

Appendix A: Fun Matrix Facts

For convenience, we summarize several useful matrix facts here.

SQUARE MATRIX RESULTS: Let \mathbf{A} and \mathbf{B} be square matrices of the same dimension. Inverses below are assumed to exist.

- $(\mathbf{AB})^{-1} = \mathbf{B}^{-1}\mathbf{A}^{-1}$, $(\mathbf{A}^{-1})^T = (\mathbf{A}^T)^{-1}$.
- We denote the **determinant** of \mathbf{A} by $|\mathbf{A}|$.
- $|\mathbf{A}| = |\mathbf{A}^T|$, $|\mathbf{A}| = 1/|\mathbf{A}^{-1}|$
- $|\mathbf{AB}| = |\mathbf{A}||\mathbf{B}|$
- $(\mathbf{A} + \mathbf{B})^{-1} = \mathbf{A}^{-1} - \mathbf{A}^{-1}(\mathbf{A}^{-1} + \mathbf{B}^{-1})^{-1}\mathbf{A}^{-1}$
- $(\mathbf{A} + \mathbf{CBD})^{-1} = \mathbf{A}^{-1} - \mathbf{A}^{-1}\mathbf{C}(\mathbf{B}^{-1} + \mathbf{DA}^{-1}\mathbf{C})^{-1}\mathbf{DA}^{-1}$. Here, \mathbf{A} and \mathbf{B} need not be of the same dimension, and \mathbf{C} and \mathbf{D} are conformable matrices.
- The following are equivalent: (i) \mathbf{A} is **nonsingular**, (ii) $|\mathbf{A}| \neq 0$, (iii) \mathbf{A}^{-1} exists.
- We denote the **trace** of a square matrix \mathbf{A} by $\text{tr}(\mathbf{A})$.
- $\text{tr}(\mathbf{A}) = \text{tr}(\mathbf{A}^T)$, $\text{tr}(b\mathbf{A}) = b\text{tr}(\mathbf{A})$
- $\text{tr}(\mathbf{A} + \mathbf{B}) = \text{tr}(\mathbf{A}) + \text{tr}(\mathbf{B})$, $\text{tr}(\mathbf{AB}) = \text{tr}(\mathbf{BA})$
- If \mathbf{A} is $(n \times n)$ and \mathbf{x} is $(n \times 1)$, then the **quadratic form**

$$\mathbf{x}^T \mathbf{A} \mathbf{x}$$

and \mathbf{A} are **nonnegative definite** if $\mathbf{x}^T \mathbf{A} \mathbf{x} \geq 0$. The quadratic form and \mathbf{A} are **positive definite** if $\mathbf{x}^T \mathbf{A} \mathbf{x} > 0$. If \mathbf{A} is positive definite, then it is symmetric and nonsingular (so its inverse exists).

- $\mathbf{x}^T \mathbf{A} \mathbf{x} = \text{tr}(\mathbf{A} \mathbf{x} \mathbf{x}^T)$
- If \mathbf{x} is a **random vector** with mean $\boldsymbol{\mu}$ and covariance matrix \mathbf{V} , then

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

vec and vech NOTATION:

- For a $(n \times r)$ matrix \mathbf{A} , $\text{vec}(\mathbf{A})$ is defined as the $(nr \times 1)$ vector consisting of the r columns of \mathbf{A} stacked in the order $1, \dots, r$.
- If furthermore \mathbf{A} is $(n \times n)$ and symmetric, then $\text{vec}(\mathbf{A})$ contains redundant entries. The $\text{vech}(\cdot)$ operator yields the column vector containing all the distinct entries of \mathbf{A} by stacking the lower diagonal elements; e.g., for $n = 3$,

$$\mathbf{A} = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{12} & a_{22} & a_{23} \\ a_{13} & a_{23} & a_{33} \end{pmatrix} \quad \text{and} \quad \text{vech}(\mathbf{A}) = \begin{pmatrix} a_{11} \\ a_{12} \\ a_{13} \\ a_{22} \\ a_{23} \\ a_{33} \end{pmatrix}.$$

- For matrices \mathbf{A} ($a \times a$), \mathbf{B} , \mathbf{C} , \mathbf{D} ,
 - (i) $\text{tr}(\mathbf{AB}) = \{\text{vec}(\mathbf{A})\}^T \{\text{vec}(\mathbf{B}^T)\} = \{\text{vec}(\mathbf{A}^T)\}^T \{\text{vec}(\mathbf{B})\}$.
 - (ii) $\text{tr}(\mathbf{ABD}^T \mathbf{C}^T) = \{\text{vec}(\mathbf{A})\}^T (\mathbf{B} \otimes \mathbf{C}) \text{vec}(\mathbf{D})$, where \otimes represents Kronecker product.
 - (iii) For \mathbf{A} symmetric, there is a relationship between $\text{vec}(\mathbf{A})$ and $\text{vech}(\mathbf{A})$. In particular, there exists a unique matrix Φ of dimension $\{a^2 \times a(a+1)/2\}$ such that

$$\text{vec}(\mathbf{A}) = \Phi \text{vech}(\mathbf{A}).$$

Clearly, Φ is unique and of full column rank, as there is only one way to write the distinct elements of \mathbf{A} in a full, redundant vector.

