

/3.1

$$a) \quad \bar{x} = \begin{bmatrix} 5 \\ 2 \end{bmatrix}$$

$$b) \quad \underline{e}_1 = \underline{y}_1 - \bar{x}_1 \underline{1} = [4, 0, -4]'$$

$$\underline{e}_2 = \underline{y}_2 - \bar{x}_2 \underline{1} = [-1, 1, 0]'$$

$$c) \quad L_{\underline{e}_1} = \sqrt{32}; \quad L_{\underline{e}_2} = \sqrt{2}$$

Let  $\theta$  be the angle between  $\underline{e}_1$  and  $\underline{e}_2$ , then  $\cos(\theta) = -4/\sqrt{32 \times 2} = -.5$

Therefore  $n s_{11} = L_{\underline{e}_1}^2$  or  $s_{11} = 32/3$ ;  $n s_{22} = L_{\underline{e}_2}^2$  or  $s_{22} = 2/3$ ;

$n s_{12} = \underline{e}_1' \underline{e}_2$  or  $s_{12} = -4/3$ . Also,  $r_{12} = \cos(\theta) = -.5$ . Conse-

quently  $S_n = \begin{bmatrix} 32/3 & -4/3 \\ -4/3 & 2/3 \end{bmatrix}$  and  $R = \begin{bmatrix} 1 & -.5 \\ -.5 & 1 \end{bmatrix}$ .

3.7 All ellipses are centered at  $\bar{x}$ .

$$i) \quad \text{For } S = \begin{bmatrix} 5 & 4 \\ 4 & 5 \end{bmatrix}, \quad S^{-1} = \begin{bmatrix} 5/9 & -4/9 \\ -4/9 & 5/9 \end{bmatrix}$$

Eigenvalue-normalized eigenvector pairs for  $S^{-1}$  are:

$$\lambda_1 = 1, \quad \underline{e}_1' = [.707, \quad -.707]$$

$$\lambda_2 = 1/9, \quad \underline{e}_2' = [.707, \quad .707]$$

Half lengths of axes of ellipse  $(\underline{x} - \bar{x})' S^{-1} (\underline{x} - \bar{x}) \leq 1$

are  $1/\sqrt{\lambda_1} = 1$  and  $1/\sqrt{\lambda_2} = 3$  respectively. The major axis of ellipse lies in the direction of  $\underline{e}_2$ ; the minor axis lies in the direction of  $\underline{e}_1$ .

$$ii) \quad \text{For } S = \begin{bmatrix} 5 & -4 \\ -4 & 5 \end{bmatrix}, \quad S^{-1} = \begin{bmatrix} 5/9 & 4/9 \\ 4/9 & 5/9 \end{bmatrix}$$

Eigenvalue-normalized eigenvectors for  $S^{-1}$  are:

$$\lambda_1 = 1, \quad \underline{e}_1' = [.707, \quad .707]$$

$$\lambda_2 = 1/9, \quad \underline{e}_2' = [.707, \quad -.707]$$

3.9 (a) We calculate  $\bar{x} = [16, 18, 34]'$  and

$$X_c = \begin{bmatrix} -4 & -1 & -5 \\ 2 & 2 & 4 \\ -2 & -2 & -4 \\ 4 & 0 & 4 \\ 0 & 1 & 1 \end{bmatrix} \text{ and we notice } \text{col}_1(X_c) + \text{col}_2(X_c) = \text{col}_1(X_c)$$

so  $a = [1, 1, -1]'$  gives  $X_c a = 0$ .

(b)

$$S = \begin{bmatrix} 10 & 3 & 13 \\ 3 & 2.5 & 5.5 \\ 13 & 5.5 & 18.5 \end{bmatrix} \text{ so } |S| = \begin{vmatrix} 10(2.5)(18.5) + 39(15.5) + 39(15.5) \\ -(13)^2(2.5) - 9(18.5) - 55(5.5) \end{vmatrix} = 0$$

As above in a)

$$Sa = \begin{bmatrix} 10 + 3 - 13 \\ 3 + 2.5 - 5.5 \\ 13 + 5.5 - 18.5 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

(c) Check.

