

Random Vectors and Random Matrices

In this section, we extend our results on linear combinations of variables to *random vector* notation. The generalization is straightforward.

Definition (Random Vector). *A random vector ξ is a vector whose elements are random variables.*

Definition (Random Matrix). *A random matrix Ψ is a matrix whose elements are random variables.*

Definition (Expected Value of a Random Vector or Matrix). The expected value of a random vector (or matrix) is a vector (or matrix) whose elements are the expected values of the individual random variables that are the elements of the random vector.

Example (Expected Value of a Random Vector). Suppose, for example, we have two random variables \mathbf{x} and \mathbf{y} , and their expected values are 0 and 2, respectively. If we put these variables into a vector ξ , it follows that

$$E(\xi) = E \begin{bmatrix} \mathbf{x} \\ \mathbf{y} \end{bmatrix} = \begin{bmatrix} 0 \\ 2 \end{bmatrix}$$

Random Matrices and Their Expected Values

A *random matrix* Ψ is a matrix of random variables. The *expected value* of a random matrix Ψ is the matrix of expected values of the random variables in Ψ .

Result. (Variance-Covariance Matrix of a Random Vector). Given a random vector ξ with expected value μ , the variance-covariance matrix is defined as

$$\begin{aligned}\Sigma_{\xi\xi} &= E\left\{(\xi - \mu)(\xi - \mu)'\right\} \\ &= E(\xi\xi') - \mu\mu'\end{aligned}$$

If ξ is a deviation score random vector, then

$$\Sigma_{\xi\xi} = E(\xi\xi')$$

(C.P.)

Matrix Expected Value Algebra

As a generalization of results we presented in scalar algebra, we find that, for matrices of constants \mathbf{B} and \mathbf{C} , random vectors $\boldsymbol{\xi}$ and $\boldsymbol{\eta}$, random matrix \mathbf{X} , and a vector of constants \mathbf{c} ,

$$E(\mathbf{c}) = \mathbf{c} \quad (1)$$

$$E(\boldsymbol{\eta} + \boldsymbol{\xi}) = E(\boldsymbol{\eta}) + E(\boldsymbol{\xi}) \quad (2)$$

$$E(\mathbf{B}'\boldsymbol{\xi}) = \mathbf{B}'E(\boldsymbol{\xi}) \quad (3)$$

$$E(\mathbf{BXC}) = \mathbf{B}E(\mathbf{X})\mathbf{C} \quad (4)$$

Variance-Covariance Matrix of a Set of Linear Combinations

Theorem (Variance-Covariance Matrix of Linear Combinations). Given \mathbf{x} , a random vector with p variables, having variance-covariance matrix $\Sigma_{\mathbf{xx}}$. The variance-covariance matrix of any set of linear combinations $\mathbf{y} = \mathbf{B}'\mathbf{x}$ may be computed as

$$\Sigma_{\mathbf{yy}} = \mathbf{B}'\Sigma_{\mathbf{xx}}\mathbf{B} \quad (5)$$

Covariance Matrix for Two Sets of Linear Combinations

In a similar manner, we may prove the following:

Theorem (Covariance Matrix of Two Sets of Linear Combinations). Given \mathbf{x} and \mathbf{y} , two random vectors with p and q variables having covariance matrix $\Sigma_{\mathbf{xy}}$. The covariance matrix of any two sets of linear combinations $\mathbf{w} = \mathbf{B}'\mathbf{x}$ and $\mathbf{m} = \mathbf{C}'\mathbf{y}$ may be computed as

$$\Sigma_{\mathbf{wm}} = \mathbf{B}'\Sigma_{\mathbf{xy}}\mathbf{C} \quad (6)$$