

# Module 2, Part 2: Random vectors, covariance, multivariate Normal distribution

TMA4268 Statistical Learning V2022

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# Message

- We need reference group members!!
- Groups

# Overview

- Random vectors
- The covariance and correlation matrix
- The multivariate normal distribution

## Random vector

- A random vector  $\mathbf{X}_{(p \times 1)}$  is a  $p$ -dimensional vector of random variables. For example
  - Weight of cork deposits in  $p = 4$  directions (N, E, S, W).
  - Factors to predict body fat: bmi, age, weight, hip circumference,....
- Joint distribution function:  $f(\mathbf{x})$ .
- From joint distribution function to marginal (and conditional distributions).

$$f_1(x_1) = \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} f(x_1, x_2, \dots, x_p) dx_2 \cdots dx_p$$

- Cumulative distribution (definite integrals!) used to calculate probabilities.

## Moments

The moments are important properties of the distribution of  $\mathbf{X}$ .  
We will look at:

- E: Mean of random vector and random matrices.
- Cov: Covariance matrix.
- Corr: Correlation matrix.
- E and Cov of multiple linear combinations.

## The Cork deposit data

- Classical multivariate data set from Rao (1948).
- Weigth of bark deposits of  $n = 28$  cork trees in  $p = 4$  directions (N, E, S, W).

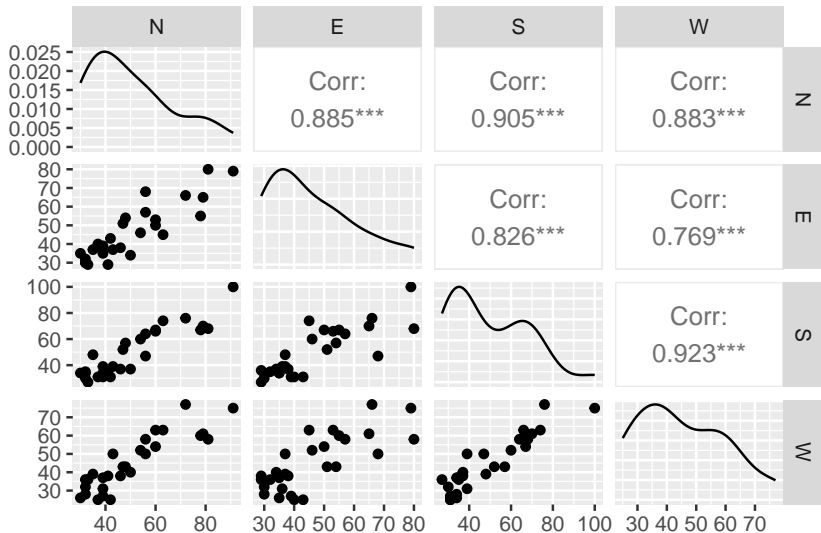
```
corkds = as.matrix(read.table("https://www.math.ntnu.no/emner/TMA4268/2019v/data/corkMKB.txt"))
dimnames(corkds)[[2]] = c("N", "E", "S", "W")
head(corkds)

##           N  E  S  W
## [1,]  72 66 76 77
## [2,]  60 53 66 63
## [3,]  56 57 64 58
## [4,]  41 29 36 38
## [5,]  32 32 35 36
## [6,]  30 35 34 26
dim(corkds)

## [1] 28 4
```

Look at the data (always the first thing to do):

```
library(GGally)
corkds <- as.data.frame(corkds)
ggpairs(corkds)
```



- Here we have a random sample of  $n = 28$  cork trees from the population and observe a  $p = 4$  dimensional random vector for each tree.
- This leads us to the definition of random vectors and a random matrix for cork trees:

$$\mathbf{X}_{(28 \times 4)} = \begin{bmatrix} X_{11} & X_{12} & X_{13} & X_{14} \\ X_{21} & X_{22} & X_{23} & X_{24} \\ X_{31} & X_{32} & X_{33} & X_{34} \\ \vdots & \vdots & \ddots & \vdots \\ X_{28,1} & X_{28,2} & X_{28,3} & X_{28,4} \end{bmatrix}$$



