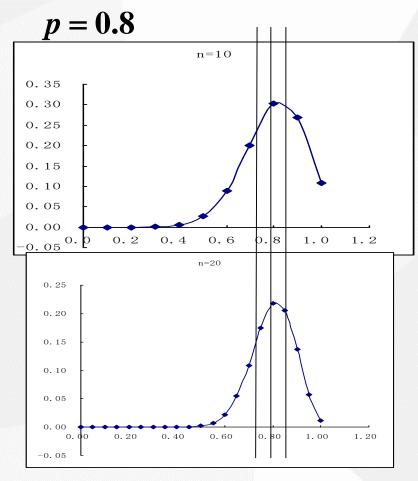
若 $\hat{\theta} = \hat{\theta}_n(X_1, \dots, X_n)$ 为参数 $\theta$  的估计量,如果

对于任意
$$\varepsilon > 0$$
,  $\lim_{n \to \infty} P\{|\hat{\theta}_n - \theta| > \varepsilon\} = 0$ 

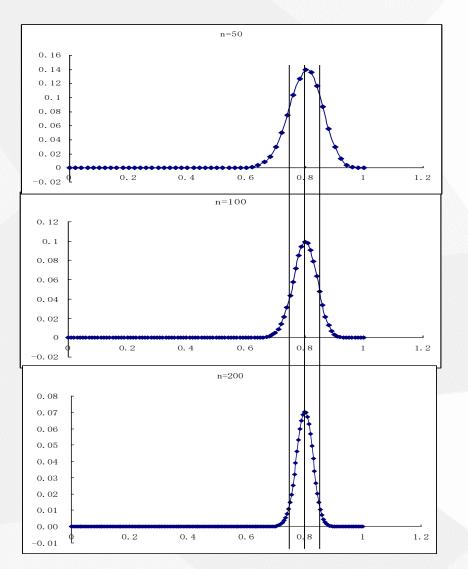
$$||\vec{x}||_{n\to\infty} P\left\{ \left| \hat{\theta}_n - \theta \right| \le \varepsilon \right\} = 1$$

则称 $\hat{\theta}$ 是 $\theta$ 的一致估计.





$$\frac{p(1-p)}{P\{|\hat{p}-p| \le \varepsilon\}} \ge 1 - \frac{n}{\varepsilon^2} \to 1$$
  
频率是概率的一致估计





$$\bar{X} = \frac{\sum_{i=1}^{n} X_i}{n} \to E(X)$$

$$E\bar{X} = \mu, \quad D\bar{X} = \frac{\sigma^2}{n}$$

由切比雪夫不等式  $P(|\bar{X} - \mu| < \varepsilon) \ge 1 - \frac{\sigma^2}{n\varepsilon^2} \xrightarrow{n \to \infty} 1$ 

样本一阶原点矩是总体一阶原点矩的一致估计

同理,样本k阶原点矩是总体k阶原点矩的一致估计

$$\frac{1}{n}\sum_{i=1}^n X_i^k \to EX^k$$



$$\frac{1}{n}\sum_{i=1}^{n}(X_{i}-\bar{X})^{2}=\frac{1}{n}\sum_{i=1}^{n}X_{i}^{2}-\left(\frac{1}{n}\sum_{i=1}^{n}X_{i}\right)^{2}\to EX^{2}-(EX)^{2}=\sigma^{2}$$

样本的二阶中心矩是总体二阶中心矩的一致估计

$$\frac{1}{n-1} \sum_{i=1}^{n} (X_i - \bar{X})^2 = \frac{n}{n-1} \frac{1}{n} \sum_{i=1}^{n} (X_i - \bar{X})^2 \to \sigma^2$$

样本方差是总体二阶中心矩的一致估计



正态总体的样本均值与样本方差的分布:

定理1 设 $X_1, \dots, X_n$ 是总体 $N(\mu, \sigma^2)$ 的样本, $\overline{X}, S^2$ 分别是样本均值与样本方差,则有:

(1) 
$$\bar{X} \sim N(\mu, \frac{\sigma^2}{n});$$
  $\frac{\bar{X} - \mu}{\sigma / \sqrt{n}} \sim N(0, 1),$ 

(2) 
$$\frac{(n-1)S^{2}}{\sigma^{2}} = \frac{\sum_{i=1}^{n} (X_{i} - \overline{X})^{2}}{\sigma^{2}} \sim \chi^{2}(n-1);$$

可以表示成n-1个相互独立的标准正态的平方和

(3)  $\bar{X}$ 与 $S^2$ 相互独立



把来自p元总体 $X \sim N_p(\mu, \Sigma)$ 容量为n的随机样本排成一个 $n \times p$ 矩阵的X:

$$X = \begin{pmatrix} X_{11} & X_{12} & \cdots & X_{1p} \\ X_{21} & X_{22} & \cdots & X_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ X_{n1} & X_{n2} & \cdots & X_{np} \end{pmatrix} \stackrel{def}{=} \begin{pmatrix} X'_{(1)} \\ X'_{(2)} \\ \vdots \\ X'_{(n)} \end{pmatrix}$$

其中 $X_{(i)}$ ( $i=1,2,\dots,n$ )是来自p元总体的一个样本,则样本数据阵就是一个随机阵.



