

1 Random vectors

- $\mathbf{Y} = (Y_1, Y_2, \dots, Y_m)^T$ is an m dimensional collection of random variables.
- it is referred to as an m dimensional random vector.
- the transpose (T or $'$) means that we focus on column vectors.

2 Means and covariances of random vectors

- Means are calculated componentwise.

$$E(\mathbf{Y}) = \boldsymbol{\mu} = (\mu_1, \dots, \mu_m)^T$$

where $\mu_j = E(Y_j)$.

- The variances and covariances of the elements of $\mathbf{Y}$ are stored in an $m \times m$ dimensional covariance matrix often denoted by $Var(\mathbf{Y})$ or $Cov(\mathbf{Y})$. This has j 'th diagonal element equal to $V(Y_j) = \sigma_j^2$, and with the element in the j 'th row, l 'th column being the covariance between Y_j and Y_l , denoted by $COV(Y_j, Y_l)$ or σ_{jl} .
- In terms of expected values, the covariance matrix is given by

$$\begin{aligned} Var(\mathbf{Y}) &= E(\mathbf{Y} - \boldsymbol{\mu})(\mathbf{Y} - \boldsymbol{\mu})^T \\ &= E(\mathbf{Y}\mathbf{Y}^T) - \boldsymbol{\mu}\boldsymbol{\mu}^T. \end{aligned}$$

3 Rules

- If $\mathbf{A}$ is a matrix and $\mathbf{c}$ a vector of scalars, then

$$E(\mathbf{A}\mathbf{Y} + \mathbf{c}) = \mathbf{A}\boldsymbol{\mu} + \mathbf{c}$$

$$Var(\mathbf{A}\mathbf{Y} + \mathbf{c}) = \mathbf{A}Var(\mathbf{Y})\mathbf{A}^T = \mathbf{A}\mathbf{V}\mathbf{A}^T.$$

- Suppose $\mathbf{X}$ is a random vector with mean $\boldsymbol{\mu}_X$ and covariance matrix $\mathbf{V}_X$ and $\mathbf{Y}$ is a random vector with mean $\boldsymbol{\mu}_Y$ and covariance matrix $\mathbf{V}_Y$. Then

$$\begin{aligned} Cov(\mathbf{X}, \mathbf{Y}) &= E[(\mathbf{X} - \boldsymbol{\mu}_X)(\mathbf{Y} - \boldsymbol{\mu}_Y)^T] \\ &= E(\mathbf{X}\mathbf{Y}^T) - \boldsymbol{\mu}_X\boldsymbol{\mu}_Y^T \end{aligned}$$

- Suppose $Cov(\mathbf{X}, \mathbf{Y}) = \mathbf{C}$. Let $\mathbf{A}$ and $\mathbf{B}$ be non random matrices and $\mathbf{c}$ and $\mathbf{d}$ non random vectors. Then

$$Cov(\mathbf{A}\mathbf{X} + \mathbf{c}, \mathbf{B}\mathbf{Y} + \mathbf{d}) = \mathbf{A}\mathbf{C}\mathbf{B}^T.$$

- If $\mathbf{A}$ is a symmetric matrix, the expectation of the *quadratic form* $\mathbf{Y}^T \mathbf{A} \mathbf{Y}$ is

$$E(\mathbf{Y}^T \mathbf{A} \mathbf{Y}) = \boldsymbol{\mu}^T \mathbf{A} \boldsymbol{\mu} + tr(\mathbf{V} \mathbf{A})$$

4 examples

Suppose that $\mathbf{X} = (X_1, X_2, X_3)'$ is a random vector having mean vector $(0, 0, 1)^T$, and covariance matrix

$$\begin{bmatrix} 1 & 0 & -1 \\ 0 & 2 & 3 \\ -1 & 3 & 7 \end{bmatrix}$$

Let $\mathbf{b} = (-1, 2, 1)^T$ and

$$\mathbf{A} = \begin{bmatrix} 1 & -1 & 2 \\ 3 & -3 & -1 \\ -1 & 0 & 1 \end{bmatrix}$$

