

## 8. Covariance Matrices

**Note:** Now is a good time to review the matrix exercises in [Homework 0](#).

**Note on Notation:** In this course, we assume all vectors to be column vectors. Therefore, while

$$\mathbf{X} = \begin{bmatrix} X^{(1)} \\ X^{(2)} \\ \vdots \\ X^{(d)} \end{bmatrix},$$

we sometimes write it as  $\mathbf{X} = (X^{(1)}, \dots, X^{(d)})^T$  to be more compact in representation.

### Example of Covariance II

4/4 points (graded)

Let  $\mathbf{X}, \mathbf{Y}$  be random variables such that

- $\mathbf{X}$  takes the values  $\pm 1$  each with probability  $0.5$
- (Conditioned on  $\mathbf{X}$ )  $\mathbf{Y}$  is chosen uniformly from the set  $\{-3\mathbf{X} - 1, -3\mathbf{X}, -3\mathbf{X} + 1\}$ .

(Round all answers to 2 decimal places.)

What is  $\text{Cov}(\mathbf{X}, \mathbf{X})$  (equivalent to  $\text{Var}(\mathbf{X})$ )?

$\text{Cov}(\mathbf{X}, \mathbf{X}) =$   □ Answer: 1.0

What is  $\text{Cov}(\mathbf{Y}, \mathbf{Y})$  (equivalent to  $\text{Var}(\mathbf{Y})$ )?

$\text{Cov}(\mathbf{Y}, \mathbf{Y}) =$   □ Answer: 9.67

What is  $\text{Cov}(\mathbf{X}, \mathbf{Y})$ ?

$\text{Cov}(\mathbf{X}, \mathbf{Y}) =$   □ Answer: -3.00

What is  $\text{Cov}(\mathbf{Y}, \mathbf{X})$ ?

$\text{Cov}(\mathbf{Y}, \mathbf{X}) =$   □ Answer: -3.00

**Solution:**

Observe that  $\mathbb{E}[\mathbf{X}]$  and  $\mathbb{E}[\mathbf{Y}]$  are both zero, since  $\mathbf{X}$  is uniformly distributed over  $\{\pm 1\}$  and  $\mathbf{Y}$  is uniformly distributed over the set  $\{-4, -3, -2, 2, 3, 4\}$ .

- $\text{Cov}(\mathbf{X}, \mathbf{X})$  is the variance of  $\mathbf{X}$ , which equals  $\mathbb{E}[\mathbf{X}^2] - \mathbb{E}[\mathbf{X}]^2 = p + (1 - p) = 1$ .
- $\text{Cov}(\mathbf{Y}, \mathbf{Y})$  is the variance of  $\mathbf{Y}$ , which equals  $\mathbb{E}[\mathbf{Y}^2] - \mathbb{E}[\mathbf{Y}]^2 = \frac{16+9+4+4+9+16}{6} = \frac{29}{3} \approx 9.67$ .
- $\text{Cov}(\mathbf{X}, \mathbf{Y})$  and  $\text{Cov}(\mathbf{Y}, \mathbf{X})$  are always equal, by the symmetry of the definition. Observe that the joint density of  $(\mathbf{X}, \mathbf{Y})$  is uniform over the pairs  $(1, -4), (1, -3), (1, -2), (-1, 2), (-1, 3), (-1, 4)$ . Thus, either covariance can be computed as  $\mathbb{E}[\mathbf{XY}] - \mathbb{E}[\mathbf{X}]\mathbb{E}[\mathbf{Y}] = \frac{-4-3-2-2-3-4}{6} = -3$ .

Answers are displayed within the problem

Covariance Matrix

4/4 points (graded)  
Given random variables  $X^{(1)}, X^{(2)}, \dots, X^{(d)}$ , one can write down the **covariance matrix**  $\Sigma$ , where  $\Sigma_{i,j} = \text{Cov}(X^{(i)}, X^{(j)})$ .

Let  $X^{(1)}, X^{(2)}$  be random variables such that

- $X^{(1)}$  takes the values  $\pm 1$  each with probability **0.5**
- (Conditioned on  $X^{(1)}$ )  $X^{(2)}$  is chosen uniformly from the set  $\{-3X^{(1)} - 1, -3X^{(1)}, -3X^{(1)} + 1\}$ .

What is the covariance matrix  $\Sigma$ ?

