

MULTIVARIATE DATA

**Reference:** Johnson & Wichern (2002) *Applied Multivariate Statistical Analysis* Chapter 1 and 3.

**1 Multivariate Random Sample**

Let  $X_{i1}, X_{i2}, \dots, X_{in}$  be  $n$  observations of the  $i^{\text{th}}$  random variable  $\underline{X}_i$  ( $i = 1, 2, \dots, p$ ), then  $\underline{X}_j^T = (X_{1j} \ X_{2j} \ \dots \ X_{pj})$ ,  $j = 1, 2, \dots, n$ , is the  $j^{\text{th}}$  multivariate observation for random vector  $\underline{X}$ . Let  $\underline{\mu}$  and  $\Sigma$  be the mean and covariance of  $\underline{X}$ . That is, if

$$\underline{\mu} = \begin{pmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_p \end{pmatrix} \quad \text{and} \quad \Sigma = \begin{pmatrix} \sigma_{11} & \sigma_{12} & \dots & \sigma_{1p} \\ \sigma_{21} & \sigma_{22} & \dots & \sigma_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{p1} & \sigma_{p2} & \dots & \sigma_{pp} \end{pmatrix}$$

such that  $\sigma_{ik} = \sigma_{ki}$  for all  $i$  and  $k$ , then  $\mu_i$  and  $\sigma_{ii}$  are respectively the mean and variance of the random observation  $X_i$  ( $i = 1, 2, \dots, p$ ) and

$$\text{Cov}(X_i, X_k) = \sigma_{ik} = \sigma_{ki} \quad \text{for } i, k = 1, 2, \dots, p.$$

Note :  $n$  = sample size;  $p$  = number of variables ( $p$ -dimension) in the random vector.

The entire data set can be placed in an  $n \times p$  matrix:

sample  
data  
matrix

$$\mathcal{X} = \begin{pmatrix} \underline{X}_1^T \\ \underline{X}_2^T \\ \vdots \\ \underline{X}_n^T \end{pmatrix} = \begin{pmatrix} x_{11} & x_{12} & \dots & x_{1p} \\ x_{21} & x_{22} & \dots & x_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \dots & x_{np} \end{pmatrix}$$

variable = columns  
obs = rows

## 2 Descriptive Statistics

### (a) Sample Mean Vector $\bar{X}_n$

The sample mean of the random variable  $X_i$  using the above random sample is given by

$$\bar{X}_{in} = \frac{1}{n} \sum_{j=1}^n X_{ij}.$$

Note that  $\mathbb{E}(\bar{X}_{in}) = \mu_i$ , that is  $\bar{X}_{in}$  is an unbiased estimator  $\mu_i$ .

*expect*

The sample mean vector of multivariate sample is given by

$$\bar{X}_n = \frac{1}{n} \sum_{j=1}^n \mathbf{X}_j = \begin{pmatrix} \bar{X}_{1n} \\ \bar{X}_{2n} \\ \vdots \\ \bar{X}_{pn} \end{pmatrix} \quad p \times 1$$

Hence,  $\mathbb{E}(\bar{X}_n) = \boldsymbol{\mu}$ , that is,  $\bar{X}_n$  is an unbiased estimator of  $\boldsymbol{\mu}$ .

### (b) Sample Variances

- $S_i^{*2} = S_{ii}^*$  - bias estimator of  $\sigma_{ii}$
- $S_i^2 = S_{ii}$  - unbiased estimator of  $\sigma_{ii}$

Define

$$S_{ii}^* = S_i^{*2} = \frac{1}{n} \sum_{j=1}^n (X_{ij} - \bar{X}_{in})^2$$

*\* biased estimator of  $\sigma_{ii}$*

and

$$S_{ii} = S_i^2 = \frac{1}{n-1} \sum_{j=1}^n (X_{ij} - \bar{X}_{in})^2$$

*unbiased*

Then

- $\mathbb{E}(S_i^{*2}) = \mathbb{E}(S_{ii}^*) = \frac{n-1}{n} \sigma_{ii}$  - implies  $S_{ii}^*$  is a bias estimator of  $\sigma_{ii}$ .
- $\mathbb{E}(S_i^2) = \mathbb{E}(S_{ii}) = \sigma_{ii}$  - implies  $S_{ii}$  is an unbiased estimator of  $\sigma_{ii}$ .