3.14 a) From first principles we have

$$\underline{b}' \underline{x}_1 = [2 \ 3] \begin{bmatrix} 9 \\ 1 \end{bmatrix} = 21$$

Similarly  $\underline{b}' \underline{x}_2 = 19$  and  $\underline{b}' \underline{x}_3 = 8$  so

$$\text{sample mean} = \frac{21+19+8}{3} = 16$$

$$\text{sample variance} = \frac{(21-16)^2 + (19-16)^2 + (8-16)^2}{2} = 49$$

$$\text{Also } \underline{c}' \underline{x}_1 = [-1 \ 2] \begin{bmatrix} 9 \\ 1 \end{bmatrix} = -7; \quad \underline{c}' \underline{x}_2 = 1 \quad \text{and} \quad \underline{c}' \underline{x}_3 = 3$$

so

$$\text{sample mean} = -1$$

$$\text{sample variance} = 28$$

$$\text{Finally sample covariance} = \frac{(21-16)(-7+1) + (19-16)(1+1) + (8-16)(3+1)}{2} = -28.$$

$$\text{b) } \underline{\bar{x}}' = [5 \ 2] \quad \text{and} \quad \underline{S} = \begin{bmatrix} 16 & -2 \\ -2 & 1 \end{bmatrix}$$

Using (3-36)

$$\begin{aligned} \text{3.16} \quad \text{Since} \quad \underline{\hat{\Sigma}}_V &= E(\underline{V} - \underline{\mu}_V)(\underline{V} - \underline{\mu}_V)' \\ &= E(\underline{V}\underline{V}' - \underline{V}\underline{\mu}_V' - \underline{\mu}_V\underline{V}' + \underline{\mu}_V\underline{\mu}_V') \\ &= E(\underline{V}\underline{V}') - E(\underline{V})\underline{\mu}_V' - \underline{\mu}_V E(\underline{V}') + \underline{\mu}_V\underline{\mu}_V' \\ &= E(\underline{V}\underline{V}') - \underline{\mu}_V\underline{\mu}_V' - \underline{\mu}_V\underline{\mu}_V' + \underline{\mu}_V\underline{\mu}_V' \\ &= E(\underline{V}\underline{V}') - \underline{\mu}_V\underline{\mu}_V'. \end{aligned}$$

$$\text{we have } E(\underline{V}\underline{V}') = \underline{\hat{\Sigma}} + \underline{\mu}_V\underline{\mu}_V'.$$

3.17

Hint in the Text.

4.2 (a) We are given  $p = 2$ ,  $\mu = \begin{bmatrix} 0 \\ 2 \end{bmatrix}$ ,  $\Sigma = \begin{bmatrix} 2 & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & 1 \end{bmatrix}$  so  $|\Sigma| = 3/2$

and

$$\Sigma^{-1} = \begin{bmatrix} \frac{2}{3} & \frac{2}{3\sqrt{2}} \\ -\frac{2}{3\sqrt{2}} & \frac{4}{3} \end{bmatrix}$$

$$f(x) = \frac{1}{(2\pi)\sqrt{3/2}} \exp \left( -\frac{1}{2} \left[ \frac{2}{3}x_1^2 - \frac{2\sqrt{2}}{3}x_1(x_2 - 2) + \frac{4}{3}(x_2 - 2)^2 \right] \right)$$

(b)

$$\frac{2}{3}x_1^2 - \frac{2\sqrt{2}}{3}x_1(x_2 - 2) + \frac{4}{3}(x_2 - 2)^2$$

(c)  $c^2 = \chi^2_2(.5) = 1.39$ . Ellipse centered at  $[0, 2]'$  with the major axis having half-length  $\sqrt{\lambda_1} c = \sqrt{2.366\sqrt{1.39}} = 1.81$ . The major axis lies in the direction  $e = [.888, .460]'$ . The minor axis lies in the direction  $e = [-.460, .888]'$  and has half-length  $\sqrt{\lambda_2} c = \sqrt{.634\sqrt{1.39}} = .94$ .