$\Sigma_{1,1} =$ 

1

Answer: 1.0

$\Sigma_{1,2} =$ 

-3

Answer: -3.00

$\Sigma_{2,1} =$ 

-3

Answer: -3.00

$\Sigma_{2,2} =$ 

29/3

Answer: 9.67

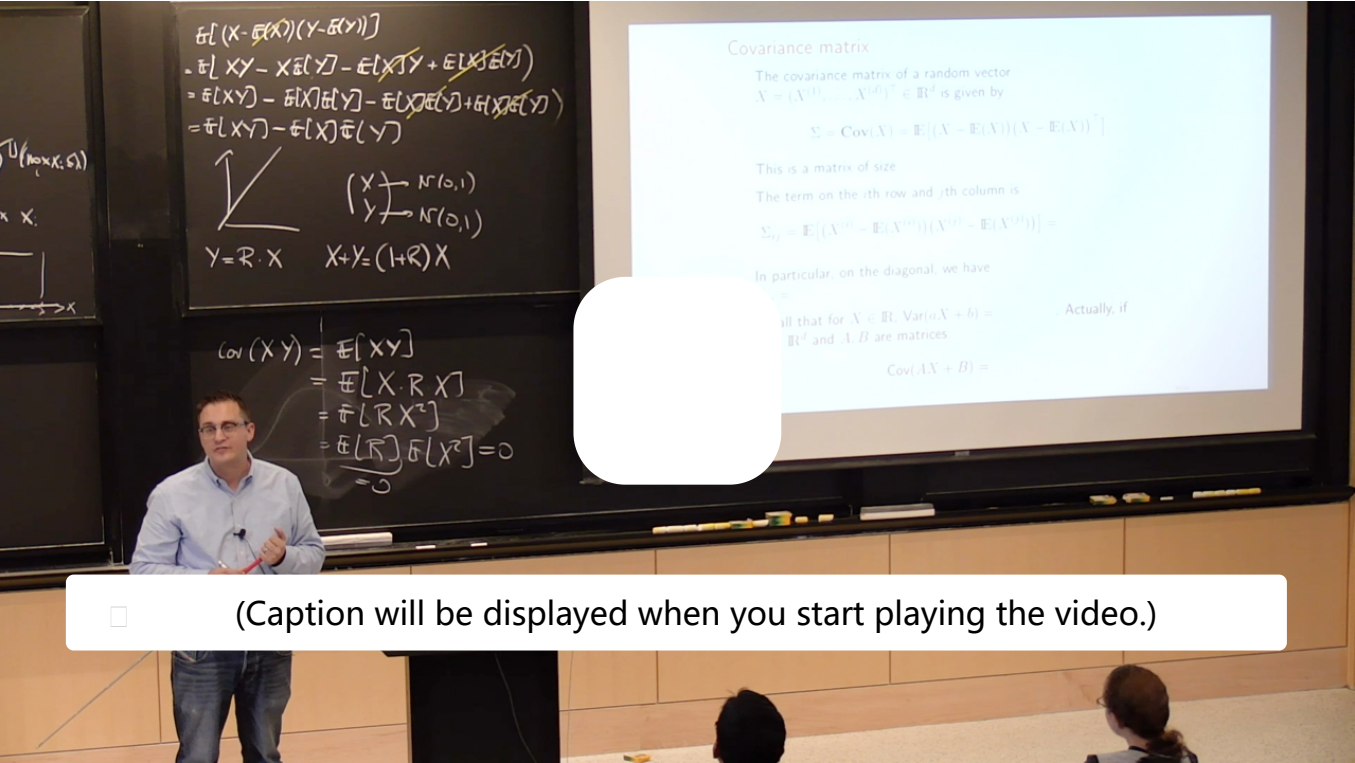
Solution:

Using the answer to the previous question, the  $2 \times 2$  covariance matrix  $\Sigma$  evaluates to

$$\Sigma = \begin{pmatrix} \Sigma_{1,1} & \Sigma_{1,2} \\ \Sigma_{2,1} & \Sigma_{2,2} \end{pmatrix} = \begin{pmatrix} 1 & -3 \\ -3 & \frac{29}{3} \end{pmatrix}$$

Answers are displayed within the problem

Covariance Matrix: Definitions



(Caption will be displayed when you start playing the video.)

in a simple way, which is by informing the matrix that's covariance of xx, covariance of yy, covariance of xy, and covariance of yx. So clearly, it's a symmetric matrix, because these are symmetric numbers. And so all I'm saying is that I can gather all the information about covariance and variance in one matrix. In this case, it's 2 by 2. You can do that more generally, when you have, say, d by d. If you have a vector of size d, you can talk about its covariance matrix. And each entry on the diagonal will just be a variance term,

Here is a compact formula for the covariance matrix using vector notation.