**Note:**  $S_{ii} = \frac{n}{n-1} S_{ii}^*$ .

*switch between two variance matrices*

The square root of the sample variance is known as the sample standard deviation.

*$\sqrt{\phantom{x}}$*

(c) Sample Covariances  $S_{ik}^*$  and  $S_{ik}$ : *bias* *unbiased*

The sample covariance gives a measure of association between two variables. A bias sample covariance between  $X_i$  and  $X_k$  is

$$S_{ik}^* = \frac{1}{n} \sum_{j=1}^n (X_{ij} - \bar{X}_i) (X_{kj} - \bar{X}_k).$$

*pair's variables* *dev. var i* *dev. var k*

and an unbiased sample covariance between  $X_i$  and  $X_k$  is

$$S_{ik} = \frac{1}{n-1} \sum_{j=1}^n (X_{ij} - \bar{X}_i) (X_{kj} - \bar{X}_k).$$

**Note:** (1)  $S_{ij} = \frac{n}{n-1} S_{ij}^*$ . (2)  $E(S_{ij}^*) = \frac{n-1}{n} \sigma_{ij}$ .  
 (3)  $E(S_{ij}) = \sigma_{ij}$  (4) When  $i = k$ ,  $S_{ik}^* = S_i^{*2}$  and  $S_{ik} = S_i^2$ .  
 (5)  $S_{ik}^* = S_{ki}^*$  and (6)  $S_{ik} = S_{ki}$  for all  $i$  and  $k$ .

(d) Sample Covariance Matrices  $\mathcal{S}_n$  and  $\mathcal{S}$ :

The bias sample covariance matrix  $\mathcal{S}_n$  and unbiased sample covariance matrix  $\mathcal{S}$  are given by

$$\mathcal{S}_n^* = \mathcal{S}_n = \begin{pmatrix} S_{11}^* & S_{12}^* & \dots & S_{1p}^* \\ S_{21}^* & S_{22}^* & \dots & S_{2p}^* \\ \vdots & \vdots & \ddots & \vdots \\ S_{p1}^* & S_{p2}^* & \dots & S_{pp}^* \end{pmatrix} = \frac{1}{n} \sum_{j=1}^n (\mathbf{X}_j - \bar{\mathbf{X}}_n) (\mathbf{X}_j - \bar{\mathbf{X}}_n)^T \quad \text{and}$$

*variances* *covariances* *symmetric / square*

$$\mathcal{S} = \begin{pmatrix} S_{11} & S_{12} & \dots & S_{1p} \\ S_{21} & S_{22} & \dots & S_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ S_{p1} & S_{p2} & \dots & S_{pp} \end{pmatrix} = \frac{1}{n-1} \sum_{j=1}^n (\mathbf{X}_j - \bar{\mathbf{X}}_n) (\mathbf{X}_j - \bar{\mathbf{X}}_n)^T.$$

Note that  $\mathcal{S} = \frac{n}{n-1} \mathcal{S}_n$ .

(e) Generalized variance *single value!*

Generalized sample variance is determinant of the sample covariance matrix  $|\mathcal{S}|$ .

(f) Sample Correlation  $R_{ij}$ 

Sample correlation coefficient is a measure of the linear association between two random variables. This does not depend on the unit of measurement.

Sample correlation coefficient between random variables  $X_i$  and  $X_j$  is defined as

$$R_{ik} = \frac{\text{Covariance}}{\sqrt{\text{Variance}_i \sqrt{\text{Variance}_k}}} = \frac{\sum_{j=1}^n (X_{ij} - \bar{X}_i)(X_{kj} - \bar{X}_k)}{\sqrt{\sum_{j=1}^n (X_{ij} - \bar{X}_i)^2} \sqrt{\sum_{j=1}^n (X_{kj} - \bar{X}_k)^2}}$$

for  $i \neq k = 1, 2, \dots, p$ .