## The mean vector

- **Remember** for a univariate SV  $X \sim f(x)$  the expected value (mean) is defined as

$$E(X) = \int_{\mathcal{R}} x f(x) dx$$

- For a **Random vector**  $\mathbf{X}_{(p \times 1)}$ , the mean vector  $\boldsymbol{\mu}_{(p \times 1)}$  is

$$\mathbf{X}_{(p \times 1)} = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_p \end{bmatrix}, \text{ and } \boldsymbol{\mu}_{(p \times 1)} = E(\mathbf{X}) = \begin{bmatrix} E(X_1) \\ E(X_2) \\ \vdots \\ E(X_p) \end{bmatrix}.$$

**Note** that  $E(X_j)$  is calculated from the marginal distribution of  $X_j$  and contains no information about dependencies between  $X_j$  and  $X_k$ ,  $k \neq j$ .

- Same rule for random matrices.

## Rules for the mean I

- Random matrix  $\mathbf{X}_{(n \times p)}$  and random matrix  $\mathbf{Y}_{(n \times p)}$ :

$$\mathbf{E}(\mathbf{X} + \mathbf{Y}) = \mathbf{E}(\mathbf{X}) + \mathbf{E}(\mathbf{Y}) .$$

(Rules of vector addition)

## Rules for the mean II

- Random matrix  $\mathbf{X}_{(n \times p)}$  and conformable constant matrices  $\mathbf{A}$  and  $\mathbf{B}$ :

$$\mathbf{E}(\mathbf{A}\mathbf{X}\mathbf{B}) = \mathbf{A}\mathbf{E}(\mathbf{X})\mathbf{B}$$

Proof: Board

Q:

- What are the univariate analogue to the formulas on the previous two slides (which you studied in your first introductory course in statistics)?

## The covariance

In the introductory statistics course we defined the covariance

$$\begin{aligned}\rho_{ij} &= \text{Cov}(X_i, X_j) = \text{E}[(X_i - \mu_i)(X_j - \mu_j)] \\ &= \text{E}(X_i \cdot X_j) - \mu_i \mu_j .\end{aligned}$$

- What is the covariance called when  $i = j$ ?
- What does it mean when the covariance is
  - negative
  - zero
  - positive?

Make a scatter plot for negative, zero and positive correlation (see also R example).

## Variance-covariance matrix

- Consider random vector  $\mathbf{X}_{(p \times 1)}$  with mean vector  $\boldsymbol{\mu}_{(p \times 1)}$ :

$$\mathbf{X}_{(p \times 1)} = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_p \end{bmatrix}, \text{ and } \boldsymbol{\mu}_{(p \times 1)} = \mathbb{E}(\mathbf{X}) = \begin{bmatrix} \mathbb{E}(X_1) \\ \mathbb{E}(X_2) \\ \vdots \\ \mathbb{E}(X_p) \end{bmatrix}$$

- Variance-covariance matrix  $\boldsymbol{\Sigma}$  (real and symmetric)

$$\begin{aligned} \boldsymbol{\Sigma} &= \text{Cov}(\mathbf{X}) = \mathbb{E}[(\mathbf{X} - \boldsymbol{\mu})(\mathbf{X} - \boldsymbol{\mu})^T] \\ &= \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \cdots & \sigma_{1p} \\ \sigma_{12} & \sigma_2^2 & \cdots & \sigma_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{1p} & \sigma_{2p} & \cdots & \sigma_p^2 \end{bmatrix} = \mathbb{E}(\mathbf{X}\mathbf{X}^T) - \boldsymbol{\mu}\boldsymbol{\mu}^T \end{aligned}$$

- The diagonal elements in  $\Sigma$ ,  $\sigma_{ii} = \sigma_i^2$ , are variances.
- The off-diagonal elements are covariances  
 $\sigma_{ij} = E[(X_i - \mu_i)(X_j - \mu_j)] = \sigma_{ji}.$
- $\Sigma$  is called variance, covariance and variance-covariance matrix and denoted both  $\text{Var}(\mathbf{X})$  and  $\text{Cov}(\mathbf{X})$ .