INVERSE OF PARTITIONED MATRIX: Consider a generic $(k \times k)$ matrix

$$\mathbf{C} = \begin{pmatrix} \mathbf{C}_{11} & \mathbf{C}_{12} \\ \mathbf{C}_{21} & \mathbf{C}_{22} \end{pmatrix},$$

where the \mathbf{C}_{ij} are submatrices such that \mathbf{C}_{11} is $(k_1 \times k_1)$ and \mathbf{C}_{22} is $(k_2 \times k_2)$ such that $k = k_1 + k_2$, and \mathbf{C}_{11}^{-1} and \mathbf{C}_{22}^{-1} exist, as do all other inverses below. Then

$$\mathbf{C}^{-1} = \begin{pmatrix} \mathbf{D}_{11} & \mathbf{D}_{12} \\ \mathbf{D}_{21} & \mathbf{D}_{22} \end{pmatrix},$$

where

$$\begin{aligned} \mathbf{D}_{11} &= (\mathbf{C}_{11} - \mathbf{C}_{12}\mathbf{C}_{22}^{-1}\mathbf{C}_{21})^{-1} \\ \mathbf{D}_{22} &= (\mathbf{C}_{22} - \mathbf{C}_{21}\mathbf{C}_{11}^{-1}\mathbf{C}_{12})^{-1} = \mathbf{C}_{22}^{-1} + \mathbf{C}_{22}^{-1}\mathbf{C}_{21}\mathbf{D}_{11}\mathbf{C}_{12}\mathbf{C}_{22}^{-1} \\ \mathbf{D}_{12} &= -\mathbf{C}_{11}^{-1}\mathbf{C}_{12}\mathbf{D}_{22} = -\mathbf{D}_{11}\mathbf{C}_{12}\mathbf{C}_{22}^{-1} \\ \mathbf{D}_{21} &= -\mathbf{C}_{22}^{-1}\mathbf{C}_{21}\mathbf{D}_{11}. \end{aligned}$$

MATRIX DIFFERENTIATION: Let \mathbf{x} be a $(n \times 1)$ vector depending on a $(p \times 1)$ vector β , and let \mathbf{A} be a $(n \times n)$ square matrix.

- For quadratic form $Q = \mathbf{x}^T \mathbf{A} \mathbf{x}$, $\partial Q / \partial \mathbf{x} = 2\mathbf{A} \mathbf{x}$. Note that this is a $(n \times 1)$ vector.
- The chain rule then gives $\partial Q / \partial \beta = (\partial \mathbf{x} / \partial \beta)(\partial Q / \partial \mathbf{x})$. Note that $\partial \mathbf{x} / \partial \beta$ is a $(p \times n)$ matrix.

Let $\mathbf{V}(\xi)$ be a $(n \times n)$ nonsingular matrix depending on a $(q \times 1)$ (parameter) vector ξ .

- If ξ_k is the k th element of ξ , then $\partial / \partial \xi_k \mathbf{V}(\xi)$ is the $(n \times n)$ matrix whose (ℓ, p) element is the partial derivative of the (ℓ, p) element of $\mathbf{V}(\xi)$ with respect to ξ_k .
- $\partial / \partial \xi_k \{\log |\mathbf{V}(\xi)|\} = \text{tr} \left[\mathbf{V}^{-1}(\xi) \{\partial / \partial \xi_k \mathbf{V}(\xi)\} \right]$.
- $\partial / \partial \xi_k \mathbf{V}^{-1}(\xi) = -\mathbf{V}^{-1}(\xi) \{\partial / \partial \xi_k \mathbf{V}(\xi)\} \mathbf{V}^{-1}(\xi)$.
- For quadratic form $Q = \mathbf{x}^T \mathbf{V}(\xi) \mathbf{x}$, $\partial Q / \partial \xi_k = \mathbf{x}^T \{\partial / \partial \xi_k \mathbf{V}(\xi)\} \mathbf{x}$. Thus, from the previous result,

$$\partial / \partial \xi_k \{\mathbf{x}^T \mathbf{V}^{-1}(\xi) \mathbf{x}\} = -\mathbf{x}^T \mathbf{V}^{-1}(\xi) \{\partial / \partial \xi_k \mathbf{V}(\xi)\} \mathbf{V}^{-1}(\xi) \mathbf{x}.$$