

## ANSWER SHEET 9

**Assignment 1.** a) The assumptions imply that  $A$  is injective. If  $v \in \mathbb{R}^p \setminus \{0\}$  then

$$v^T B v = v^T A^T \Omega A v = (A v)^T \Omega (A v) > 0$$

since  $A v \neq 0$  and  $\Omega$  is positive definite. Thus  $B$  is positive definite and in particular invertible. The special case  $\Omega = I_n$  shows that  $A^T A$  is strictly positive definite.

b) Choose  $A = (1, 1)^T$  and

$$\Omega = \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix},$$

then  $A^T \Omega A = 0$ .

**Remark.** If  $\Omega$  has one positive and one negative eigenvalues, we can always find an injective  $A$  such that  $A^T \Omega A = 0$ .

**Assignment 2.** We shall use the following fact. If  $X_1$  and  $X_2$  are independent, and  $Y_1$  and  $X_2$  are independent, and  $X_1$  and  $Y_1$  have the same distribution, then for any (measurable) function  $g$ ,  $g(X_1, X_2)$  and  $g(Y_1, X_2)$  have the same distribution.

- (i) Take  $c^T = (1, 0)$
- (ii) Take  $c^T = (0, 1)$  and use (i). And take  $c^T = (-1, 0)$ , to get  $-X \sim X$ , so that  $\mathbb{E}[-X] = \mathbb{E}[X]$ , and then  $\mathbb{E}X = 0$ .
- (iii) Take  $c^T = (1, 1)/\sqrt{2}$ . Then

$$X \sim (X + Y)/\sqrt{2} \sim (X_1 + X_2)/\sqrt{2}.$$

- (iv) We know that this is true for  $n = 1, 2$ . Suppose that this is true for  $n$  and write

$$(X_1 + \cdots + X_{n+1})/\sqrt{n+1} = \sqrt{n/(n+1)}[(X_1 + \cdots + X_n)/\sqrt{n}] + \sqrt{1/(n+1)}X_{n+1}.$$

This has the same distribution as  $\sqrt{n/(n+1)}X + \sqrt{1/(n+1)}Y$  by the induction hypothesis. Now choose  $c^T = (\sqrt{n}, 1)/\sqrt{n+1}$

- (v) Since  $X$  has zero mean and finite variance  $\sigma^2$ , by the central limit theorem

$$(X_1 + \cdots + X_n)/\sqrt{n} \xrightarrow{d} N(0, \sigma^2).$$

By (v) this gives  $X \sim N(0, \sigma^2)$ , and by (ii)  $Y \sim N(0, \sigma^2)$ .

- (vi) Let  $U \sim U[0, 1]$  and

$$(X, Y) = (\cos(2\pi U), \sin(2\pi U)),$$

then by symmetry  $c^T(X, Y)$  has the same distribution for all  $c \in S^1$  but  $X$  and  $Y$  are not Gaussian. This is the uniform distribution on the unit circle.

**Assignment 3.**

- a) The parameters  $\alpha_1$  and  $\beta_1$  are only influenced by the rats in the first group, while  $\alpha_2$  and  $\beta_2$  are only influenced by the second group. Thus

$$\begin{aligned} \begin{bmatrix} y_{11} \\ y_{21} \\ y_{31} \end{bmatrix} &= \begin{bmatrix} 1 & x_{11} \\ 1 & x_{21} \\ 1 & x_{31} \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \beta_1 \end{bmatrix} + \begin{bmatrix} \varepsilon_{11} \\ \varepsilon_{21} \\ \varepsilon_{31} \end{bmatrix}, & \text{for group 1,} \\ \begin{bmatrix} y_{12} \\ y_{22} \\ y_{32} \end{bmatrix} &= \begin{bmatrix} 1 & x_{12} \\ 1 & x_{22} \\ 1 & x_{32} \end{bmatrix} \begin{bmatrix} \alpha_2 \\ \beta_2 \end{bmatrix} + \begin{bmatrix} \varepsilon_{12} \\ \varepsilon_{22} \\ \varepsilon_{32} \end{bmatrix}, & \text{for group 2.} \end{aligned}$$

The model for the two groups together is obtained by combining the two previous models into

$$y = \begin{bmatrix} y_{11} \\ y_{21} \\ y_{31} \\ y_{12} \\ y_{22} \\ y_{32} \end{bmatrix}, \quad X = \begin{bmatrix} 1 & 0 & x_{11} & 0 \\ 1 & 0 & x_{21} & 0 \\ 1 & 0 & x_{31} & 0 \\ 0 & 1 & 0 & x_{12} \\ 0 & 1 & 0 & x_{22} \\ 0 & 1 & 0 & x_{32} \end{bmatrix}, \quad \beta = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \beta_1 \\ \beta_2 \end{bmatrix}, \quad \varepsilon = \begin{bmatrix} \varepsilon_{11} \\ \varepsilon_{21} \\ \varepsilon_{31} \\ \varepsilon_{12} \\ \varepsilon_{22} \\ \varepsilon_{32} \end{bmatrix}.$$