Exercise: the variance-covariance matrix

Let  $\mathbf{X}_{4 \times 1}$  have variance-covariance matrix

$$\Sigma = \begin{bmatrix} 2 & 1 & 0 & 0 \\ 1 & 2 & 0 & 1 \\ 0 & 0 & 2 & 1 \\ 0 & 1 & 1 & 2 \end{bmatrix}.$$

Explain what this means.

## Correlation matrix

Correlation matrix  $\boldsymbol{\rho}$  (real and symmetric)

$$\boldsymbol{\rho} = \begin{bmatrix} \frac{\sigma_1^2}{\sqrt{\sigma_1^2 \sigma_1^2}} & \frac{\sigma_{12}}{\sqrt{\sigma_1^2 \sigma_2^2}} & \cdots & \frac{\sigma_{1p}}{\sqrt{\sigma_1^2 \sigma_p^2}} \\ \frac{\sigma_{12}}{\sqrt{\sigma_1^2 \sigma_2^2}} & \frac{\sigma_2^2}{\sqrt{\sigma_2^2 \sigma_2^2}} & \cdots & \frac{\sigma_{2p}}{\sqrt{\sigma_2^2 \sigma_p^2}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\sigma_{1p}}{\sqrt{\sigma_1^2 \sigma_p^2}} & \frac{\sigma_{2p}}{\sqrt{\sigma_2^2 \sigma_p^2}} & \cdots & \frac{\sigma_p^2}{\sqrt{\sigma_p^2 \sigma_p^2}} \end{bmatrix} = \begin{bmatrix} 1 & \rho_{12} & \cdots & \rho_{1p} \\ \rho_{12} & 1 & \cdots & \rho_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{1p} & \rho_{2p} & \cdots & 1 \end{bmatrix}$$

$$\boldsymbol{\rho} = (\mathbf{V}^{\frac{1}{2}})^{-1} \boldsymbol{\Sigma} (\mathbf{V}^{\frac{1}{2}})^{-1}, \text{ where } \mathbf{V}^{\frac{1}{2}} = \begin{bmatrix} \sqrt{\sigma_1^2} & 0 & \cdots & 0 \\ 0 & \sqrt{\sigma_2^2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sqrt{\sigma_p^2} \end{bmatrix}$$

## Exercise: the correlation matrix

Let  $\mathbf{X}_{4 \times 1}$  have variance-covariance matrix

$$\Sigma = \begin{bmatrix} 2 & 1 & 0 & 0 \\ 1 & 2 & 0 & 1 \\ 0 & 0 & 2 & 1 \\ 0 & 1 & 1 & 2 \end{bmatrix}.$$

Find the correlation matrix.

**A:**

## Linear combinations

Consider a random vector  $\mathbf{X}_{(p \times 1)}$  with mean vector  $\boldsymbol{\mu} = \mathbb{E}(\mathbf{X})$  and variance-covariance matrix  $\boldsymbol{\Sigma} = \text{Cov}(\mathbf{X})$ .

The linear combinations

$$\mathbf{Z} = \mathbf{C}\mathbf{X} = \begin{bmatrix} \sum_{j=1}^p c_{1j}X_j \\ \sum_{j=1}^p c_{2j}X_j \\ \vdots \\ \sum_{j=1}^p c_{kj}X_j \end{bmatrix}$$

have

$$\mathbb{E}(\mathbf{Z}) = \mathbb{E}(\mathbf{C}\mathbf{X}) = \mathbf{C}\boldsymbol{\mu}$$

$$\text{Cov}(\mathbf{Z}) = \text{Cov}(\mathbf{C}\mathbf{X}) = \mathbf{C}\boldsymbol{\Sigma}\mathbf{C}^T$$

**Exercise:** Follow the proof (board) - what are the most important transitions?

## Exercise: Linear combinations

$$\mathbf{X} = \begin{bmatrix} X_N \\ X_E \\ X_S \\ X_W \end{bmatrix}, \boldsymbol{\mu} = \begin{bmatrix} \mu_N \\ \mu_E \\ \mu_S \\ \mu_W \end{bmatrix}, \text{ and } \boldsymbol{\Sigma} = \begin{bmatrix} \sigma_N^2 & \sigma_{NE} & \sigma_{NS} & \sigma_{NW} \\ \sigma_{NE} & \sigma_E^2 & \sigma_{ES} & \sigma_{EW} \\ \sigma_{NS} & \sigma_{SE} & \sigma_S^2 & \sigma_{SW} \\ \sigma_{NW} & \sigma_{EW} & \sigma_{SW} & \sigma_W^2 \end{bmatrix}$$

