

$$\begin{aligned}
 1.1 \quad a \quad \text{Cov}(A\underline{x}, B\underline{y}) &= E[(A\underline{x} - A\underline{\mu}_x)(B\underline{y} - B\underline{\mu}_y)^T] \\
 &= E[A(\underline{x} - \underline{\mu}_x)(\underline{y} - \underline{\mu}_y)^T B^T] \\
 &= A E[(\underline{x} - \underline{\mu}_x)(\underline{y} - \underline{\mu}_y)^T] B^T \\
 &= A \text{Cov}(\underline{x}, \underline{y}) B^T
 \end{aligned}$$

$$\begin{aligned}
 b \quad \text{Cov}(\underline{x}, \underline{y}) &= E[(\underline{x} - \underline{\mu}_x)(\underline{y} - \underline{\mu}_y)^T] \\
 &= E[\underline{x}\underline{y}^T - \underline{x}\underline{\mu}_y^T - \underline{\mu}_x\underline{y}^T + \underline{\mu}_x\underline{\mu}_y^T] \\
 &= E[\underline{x}\underline{y}^T] - \underline{\mu}_x\underline{\mu}_y^T - \underline{\mu}_x\underline{\mu}_y^T + \underline{\mu}_x\underline{\mu}_y^T \\
 &= E[\underline{x}\underline{y}^T] - E\underline{x} E\underline{y}^T
 \end{aligned}$$

$$\begin{aligned}
 c \quad \text{Var}(\underline{x} - \underline{a}) &= E[(\underline{x} - \underline{a} - (\underline{\mu}_x - \underline{a}))(\underline{x} - \underline{a} - (\underline{\mu}_x - \underline{a}))^T] \\
 &= E[(\underline{x} - \underline{\mu}_x)(\underline{x} - \underline{\mu}_x)^T] \\
 &= \text{Var} \underline{x}
 \end{aligned}$$

$$\begin{aligned}
 1.2 \quad \sum_i (\underline{y}_i - \bar{\underline{y}})(\underline{y}_i - \bar{\underline{y}})^T &= \sum_i (\underline{y}_i \underline{y}_i^T - \underline{y}_i \bar{\underline{y}}^T - \bar{\underline{y}} \underline{y}_i^T + \bar{\underline{y}} \bar{\underline{y}}^T) \\
 &= \sum_i \underline{y}_i \underline{y}_i^T - n \bar{\underline{y}} \bar{\underline{y}}^T - n \bar{\underline{y}} \bar{\underline{y}}^T + n \bar{\underline{y}} \bar{\underline{y}}^T \\
 &= \sum_i \underline{y}_i \underline{y}_i^T - n \bar{\underline{y}} \bar{\underline{y}}^T
 \end{aligned}$$

$$\begin{aligned}
 1.3 \quad a \quad \text{Var}(\sum_i a_i \underline{x}_i) &= \text{Cov}(\sum_i a_i \underline{x}_i, \sum_j a_j \underline{x}_j) \\
 &= \sum_i \sum_j a_i a_j \text{Cov}(\underline{x}_i, \underline{x}_j) \\
 &= \sum_i a_i^2 \text{Var} \underline{x}_i + \sum_i \sum_{j \neq i} a_i a_j 0 \\
 &= (\sum_i a_i^2) \Sigma
 \end{aligned}$$

$$\begin{aligned}
 b \quad \text{Cov}(\sum_i a_i \underline{x}_i, \sum_j b_j \underline{x}_j) &= \sum_i \sum_j a_i b_j \text{Cov}(\underline{x}_i, \underline{x}_j) \\
 &= \sum_i a_i b_i \text{Var} \underline{x}_i + \sum_i \sum_{j \neq i} a_i b_j 0 \\
 &= (\sum_i a_i b_i) \Sigma \\
 &= 0
 \end{aligned}$$

$$\Leftrightarrow \sum_i a_i b_i = 0, \quad \text{as } \Sigma > 0$$

$$1.4 \quad E \underline{x} = \underline{\theta}, \quad \text{Var } \underline{x} = \Sigma$$

$$\begin{aligned} E[\underline{x}^T A \underline{x}] &= E\left[\sum_i \sum_j a_{ij} x_i x_j\right] = \sum_i \sum_j a_{ij} E[x_i x_j] \\ &= \sum_i \sum_j a_{ij} (\text{Cov}(x_i, x_j) + E x_i E x_j) \\ &= \sum_i \sum_j a_{ij} c_{ij} + \sum_i \sum_j a_{ij} \theta_i \theta_j \\ &= \sum_i \sum_j a_{ij} c_{ji} + \underline{\theta}^T A \underline{\theta} \\ &= \sum_i (A \Sigma)_{ii} + \underline{\theta}^T A \underline{\theta} \\ &= \text{tr}(A \Sigma) + \underline{\theta}^T A \underline{\theta} \end{aligned}$$

$$1.5 \quad \underline{y} = K \underline{\beta} + \underline{u} \quad K \text{ } n \times p \quad \text{rank } K = p \quad E \underline{u} = \underline{0} \quad P = K(K^T K)^{-1} K^T$$

