

**Mathematical Statistics, Winter semester 2021/22**  
Solutions to Problem sheet 2

4) Suppose that

$$Y_i = \theta + \varepsilon_i, \quad i = 1, \dots, n,$$

holds for some  $\theta \in \Theta := \mathbb{R}$ , where  $\varepsilon_1, \dots, \varepsilon_n$  are independent random variables such that  $E\varepsilon_i = 0$  and  $\text{var}(\varepsilon_i) = \sigma_i^2 > 0$  for  $i = 1, \dots, n$ .

Compute the best linear estimator of  $\theta$ .

**Solution**

We rewrite this regression model in vector/matrix form:

$$\underbrace{\begin{pmatrix} Y_1 \\ \vdots \\ Y_n \end{pmatrix}}_{=:Y} = \underbrace{\begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix}}_{=:X} \theta + \underbrace{\begin{pmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_n \end{pmatrix}}_{=: \varepsilon},$$

where  $E\varepsilon = 0_n$  and  $\text{Cov}(\varepsilon) = \Sigma := \begin{pmatrix} \sigma_1^2 & 0 & \cdots & \cdots & 0 \\ 0 & \sigma_2^2 & 0 & \cdots & 0 \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ 0 & \cdots & 0 & \sigma_{n-1}^2 & 0 \\ 0 & \cdots & \cdots & 0 & \sigma_n^2 \end{pmatrix}.$

The inverse matrix of  $\Sigma$  is equal to  $\Sigma^{-1} = \begin{pmatrix} 1/\sigma_1^2 & 0 & \cdots & \cdots & 0 \\ 0 & 1/\sigma_2^2 & 0 & \cdots & 0 \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ 0 & \cdots & 0 & 1/\sigma_{n-1}^2 & 0 \\ 0 & \cdots & \cdots & 0 & 1/\sigma_n^2 \end{pmatrix}.$

According to Problem 1 (1st Problem sheet), the best linear unbiased estimator of  $\theta$  has the form

$$\hat{\theta} = (X^T \Sigma^{-1} X)^{-1} X^T \Sigma^{-1} Y = \frac{\sum_{i=1}^n \sigma_i^{-2} Y_i}{\sum_{i=1}^n \sigma_i^{-2}}.$$

5) Consider the linear regression model

$$\underbrace{\begin{pmatrix} Y_{11} \\ \vdots \\ Y_{1n_1} \\ \vdots \\ Y_{k1} \\ \vdots \\ Y_{kn_k} \end{pmatrix}}_{=:Y} = \underbrace{\begin{pmatrix} \mathbb{1}_{n_1} & & \\ & \ddots & \\ & & \mathbb{1}_{n_k} \end{pmatrix}}_{=:X} \underbrace{\begin{pmatrix} \beta_1 \\ \vdots \\ \beta_k \end{pmatrix}}_{=: \beta} + \underbrace{\begin{pmatrix} \varepsilon_{11} \\ \vdots \\ \varepsilon_{1n_1} \\ \vdots \\ \varepsilon_{k1} \\ \vdots \\ \varepsilon_{kn_k} \end{pmatrix}}_{=: \varepsilon},$$

where  $\beta_1, \dots, \beta_k$  are unknown parameters.

Compute the least squares estimator  $\hat{\beta}$  of  $\beta$  and compute  $X\hat{\beta}$ .

### Solution

We have that

$$X^T X = \begin{pmatrix} n_1 & & \\ & \ddots & \\ & & n_k \end{pmatrix},$$

and so

$$(X^T X)^{-1} = \begin{pmatrix} 1/n_1 & & \\ & \ddots & \\ & & 1/n_k \end{pmatrix}.$$

Since

$$X^T Y = \begin{pmatrix} \sum_{j=1}^{n_1} Y_{1j} \\ \vdots \\ \sum_{j=1}^{n_k} Y_{kj} \end{pmatrix}$$

we obtain that

$$\hat{\beta} = \begin{pmatrix} (1/n_1) \sum_{j=1}^{n_1} Y_{1j} \\ \vdots \\ (1/n_k) \sum_{j=1}^{n_k} Y_{kj} \end{pmatrix} =: \begin{pmatrix} \bar{Y}_{1\cdot} \\ \vdots \\ \bar{Y}_{k\cdot} \end{pmatrix}$$

and

$$X\hat{\beta} = \begin{pmatrix} \bar{Y}_{1\cdot} \mathbb{1}_{n_1} \\ \vdots \\ \bar{Y}_{k\cdot} \mathbb{1}_{n_k} \end{pmatrix}.$$

6) Consider the model

$$Y_{ij} = \mu + \alpha_i + \varepsilon_{ij} \quad (1 \leq i \leq k, 1 \leq j \leq m).$$

Rewrite this model in vector/matrix form  $Y = \bar{X}\theta + \varepsilon$ , where  $\theta = (\mu, \alpha_1, \dots, \alpha_k)^T$  is the unknown parameter.

What is the rank of the matrix  $\bar{X}$ ?

Compute the least squares estimator of  $\theta$  under the side condition  $\sum_{i=1}^k \alpha_i = 0$ .

*Hint: Consider the linear model from exercise 5). Since*

$$\{\bar{X}\theta: \theta \in \mathbb{R}^{k+1}\} = \{X\beta: \beta \in \mathbb{R}^k\},$$

$\hat{\theta}$  can be chosen such that  $\bar{X}\hat{\theta} = X\hat{\beta}$ .

### Solution

The model can be rewritten as

$$\underbrace{\begin{pmatrix} Y_{11} \\ \vdots \\ Y_{1m} \\ \vdots \\ Y_{k1} \\ \vdots \\ Y_{km} \end{pmatrix}}_{=:Y} = \underbrace{\begin{pmatrix} & & \mathbb{1}_m & & \\ & & & \ddots & \\ \mathbb{1}_{km} & & & & \\ & & & & \mathbb{1}_m \end{pmatrix}}_{=: \bar{X}} \underbrace{\begin{pmatrix} \mu \\ \alpha_1 \\ \vdots \\ \alpha_k \end{pmatrix}}_{=: \theta} + \underbrace{\begin{pmatrix} \varepsilon_{11} \\ \vdots \\ \varepsilon_{1m} \\ \vdots \\ \varepsilon_{k1} \\ \vdots \\ \varepsilon_{km} \end{pmatrix}}_{=: \varepsilon}.$$

The matrix  $\bar{X}$  has rank  $k$  since the last  $k$  columns of  $\bar{X}$  are linearly independent and the first column can be written as the sum of the last  $k$  columns.

It follows from Exercise 5 that the least squares estimator  $\hat{\theta} = (\hat{\mu}, \hat{\alpha}_1, \dots, \hat{\alpha}_k)^T$  of  $\theta$  has to satisfy

$$\hat{\mu} + \hat{\alpha}_1 = \bar{Y}_1.$$

$$\hat{\mu} + \hat{\alpha}_k = \bar{Y}_k.$$

The side conditions yield that

$$\hat{\alpha}_1 = \bar{Y}_1 - \bar{Y}_.$$

$$\hat{\alpha}_k = \bar{Y}_k - \bar{Y}_.$$

and

$$\mu = \bar{Y}_.,$$

where  $\bar{Y}_. = (1/k) \sum_{i=1}^k \bar{Y}_i = \frac{1}{km} \sum_{i=1}^k \sum_{j=1}^m Y_{ij}$ .