Scientists would like to compare the following three *contrasts*: N-S, E+W and (E+W)-(N+S), and define a new random vector  $\mathbf{Y}_{(3 \times 1)} = \mathbf{C}_{(3 \times 4)} \mathbf{X}_{(4 \times 1)}$  giving the three contrasts.

- Write down  $\mathbf{C}$ .
- Explain how to find  $E(Y_1)$  and  $\text{Cov}(Y_1, Y_3)$ .
- Use R to find the mean vector, covariance matrix and correlations matrix of  $\mathbf{Y}$ , when the mean vector and covariance matrix for  $\mathbf{X}$  given below.

```
corkds <- as.matrix(read.table("https://www.math.ntnu.no/emner/TMA4268/2019v/data/corkMKB.txt"))
dimnames(corkds)[[2]] <- c("N", "E", "S", "W")
mu = apply(corkds, 2, mean)
mu
Sigma = var(corkds)
Sigma
```

```
##           N           E           S           W
## 50.53571 46.17857 49.67857 45.17857
##           N           E           S           W
## N 290.4061 223.7526 288.4378 226.2712
## E 223.7526 219.9299 229.0595 171.3743
## S 288.4378 229.0595 350.0040 259.5410
## W 226.2712 171.3743 259.5410 226.0040
```

```
(C <- matrix(c(1, 0, -1, 0, 0, 1, 0, 1, -1, 1, -1, 1), byrow = T, nrow = 3))
```

```
##      [,1] [,2] [,3] [,4]
## [1,]    1    0   -1    0
## [2,]    0    1    0    1
## [3,]   -1    1   -1    1
```

```
C %*% Sigma %*% t(C)
```

```
##           [,1]           [,2]           [,3]
## [1,] 63.53439 -38.57672 21.02116
## [2,] -38.57672 788.68254 -149.94180
## [3,] 21.02116 -149.94180 128.71958
```

## The covariance matrix - more requirements?

Random vector  $\mathbf{X}_{(p \times 1)}$  with mean vector  $\boldsymbol{\mu}_{(p \times 1)}$  and covariance matrix

$$\boldsymbol{\Sigma} = \text{Cov}(\mathbf{X}) = \text{E}[(\mathbf{X} - \boldsymbol{\mu})(\mathbf{X} - \boldsymbol{\mu})^T] = \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \cdots & \sigma_{1p} \\ \sigma_{12} & \sigma_2^2 & \cdots & \sigma_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{1p} & \sigma_{2p} & \cdots & \sigma_p^2 \end{bmatrix}$$



- The covariance matrix is by construction symmetric, and it is common to require that the covariance matrix is positive semidefinite. This means that, for every vector  $\mathbf{b} \neq \mathbf{0}$

$$\mathbf{b}^T \Sigma \mathbf{b} \geq 0 .$$

- Why do you think that is?

- The covariance matrix is by construction symmetric, and it is common to require that the covariance matrix is positive semidefinite. This means that, for every vector  $\mathbf{b} \neq \mathbf{0}$

$$\mathbf{b}^T \Sigma \mathbf{b} \geq 0 .$$

- Why do you think that is?

Hint: Is it possible that the variance of the linear combination  $Y = \mathbf{b}^T \mathbf{X}$  is negative?

## Random vectors - Single-choice exercise

Quizz on [www.menti.com](https://www.menti.com) joint at 23 38 27 0

### Question 1: Mean of sum

$\mathbf{X}$  and  $\mathbf{Y}$  are two bivariate random vectors with  $E(\mathbf{X}) = (1, 2)^T$  and  $E(\mathbf{Y}) = (2, 0)^T$ . What is  $E(\mathbf{X} + \mathbf{Y})$ ?

