

Expectations, Variances, and Distributions of Random Vectors

Supplement to Casella and Berger Section 4.6

A note on notation

Typically, we denote a random variable by an uppercase letter (e.g., X, Y, Z), and a specific realization of that variable by a lowercase letter (e.g., x, y, z). However, when we move to random vectors, this convention conflicts with the notational convention in linear algebra of using lowercase letters for vectors (e.g., \vec{x} or \mathbf{x}), and uppercase letters for matrices (e.g., \mathbf{X}). Thus, some textbooks adopt the lowercase notation for random vectors from linear algebra. We will adopt this convention here.

Note that Casella and Berger, on the other hand, continue to use uppercase letters for random vectors and lowercase letters for realizations of those random vectors, but in boldface.

All vectors will be assumed to be column vectors, unless otherwise specified.

Expectation of random vectors

Let y_1, y_2, \dots, y_n be a set of random variables, and define the random vector \mathbf{y} as

$$\mathbf{y} = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix}.$$

Note that Casella and Berger leave random vectors in vector notation, $\mathbf{y} = (y_1, y_2, \dots, y_n)$, rather than matrix notation, but matrix notation will be more clear for our purposes.

Definition 1. Suppose that $E(y_i) = \mu_i$ for $i = 1, \dots, n$, and define the $n \times 1$ vector $\boldsymbol{\mu} = \{\mu_i\}$, where the set notation denotes the elements of the vector, i.e.,

$$\boldsymbol{\mu} = \begin{pmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_n \end{pmatrix}.$$

Then the **expected value of \mathbf{y}** is defined as the vector of expected values of its elements:

$$E(\mathbf{y}) = \boldsymbol{\mu} = \begin{pmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_n \end{pmatrix}.$$

Result 1. If $\mathbf{g}(\mathbf{y})$ is a linear function from \mathbb{R}^n to \mathbb{R}^m , then $E(\mathbf{g}(\mathbf{y})) = \mathbf{g}(E(\mathbf{y}))$.

For example, if $\mathbf{A} : p \times n$, $\mathbf{b} : r \times 1$, and $\mathbf{C} : p \times r$ are matrices of constants, then

$$E(\mathbf{A}\mathbf{y}\mathbf{b}' + \mathbf{C}) = \mathbf{A}E(\mathbf{y})\mathbf{b}' + \mathbf{C} = \mathbf{A}\boldsymbol{\mu}\mathbf{b}' + \mathbf{C}.$$

Variance and covariance of random vectors

Let \mathbf{x} be an $n \times 1$ random vector, and let \mathbf{y} be an $r \times 1$ random vector.

Definition 2. The **covariance of \mathbf{x} and \mathbf{y}** is

$$\text{Cov}(\mathbf{x}, \mathbf{y}) = E[(\mathbf{x} - E(\mathbf{x}))(\mathbf{y} - E(\mathbf{y}))'].$$

Note that this matrix has dimension $n \times r$, and the $(i, j)^{th}$ element of $\text{Cov}(\mathbf{x}, \mathbf{y})$ is $\text{Cov}(x_i, y_j)$.

Definition 3. The **variance of \mathbf{x}** is the $n \times n$ matrix

$$\text{Var}(\mathbf{x}) = \text{Cov}(\mathbf{x}, \mathbf{x}) = E[(\mathbf{x} - E(\mathbf{x}))(\mathbf{x} - E(\mathbf{x}))'].$$

The following results follow from the definitions of expectation and covariance of random vectors, and from properties of matrices.

Result 2. $\text{Cov}(\mathbf{x}, \mathbf{y}) = E(\mathbf{x}\mathbf{y}') - E(\mathbf{x})E(\mathbf{y})'$.

Result 3. $\text{Var}(\mathbf{x}) = E(\mathbf{x}\mathbf{x}') - E(\mathbf{x})E(\mathbf{x})'$.

Result 4. For any constant matrices $\mathbf{A} : m \times n$ and $\mathbf{B} : p \times r$,

$$\text{Cov}(\mathbf{Ax}, \mathbf{By}) = \mathbf{ACov}(\mathbf{x}, \mathbf{y})\mathbf{B}'.$$

Result 5. For any constant matrix $\mathbf{A} : m \times n$,

$$\text{Var}(\mathbf{Ax}) = \text{Cov}(\mathbf{Ax}, \mathbf{Ax}) = \mathbf{A}\text{Var}(\mathbf{x})\mathbf{A}'.$$

Result 6. $\text{Var}(\mathbf{x})$ is a symmetric non-negative definite matrix.

