

THE DISTRIBUTION
OF $C\hat{\beta}$ WHEN $C\beta$
IS ESTIMABLE

THE MULTIVARIATE STANDARD NORMAL DISTRIBUTION

Suppose $z_1, \dots, z_n \stackrel{\text{iid}}{\sim} N(0, 1)$.

$$\text{Let } \underline{z} = \begin{bmatrix} z_1 \\ \vdots \\ z_n \end{bmatrix}.$$

Then $E(\underline{z}) = \underline{0}$ and $\text{Var}(\underline{z}) = \underline{I}_{n \times n}$.

The random vector \underline{z} has the multivariate standard normal distribution denoted

$$\underline{z} \sim N(\underline{0}, \underline{I}_{n \times n}).$$

THE MULTIVARIATE NORMAL DISTRIBUTION

Suppose $\underline{z} \sim N(\underline{0}, \underline{I}_{n \times n})$,

A is an $m \times n$ matrix of constants,
and $\underline{\mu}$ is a $m \times 1$ vector of constants.

Then $\underline{w} = \underline{\mu} + A \underline{z}$ has a
multivariate normal distribution.

$$\begin{aligned} E(\underline{w}) &= E(\underline{\mu} + A\underline{z}) = \underline{\mu} + E(A\underline{z}) \\ &= \underline{\mu} + A E(\underline{z}) = \underline{\mu} + A \underline{0} \\ &= \underline{\mu}. \end{aligned}$$

$$\begin{aligned} \text{Var}(\underline{w}) &= \text{Var}(\underline{\mu} + A\underline{z}) = \text{Var}(A\underline{z}) \\ &= A \text{Var}(\underline{z}) A' = A I A' \\ &= AA' \equiv \Sigma \end{aligned}$$

We write $\underline{w} \sim N(\underline{\mu}, \Sigma)$.

When Σ is nonsingular, the probability density function of

\underline{w} is

$$(2\pi)^{-m/2} |\Sigma|^{-1/2} \exp\left\{-\frac{1}{2}(\underline{w}-\underline{\mu})' \Sigma^{-1}(\underline{w}-\underline{\mu})\right\}.$$

LINEAR TRANSFORMATIONS OF
MULTIVARIATE NORMAL RANDOM
VECTORS ARE MULTIVARIATE
NORMAL RANDOM VECTORS.

For example, suppose $\underline{W} \sim N(\underline{\mu}, \underline{\Sigma})$
 \underline{a} is a $k \times 1$ vector of constants,
and B is a $k \times m$ matrix of
constants.

Then $\underline{a} + B\underline{w} \sim N(\underline{a} + B\underline{\mu}, B\Sigma B')$.

To see this, note that

$$E(\underline{a} + B\underline{w}) = \underline{a} + E(B\underline{w})$$

$$= \underline{a} + B E(\underline{w})$$

$$= \underline{a} + B\underline{\mu} \quad \text{and}$$

$$\text{Var}(\underline{a} + B\underline{w}) = \text{Var}(B\underline{w}) = B \text{Var}(\underline{w}) B'$$

$$= B\Sigma B'$$

Furthermore, $\underline{w} \stackrel{d}{=} \underline{\mu} + A \underline{z}$, where

$AA' = \Sigma$. Thus,

$$\begin{aligned} \underline{a} + B \underline{w} &\stackrel{d}{=} \underline{a} + B(\underline{\mu} + A \underline{z}) \\ &= \underline{a} + B \underline{\mu} + BA \underline{z}, \end{aligned}$$

which is of the form:

(vector of constants) + (matrix of constants) (multivariate standard normal).

It follows that in the normal theory Gauss-Markov model

$$Y = X\beta + \varepsilon, \quad \varepsilon \sim N(0, \sigma^2 I)$$

$$Y \sim N(X\beta, \sigma^2 I).$$

Likewise, for estimable $C\beta$,

$$C\hat{\beta} = C(X'X)^{-1}X'y$$

must also have a multivariate normal distribution.

To derive $E(C\hat{\beta})$ and $\text{Var}(C\hat{\beta})$,
we use the fact that $C\beta$
is estimable to write

$$C = AX$$

for some matrix A .

Thus, we have

$$\begin{aligned} C\hat{\beta} &= C(X'X)^{-1}X'y \\ &= AX(X'X)^{-1}X'y \\ &= AP_X y. \end{aligned}$$

$$E(C\hat{\beta}) = E(AP_x y)$$

$$= AP_x E(y)$$

$$= AP_x X \beta$$

$$= AX \beta$$

$$= C\beta.$$

$$\begin{aligned}
\text{Var}(C\hat{\beta}) &= \text{Var}(AP_x y) \\
&= AP_x \text{Var}(y) (AP_x)' \\
&= AP_x (\sigma^2 I) P_x' A' \\
&= \sigma^2 AP_x P_x' A' \\
&= \sigma^2 AP_x A' \\
&= \sigma^2 AX(X'X)^{-1}X'A' \\
&= \sigma^2 C(X'X)^{-1}C'.
\end{aligned}$$

Thus,

$$C\hat{\beta} \sim N(C\beta, \sigma^2 C(X'X)^{-1}C').$$