- A:  $(1.5, 1)^T$
- B:  $(3, 2)^T$
- C:  $(-1, 2)^T$
- D:  $(1, -2)^T$

## Question 2: Mean of linear combination

$\mathbf{X}$  is a 2-dimensional random vector with  $E(\mathbf{X}) = (2, 5)^T$ , and  $\mathbf{b} = (0.5, 0.5)^T$  is a constant vector. What is  $E(\mathbf{b}^T \mathbf{X})$ ?

- A: 3.5
- B: 7
- C: 2
- D: 5

### Question 3: Covariance

$\mathbf{X}$  is a  $p$ -dimensional random vector with mean  $\boldsymbol{\mu}$ . Which of the following defines the covariance matrix?

- A:  $E[(\mathbf{X} - \boldsymbol{\mu})^T(\mathbf{X} - \boldsymbol{\mu})]$
- B:  $E[(\mathbf{X} - \boldsymbol{\mu})(\mathbf{X} - \boldsymbol{\mu})^T]$
- C:  $E[(\mathbf{X} - \boldsymbol{\mu})(\mathbf{X} - \boldsymbol{\mu})]$
- D:  $E[(\mathbf{X} - \boldsymbol{\mu})^T(\mathbf{X} - \boldsymbol{\mu})^T]$

### Question 4: Mean of linear combinations

$\mathbf{X}$  is a  $p$ -dimensional random vector with mean  $\boldsymbol{\mu}$  and covariance matrix  $\boldsymbol{\Sigma}$ .  $\mathbf{C}$  is a constant matrix. What is then the mean of the  $k$ -dimensional random vector  $\mathbf{Y} = \mathbf{C}\mathbf{X}$ ?

- A:  $\mathbf{C}\boldsymbol{\mu}$
- B:  $\mathbf{C}\boldsymbol{\Sigma}$
- C:  $\mathbf{C}\boldsymbol{\mu}\mathbf{C}^T$
- D:  $\mathbf{C}\boldsymbol{\Sigma}\mathbf{C}^T$

### Question 5: Covariance of linear combinations

$\mathbf{X}$  is a  $p$ -dimensional random vector with mean  $\boldsymbol{\mu}$  and covariance matrix  $\boldsymbol{\Sigma}$ .  $\mathbf{C}$  is a constant matrix. What is then the covariance of the  $k$ -dimensional random vector  $\mathbf{Y} = \mathbf{C}\mathbf{X}$ ?

- A:  $\mathbf{C}\boldsymbol{\mu}$
- B:  $\mathbf{C}\boldsymbol{\Sigma}$
- C:  $\mathbf{C}\boldsymbol{\mu}\mathbf{C}^T$
- D:  $\mathbf{C}\boldsymbol{\Sigma}\mathbf{C}^T$



### Question 6: Correlation

$\mathbf{X}$  is a 2-dimensional random vector with covariance matrix

$$\Sigma = \begin{bmatrix} 4 & 0.8 \\ 0.8 & 1 \end{bmatrix}$$

Then the correlation between the two elements of  $\mathbf{X}$  are:

- A: 0.10
- B: 0.25
- C: 0.40
- D: 0.80

## Question 7

$\mathbf{X}$  is a 2-dimensional random vector with mean  $\boldsymbol{\mu}$  and covariance matrix  $\boldsymbol{\Sigma}$ .

Are these sufficient to totally describe the random vector  $\mathbf{X}$ ?

- A: Yes
- B: No

---

<sup>1</sup>Show the Datasaurus data: <https://cran.r-project.org/web/packages/datasauRus/vignettes/Datasaurus.html>

## Question 7

$\mathbf{X}$  is a 2-dimensional random vector with mean  $\boldsymbol{\mu}$  and covariance matrix  $\boldsymbol{\Sigma}$ .

Are these sufficient to totally describe the random vector  $\mathbf{X}$ ?