$$a \quad P^T = (K^T)^T (K^T (K^T)^T)^{-1} K^T = K(K^T K)^{-1} K^T = P$$

$$\begin{aligned} P^2 &= K(K^T K)^{-1} K^T K(K^T K)^{-1} K^T = K I_p (K^T K)^{-1} K^T \\ &= K(K^T K)^{-1} K^T = P \end{aligned}$$

$$(I_n - P)^T = I_n^T - P^T = I_n - P$$

$$(I_n - P)^2 = (I_n - P)(I_n - P) = I_n - P - P + P = I_n - P$$

$$\begin{aligned} b \quad (I_n - P)K &= K - PK = K - K(K^T K)^{-1} K^T K \\ &= K - K I_p = K - K = 0 \end{aligned}$$

$$\begin{aligned} c \quad \text{rank}(I_n - P) &= \text{tr}(I_n - P) = n - \text{tr } P = n - \text{rank } P \\ &= n - p \quad (\text{cf. A6.3}) \end{aligned}$$

$$\begin{aligned} d \quad \underline{y}^T (I_n - P) \underline{y} &= (K \underline{\beta} + \underline{u})^T (I_n - P) (K \underline{\beta} + \underline{u}) \\ &= \underline{\beta}^T K^T (I_n - P) K \underline{\beta} + \underline{\beta}^T K^T (I_n - P) \underline{u} \\ &\quad + \underline{u}^T (I_n - P) K \underline{\beta} + \underline{u}^T (I_n - P) \underline{u} \\ &= \underline{\beta}^T K^T 0 \underline{\beta} + \underline{\beta}^T 0^T \underline{u} \\ &\quad + \underline{u}^T 0 \underline{\beta} + \underline{u}^T (I_n - P) \underline{u} \\ &= 0 + 0 + 0 + \underline{u}^T (I_n - P) \underline{u} \\ &= \underline{u}^T (I_n - P) \underline{u} \end{aligned}$$

Extra (Ch. 1)

$$Y = \sum_i \sum_j a_{ij} x_i x_j^T$$

Rename  $a_{ij} := \frac{1}{2} (a_{ij} + a_{ji})$

$$\begin{aligned} y_{rs} &= \sum_i \sum_j a_{ij} x_{ir} x_{js} = \sum_i x_{ir} \sum_j a_{ij} x_{js} = \sum_i x_{ir} (AX)_{is} \\ &= \sum_i x_{ri}^T (AX)_{is} = (X^T A X)_{rs} \end{aligned}$$

Hence  $Y = X^T A X$ ,  $A$  symmetric

1.6

$\underline{x}_1, \dots, \underline{x}_n$  sample from  $d$ -dim. distribution

$$g_{rs} = (\underline{x}_r - \bar{\underline{x}})^T \hat{\Sigma}^{-1} (\underline{x}_s - \bar{\underline{x}}), \quad \hat{\Sigma} = \frac{1}{n} Q = \frac{1}{n} \tilde{X}^T \tilde{X}$$

$$\begin{aligned} a \quad \sum_r g_{rr} &= \sum_r (\underline{x}_r - \bar{\underline{x}})^T \hat{\Sigma}^{-1} (\underline{x}_r - \bar{\underline{x}}) \\ &= \sum_r \text{tr} (\underline{x}_r - \bar{\underline{x}})^T \hat{\Sigma}^{-1} (\underline{x}_r - \bar{\underline{x}}) \\ &= \sum_r \text{tr} \hat{\Sigma}^{-1} (\underline{x}_r - \bar{\underline{x}}) (\underline{x}_r - \bar{\underline{x}})^T \\ &= \text{tr} \left( \hat{\Sigma}^{-1} \sum_r (\underline{x}_r - \bar{\underline{x}}) (\underline{x}_r - \bar{\underline{x}})^T \right) \\ &= \text{tr} \left( \hat{\Sigma}^{-1} n \hat{\Sigma} \right) \\ &= n \text{tr} (\mathbf{I}_d) \\ &= nd \end{aligned}$$

$$E[g_{rr}] = \frac{1}{n} E \left[ \sum_r g_{rr} \right] = \frac{1}{n} nd = d$$

$$\begin{aligned} b \quad \sum_s g_{rs} &= (\underline{x}_r - \bar{\underline{x}})^T \hat{\Sigma}^{-1} \sum_s (\underline{x}_s - \bar{\underline{x}}) \\ &= (\underline{x}_r - \bar{\underline{x}})^T \hat{\Sigma}^{-1} \underline{0} \\ &= 0 \end{aligned}$$

$$\begin{aligned} \sum_s g_{rs} &= g_{rr} + \sum_{s \neq r} g_{rs} \Leftrightarrow \sum_{s \neq r} g_{rs} = \sum_s g_{rs} - g_{rr} \\ &\Rightarrow \sum_{s \neq r} g_{rs} = 0 - g_{rr} \end{aligned}$$

$$\begin{aligned} E[g_{rs}] &= \frac{1}{n-1} E \left[ \sum_{r \neq s} g_{rs} \right] = \frac{1}{n-1} E[-g_{rr}] \\ &= -\frac{d}{n-1} \end{aligned}$$