

## Lecture 18: Random variable generation using Covariance Matrix

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This is preliminary work and has not been reviewed by instructor. If you have comments about typos, errors, notation inconsistencies, etc., please email the scribes.

## 18.1 Introduction

A Covariance matrix is a square matrix that contains the variances and covariances associated with several variables. The diagonal elements of the matrix contain the variances of the variables and the off-diagonal elements contain the covariances between all possible pairs of variables.

## 18.2 Covariance and Covariance Matrix:

If  $x, y$  have means  $\mu_x, \mu_y$  respectively then Covariance is as follows:

$$\text{cov}(x, y) := \mathbb{E}[(x - \mu_x)(y - \mu_y)] := \text{cov}(y, x)$$

Covariance Matrix for random variables  $x$  and  $y$  represented by vector  $Z = \begin{bmatrix} x \\ y \end{bmatrix}$  is given by:

$$\begin{aligned} \text{cov}(Z) &= \begin{bmatrix} \text{cov}(x, x) & \text{cov}(x, y) \\ \text{cov}(y, x) & \text{cov}(y, y) \end{bmatrix} \\ &= \begin{bmatrix} \text{var}(x) & \text{cov}(x, y) \\ \text{cov}(y, x) & \text{var}(y) \end{bmatrix} \end{aligned}$$

## 18.3 Goal: Play GOD

The goal is to generate random variables  $x^*$  and  $y^*$  represented by vector  $Z = \begin{bmatrix} x^* \\ y^* \end{bmatrix}$  for a given covariance  $\text{cov}(x, y)$  and covariance matrix  $\text{cov}(Z^*)$ .

Tricks to transform random variables: -

- If  $Z$  has mean  $\mu$  then  $Z + k$  has mean  $\mu + k$ .
- If  $Z$  has covariance matrix  $\mathbf{C}$ , then  $\mathbf{A}Z$  has covariance matrix  $\mathbf{A}\mathbf{C}\mathbf{A}^T$ .

**Solution:**

Let  $x, y \stackrel{iid}{\sim} N(0, 1)$

**NOTE:**  $\stackrel{iid}{\sim}$  indicates the variables  $x, y$  are drawn independently and indentially distributed.

Then build  $Z$  as follows:  $Z = \begin{bmatrix} x \\ y \end{bmatrix}$

Since  $\text{var}(x) = \text{var}(y) = 1$  and  $\text{cov}(x, y) = 0$  as  $x$  is independent of  $y$ , Covariance matrix is given by:

$$\text{cov}(Z) = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} := \mathbf{I}_2$$

Multiply  $Z$  by a matrix  $\mathbf{A}$  to obtain,  $Z^* = \mathbf{A}Z$  such that

$$\begin{aligned} \text{cov}(Z^*) &= \mathbf{A}\mathbf{A}^T \\ &= \mathbf{A}\mathbf{A}^T \\ &\Rightarrow \mathbf{A} = \sqrt{\mathbf{C}^*} \end{aligned}$$

where  $\sqrt{\mathbf{C}}$  is the matrix such that  $\sqrt{\mathbf{C}^*} * \sqrt{\mathbf{C}^*} = \mathbf{C}$ . If  $\mathbf{C}$  is symmetric then  $\sqrt{\mathbf{C}}$  is also symmetric. i.e.  $\mathbf{C} = \sqrt{\mathbf{C}^T}$ .

$$\therefore \text{cov}(Z^*) = \text{cov}(\mathbf{A}Z) = \mathbf{A}\mathbf{A}^T = \sqrt{\mathbf{C}^*} * (\sqrt{\mathbf{C}^*})^T = \sqrt{\mathbf{C}^*} * \sqrt{\mathbf{C}^*} = \mathbf{C}^*$$