Let  $\mathbf{X} = \begin{pmatrix} X^{(1)} \\ \vdots \\ X^{(d)} \end{pmatrix}$  be a random vector of size  $d \times 1$ .

Let  $\boldsymbol{\mu} \triangleq \mathbb{E}[\mathbf{X}]$  denote the **entry-wise** mean, i.e.

$$\mathbb{E}[\mathbf{X}] = \begin{pmatrix} \mathbb{E}[X^{(1)}] \\ \vdots \\ \mathbb{E}[X^{(d)}] \end{pmatrix}.$$

Consider the vector outer product (refer to [Homework 0](#))  $(\mathbf{X} - \boldsymbol{\mu})(\mathbf{X} - \boldsymbol{\mu})^T$ , which is a random  $d \times d$  matrix. Then the **covariance matrix**  $\boldsymbol{\Sigma}$  can be written as

$$\boldsymbol{\Sigma} = \mathbb{E}[(\mathbf{X} - \boldsymbol{\mu})(\mathbf{X} - \boldsymbol{\mu})^T].$$

**Note:** The following exercises will be discussed as properties of covariance in the video that follows, but we encourage you attempt these exercises before watching the video.

### Covariance Matrix: Properties I

1/1 point (graded)

Let  $\mathbf{X}$  be a random vector and let  $\mathbf{Y} = \mathbf{X} + \mathbf{B}$ , where  $\mathbf{B}$  is a constant vector. Let  $\boldsymbol{\mu}_{\mathbf{X}}$  be the mean vector of  $\mathbf{X}$  and let  $\boldsymbol{\Sigma}_{\mathbf{X}}$  be the covariance matrix of  $\mathbf{X}$ . Select from the following all statements that are correct.

- ☐ The covariance matrix of  $\mathbf{Y}$  could potentially be equal to  $\boldsymbol{\Sigma}_{\mathbf{X}}$  only under some conditions imposed on  $\mathbf{B}$
- ☒ The covariance matrix of  $\mathbf{Y}$  is the same as  $\boldsymbol{\Sigma}_{\mathbf{X}}$  for all vectors  $\mathbf{B}$  ☐
- ☒ The covariance matrix of  $\mathbf{Y}$  has the same size as the matrix  $\boldsymbol{\Sigma}_{\mathbf{X}}$  ☐
- ☐ The covariance matrix of  $\mathbf{Y}$  is the same as  $\boldsymbol{\Sigma}_{\mathbf{X}}$  if and only if vector  $\mathbf{B}$  is equal to 0

☐

**Solution:**

Choices 2 and 3 are correct. Let the covariance matrix of  $\mathbf{Y}$  be denoted  $\boldsymbol{\Sigma}_{\mathbf{Y}}$ . Note that  $\mathbb{E}[\mathbf{X} + \mathbf{B}] = \boldsymbol{\mu}_{\mathbf{X}} + \mathbf{B}$  for any vector  $\mathbf{B}$ .

$$\boldsymbol{\Sigma}_{\mathbf{Y}} = \mathbb{E}\left[(\mathbf{X} + \mathbf{B} - \boldsymbol{\mu}_{\mathbf{X}} - \mathbf{B})(\mathbf{X} + \mathbf{B} - \boldsymbol{\mu}_{\mathbf{X}} - \mathbf{B})^T\right] = \boldsymbol{\Sigma}_{\mathbf{X}}$$

Since choice 2 is correct, choices 1 and 4 that impose certain conditions on  $\mathbf{B}$  are technically incorrect as we do not require that  $\mathbf{B}$  satisfy some conditions for  $\boldsymbol{\Sigma}_{\mathbf{Y}}$  to be the same as  $\boldsymbol{\Sigma}_{\mathbf{X}}$ .

提交

你已经尝试了1次（总共可以尝试2次）

☐ Answers are displayed within the problem

### Covariance Matrix: Properties II

1/1 point (graded)

Let  $\mathbf{X}$  be a random vector of size  $d \times 1$  and let  $\mathbf{Y} = \mathbf{A}\mathbf{X} + \mathbf{B}$ , where  $\mathbf{A}$  is a constant matrix of size  $n \times d$  and  $\mathbf{B}$  is a constant vector of size  $n \times 1$ . Let  $\boldsymbol{\mu}_{\mathbf{X}}$  be the mean vector of  $\mathbf{X}$  and let  $\boldsymbol{\Sigma}_{\mathbf{X}}$  be the covariance matrix of  $\mathbf{X}$ . Let  $\boldsymbol{\mu}_{\mathbf{Y}}$  be the mean vector of  $\mathbf{Y}$  and let  $\boldsymbol{\Sigma}_{\mathbf{Y}}$  be the covariance matrix of  $\mathbf{Y}$ .