1. What is $\mathbf{AX} + \mathbf{b}$ in terms of the elements of $\mathbf{X}$, $\mathbf{A}$ and $\mathbf{b}$?
2. What is the mean of $\mathbf{AX} + \mathbf{b}$?
3. What is the covariance matrix of $\mathbf{AX} + \mathbf{b}$?
4. Where

$$\mathbf{M} = \begin{bmatrix} 1 & -1 & 2 \\ -1 & -3 & -1 \\ 2 & -1 & -1 \end{bmatrix}$$

What is the mean of $\mathbf{X}^T \mathbf{M} \mathbf{X} + 17$?

5. Suppose that $\mathbf{Y}$ has mean vector $(1, 2, 3)^T$, and covariance matrix

$$\begin{bmatrix} 9 & 0 & 0 \\ 0 & 4 & 3 \\ 0 & 3 & 16 \end{bmatrix}$$

Let $\mathbf{c} = (1, 0, 0)^T$ and

$$\mathbf{B} = \begin{bmatrix} 1 & 2 & 3 \\ 0 & 1 & 0 \\ -1 & -2 & -3 \end{bmatrix}$$

and suppose that the covariance between $\mathbf{X}$ and $\mathbf{Y}$ is

$$\text{Cov}(\mathbf{X}, \mathbf{Y}) = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 1 & -1 \\ -1 & 3 & 4 \end{bmatrix}$$

- (a) What is the mean of $\mathbf{AX} + \mathbf{BY} + \mathbf{b} - \mathbf{c}$?
- (b) What is the covariance of X_1 with Y_2 ?
- (c) What is the covariance matrix of $\mathbf{AX} + \mathbf{b}$ with $\mathbf{BY} - \mathbf{c}$?

Let μ and Σ denote the mean and covariance matrix of X . The following gives the solutions to the problems above apart from the matrix arithmetic. You can check your calculations by running the R code on the next page.

1. $AX + b = (X_1 - X_2 + 2X_3, 3X_1 - 3X_2 - X_3, -X_1 + X_3)^T$
2. $E(AX + b) = AE(X) + b$
3. $V(AX + b) = Cov(AX + b, AX + b) = Cov(AX, AX) = ACov(X, X)A^T = A\Sigma A^T$
4. $E(X^T MX + 17) = 17 + E(X^T MX) = 17 + \mu^T M \mu + \text{tr}(M \Sigma)$
5. (a) $E(AX + BY + b - c) = AE(X) + BE(Y) + b - c$
 (b) this is the (1,2) element of $Cov(X, Y)$, which is equal to 0
 (c) $Cov(AX + b, BY - c) = Cov(AX, BY) = ACov(X, Y)B^T$

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ux=c(0,0,1)
Sx=matrix(c(1,0,-1,0,2,3,-1,3,7),byrow=T,ncol=3)
Sx

b=c(-1,2,1)
A=matrix(c(1,-1,2,3,-3,-1,-1,0,1),byrow=T,ncol=3)

A%%ux+b    #mean of AX+b
A%%Sx%%t(A) #covariance of AX+b

M=matrix(c(1,-1,2,-1,-3,-1,2,-1,-1),byrow=T,ncol=3)
Sx%%M # SxM
sum(diag(Sx%%M)) # trace of SxM

#mean of X'MX+17
t(ux)%%M%%ux+sum(diag(Sx%%M))+17 #requires M to be symmetric

c=c(1,0,0)
B=matrix(c(1,2,3,0,1,0,-1,-2,-3),byrow=T,ncol=3)
CovXY=matrix(c(1,0,-1,2,1,-1,-1,3,4),byrow=T,ncol=3)
uy=c(1,2,3)

CovXY[1,2] #covariance of X1 with Y2 is 1,2 element of CovXY

A%%ux+B%%uy+b-c #mean of AX+BY+b-c
A%%CovXY%%t(B) #COV(AX+b,BY+c)

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