4.3 We apply Result 4.5 that relates zero covariance to statistical independence

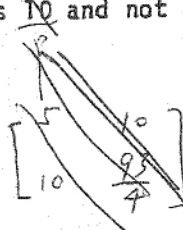
a) No,  $\sigma_{12} \neq 0$

b) Yes,  $\sigma_{23} = 0$

c) Yes,  $\sigma_{13} = \sigma_{23} = 0$

d) Yes, by Result 4.3,  $(X_1 + X_2)/2$  and  $X_3$  are jointly normal and their covariance is  $\frac{1}{4}\sigma_{13} + \frac{1}{4}\sigma_{23} = 0$ .

e) No, by Result 4.3 with  $A = \begin{bmatrix} 0 & 1 & 0 \\ -\frac{5}{2} & 1 & -1 \end{bmatrix}$ , form  $A \neq A'$  to see that the covariance is  $\frac{10}{4}$  and not 0.



$$\Sigma' = \begin{bmatrix} 5 & 10 \\ 10 & \frac{93}{4} \end{bmatrix}$$

- 4.4 a)  $3x_1 - 2x_2 + x_3$  is  $N(13, 9)$   
 b) Require  $\text{Cov}(x_2, x_2 - a_1 x_1 - a_3 x_3) = 3 - a_1 - 2a_3 = 0$ . Thus any  $\underline{a}' = [a_1, a_3]$  of the form  $\underline{a}' = [3 - 2a_3, a_3]$  will meet the requirement. As an example,  $\underline{a}' = [1, 1]$ .
- 4.5 a)  $x_1 | x_2$  is  $N(\frac{1}{\sqrt{2}}(x_2 - 2), \frac{3}{2})$   
 b)  $x_2 | x_1, x_3$  is  $N(-2x_1 - 5, 1)$   
 c)  $x_3 | x_1, x_2$  is  $N(\frac{1}{2}(x_1 + x_2 + 3), \frac{1}{2})$

4.10 Hint in the Text.

4.11 Hint in the Text.

4.13

(a) By using the exercise 4.11, we can write that

$$|\Sigma| = |\Sigma_{22}| |\Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21}| \quad \text{for } |\Sigma_{22}| \neq 0$$

(b)

$$\Sigma^{-1} = \begin{bmatrix} I & 0 \\ -\Sigma_{22}^{-1} \Sigma_{21} & I \end{bmatrix} \begin{bmatrix} (\Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21})^{-1} & 0 \\ 0' & \Sigma_{22}^{-1} \end{bmatrix} \begin{bmatrix} I & -\Sigma_{12} \Sigma_{22}^{-1} \\ 0 & I \end{bmatrix}$$

$$\begin{aligned} (x - \mu)' \Sigma^{-1} (x - \mu) &= \begin{bmatrix} x_1 - \mu_1 \\ x_2 - \mu_2 \end{bmatrix}' \begin{bmatrix} I & 0 \\ -\Sigma_{22}^{-1} \Sigma_{21} & I \end{bmatrix} \\ &\times \begin{bmatrix} (\Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21})^{-1} & 0 \\ 0' & \Sigma_{22}^{-1} \end{bmatrix} \begin{bmatrix} I & -\Sigma_{12} \Sigma_{22}^{-1} \\ 0 & I \end{bmatrix} \begin{bmatrix} x_1 - \mu_1 \\ x_2 - \mu_2 \end{bmatrix} \\ &= \begin{bmatrix} x_1 - \mu_1 - \Sigma_{12} \Sigma_{22}^{-1} (x_2 - \mu_2) \\ x_2 - \mu_2 \end{bmatrix}' \begin{bmatrix} (\Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21})^{-1} & 0 \\ 0' & \Sigma_{22}^{-1} \end{bmatrix} \\ &\times \begin{bmatrix} x_1 - \mu_1 - \Sigma_{12} \Sigma_{22}^{-1} (x_2 - \mu_2) \\ x_2 - \mu_2 \end{bmatrix} \\ &= [x_1 - \mu_1 - \Sigma_{12} \Sigma_{22}^{-1} (x_2 - \mu_2)]' (\Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21})^{-1} \\ &\times [x_1 - \mu_1 - \Sigma_{12} \Sigma_{22}^{-1} (x_2 - \mu_2)] + (x_2 - \mu_2)' \Sigma_{22}^{-1} (x_2 - \mu_2) \end{aligned}$$

