

2.4

y stoch. vector with $E y = \underline{\theta}$ and $\text{Var } y = \Sigma$

a $\Sigma > 0$

Indirect: $\exists \underline{a} \neq \underline{0} : \underline{a}^T y = b$

$$\Leftrightarrow \exists \underline{a} \neq \underline{0} : \text{Var } \underline{a}^T y = 0$$

$$\Leftrightarrow \exists \underline{a} \neq \underline{0} : \underline{a}^T \Sigma \underline{a} = 0 \quad \text{inconsistency}$$

Hence $\forall \underline{a} \neq \underline{0} : \underline{a}^T y \neq b$

b $\det \Sigma = 0 \Leftrightarrow \Sigma \geq 0$

$$\Leftrightarrow \exists \underline{a} \neq \underline{0} : \underline{a}^T \Sigma \underline{a} = 0$$

$$\Leftrightarrow \exists \underline{a} \neq \underline{0} : \text{Var } \underline{a}^T y = 0$$

$$\Leftrightarrow \exists \underline{a} \neq \underline{0} : \underline{a}^T y = b$$

Note that $b = \underline{a}^T y \Rightarrow b = \underline{a}^T E y \Rightarrow b = \underline{a}^T \underline{\theta}$

Hence $\exists \underline{a} \neq \underline{0} : \underline{a}^T y = \underline{a}^T \underline{\theta}$

$$\Leftrightarrow \exists \underline{a} \neq \underline{0} : \underline{a}^T (y - \underline{\theta}) = 0$$

2.5

$$\underline{y} = X\underline{\beta} + \underline{\varepsilon} \quad X \text{ } n \times p \quad \underline{\varepsilon} \sim N_n(\underline{0}, \sigma^2 \underline{I}_n)$$

$$\text{rank } X = p < n$$

residuals $\underline{e} = (\underline{I}_n - P)\underline{y}$, $P = X(X^T X)^{-1} X^T$

a $\text{Var } \underline{e} = (\underline{I}_n - P) \sigma^2 \underline{I}_n (\underline{I}_n - P) = \sigma^2 (\underline{I}_n - P)$

$$\text{rank } (\underline{I}_n - P) = n - p < n$$

b $\forall \underline{\ell} : \underline{\ell}^T \underline{e} = \underline{\ell}^T (\underline{I}_n - P)\underline{y}$

$$= ((\underline{I}_n - P)\underline{\ell})^T \underline{y} \sim N(0, \sigma^2 \underline{\ell}^T (\underline{I}_n - P)\underline{\ell})$$

cf. ex. 1.5.6 of 2.5a

$\Rightarrow \underline{e}$ is singular multidimensional normal
as $\underline{I}_n - P \geq 0$.

c $X = \begin{bmatrix} \underline{1}_n & \underline{x}_n^{(1)} & \underline{x}_n^{(2)} & \dots & \underline{x}_n^{(p-1)} \end{bmatrix}$

$$\underline{X}^T (\underline{I}_n - P) = \underline{X}^T (\underline{I}_n - \underline{X}(\underline{X}^T \underline{X})^{-1} \underline{X}^T)$$

$$= \underline{X}^T - \underline{X}^T \underline{X} (\underline{X}^T \underline{X})^{-1} \underline{X}^T = \underline{X}^T - \underline{X}^T$$

$$= \underline{0}^T = \begin{bmatrix} \underline{0} & \underline{0} & \dots & \underline{0} \end{bmatrix}^T$$

$$\Rightarrow \underline{1}_n^T (\underline{I}_n - P) = \underline{0}^T$$

$$\Rightarrow \underline{1}_n^T (\underline{I}_n - P) \underline{y} = 0$$

$$\Rightarrow \underline{1}_n^T \underline{e} = 0$$

2.6 $y_i \sim N_d(\underline{\theta}_i, \Sigma_i)$, $i=1, \dots, m$, independent

$$a \quad M_{\sum_i a_i y_i}(\underline{t}) = \prod_i M_{a_i y_i}(\underline{t}) = \prod_i M_{y_i}(a_i \underline{t})$$

$$= \prod_i \exp(\underline{t}^T (a_i \underline{\theta}_i) + \frac{1}{2} (a_i \underline{t})^T \Sigma_i (a_i \underline{t}))$$

$$= \exp(\underline{t}^T \sum_i a_i \underline{\theta}_i + \frac{1}{2} \sum_i a_i^2 \underline{t}^T \Sigma_i \underline{t})$$

$$= \exp(\underline{t}^T \sum_i a_i \underline{\theta}_i + \frac{1}{2} \underline{t}^T (\sum_i a_i^2 \Sigma_i) \underline{t})$$

$$\Leftrightarrow \sum_i a_i y_i \sim N_d(\sum_i a_i \underline{\theta}_i, \sum_i a_i^2 \Sigma_i)$$

$$b \quad \forall \underline{\lambda} : \underline{\lambda}^T y_i \sim N(\underline{\lambda}^T \underline{\theta}_i, \underline{\lambda}^T \Sigma_i \underline{\lambda}), \quad i=1, \dots, m$$

$$\Rightarrow \forall \underline{\lambda} : \sum_i a_i \underline{\lambda}^T y_i \sim N(\sum_i a_i \underline{\lambda}^T \underline{\theta}_i, \sum_i a_i^2 \underline{\lambda}^T \Sigma_i \underline{\lambda})$$

$$\Leftrightarrow \forall \underline{\lambda} : \underline{\lambda}^T \sum_i a_i y_i \sim N(\underline{\lambda}^T \sum_i a_i \underline{\theta}_i, \underline{\lambda}^T (\sum_i a_i^2 \Sigma_i) \underline{\lambda})$$

$$\Leftrightarrow \sum_i a_i y_i \sim N_d(\sum_i a_i \underline{\theta}_i, \sum_i a_i^2 \Sigma_i)$$