Select from the following all statements that are correct.

- ☒  $\Sigma_Y$  is the same as covariance matrix of  $AX$  ☐
- ☒  $\Sigma_Y$  is of size  $n \times n$  ☐
- ☐  $\Sigma_Y = A^2 \Sigma_X$
- ☒  $\Sigma_Y = A \Sigma_X A^T$  ☐
- ☐  $\Sigma_Y = A^T \Sigma_X A$

☐

Solution:

As  $Y$  is an  $n \times 1$  random vector,  $\Sigma_Y$  is of size  $n \times n$ .

From the previous problem we know that  $\Sigma_Y$  is the same as the covariance matrix of  $AX$ . Therefore, it suffices to find this matrix, which we denote  $\Sigma_{AX}$ .

$$\begin{aligned}\Sigma_{AX} &= \mathbb{E} \left[ (AX - A\mu_X) (AX - A\mu_X)^T \right] \\ &= \mathbb{E} \left[ A (X - \mu_X) (X^T A^T - \mu_X^T A^T) \right] \\ &= \mathbb{E} \left[ A (X - \mu_X) (X - \mu_X)^T A^T \right] \\ &= A \mathbb{E} \left[ (X - \mu_X) (X - \mu_X)^T \right] A^T \\ &= A \Sigma_X A^T.\end{aligned}$$

Therefore, choices 1, 2, and 4 are correct.

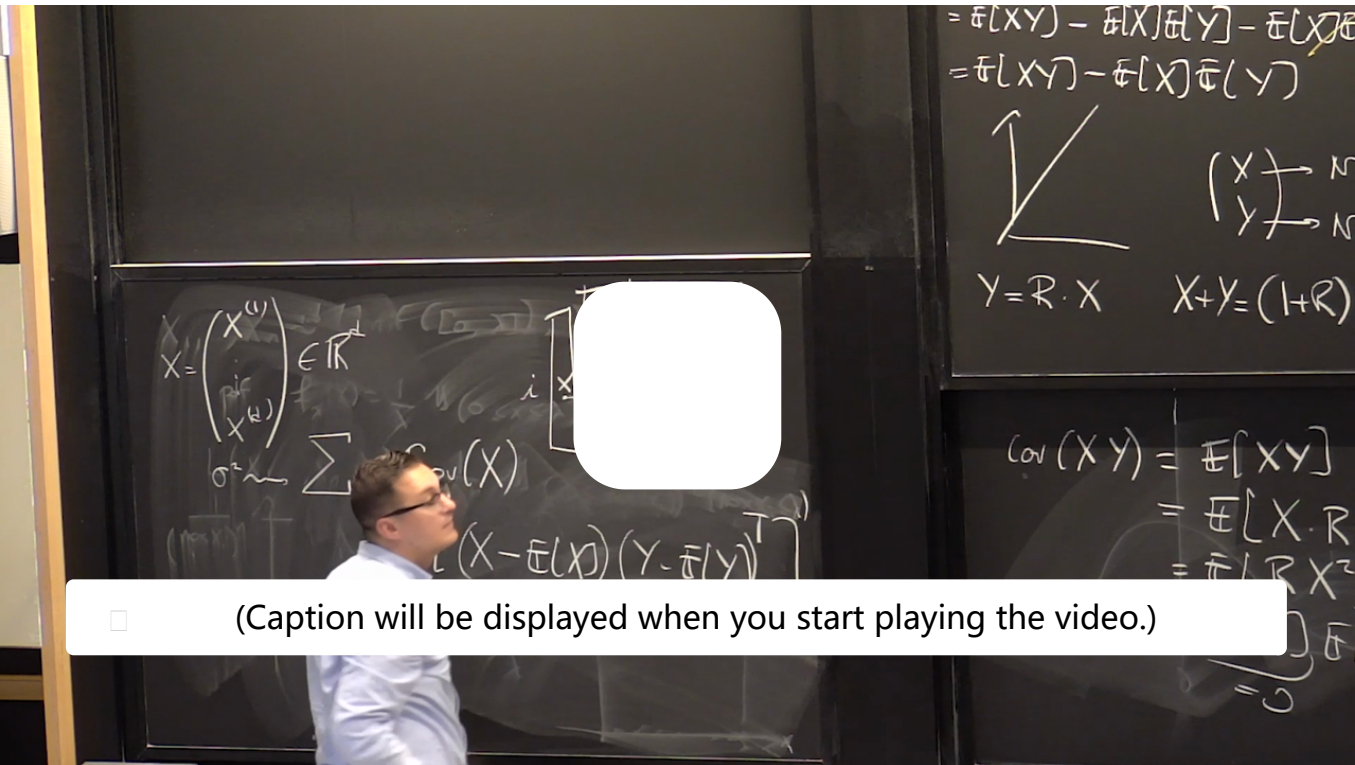
Choices 3 and 5 are not correct in general (even if  $A$  is a square matrix) because matrix multiplication is not commutative.