(c) The marginal distribution of  $X_2$

$$\begin{aligned} &(x_2 - \mu_2)' \Sigma_{22}^{-1} (x_2 - \mu_2) \\ &\Rightarrow N(\mu_2, \Sigma_{22}) \end{aligned}$$

The conditional distribution of  $X_1 | X_2 = x_2$

$$\begin{aligned} &[x_1 - \mu_1 - \Sigma_{12} \Sigma_{22}^{-1} (x_2 - \mu_2)]' (\Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21})^{-1} [x_1 - \mu_1 - \Sigma_{12} \Sigma_{22}^{-1} (x_2 - \mu_2)] \\ &\Rightarrow N(\mu_1 + \Sigma_{12} \Sigma_{22}^{-1} (x_2 - \mu_2), \Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21}) \end{aligned}$$

4.18 By Result 4.11 we know that the maximum likelihood estimates of  $\underline{\mu}$  and  $\underline{\Sigma}$  are  $\bar{\underline{x}} = [4, 6]'$  and

$$\begin{aligned} \frac{1}{n} \sum_{j=1}^n (\underline{x}_j - \bar{\underline{x}})(\underline{x}_j - \bar{\underline{x}})' &= \frac{1}{4} \left\{ \begin{pmatrix} 3 \\ 6 \end{pmatrix} - \begin{pmatrix} 4 \\ 6 \end{pmatrix} \begin{pmatrix} 3 \\ 6 \end{pmatrix} - \begin{pmatrix} 4 \\ 6 \end{pmatrix} \begin{pmatrix} 3 \\ 6 \end{pmatrix}' + \begin{pmatrix} 4 \\ 4 \end{pmatrix} - \begin{pmatrix} 4 \\ 6 \end{pmatrix} \begin{pmatrix} 4 \\ 4 \end{pmatrix} - \begin{pmatrix} 4 \\ 6 \end{pmatrix} \begin{pmatrix} 4 \\ 4 \end{pmatrix}' \right. \\ &\quad \left. + \begin{pmatrix} 5 \\ 7 \end{pmatrix} - \begin{pmatrix} 4 \\ 6 \end{pmatrix} \begin{pmatrix} 5 \\ 7 \end{pmatrix} - \begin{pmatrix} 4 \\ 6 \end{pmatrix} \begin{pmatrix} 5 \\ 7 \end{pmatrix}' + \begin{pmatrix} 4 \\ 7 \end{pmatrix} - \begin{pmatrix} 4 \\ 6 \end{pmatrix} \begin{pmatrix} 4 \\ 7 \end{pmatrix} - \begin{pmatrix} 4 \\ 6 \end{pmatrix} \begin{pmatrix} 4 \\ 7 \end{pmatrix}' \right\} \\ &= \frac{1}{4} \left\{ \begin{bmatrix} -1 \\ 0 \end{bmatrix} \begin{bmatrix} -1 & 0 \end{bmatrix} + \begin{bmatrix} 0 \\ -2 \end{bmatrix} \begin{bmatrix} 0 & -2 \end{bmatrix} + \begin{bmatrix} 1 \\ 1 \end{bmatrix} \begin{bmatrix} 1 & 1 \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} \begin{bmatrix} 0 & 1 \end{bmatrix} \right\} \\ &= \frac{1}{4} \begin{bmatrix} 2 & 1 \\ 1 & 6 \end{bmatrix} \end{aligned}$$

4.21 (a)  $\bar{\underline{X}}$  is distributed  $N_4(\underline{\mu}, n^{-1}\underline{\Sigma})$

(b)  $\underline{X}_1 - \underline{\mu}$  is distributed  $N_4(0, \underline{\Sigma})$  so  $(\underline{X}_1 - \underline{\mu})' \underline{\Sigma}^{-1} (\underline{X}_1 - \underline{\mu})$  is distributed as chi-square with p degrees of freedom.