2.7 $y_i \sim N_d(\underline{0}, \Sigma)$, $i=1, \dots, m$, independent

$$\text{Set } \underline{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{bmatrix} \quad \text{or} \quad \underline{\lambda} = \begin{bmatrix} \underline{\lambda}_1 \\ \underline{\lambda}_2 \\ \vdots \\ \underline{\lambda}_m \end{bmatrix}$$

$$\forall \underline{\lambda}_i : \underline{\lambda}_i^T y_i \sim N(0, \underline{\lambda}_i^T \Sigma \underline{\lambda}_i) \wedge \text{Cov}(y_i, y_j) = 0$$

$$\Leftrightarrow \forall \underline{\lambda} : \underline{\lambda}^T \underline{y} \sim N(0, \sum_i \underline{\lambda}_i^T \Sigma \underline{\lambda}_i)$$

$$\Leftrightarrow \forall \underline{\lambda} : \underline{\lambda}^T \underline{y} \sim N(0, \underline{\lambda}^T (I_m \otimes \Sigma) \underline{\lambda})$$

$$\Leftrightarrow \underline{y} \sim N_{md}(\underline{0}, I_m \otimes \Sigma)$$

2.8

 $y_i \sim N(\theta, \sigma^2), i=1, \dots, n, \text{ independent}$

$$\Leftrightarrow \underline{y} = [y_1, \dots, y_n]^T \sim N_n(\theta \underline{1}_n, \sigma^2 \underline{I}_n)$$

$$Q = \sum_i (y_i - \bar{y})^2 = (\underline{y} - \bar{y} \underline{1}_n)^T (\underline{y} - \bar{y} \underline{1}_n)$$

$$a \quad \bar{y} = \frac{1}{n} \sum_i y_i = \frac{1}{n} \underline{1}_n^T \underline{y} = A_1 \underline{y}$$

$$y_i - \bar{y} = \left([1 \ 0 \ \dots \ 0] - \frac{1}{n} \underline{1}_n^T \right) \underline{y} = A_2 \underline{y}$$

$$A_1 A_2^T = \frac{1}{n} \underline{1}_n^T \left([1 \ 0 \ \dots \ 0]^T - \frac{1}{n} \underline{1}_n \right) = \frac{1}{n} \left(1 - \frac{1}{n} n \right) = 0$$

$\Leftrightarrow \bar{y}$ and $y_i - \bar{y}$ independent cf. satn. 2.1 (v)

$\Rightarrow \bar{y}$ and $y_i - \bar{y}$ independent, $i=1, \dots, n$

$\Rightarrow \bar{y}$ and Q independent

$$b \quad Q = \left(\underline{y} - \frac{1}{n} \underline{1}_n^T \underline{y} \underline{1}_n \right)^T \left(\underline{y} - \frac{1}{n} \underline{1}_n^T \underline{y} \underline{1}_n \right)$$

$$= \left(\underline{y} - \frac{1}{n} \underline{1}_n \underline{1}_n^T \underline{y} \right)^T \left(\underline{y} - \frac{1}{n} \underline{1}_n \underline{1}_n^T \underline{y} \right)$$

$$= \underline{y}^T \left(\underline{I}_n - \frac{1}{n} \underline{1}_n \underline{1}_n^T \right)^T \left(\underline{I}_n - \frac{1}{n} \underline{1}_n \underline{1}_n^T \right) \underline{y}$$

$$= \underline{y}^T \left(\underline{I}_n - \frac{1}{n} \underline{1}_n \underline{1}_n^T \right) \left(\underline{I}_n - \frac{1}{n} \underline{1}_n \underline{1}_n^T \right) \underline{y}$$

$$= \underline{y}^T \left(\underline{I}_n - \frac{1}{n} \underline{1}_n \underline{1}_n^T - \frac{1}{n} \underline{1}_n \underline{1}_n^T + \frac{1}{n^2} \underline{1}_n n \underline{1}_n^T \right) \underline{y}$$

$$= \underline{y}^T \left(\underline{I}_n - \frac{1}{n} \underline{1}_n \underline{1}_n^T \right) \underline{y} = \underline{y}^T A \underline{y}$$

The calculations show that $A^T = A$ and $A^2 = A$,
also notice $\text{rank } A = \text{tr } A = n-1$, cf. A 6.1

Let $u_i = y_i - \theta$, $i=1, \dots, n$, $u_i \sim N(0, \sigma^2)$ independent

$$Q = (\underline{u} + \underline{\theta})^T A (\underline{u} + \underline{\theta}) = \underline{u}^T A \underline{u} + 2 \underline{u}^T A \underline{\theta} + \underline{\theta}^T A \underline{\theta}$$

$$\text{Note: } A \underline{\theta} = \left(\underline{I}_n - \frac{1}{n} \underline{1}_n \underline{1}_n^T \right) \theta \underline{1}_n = \theta \left(\underline{1}_n - \frac{1}{n} \underline{1}_n \underline{1}_n^T \underline{1}_n \right)$$

$$= \theta (\underline{1}_n - \underline{1}_n) = \underline{0}$$

$$\text{Hence } Q = \underline{y}^T A \underline{y} = \underline{u}^T A \underline{u} \sim \chi^2(n-1) \text{ cf. A 6.5}$$