Multivariate normal (MVN) distribution

Definition 4. Suppose that random vector $\mathbf{y} : n \times 1$ with support \mathbb{R}^n has joint probability density function,

$$f(\mathbf{y}) = \frac{\exp\left\{-\frac{1}{2}(\mathbf{y} - \boldsymbol{\mu})'\boldsymbol{\Sigma}^{-1}(\mathbf{y} - \boldsymbol{\mu})\right\}}{|\boldsymbol{\Sigma}|^{\frac{1}{2}}(2\pi)^{\frac{n}{2}}},$$

for $\boldsymbol{\mu} : n \times 1 \in \mathbb{R}^n$ and positive definite matrix $\boldsymbol{\Sigma} : n \times n$. Then \mathbf{y} is said to have a **multivariate normal distribution** with mean $\boldsymbol{\mu}$ and variance $\boldsymbol{\Sigma}$, denoted by $\mathbf{y} \sim N_n(\boldsymbol{\mu}, \boldsymbol{\Sigma})$.

If $\boldsymbol{\Sigma} = \sigma^2\mathbf{I}_n$, where $\sigma^2 > 0$ and \mathbf{I}_n is an $n \times n$ identity matrix, then the pdf simplifies to

$$f(\mathbf{y}) = \frac{\exp\left\{-\frac{1}{2\sigma^2}(\mathbf{y} - \boldsymbol{\mu})'(\mathbf{y} - \boldsymbol{\mu})\right\}}{(2\pi\sigma^2)^{\frac{n}{2}}} = \frac{\exp\left\{-\frac{1}{2\sigma^2}\sum_{i=1}^n(y_i - \mu_i)^2\right\}}{(2\pi\sigma^2)^{\frac{n}{2}}}.$$

Properties of the MVN distribution

The following properties hold for the multivariate normal distribution.

Result 7. Suppose $\mathbf{y} \sim N_n(\boldsymbol{\mu}, \boldsymbol{\Sigma})$, where $\boldsymbol{\Sigma}$ is positive definite. Then the following results can be established.

a. Moment generating function:

$$M_{\mathbf{y}}(t) = E[\exp(\mathbf{t}'\mathbf{y})] = \exp\left\{\mathbf{t}'\boldsymbol{\mu} + \frac{1}{2}\mathbf{t}'\boldsymbol{\Sigma}\mathbf{t}\right\}.$$

b. $E(\mathbf{y}) = \boldsymbol{\mu}$.

c. $\text{Var}(\mathbf{y}) = \boldsymbol{\Sigma}$.

d. If \mathbf{A} is an $r \times n$ matrix of constants, then

$$\mathbf{Ay} \sim N_r(\mathbf{A}\boldsymbol{\mu}, \mathbf{A}\boldsymbol{\Sigma}\mathbf{A}').$$

e. Suppose that \mathbf{y} is a $(p + q) \times 1$ random vector with distribution $\mathbf{y} \sim N_{p+q}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$, where

$$\boldsymbol{\Sigma} = \begin{pmatrix} \boldsymbol{\Sigma}_1 & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\Sigma}_2 \end{pmatrix} = \boldsymbol{\Sigma}_1 \otimes \boldsymbol{\Sigma}_2,$$

where $\boldsymbol{\Sigma}_1$ is $p \times p$ and $\boldsymbol{\Sigma}_2$ is $q \times q$. If we partition \mathbf{y} as

$$\mathbf{y} = \begin{pmatrix} \mathbf{y}_1 \\ \mathbf{y}_2 \end{pmatrix}$$

with $\mathbf{y}_1 : p \times 1$ and $\mathbf{y}_2 : q \times 1$, then \mathbf{y}_1 is independent of \mathbf{y}_2 . This result says that if two random vectors \mathbf{y}_1 and \mathbf{y}_2 are uncorrelated and have a joint multivariate normal distribution, then the random vectors are independent.

f. Let \mathbf{y} be an $n \times 1$ random vector with distribution $\mathbf{y} \sim N_n(\boldsymbol{\mu}, \boldsymbol{\Sigma})$. The MVN density function is constant for all \mathbf{y} that satisfy

$$(\mathbf{y} - \boldsymbol{\mu})' \boldsymbol{\Sigma}^{-1} (\mathbf{y} - \boldsymbol{\mu}) = c.$$

The above equation is the equation of an n -dimensional ellipsoid.

