

Matrix Algebra Marathon

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1 Statistics

1.1 Exercise

Exercise 2.6.2.

Given ℓ vectors $\mathbf{x}_1, \dots, \mathbf{x}_\ell \in \mathbb{R}^n$, the covariance matrix $\mathbf{C} \in \mathbb{S}_+^n$ is defined by

$$\mathbf{C} := \frac{1}{\ell} \sum_{i=1}^{\ell} (\mathbf{x}_i - \mathbf{m})(\mathbf{x}_i - \mathbf{m})^{\mathrm{T}}. \quad (1)$$

where

$$\mathbf{m} := \frac{1}{\ell} \sum_{i=1}^{\ell} \mathbf{x}_i. \quad (2)$$

Show that the $n \times \ell$ matrix $\mathbf{X} := [\mathbf{x}_1, \dots, \mathbf{x}_\ell]$ satisfies

$$\mathbf{C} + \mathbf{m}\mathbf{m}^{\mathrm{T}} = \frac{1}{\ell} \mathbf{X}\mathbf{X}^{\mathrm{T}}. \quad (3)$$

Proof. Let $\mathbf{x}_1, \dots, \mathbf{x}_\ell \in \mathbb{R}^n$.

$$\begin{aligned}
\mathbf{C} + \mathbf{m}\mathbf{m}^\mathsf{T} &= \frac{1}{\ell} \sum_{i=1}^{\ell} (\mathbf{x}_i - \mathbf{m})(\mathbf{x}_i - \mathbf{m})^\mathsf{T} + \mathbf{m}\mathbf{m}^\mathsf{T} \\
&= \frac{1}{\ell} \sum_{i=1}^{\ell} (\mathbf{x}_i - \mathbf{m})(\mathbf{x}_i^\mathsf{T} - \mathbf{m}^\mathsf{T}) + \mathbf{m}\mathbf{m}^\mathsf{T} \\
&= \frac{1}{\ell} \sum_{i=1}^{\ell} (\mathbf{x}_i \mathbf{x}_i^\mathsf{T} - \mathbf{x}_i \mathbf{m}^\mathsf{T} - \mathbf{m} \mathbf{x}_i^\mathsf{T} + \mathbf{m} \mathbf{m}^\mathsf{T}) + \mathbf{m}\mathbf{m}^\mathsf{T} \\
&= \frac{1}{\ell} \left(\sum_{i=1}^{\ell} \mathbf{x}_i \mathbf{x}_i^\mathsf{T} - \sum_{i=1}^{\ell} \mathbf{x}_i \mathbf{m}^\mathsf{T} - \sum_{i=1}^{\ell} \mathbf{m} \mathbf{x}_i^\mathsf{T} + \sum_{i=1}^{\ell} \mathbf{m} \mathbf{m}^\mathsf{T} \right) + \mathbf{m}\mathbf{m}^\mathsf{T} \\
&= \frac{1}{\ell} \sum_{i=1}^{\ell} \mathbf{x}_i \mathbf{x}_i^\mathsf{T} - \left(\frac{1}{\ell} \sum_{i=1}^{\ell} \mathbf{x}_i \right) \mathbf{m}^\mathsf{T} - \mathbf{m} \left(\frac{1}{\ell} \sum_{i=1}^{\ell} \mathbf{x}_i^\mathsf{T} \right) + \frac{1}{\ell} \sum_{i=1}^{\ell} \mathbf{m} \mathbf{m}^\mathsf{T} + \mathbf{m}\mathbf{m}^\mathsf{T} \\
&= \frac{1}{\ell} \sum_{i=1}^{\ell} \mathbf{x}_i \mathbf{x}_i^\mathsf{T} - \mathbf{m} \mathbf{m}^\mathsf{T} - \mathbf{m} \left(\frac{1}{\ell} \sum_{i=1}^{\ell} \mathbf{x}_i^\mathsf{T} \right) + \mathbf{m} \mathbf{m}^\mathsf{T} + \mathbf{m}\mathbf{m}^\mathsf{T} \\
&= \frac{1}{\ell} \sum_{i=1}^{\ell} \mathbf{x}_i \mathbf{x}_i^\mathsf{T} - \mathbf{m} \left(\frac{1}{\ell} \sum_{i=1}^{\ell} \mathbf{x}_i \right)^\mathsf{T} + \mathbf{m}\mathbf{m}^\mathsf{T} \\
&= \frac{1}{\ell} \sum_{i=1}^{\ell} \mathbf{x}_i \mathbf{x}_i^\mathsf{T} - \mathbf{m} \mathbf{m}^\mathsf{T} + \mathbf{m}\mathbf{m}^\mathsf{T} \\
&= \frac{1}{\ell} \sum_{i=1}^{\ell} \mathbf{x}_i \mathbf{x}_i^\mathsf{T}
\end{aligned}$$

$$\begin{aligned}
\frac{1}{\ell} \mathbf{X} \mathbf{X}^\mathsf{T} &= \frac{1}{\ell} [\mathbf{x}_1, \dots, \mathbf{x}_\ell] \begin{bmatrix} \mathbf{x}_1^\mathsf{T} \\ \vdots \\ \mathbf{x}_\ell^\mathsf{T} \end{bmatrix} \\
&= \frac{1}{\ell} \sum_{i=1}^{\ell} \mathbf{x}_i \mathbf{x}_i^\mathsf{T}
\end{aligned}$$

Thus, we get (3). □

2 Idempotent Matrices

2.1 Exercise

Exercise 2.7.2.