Properties of  $R_{ik}$ :

- (1) Sample correlation  $R_{ik}$  must lie between  $-1$  and  $1$ , that is,  $-1 \leq R_{ik} \leq 1$  for all  $i, k$ .
- (2) If  $R_{ik} = 0$ , there is no association between variables  $X_i$  and  $X_k$ . Otherwise, the sign of  $R_{ik}$  gives the direction of association.
- (3)  $R_{ik}$  remains unchanged if the random variables  $X_i$  and  $X_k$  are transformed to random variables  $Y_i$  and  $Y_k$  such that  $Y_i = aX_i + b$ ,  $Y_k = cX_k + d$  where  $a, b, c$  and  $d$  are constants and  $a$  and  $c$  have the same sign (that is,  $ac > 0$ ).

-1



Strong neg linear association

+1



Strong positive assoc

(g) Sample Correlation Matrix  $\mathcal{R}_n$ 

$$\mathcal{R}_n = \begin{pmatrix} R_{11} & R_{12} & \dots & R_{1p} \\ R_{21} & R_{22} & \dots & R_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ R_{p1} & R_{p2} & \dots & R_{pp} \end{pmatrix} = I$$

# Example 1.1

Four receipts from a bookstore

	$R_1$	$R_2$	$R_3$	$R_4$
Variable: sales (\$)	\$42	\$52	\$48	\$58
Variables: number of books	4	5	4	3

$$X_{n \times p} = \begin{matrix} & \begin{matrix} X_1 & X_2 \end{matrix} \\ \begin{matrix} (4 \times 2) \end{matrix} & \begin{bmatrix} 42 & 4 \\ 52 & 5 \\ 48 & 4 \\ 58 & 3 \end{bmatrix} \end{matrix}$$

first obs (from  $R_1$ )

Find the sample mean vector  $\bar{X}$

first find the mean of each variable

$$\bar{x}_k = \frac{1}{n} \sum_{i=1}^n x_{ik}$$

$$\bar{x}_1 = \frac{1}{4} (42 + 52 + 48 + 58) = 50$$

$$\bar{x}_2 = \frac{1}{4} (4 + 5 + 4 + 3) = 4$$

$$\bar{X} = \begin{bmatrix} \bar{x}_1 \\ \bar{x}_2 \end{bmatrix} = \begin{bmatrix} 50 \\ 4 \end{bmatrix}$$

Find the sample biased covariance matrix  $S^*$

first find the variances

$$S_{kk}^* = \frac{1}{n} \sum_{i=1}^n (x_{ik} - \bar{x}_k)^2$$

$$S_{11}^* = \frac{1}{4} ((42-50)^2 + (52-50)^2 + (48-50)^2 + (58-50)^2) = 34$$

$$S_{22}^* = \frac{1}{4} ((4-4)^2 + (5-4)^2 + (4-4)^2 + (3-4)^2) = 0.5$$

then find the biased covariance

$$S_{ik}^* = \frac{1}{n} \sum_{i=1}^n (x_{ij} - \bar{x}_i)(x_{jk} - \bar{x}_k)$$

$$= \frac{1}{4} \left( (42-50)(4-4) + (52-50)(5-4) + (48-50)(4-4) + (58-50)(3-4) \right) = -1.5 = s_{12}^* = s_{21}^*$$

construct the matrix

$$S^* = \begin{bmatrix} s_{11} & s_{12} \\ s_{21} & s_{22} \end{bmatrix} = \begin{bmatrix} 34 & -1.5 \\ -1.5 & 0.5 \end{bmatrix}$$

To find the Generalised variance

$$|S| = \begin{vmatrix} 34 & -1.5 \\ -1.5 & 0.5 \end{vmatrix}$$

$$= ad - bc$$

$$= s_{11} s_{22} - s_{12} s_{21}$$

$$= 34 \times 0.5 - (-1.5 \times -1.5)$$

$$= 14.75$$

Find the sample correlation matrix

$$R_{ik} = \frac{s_{ik}}{\sqrt{s_{ii}} \sqrt{s_{kk}}} = \frac{-1.5}{\sqrt{34} \sqrt{0.5}} = -0.36$$

$$R = \begin{bmatrix} 1 & -0.36 \\ -0.36 & 1 \end{bmatrix}$$