- A: Yes
- B: No

Why?<sup>1</sup>

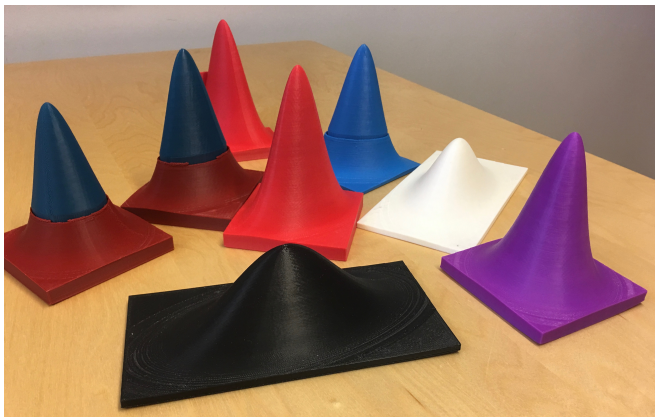
---

<sup>1</sup>Show the Datasaurus data: <https://cran.r-project.org/web/packages/datasauRus/vignettes/Datasaurus.html>

# The multivariate normal distribution

Why is the mvN so popular?

- Many natural phenomena may be modelled using this distribution (just as in the univariate case).
- Multivariate version of the central limit theorem- the sample mean will be approximately multivariate normal for large samples.
- Good interpretability of the covariance.
- Mathematically tractable.
- Building block in many models and methods.



3D multivariate Normal distributions

## The multivariate normal (mvN) pdf

The random vector  $\mathbf{X}_{p \times 1}$  is multivariate normal  $N_p$  with mean  $\boldsymbol{\mu}$  and (positive definite) covariate matrix  $\boldsymbol{\Sigma}$ . The pdf is:

$$f(\mathbf{x}) = \frac{1}{(2\pi)^{\frac{p}{2}} |\boldsymbol{\Sigma}|^{\frac{1}{2}}} \exp\left\{-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1}(\mathbf{x} - \boldsymbol{\mu})\right\}$$

### Questions:

- How does this compare to the univariate version?

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left\{-\frac{1}{2\sigma^2}(x - \mu)^2\right\}$$

- Why do we need the constant in front of the exp?
- What is the dimension of the part in exp?
- What happens if the determinant  $|\boldsymbol{\Sigma}| = 0$  (degenerate case)?

## Four useful properties of the mvN

Let  $\mathbf{X}_{(p \times 1)}$  be a random vector from  $N_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ .

1. The graphical contours of the mvN are ellipsoids (can be shown using spectral decomposition).
2. Linear combinations of components of  $\mathbf{X}$  are (multivariate) normal.
3. All subsets of the components of  $\mathbf{X}$  are (multivariate) normal (special case of the above).
4. Zero covariance implies that the corresponding components are independently distributed (in contrast to general distributions).

If you need a refresh, you might find that video useful:

<https://www.youtube.com/watch?v=eho8xH3E6mE>

All of these are proven in TMA4267 Linear Statistical Models.

The result 4 is rather useful! If you have a bivariate normal and observed covariance 0, then your variables are independent.



## Contours of multivariate normal distribution

- Contours of constant density for the  $p$ -dimensional normal distribution are ellipsoids defined by  $\mathbf{x}$  such that

$$(\mathbf{x} - \boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1} (\mathbf{x} - \boldsymbol{\mu}) = b$$

where  $b > 0$  is a constant.

- These ellipsoids are centered at  $\boldsymbol{\mu}$  and have axes  $\pm\sqrt{b\lambda_i}\mathbf{e}_i$ , where  $\boldsymbol{\Sigma}\mathbf{e}_i = \lambda_i\mathbf{e}_i$  (eigenvector for  $\lambda_i$ ), for  $i = 1, \dots, p$ .
- To see this the spectral decomposition of the covariance matrix is useful.

Note:

*In M4: Classification the mvN is very important and we will often draw contours of the mvN as ellipses (in 2D space). This is the reason why we do that.*