Conditional MVN distributions

Let \mathbf{y} be a $(p + q) \times 1$ random vector and denote a realization of the random vector by $\check{\mathbf{y}}$. Suppose that \mathbf{y} is distributed as $\mathbf{y} \sim N_{p+q}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$. Partition \mathbf{y} as

$$\mathbf{y} = \begin{pmatrix} \mathbf{y}_1 \\ \mathbf{y}_2 \end{pmatrix}$$

with $\mathbf{y}_1 : p \times 1$ and $\mathbf{y}_2 : q \times 1$. Partition $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$ conformably, as

$$\boldsymbol{\mu} = \begin{pmatrix} \boldsymbol{\mu}_1 \\ \boldsymbol{\mu}_2 \end{pmatrix},$$

and

$$\boldsymbol{\Sigma} = \begin{pmatrix} \boldsymbol{\Sigma}_{11} & \boldsymbol{\Sigma}_{12} \\ \boldsymbol{\Sigma}_{21} & \boldsymbol{\Sigma}_{22} \end{pmatrix}.$$

If $\boldsymbol{\Sigma}_{22}$ is positive definite, then conditional on $\mathbf{y}_2 = \check{\mathbf{y}}$, \mathbf{y}_1 has the multivariate normal distribution

$$\mathbf{y}_1 | \mathbf{y}_2 = \check{\mathbf{y}} \sim N_p(\boldsymbol{\mu}_{1 \cdot 2}, \boldsymbol{\Sigma}_{11 \cdot 2}),$$

where

$$\boldsymbol{\mu}_{1 \cdot 2} := \boldsymbol{\mu}_1 + \boldsymbol{\Sigma}_{12} \boldsymbol{\Sigma}_{22}^{-1} (\check{\mathbf{y}}_2 - \boldsymbol{\mu}_2),$$

and

$$\boldsymbol{\Sigma}_{11 \cdot 2} := \boldsymbol{\Sigma}_{11} - \boldsymbol{\Sigma}_{12} \boldsymbol{\Sigma}_{22}^{-1} \boldsymbol{\Sigma}_{21}.$$

MVN distribution's relation to the chi-squared distribution

Given an $n \times 1$ random vector \mathbf{x} and $n \times n$ constant matrix \mathbf{A} , the random variable $Q = \mathbf{x}'\mathbf{A}\mathbf{x}$ is called a **quadratic form in \mathbf{x}** . We will further examine distributions of quadratic forms in Stat 502¹, but for now, we discuss one specific example.

Definition 5. Suppose $\mathbf{x} \sim N_n(\boldsymbol{\mu}, \mathbf{I}_n)$. Define the random variable $Q = \mathbf{x}'\mathbf{x}$. Then Q is said to have a **noncentral chi-squared distribution** with n degrees of freedom and noncentrality parameter $\lambda = \boldsymbol{\mu}'\boldsymbol{\mu}/2$. This is denoted by $Q \sim \chi^2(n, \lambda)$.

If $\boldsymbol{\mu} = \mathbf{0}$, then $\lambda = 0$, and Q is said to have a **central chi-squared distribution** with n degrees of freedom, denoted by $Q \sim \chi^2(n)$.

The following results summarize some basic properties of noncentral chi-squared distributions.

Result 8. Let $Q \sim \chi^2_{n,\lambda}$. Then the following properties hold.

a. Probability density function:

$$f_Q(q) = \sum_{j=0}^{\infty} \frac{e^{-\lambda} \lambda^j}{j!} f_{n+2j}(q),$$

where $f_{n+2j}(q)$ is the density function for a central chi-squared random variable having $n + 2j$ degrees of freedom. That is,

$$f_i(q) = \frac{e^{-q/2} q^{i/2-1}}{2^{i/2} \Gamma(i/2)}.$$

b. Moment generating function:

$$M_Q(t) = (1 - 2t)^{-n/2} \exp[2t\lambda/(1 - 2t)].$$

c. $E(Q) = n + 2\lambda$.

d. $Var(Q) = 2n + 8\lambda$.

e. If $Q_i \stackrel{ind}{\sim} \chi^2(\nu_i, \lambda_i)$ for $i = 1, \dots, k$, then

$$\sum_{i=1}^k Q_i \sim \chi^2 \left(\sum_{i=1}^k \nu_i, \sum_{i=1}^k \lambda_i \right).$$

References

Much of this material was taken directly from Dr. Robert Boik's Stat 505 Lecture Notes, *A Pair of Primers: Primer on Matrix Analysis and Primer on Linear Statistical Models*, Fall 2007 edition.

¹It turns out that the sample variance can be expressed as a quadratic form.