(c) Using Part a),

$$(\bar{\underline{X}} - \underline{\mu})' (n^{-1}\underline{\Sigma})^{-1} (\bar{\underline{X}} - \underline{\mu}) = n(\bar{\underline{X}} - \underline{\mu})' \underline{\Sigma}^{-1} (\bar{\underline{X}} - \underline{\mu})$$

is distributed as chi-square with p degrees of freedom.

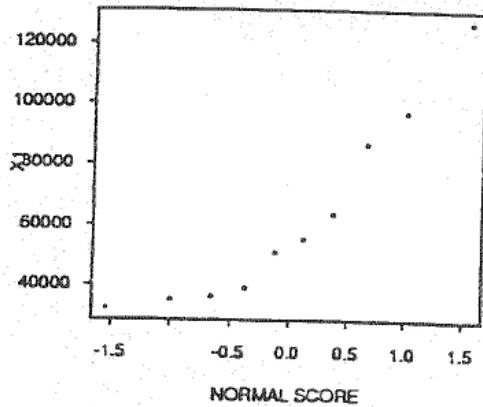
(d) Approximately distributed as chi-square with p degrees of freedom. Since the sample size is large,  $\underline{\Sigma}$  can be replaced by S.

4.24

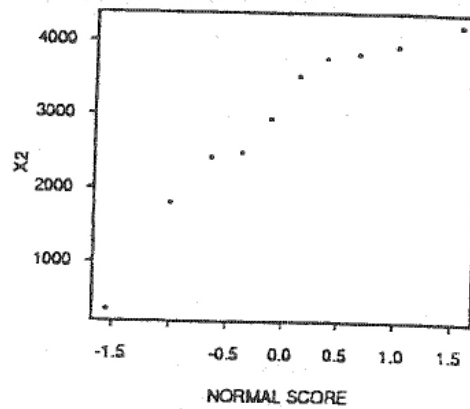
(a).  $Q-Q$  plots are given below.  $X_1$  has long left hand tails, but  $X_2$  has a long right hand tail.

(b). The critical point for  $\alpha = 0.10$  when  $n = 10$  is 0.9351. Calculated values of  $r_Q$  for  $X_1, X_2$  are 0.93617, 0.94798 respectively. Since they are larger than 0.9351, we do not reject the hypothesis of normality for each variable.