提交

你已经尝试了3次（总共可以尝试3次）

☐ Answers are displayed within the problem

Covariance Matrix: Affine Transformation



☐ (Caption will be displayed when you start playing the video.)

non-negative, right?

So if I give you a covariance matrix with a negative entry on the diagonal, you can probably just-- you can skip and say you made a mistake. OK, now recall that for  $x$  and  $y$ , if I look at the variance of a linear and a fine transformation of  $x$ , so something of the form  $AX$  plus  $B$ , what is this?

a squared variance of  $x$ .

And since the covariance matrix is just a multivariate, a matrix generalization of the variance, it's going to have similar properties. In particular, it should, because I know that if I do a linear transformation, then at least

Effect of Linear Transformations of Covariance Matrix

4/4 points (graded)

Let  $\mathbf{X} = \begin{pmatrix} X^{(1)} \\ X^{(2)} \end{pmatrix}$  be a random vector with covariance Matrix  $\Sigma_{\mathbf{X}} = \begin{pmatrix} 1 & 1/2 \\ 1/2 & 1 \end{pmatrix}$ .

Let  $\mathbf{Y} = \mathbf{M}\mathbf{X}$ , where  $\mathbf{M} = \begin{pmatrix} 1 & -1 \\ 1 & 1 \end{pmatrix}$ .

Observe that  $\mathbf{Y}^{(1)} = \mathbf{X}^{(1)} - \mathbf{X}^{(2)}$  and  $\mathbf{Y}^{(2)} = \mathbf{X}^{(1)} + \mathbf{X}^{(2)}$ . What is the new covariance matrix  $\Sigma_{\mathbf{Y}}$ ?

$(\Sigma_{\mathbf{Y}})_{1,1} =$   ☐ Answer: 1  $(\Sigma_{\mathbf{Y}})_{1,2} =$   ☐ Answer: 0.0

$(\Sigma_{\mathbf{Y}})_{2,1} =$   ☐ Answer: 0.0  $(\Sigma_{\mathbf{Y}})_{2,2} =$   ☐ Answer: 3

Solution:

Recall from an earlier problem that for any pair of random variables  $A, B$  with the same variance  $\mathbf{Var}(A) = \mathbf{Var}(B) = \sigma^2$ ,  $\mathbf{Cov}(A - B, A + B) = \mathbf{Var}(A) - \mathbf{Var}(B) = 0$ .

Therefore, given the matrix  $\mathbf{M}$ ,  $\Sigma_{\mathbf{Y}}$  must be a diagonal matrix.

We have  $\mathbf{Cov}(\mathbf{Y}^{(1)}, \mathbf{Y}^{(1)}) = \mathbf{Cov}(\mathbf{X}^{(1)} - \mathbf{X}^{(2)}, \mathbf{X}^{(1)} - \mathbf{X}^{(2)}) = \mathbf{Cov}(\mathbf{X}^{(1)}, \mathbf{X}^{(1)}) - 2\mathbf{Cov}(\mathbf{X}^{(1)}, \mathbf{X}^{(2)}) + \mathbf{Cov}(\mathbf{X}^{(2)}, \mathbf{X}^{(2)}) = 1 - 1 + 1 = 1$ .

Similarly,  $\mathbf{Cov}(\mathbf{Y}^{(2)}, \mathbf{Y}^{(2)}) = \mathbf{Cov}(\mathbf{X}^{(1)} + \mathbf{X}^{(2)}, \mathbf{X}^{(1)} + \mathbf{X}^{(2)}) = \mathbf{Cov}(\mathbf{X}^{(1)}, \mathbf{X}^{(1)}) + 2\mathbf{Cov}(\mathbf{X}^{(1)}, \mathbf{X}^{(2)}) + \mathbf{Cov}(\mathbf{X}^{(2)}, \mathbf{X}^{(2)}) = 1 + 1 + 1 = 3$ .

提交

 你已经尝试了1次（总共可以尝试3次）

☐ Answers are displayed within the problem

讨论

显示讨论

主题: Unit 3 Methods of Estimation:Lecture 10: Consistency of MLE, Covariance Matrices, and Multivariate Statistics / 8. Covariance Matrices