- b) The models assume that (i)  $\beta_1 = \beta_2$ , (ii)  $\alpha_1 = \alpha_2$  et (iii)  $\alpha_1 = \alpha_2$  et  $\beta_1 = \beta_2$ . In order to fulfill these assumptions we need to fix some parameters to 0, hence we should re-write the model using  $\alpha_2 - \alpha_1$  and  $\beta_2 - \beta_1$  as parameters. We can for example write the model for group 2 in terms of the difference w.r.t. group 1 :

$$\begin{bmatrix} y_{12} \\ y_{22} \\ y_{32} \end{bmatrix} = \begin{bmatrix} 1 & x_{12} \\ 1 & x_{22} \\ 1 & x_{32} \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \beta_1 \end{bmatrix} + \begin{bmatrix} 1 & x_{12} \\ 1 & x_{22} \\ 1 & x_{32} \end{bmatrix} \begin{bmatrix} \alpha_2 - \alpha_1 \\ \beta_2 - \beta_1 \end{bmatrix} + \begin{bmatrix} \varepsilon_{12} \\ \varepsilon_{22} \\ \varepsilon_{32} \end{bmatrix}.$$

With this formulation, the parameters  $\alpha_1$  and  $\beta_1$  are now common to the two groups, and the new parameters  $\alpha_2 - \alpha_1$  and  $\beta_2 - \beta_1$  represent the difference between the groups.

The model for the two groups combined is written as :

$$y_{jg} = \mu + \mu_d \delta_{2g} + (\gamma + \gamma_d \delta_{2g}) x_{jg} + \varepsilon_{jg}, \quad j = 1, 2, 3 \quad g = 1, 2,$$

with design matrix and parameters vector

$$X = \begin{bmatrix} 1 & 0 & x_{11} & 0 \\ 1 & 0 & x_{21} & 0 \\ 1 & 0 & x_{31} & 0 \\ 1 & 1 & x_{12} & x_{12} \\ 1 & 1 & x_{22} & x_{22} \\ 1 & 1 & x_{32} & x_{32} \end{bmatrix}, \quad \beta = \begin{bmatrix} \mu \\ \mu_d \\ \gamma \\ \gamma_d \end{bmatrix} \quad \left( = \begin{bmatrix} \alpha_1 \\ \alpha_2 - \alpha_1 \\ \beta_1 \\ \beta_2 - \beta_1 \end{bmatrix} \right).$$

We have used the indicator function  $\delta_{2g}$  that takes value 1 for the group 2 and 0 otherwise. It is represented by the second column of  $X$  above.

The submodels assume (i)  $\gamma_d = 0$ , (ii)  $\mu_d = 0$ , (iii)  $\mu_d = \gamma_d = 0$  and thus we suppress the following columns  $X$  : (i) 4, (ii) 2, (iii) 2 et 4.

#### Assignment 4.

- a) If  $Y \in \mathbb{R}^n$  follows a multivariate normal  $N_n(X\beta, \sigma^2 I)$ , then  $Z = Q^T Y$  follows a multivariate Normal distribution with expected value

$$\mathbb{E}(Z) = Q^T X\beta = Q^T Q R\beta = R\beta$$

and covariance

$$\text{Var } Z = \sigma^2 Q^T Q = \sigma^2 I.$$

- b) By direct computation and using the fact that  $Q$  is orthogonal we find

$$\begin{aligned} u = Q^T \hat{y} &= Q^T X(X^T X)^{-1} X^T y \\ &= Q^T Q R((QR)^T QR)^{-1} (QR)^T y \\ &= Q^T Q R(R^T Q^T Q R)^{-1} R^T Q^T y \\ &= R(R^T R)^{-1} R^T Q^T y \\ &= \begin{bmatrix} R_1 \\ 0 \end{bmatrix} \left( \begin{bmatrix} R_1^T & 0 \end{bmatrix} \begin{bmatrix} R_1 \\ 0 \end{bmatrix} \right)^{-1} \begin{bmatrix} R_1^T & 0 \end{bmatrix} \begin{bmatrix} Q_1^T \\ Q_2^T \end{bmatrix} y \\ &= \begin{bmatrix} R_1 \\ 0 \end{bmatrix} (R_1^T R_1)^{-1} R_1^T Q_1^T y \\ &= \begin{bmatrix} R_1 \\ 0 \end{bmatrix} R_1^{-1} R_1^{-T} R_1^T Q_1^T y \\ &= \begin{bmatrix} R_1 R_1^{-1} Q_1^T y \\ 0 \end{bmatrix} \\ &= \begin{bmatrix} Q_1^T y \\ 0 \end{bmatrix}, \end{aligned}$$

where  $R_1$  is invertible since it's upper triangular with positive diagonal elements.