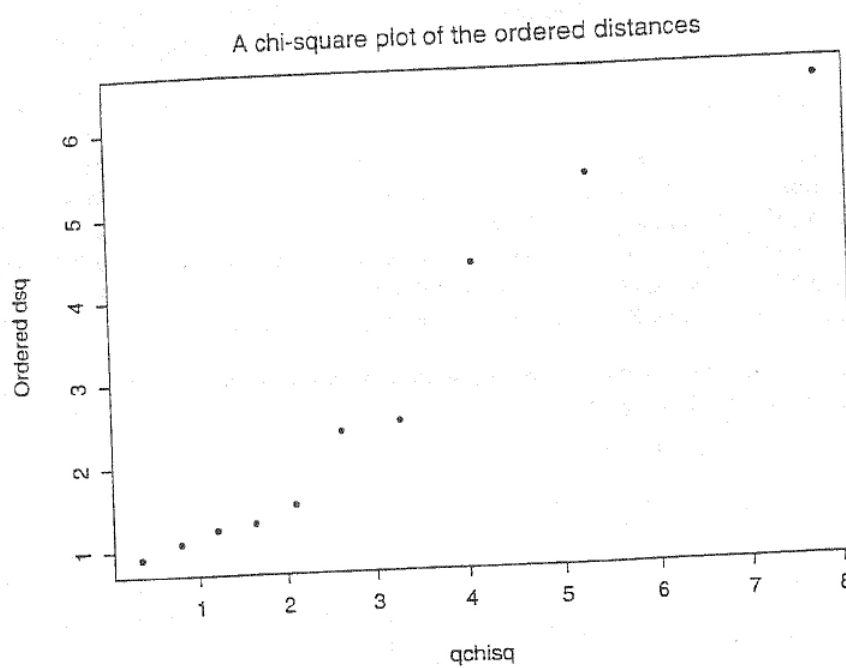
Q-Q PLOT FOR  $X_1$



Q-Q PLOT FOR  $X_2$



4.25. 10 largest U. S. industrial corporations data

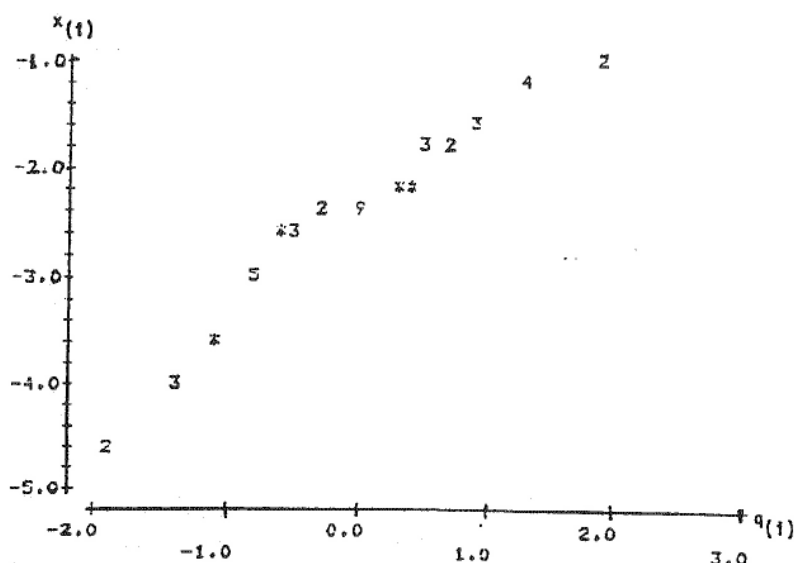


XBAR	S	sales	profits	assets
62309.1	1000509114	25575600	1511827230	
2927.3	25575600	1430020	45654618	
81248.4	1511827230	45654618	2980489782	

Ordered	dsq	qchisq
1	0.9078	0.3518
2	1.0749	0.7978
3	1.2284	1.2125
4	1.2963	1.6416
5	1.5003	2.1095
6	2.3614	2.6430
7	2.4713	3.2831
8	4.3524	4.1083
9	5.3677	5.3170
10	6.4396	7.8147



4.27 Q-Q plot is shown below.



The Q-Q plot is reasonably straight.  $r_Q = .978$  ( $\lambda=0$ )

For  $\lambda = 1/4$ ,  $r_Q = .993$  so  $\lambda = 1/4$  is a little better choice for the normalizing transformation.

#### 4.30

(a).  $\hat{\lambda}_1 = 1.0$ . There is no need for transformation.  $r_Q = 0.98659 > 0.9198$  where 0.9198 is the critical point for testing normality with  $\alpha = 0.05$  when  $n=10$ . We accept the null hypothesis of normality.

(b).  $\hat{\lambda}_2 = 0.5$ . After the transformation,  $r_Q = 0.97546 > 0.9198$  where 0.9198 is the critical point for testing normality with  $\alpha = 0.05$  when  $n=10$ . We accept the null hypothesis of normality.

(c).  $(\hat{\lambda}_1, \hat{\lambda}_2) = (0.5, 0.4)$ . They are different from results obtained in (a), (b) because the likelihood is flat due to the small sample size.

#### 4.36

Marginal Normality:

	$X_1$	$X_2$	$X_3$	$X_4$	$X_5$	$X_6$	$X_7$
$r_Q$	0.98674	0.98496	0.99561	0.98554	0.92155*	0.92558*	0.87316*

\*: significant at 5 % level (the critical point = 0.9787 for  $n=55$ ).

Multivariate Normality: the  $\chi^2$  plot does not look like normal.

PROBLEM 4.36

