

Matrix Arithmetic

$$\mathbf{A} + \mathbf{B} = \mathbf{B} + \mathbf{A}$$

$$(\mathbf{A} + \mathbf{B}) + \mathbf{C} = \mathbf{A} + (\mathbf{B} + \mathbf{C})$$

$$(\mathbf{AB})\mathbf{C} = \mathbf{A}(\mathbf{BC})$$

$$\mathbf{A}(\mathbf{B} + \mathbf{C}) = \mathbf{AB} + \mathbf{AC}$$

$$(\mathbf{A} + \mathbf{B})(\mathbf{C} + \mathbf{D}) = \mathbf{AC} + \mathbf{AD} + \mathbf{BC} + \mathbf{BD}$$

Idempotent

If

$$\mathbf{A}^2 = \mathbf{A}$$

then \mathbf{A} is called **idempotent**.

The property $\mathbf{A}^2 = \mathbf{A}$ implies

$$\mathbf{A}^m = \mathbf{A}$$

for any positive integer m .

Determinant

For a 2×2 matrix: $\mathbf{A} = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$
the determinant is defined as:

$$|\mathbf{A}| = ad - bc$$

and the inverse is:

$$\mathbf{A}^{-1} = \frac{1}{ad - bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}$$

Transpose and Trace of a Matrix

$$(\mathbf{A} + \mathbf{B})' = \mathbf{A}' + \mathbf{B}'$$

$$(\mathbf{AB})' = \mathbf{B}'\mathbf{A}'$$

$$(\mathbf{ABC})' = \mathbf{C}'\mathbf{B}'\mathbf{A}'$$

$$\text{tr}(c\mathbf{A}) = c \times \text{tr}(\mathbf{A})$$

$$\text{tr}(\mathbf{A} + \mathbf{B}) = \text{tr}(\mathbf{A}) + \text{tr}(\mathbf{B})$$

$$\text{tr}(\mathbf{A}') = \text{tr}(\mathbf{A})$$

$$\text{tr}(\mathbf{AB}) = \text{tr}(\mathbf{BA})$$

Rank of a Matrix

The **rank** of an $r \times c$ matrix \mathbf{A} is the number of linearly independent rows (or columns), $\text{rank}(\mathbf{A})$.

- $\text{rank}(\mathbf{A}) \leq \min(r, c)$
- $\text{rank}(\mathbf{A}) = \min(r, c) \Rightarrow \mathbf{A}$ is of full rank.
- If \mathbf{A} is an $n \times n$ matrix, then:
 $\text{rank}(\mathbf{A}) = n \Leftrightarrow \mathbf{A}^{-1}$ exists $\Leftrightarrow |\mathbf{A}| \neq 0$
- $\text{rank}(\mathbf{A}) = \text{rank}(\mathbf{A}'\mathbf{A}) = \text{rank}(\mathbf{A}\mathbf{A}')$
- If \mathbf{A} is idempotent, then $\text{rank}(\mathbf{A}) = \text{tr}(\mathbf{A})$

Expectation and Variance

Let \mathbf{Y} be a random vector with mean $\boldsymbol{\mu}$. The **variance-covariance matrix** $\boldsymbol{\Sigma}$ is:

$$\text{Var}(\mathbf{Y}) = E[(\mathbf{Y} - \boldsymbol{\mu})(\mathbf{Y} - \boldsymbol{\mu})'] = \boldsymbol{\Sigma}$$

Let \mathbf{A} and \mathbf{B} be nonrandom (constant) matrices.

$$\text{a) } E(\mathbf{A} + \mathbf{B}\mathbf{Y}) = \mathbf{A} + \mathbf{B}\boldsymbol{\mu} \quad 11.1.1a$$

$$\text{b) } \text{Var}(\mathbf{A} + \mathbf{B}\mathbf{Y}) = \mathbf{B}\boldsymbol{\Sigma}\mathbf{B}' \quad 11.1.1b$$

$$\text{c) } E(\mathbf{Y}'\mathbf{A}\mathbf{Y}) = \text{tr}(\mathbf{A}\boldsymbol{\Sigma}) + \boldsymbol{\mu}'\mathbf{A}\boldsymbol{\mu} \quad 12.1.1$$

Matrix Inverse

$$\mathbf{A}\mathbf{A}^{-1} = \mathbf{A}^{-1}\mathbf{A} = \mathbf{I}$$

$$(\mathbf{A}^{-1})^{-1} = \mathbf{A}$$

$$(\mathbf{A}')^{-1} = (\mathbf{A}^{-1})'$$

$$(\mathbf{AB})^{-1} = \mathbf{B}^{-1}\mathbf{A}^{-1}$$

$$(\mathbf{ABC})^{-1} = \mathbf{C}^{-1}\mathbf{B}^{-1}\mathbf{A}^{-1}$$

If \mathbf{A}^{-1} does not exist, we say \mathbf{A} is **singular**.

The Conditional Inverse \mathbf{A}^c

Let \mathbf{A} be a matrix. If a matrix \mathbf{G} satisfies:

$$\mathbf{AGA} = \mathbf{A}$$

then \mathbf{G} is called a **conditional inverse** of \mathbf{A} .

- If \mathbf{A} is a square, nonsingular matrix, then the unique conditional inverse of \mathbf{A} is \mathbf{A}^{-1} . Otherwise, \mathbf{A}^c is not unique.
- $\text{rank}(\mathbf{A}) = \text{rank}(\mathbf{A}^c\mathbf{A})$
- $\mathbf{A}^c\mathbf{A}$ is idempotent, so $\text{rank}(\mathbf{A}) = \text{tr}(\mathbf{A}^c\mathbf{A})$

Quadratic Forms: Theorem 12.1.2

Suppose $\mathbf{Y} \sim N_n(\boldsymbol{\mu}, \boldsymbol{\Sigma})$, and let \mathbf{A} and \mathbf{B} be constant matrices. Then

$$\text{a) } \text{Var}(\mathbf{Y}'\mathbf{A}\mathbf{Y}) = 2\text{tr}(\mathbf{A}\boldsymbol{\Sigma}\mathbf{A}\boldsymbol{\Sigma}) + 4\boldsymbol{\mu}'\mathbf{A}\boldsymbol{\Sigma}\mathbf{A}\boldsymbol{\mu}$$

$$\text{b) } \text{Cov}(\mathbf{Y}, \mathbf{Y}'\mathbf{A}\mathbf{Y}) = 2\boldsymbol{\Sigma}\mathbf{A}\boldsymbol{\mu}$$

$$\text{c) } \text{Cov}(\mathbf{B}\mathbf{Y}, \mathbf{Y}'\mathbf{A}\mathbf{Y}) = 2\mathbf{B}\boldsymbol{\Sigma}\mathbf{A}\boldsymbol{\mu}$$