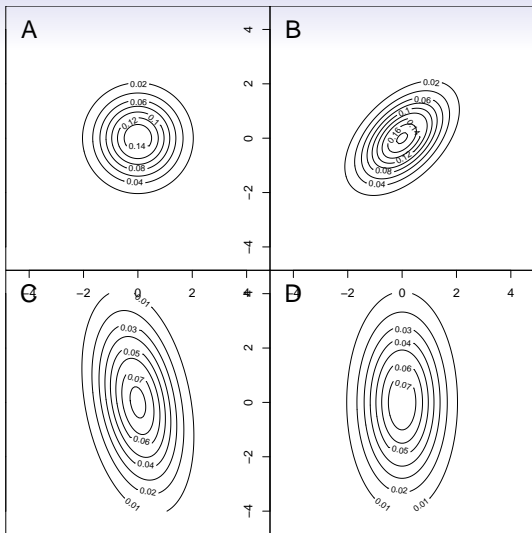
Identify the mvNs from their contours

$$\text{Let } \Sigma = \begin{bmatrix} \sigma_x^2 & \rho\sigma_x\sigma_y \\ \rho\sigma_x\sigma_y & \sigma_y^2 \end{bmatrix}.$$

The following four figure contours have been generated:

- 1:  $\sigma_x = 1, \sigma_y = 2, \rho = -0.3$
- 2:  $\sigma_x = 1, \sigma_y = 1, \rho = 0$
- 3:  $\sigma_x = 1, \sigma_y = 1, \rho = 0.5$
- 4:  $\sigma_x = 1, \sigma_y = 2, \rho = 0$

**Match the distributions to the figures on the next slide.**



Take a look at the contour plots - when are the contours circles, when ellipses?

## Multiple choice - multivariate normal

A second quizz on [www.menti.com](http://www.menti.com) join at 1624 7290

Choose the correct answer. Let's go!

## Question 1: Multivariate normal pdf

The probability density function is  $(\frac{1}{2\pi})^{\frac{p}{2}} \det(\Sigma)^{-\frac{1}{2}} \exp\{-\frac{1}{2}Q\}$  where  $Q$  is

- A:  $(\mathbf{x} - \boldsymbol{\mu})^T \Sigma^{-1} (\mathbf{x} - \boldsymbol{\mu})$
- B:  $(\mathbf{x} - \boldsymbol{\mu}) \Sigma (\mathbf{x} - \boldsymbol{\mu})^T$
- C:  $\Sigma - \boldsymbol{\mu}$

## Question 2: Trivariate normal pdf

What graphical form has the solution to  $f(\mathbf{x}) = \text{constant}$ ?

- A: Circle
- B: Parabola
- C: Ellipsoid
- D: Bell shape

### Question 3: Multivariate normal distribution

$\mathbf{X}_p \sim N_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ , and  $\mathbf{C}$  is a  $k \times p$  constant matrix.  $\mathbf{Y} = \mathbf{C}\mathbf{X}$  is

- A: Chi-squared with  $k$  degrees of freedom
- B: Multivariate normal with mean  $k\boldsymbol{\mu}$
- C: Chi-squared with  $p$  degrees of freedom
- D: Multivariate normal with mean  $\mathbf{C}\boldsymbol{\mu}$



## Question 4: Independence

Let  $\mathbf{X} \sim N_3(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ , with

$$\boldsymbol{\Sigma} = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 3 & 2 \\ 0 & 2 & 5 \end{bmatrix}.$$

Which two variables are independent?

- A:  $X_1$  and  $X_2$
- B:  $X_1$  and  $X_3$
- C:  $X_2$  and  $X_3$
- D: None – but two are uncorrelated.

### Question 5: Constructing independent variables?

Let  $\mathbf{X} \sim N_p(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ . How can I construct a vector of independent standard normal variables from  $\mathbf{X}$ ?

- A:  $\boldsymbol{\Sigma}(\mathbf{X} - \boldsymbol{\mu})$
- B:  $\boldsymbol{\Sigma}^{-1}(\mathbf{X} + \boldsymbol{\mu})$
- C:  $\boldsymbol{\Sigma}^{-\frac{1}{2}}(\mathbf{X} - \boldsymbol{\mu})$
- D:  $\boldsymbol{\Sigma}^{\frac{1}{2}}(\mathbf{X} + \boldsymbol{\mu})$



## Main Concepts:

- Mean of a random vector
  - Linear operator
- Variance-covariance Matrix
  - Correlation Matrix
- 

Multinormal distribution

## Further reading/resources

- Videos on YouTube by the authors of ISL, Chapter 2

# Acknowledgements

Thanks to Mette Langaas, who developed the first slide set in 2018 and 2019, and to Julia Debik for contributing to this module.