#### 一. 多元正态总体样本的数字特征

对于多元统计分析,我们常引入以下多元正态总体样本的相关量.

(1) 样本的均值向量
$$\bar{X}$$
:  $\bar{X} = \begin{pmatrix} \frac{1}{n} \sum_{i=1}^{n} X_{i1} \\ \vdots \\ \frac{1}{n} \sum_{i=1}^{n} X_{ip} \end{pmatrix}$ 

(2) 样本离差阵(交叉乘积阵) L:

$$\begin{pmatrix} X_{11} - \frac{1}{n} \sum_{i=1}^{n} X_{i1} & X_{12} - \frac{1}{n} \sum_{i=1}^{n} X_{i2} & \cdots & X_{1p} - \frac{1}{n} \sum_{i=1}^{n} X_{ip} \\ X_{21} - \frac{1}{n} \sum_{i=1}^{n} X_{i1} & X_{22} - \frac{1}{n} \sum_{i=1}^{n} X_{i2} & \cdots & X_{2p} - \frac{1}{n} \sum_{i=1}^{n} X_{ip} \\ \vdots & \vdots & \ddots & \vdots \\ X_{n1} - \frac{1}{n} \sum_{i=1}^{n} X_{i1} & X_{n2} - \frac{1}{n} \sum_{i=1}^{n} X_{i2} & \cdots & X_{np} - \frac{1}{n} \sum_{i=1}^{n} X_{ip} \end{pmatrix}^{T} \begin{pmatrix} X_{11} - \frac{1}{n} \sum_{i=1}^{n} X_{i1} & X_{12} - \frac{1}{n} \sum_{i=1}^{n} X_{i2} & \cdots & X_{1p} - \frac{1}{n} \sum_{i=1}^{n} X_{ip} \\ X_{21} - \frac{1}{n} \sum_{i=1}^{n} X_{i1} & X_{22} - \frac{1}{n} \sum_{i=1}^{n} X_{i2} & \cdots & X_{2p} - \frac{1}{n} \sum_{i=1}^{n} X_{ip} \\ \vdots & \vdots & \ddots & \vdots \\ X_{n1} - \frac{1}{n} \sum_{i=1}^{n} X_{i1} & X_{n2} - \frac{1}{n} \sum_{i=1}^{n} X_{i2} & \cdots & X_{np} - \frac{1}{n} \sum_{i=1}^{n} X_{ip} \end{pmatrix}^{T} \begin{pmatrix} X_{11} - \frac{1}{n} \sum_{i=1}^{n} X_{i1} & X_{22} - \frac{1}{n} \sum_{i=1}^{n} X_{i2} & \cdots & X_{2p} - \frac{1}{n} \sum_{i=1}^{n} X_{ip} \\ \vdots & \vdots & \ddots & \vdots \\ X_{n1} - \frac{1}{n} \sum_{i=1}^{n} X_{i1} & X_{n2} - \frac{1}{n} \sum_{i=1}^{n} X_{i2} & \cdots & X_{np} - \frac{1}{n} \sum_{i=1}^{n} X_{ip} \end{pmatrix}^{T} \begin{pmatrix} X_{11} - \frac{1}{n} \sum_{i=1}^{n} X_{i1} & X_{22} - \frac{1}{n} \sum_{i=1}^{n} X_{i2} & \cdots & X_{2p} - \frac{1}{n} \sum_{i=1}^{n} X_{ip} \\ \vdots & \vdots & \ddots & \vdots \\ X_{n1} - \frac{1}{n} \sum_{i=1}^{n} X_{i1} & X_{n2} - \frac{1}{n} \sum_{i=1}^{n} X_{i2} & \cdots & X_{np} - \frac{1}{n} \sum_{i=1}^{n} X_{ip} \end{pmatrix}$$

## (3)样本协方差阵

$$S = \frac{1}{n-1}L = \left(s_{ij}\right)_{p \times p} \quad \left( \overrightarrow{\mathbb{Z}}S^* = \frac{1}{n}L \right),$$

称为随机变量 $X_i$ 的样本方差,样本方差的平方根 $\sqrt{S_{ii}}$ 称为 $X_i$ 的样本标准差.