For  $v$  we write :

$$\begin{aligned} v = Q^T(y - \hat{y}) &= Q^T y - Q^T \hat{y} \\ &= \begin{bmatrix} Q_1^T \\ Q_2^T \end{bmatrix} y - \begin{bmatrix} Q_1^T y \\ 0 \end{bmatrix} = \begin{bmatrix} Q_1^T y \\ Q_2^T y \end{bmatrix} - \begin{bmatrix} Q_1^T y \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ Q_2^T y \end{bmatrix}, \end{aligned}$$

- c) Since  $\text{Var } Z = \sigma^2 I$  is diagonal, its diagonal entries are zero. Therefore  $Z_1 = Q_1^T Y \in \mathbb{R}^p$  and  $Z_2 = Q_2^T Y \in \mathbb{R}^{n-p}$  are independent since they are marginals of  $Z$  :

$$z = \begin{bmatrix} Q_1^T y \\ Q_2^T y \end{bmatrix} = \begin{bmatrix} z_1 \\ z_2 \end{bmatrix} = \begin{bmatrix} u_1 \\ v_2 \end{bmatrix},$$

where  $u_1 \in \mathbb{R}^p$  and  $v_2 \in \mathbb{R}^{n-p}$  are the non zero components of  $u$  and  $v$  :

$$u = \begin{bmatrix} Q_1^T y \\ 0 \end{bmatrix} = \begin{bmatrix} u_1 \\ 0 \end{bmatrix}, \quad v = \begin{bmatrix} 0 \\ Q_2^T y \end{bmatrix} = \begin{bmatrix} 0 \\ v_2 \end{bmatrix}.$$

So it follows that  $U$  and  $V$  are independent.

- d) We are going to show that  $S^2$  is a function of  $z_2$  and  $\hat{\beta}$  is a function of  $z_1$ . This will conclude the proof.

Since  $v = Q^T(y - \hat{y})$ , we have  $y - \hat{y} = Qv$ . Then

$$\begin{aligned} S^2 &= \frac{1}{n-p}(y - \hat{y})^T(y - \hat{y}) = \frac{1}{n-p}v^T Q^T Q v = \frac{1}{n-p}v^T v \\ &= \frac{1}{n-p} \begin{bmatrix} 0 & v_2^T \end{bmatrix} \begin{bmatrix} 0 \\ v_2 \end{bmatrix} = \frac{1}{n-p} v_2^T v_2 = \frac{1}{n-p} z_2^T z_2, \end{aligned}$$

is a function of  $z_2$ . A similar computation to the one in part (b) yields that

$$\hat{\beta} = (X^T X)^{-1} X^T y = R_1^{-1} Q_1^T y = R_1^{-1} u_1 = R_1^{-1} z_1,$$

is a function of  $z_1$ . The proof is done since

$$z_1 \text{ indep } z_2 \implies u_1 \text{ indep } v_2 \implies \hat{\beta} \text{ indep } S^2.$$

Indeed, measurable functions of independent variables stay independent : here  $S^2 = f(v_2)$  and  $\hat{\beta} = g(u_1)$ , hence for every  $B, C \subseteq \mathbb{R}$  (mesurable),

$$\begin{aligned} &\mathbb{P}(S^2 \in B, \hat{\beta} \in C) \\ &= \mathbb{P}(v_2 \in f^{-1}(B), u_1 \in g^{-1}(C)) \\ &= \mathbb{P}(v_2 \in f^{-1}(B)) \mathbb{P}(u_1 \in g^{-1}(C)) \\ &= \mathbb{P}(S^2 \in B) \mathbb{P}(\hat{\beta} \in C). \end{aligned}$$

#### Assignment 5.

$$X_{y \sim a-1} = \begin{pmatrix} 1 \\ 1 \\ 1 \\ 2 \\ 2 \\ 2 \end{pmatrix}; \quad X_{y \sim a+b} = \begin{pmatrix} 1 & 1 & 1 \\ 1 & 1 & 2 \\ 1 & 1 & 3 \\ 1 & 2 & 1 \\ 1 & 2 & 2 \\ 1 & 2 & 3 \end{pmatrix}.$$