

# From Data to Insights - Exercise sheet 2

discussed in week after 2nd lecture

April 26, 2024

## 1 Linear transformations of random vectors

Let  $\mathbf{X} = (X_1, \dots, X_n)^T$  be a random vector with covariance matrix  $\mathbf{C}_X$ , and let  $\mathbf{M}$  be a constant (i.e. non-random)  $m \times n$ -matrix. We can define a new random vector as

$$\mathbf{Y} = \mathbf{M} \cdot \mathbf{X} . \quad (1)$$

Show that the covariance matrix of  $\mathbf{Y}$  is given by

$$\mathbf{C}_Y = \mathbf{M} \cdot \mathbf{C}_X \cdot \mathbf{M}^T . \quad (2)$$

## 2 Fisher matrix for Gaussian random vectors

Let  $\mathbf{X} = (X_1, \dots, X_n)^T$  have a multivariate Gaussian distribution, whose covariance matrix  $\mathbf{C}$  is known. We do not know the expectation value  $\boldsymbol{\mu} = \langle \mathbf{X} \rangle$ , but we know that is given by the function

$$\boldsymbol{\mu} = \boldsymbol{\mu}(\boldsymbol{\theta}) \quad (3)$$

for some unknown parameters  $\boldsymbol{\theta} = (\theta_1, \dots, \theta_m)^T$ . I.e. we know that  $\mathbf{X}$  has the PDF

$$p(\mathbf{x}|\boldsymbol{\theta}_{\text{true}}) = \frac{1}{|2\pi\mathbf{C}|^{n/2}} \exp\left(-\frac{1}{2}[\mathbf{x} - \boldsymbol{\mu}(\boldsymbol{\theta}_{\text{true}})]^T \cdot \mathbf{C}^{-1} \cdot [\mathbf{x} - \boldsymbol{\mu}(\boldsymbol{\theta}_{\text{true}})]\right) , \quad (4)$$

but we do not know the true parameters  $\boldsymbol{\theta}_{\text{true}}$ .

In the lecture we defined the  $ij$ -element of the Fisher matrix  $\mathbf{F}$  for the parameters  $\boldsymbol{\theta}$  as

$$F_{ij} \equiv - \left\langle \frac{\partial^2}{\partial \theta_i \partial \theta_j} \ln p(\mathbf{X}|\boldsymbol{\theta}) \right|_{\boldsymbol{\theta}=\boldsymbol{\theta}_{\text{true}}} \right\rangle . \quad (5)$$

(To understand the meaning of this expression, recall how we had defined expectation values like  $\langle f(\mathbf{X}) \rangle$  in the lecture.) Show that in the above situation the Fisher matrix elements can also be written as

$$F_{ij} = \left( \frac{\partial \boldsymbol{\mu}(\boldsymbol{\theta})}{\partial \theta_i} \right)_{\boldsymbol{\theta}=\boldsymbol{\theta}_{\text{true}}}^T \mathbf{C}^{-1} \left( \frac{\partial \boldsymbol{\mu}(\boldsymbol{\theta})}{\partial \theta_j} \right)_{\boldsymbol{\theta}=\boldsymbol{\theta}_{\text{true}}} . \quad (6)$$

Now consider the one-dimensional case  $n = 1 = m$ , and give an interpretation of Equation 6.

## 3 Linear regression with Gaussian random vectors

Let  $\mathbf{X} = (X_1, \dots, X_n)^T$  have a multivariate Gaussian distribution, whose covariance matrix  $\mathbf{C}$  is known. We do not know the expectation value  $\boldsymbol{\mu} = \langle \mathbf{X} \rangle$ , but we know that is of the form

$$\boldsymbol{\mu} = a\mathbf{v} \quad (7)$$

for some known vector  $\mathbf{v}$  but an unknown amplitude  $a$ .

We now perform a measurement of  $\mathbf{X}$  and obtain the result  $\mathbf{x}$ . We want to use this measurement to estimate the amplitude  $a$ . To do so, find the value  $a_{\text{best}}$  that minimizes

$$\chi^2(a) = [\mathbf{x} - a\mathbf{v}]^T \mathbf{C}^{-1} [\mathbf{x} - a\mathbf{v}] . \quad (8)$$

In your expression for  $a_{\text{best}}$ , replace  $\mathbf{x}$  with  $\mathbf{X}$  to obtain the random variable  $A_{\text{best}}$ . What is the variance of  $A_{\text{best}}$ ? Compare this to the inverse Fisher information! In the light of the Cramer-Rao-bound, what do you conclude from that comparison for the estimator  $A_{\text{best}}$ ?

## 4 Use a computer to simulate exercise 3

On your computer (or using `jupyter.physik.uni-muenchen.de`), setup a numerical experiment that implements the situation of exercise 3. I.e.

- Choose some values for  $\mathbf{C}$  and  $\mathbf{v}$ . You also need to choose a "true" value for  $a$ ,  $a_{true}$ .
- Draw several random draws from the random variable  $\mathbf{X}$ .
- For each of these draws, calculate  $a_{best}$ .
- Is the variance of these  $a_{best}$  values consistent with your findings from Exercise 3?