### (4) 样本相关矩阵R

其中 
$$r_{ij} = \frac{S_{ij}}{\sqrt{S_{ii}}\sqrt{S_{jj}}} = \frac{1}{\sqrt{l_{ii}}} \frac{l_{ij}}{\sqrt{l_{jj}}}$$
  $(i, j = 1, 2, \dots, p).$ 



# 以下是 $\mu$ 和 $\Sigma$ 的估计的一些性质.

$$(1)\bar{X}$$
是 $\mu$ 的无偏估计, $\frac{L}{n-1}$ 是 $\Sigma$ 的无偏估计

$$(2)$$
 $\bar{X}$ 是 $\mu$ 的有效估计,  $\frac{L}{n-1}$ 是 $\Sigma$ 的有效估计

$$(3)$$
 $\bar{X}$ 是 $\mu$ 的一致估计,  $\frac{L}{n-1}$ 是 $\Sigma$ 的一致估计



设 $\bar{\chi}$ 和L分别为p元正态总体 $N_p(\mu,\Sigma)$ 的样本均值向量和样本离差阵,则

$$(1)\bar{X} \sim N_p\left(\mu, \frac{1}{n}\Sigma\right);$$

$$(2)L=\sum_{t=1}^{n}Z_{t}Z_{t}'$$
,其中 $Z_{1},Z_{2},\cdots,Z_{n}$ 独立且服从 $N_{p}(O,\Sigma)$ 分布;

(3) $\bar{X}$ 和L相互独立;



# $\chi^2$ — 分布和Wishart分布

定义1 设 $X_1, X_2, \dots, X_n$ 为 相互独立且同服从于 N(0,1) 分布的随机变量。则

$$\chi^2 = \sum_{i=1}^n X_i^2$$

所服从的分布叫做 $\chi^2$  —分布,n 称为自

由度且记为 $\chi^2 \sim \chi^2(n)$ 。



定理.设  $X_1 \sim \chi^2(n_1) X_2 \sim \chi^2(n_2)$ ,

且 $X_1$ 与 $X_2$ 相互独立,则

$$X_1 + X_2 \sim \chi^2(n_1 + n_2)$$



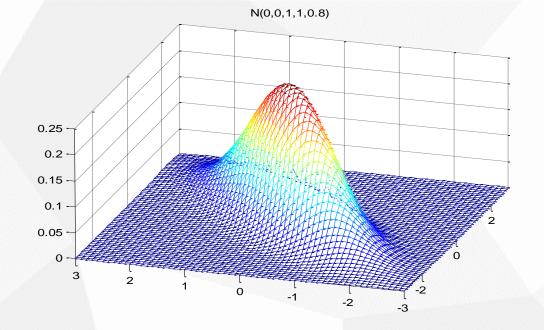
### Wishart分布

定义1 设  $X_1, X_2, \dots, X_n$  为 相互独立且同服从于分布  $N_p(0, \Sigma)$  ,令  $\boldsymbol{X} = [X_1, X_2, \dots, X_n]'$ 则

$$W = XX' = \sum_{i=1}^{n} X_i X_i'$$

所服从的分布叫做自由度为 n 的p维-维希特分布,记作  $W \sim W_p(n,\Sigma)$ 





$$X_i \sim N_2 \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & 0.8 \\ 0.8 & 1 \end{pmatrix}, i = 1, 2, 3, 4, 5$$

$$X_{1}X_{1}' + X_{2}X_{2}' + X_{3}X_{3}' + X_{4}X_{4}' + X_{5}X_{5}' \sim W_{2} \left(5, \begin{pmatrix} 1 & 0.8 \\ 0.8 & 1 \end{pmatrix}\right)$$



显然,当
$$p=1$$
, $\Sigma = \sigma^2$ 时,有 $W_1(n,\sigma^2) = \sigma^2 \chi^2(n)$ 

## Wishart分布像卡方分布一样具有加法性质,若

$$W_1 \sim W_p(n_1,\Sigma), W_2 \sim W_p(n_2,\Sigma)$$
相互独立,则

$$W_1 + W_2 \sim W_p(n_1 + n_2, \Sigma)$$



测定稻谷每亩穗数X1,每穗粒数X2,每亩稻谷产量X3,

$$X = \begin{pmatrix} X_1 \\ X_2 \\ X_3 \end{pmatrix} \sim N_3(\mu, \Sigma)$$
 求参数的无偏估计。

X1	26. 7	31.3	30. 4	33.9	34.6	33.8	30. 4	27	33. 3	30. 4	31.5	33	34
X2	73.4	59	65.9	58. 2	64.6	64.6	62. 1	71.4	64. 5	64. 1	61. 1	56	59.8
Х3	1008	959	1051	1022	1097	1103	992	945	1074	1029	1004	995	1045



$$\bar{X} = \begin{pmatrix} \bar{X}_1 \\ \bar{X}_2 \\ \bar{X}_3 \end{pmatrix} = \begin{pmatrix} 31.56 \\ 63.44 \\ 1024.92 \end{pmatrix}$$

$$S = \frac{1}{n-1}L$$

$$=\frac{1}{13-1}\begin{pmatrix} 26.7-31.56 & \cdots & 34-31.56 \\ 73.4-63.44 & \cdots & 59.8-63.44 \\ 1008-1024.92 & \cdots & 1045-1024.92 \end{pmatrix}\begin{pmatrix} 26.7-31.56 & 73.4-63.44 & 1008-1024.92 \\ \vdots & \vdots & \vdots & \vdots \\ 34-31.56 & 59.8-63.44 & 1045-1024.92 \end{pmatrix}$$

$$= \begin{pmatrix} 6.1 & -8.41 & 72.83 \\ -8.41 & 22.76 & 3.00 \\ 72.83 & 3.00 & 2172.69 \end{pmatrix}$$