## 18.4 Special Homework

Generate  $N$  random variables  $\begin{bmatrix} x_1 \\ y_1 \end{bmatrix} \begin{bmatrix} x_2 \\ y_2 \end{bmatrix} \dots \begin{bmatrix} x_N \\ y_N \end{bmatrix}$  iid according to  $N\left(\begin{bmatrix} \mu_x \\ \mu_y \end{bmatrix}, \begin{bmatrix} \sigma_x^2 & \sigma_{xy} \\ \sigma_{yx} & \sigma_y^2 \end{bmatrix}\right)$

**Solution:**

- Generate  $Z'_i = \begin{bmatrix} x'_i \\ y'_i \end{bmatrix} \sim N(0, 1)$
- Multiply each of them with  $\sqrt{\mathbf{C}}$  then:

$$Z_i = \sqrt{\mathbf{C}} * Z'_i \sim N(0, \mathbf{C}).$$

- Goal: Estimate  $\mu$  and  $\mathbf{C}$ .

$$\hat{\mu} = \frac{1}{N} \sum_{i=1}^N Z_i$$

$$\hat{\mathbf{C}} = \begin{bmatrix} \sigma_x^2 & \sigma_{xy} \\ \sigma_{yx} & \sigma_y^2 \end{bmatrix}$$

As we know,

$$\sigma_x^2 = \frac{1}{N} \sum_{i=1}^N (\mathbf{X}_i - \mu_x)^2$$

$$\sigma_y^2 = \frac{1}{N} \sum_{i=1}^N (\mathbf{Y}_i - \mu_y)^2$$

$$\sigma_{xy} = \sigma_{yx} = \frac{1}{N} \sum_{i=1}^N (\mathbf{X}_i - \mu_x)(\mathbf{Y}_i - \mu_y)$$

Therefore

$$\begin{aligned}\hat{\mathbf{C}} &= \begin{bmatrix} \frac{1}{N} \sum_{i=1}^N (\mathbf{X}_i - \mu_x)^2 & \frac{1}{N} \sum_{i=1}^N (\mathbf{X}_i - \mu_x)(\mathbf{Y}_i - \mu_y) \\ \frac{1}{N} \sum_{i=1}^N (\mathbf{X}_i - \mu_x)(\mathbf{Y}_i - \mu_y) & \frac{1}{N} \sum_{i=1}^N (\mathbf{Y}_i - \mu_y)^2 \end{bmatrix} \\ &= \frac{1}{N} \sum_{i=1}^N \begin{bmatrix} \mathbf{X}_i - \mu_x \\ \mathbf{Y}_i - \mu_y \end{bmatrix} \begin{bmatrix} \mathbf{X}_i - \mu_x & \mathbf{Y}_i - \mu_y \end{bmatrix} \\ &= \frac{1}{N} \sum_{i=1}^N (Z - \mu)(Z - \mu)^T\end{aligned}$$

- Analyze accuracy as a function of  $N$ ,  $\mu$  - error =  $\|\hat{\mu} - \mu\|_2^2$ . C-error =  $\|\hat{\mathbf{C}} - \mathbf{C}\|_2^2$

## 18.5 Covariance in case of Multiple Random Variables

Suppose we have three random variables  $w, x, y$  such that  $Z = \begin{bmatrix} w \\ x \\ y \end{bmatrix}$  then covariance of  $Z$  is as below:

$$\text{cov}(Z) = \begin{bmatrix} \sigma_w^2 & \sigma_{wx} & \sigma_{wy} \\ \sigma_{xw} & \sigma_x^2 & \sigma_{xy} \\ \sigma_{yw} & \sigma_{yx} & \sigma_y^2 \end{bmatrix} := \mathbf{C}$$

$$\hat{\mathbf{C}} = \frac{1}{N} \sum_{i=1}^N \begin{bmatrix} \mathbf{W}_i \\ \mathbf{X}_i \\ \mathbf{Y}_i \end{bmatrix} \begin{bmatrix} \mathbf{W}_i & \mathbf{X}_i & \mathbf{Y}_i \end{bmatrix}$$

## 18.6 Conclusion:

We learned about covariance matrix and how to generate random variables for a given covariance and covariance matrix.