Let $\mathbf{v} \in \Delta_\ell$ where Δ_ℓ denotes the ℓ -dimensional probabilistic simplex:
 $\Delta_\ell := \{\mathbf{x} \in \mathbb{R}_+^\ell \mid \mathbf{x}^\top \mathbf{1}_\ell = 1\}$. Show that the $\ell \times \ell$ matrix

$$\mathbf{K} := \mathbf{I} - \mathbf{1}_\ell \mathbf{v}^\top$$

satisfies $\mathbf{K}^2 = \mathbf{K}$.

Proof. Let $\mathbf{v} \in \Delta_\ell$.

$$\begin{aligned} \mathbf{K}^2 &= (\mathbf{I} - \mathbf{1}_\ell \mathbf{v}^\top)^2 \\ &= \mathbf{I} - \mathbf{1}_\ell \mathbf{v}^\top - \mathbf{1}_\ell \mathbf{v}^\top + \mathbf{1}_\ell \mathbf{v}^\top \mathbf{1}_\ell \mathbf{v}^\top \\ &= \mathbf{I} - 2\mathbf{1}_\ell \mathbf{v}^\top + \mathbf{1}_\ell (\mathbf{v}^\top \mathbf{1}_\ell) \mathbf{v}^\top \\ &= \mathbf{I} - 2\mathbf{1}_\ell \mathbf{v}^\top + \mathbf{1}_\ell \mathbf{v}^\top \\ &= \mathbf{I} - \mathbf{1}_\ell \mathbf{v}^\top \\ &= \mathbf{K} \end{aligned}$$

□

3 Trace

3.1 Definition

Definition 3.1.1. Let \mathbf{A} be an $n \times n$ square matrix. The trace of \mathbf{A} is defined as

$$\text{tr}(\mathbf{A}) = \sum_{i=1}^n A_{i,i}. \quad (4)$$

3.2 Exercise

Exercise 2.8.3.

For $\forall a, \forall b \in \mathbb{R}$ and $\forall \mathbf{X}, \forall \mathbf{Y} \in \mathbb{R}^{n \times n}$, show that

$$\text{tr}(a\mathbf{X} + b\mathbf{Y}) = a\text{tr}(\mathbf{X}) + b\text{tr}(\mathbf{Y}). \quad (5)$$

Proof. For all $a, b \in \mathbb{R}$ and $\mathbf{X}, \mathbf{Y} \in \mathbb{R}^{n \times n}$,

$$\begin{aligned} \text{tr}(a\mathbf{X} + b\mathbf{Y}) &= \sum_{i=1}^n (a\mathbf{X}_{i,i} + b\mathbf{Y}_{i,i}) \\ &= a \sum_{i=1}^n \mathbf{X}_{i,i} + b \sum_{i=1}^n \mathbf{Y}_{i,i} \\ &= a\text{tr}(\mathbf{X}) + b\text{tr}(\mathbf{Y}). \end{aligned}$$

□

Exercise 2.8.5.

Show that $\text{tr}(\mathbf{AB}) = \text{tr}(\mathbf{BA})$ for $\mathbf{A} \in \mathbb{R}^{m \times n}, \mathbf{B} \in \mathbb{R}^{n \times m}$. Then, show that $\text{tr}(\mathbf{ABC}) = \text{tr}(\mathbf{CAB}) = \text{tr}(\mathbf{BCA})$ for $\mathbf{A} \in \mathbb{R}^{m \times n}, \mathbf{B} \in \mathbb{R}^{n \times p}, \mathbf{C} \in \mathbb{R}^{p \times m}$.

Proof. Let $\mathbf{A} \in \mathbb{R}^{m \times n}, \mathbf{B} \in \mathbb{R}^{n \times m}$.

$$\begin{aligned} \text{tr}(\mathbf{AB}) &= \sum_{i=1}^m (\mathbf{AB})_{i,i} \\ &= \sum_{i=1}^m \sum_{j=1}^n A_{i,j} B_{j,i} \\ &= \sum_{j=1}^n \sum_{i=1}^m B_{j,i} A_{i,j} \\ &= \sum_{j=1}^n (\mathbf{BA})_{j,j} \\ &= \text{tr}(\mathbf{BA}) \end{aligned}$$

Thus, we get

$$\text{tr}(\mathbf{AB}) = \text{tr}(\mathbf{BA}). \quad (6)$$

Let $\mathbf{A} \in \mathbb{R}^{m \times n}, \mathbf{B} \in \mathbb{R}^{n \times p}, \mathbf{C} \in \mathbb{R}^{p \times m}$. Since (6),

$$\begin{aligned} \text{tr}(\mathbf{ABC}) &= \text{tr}((\mathbf{AB})\mathbf{C}) \\ &= \text{tr}(\mathbf{C}(\mathbf{AB})) \\ &= \text{tr}(\mathbf{CAB}). \end{aligned}$$

Moreover

$$\begin{aligned} \text{tr}(\mathbf{ABC}) &= \text{tr}(\mathbf{A}(\mathbf{BC})) \\ &= \text{tr}((\mathbf{BC})\mathbf{A}) \\ &= \text{tr}(\mathbf{BCA}). \end{aligned}$$

Therefore, it follows that

$$\text{tr}(\mathbf{ABC}) = \text{tr}(\mathbf{CAB}) = \text{tr}(\mathbf{BCA}).$$

□

Exercise 2.8.8.

For $\forall \mathbf{x}, \forall \mathbf{y} \in \mathbb{R}^n$, show that

$$\langle \mathbf{x}, \mathbf{y} \rangle = \text{tr}(\mathbf{x}\mathbf{y}^T) \quad (7)$$

Proof. Since (6),

$$\begin{aligned} \text{tr}(\mathbf{x}\mathbf{y}^T) &= \text{tr}(\mathbf{y}^T\mathbf{x}) \\ &= \text{tr}(\langle \mathbf{y}, \mathbf{x} \rangle) \\ &= \langle \mathbf{y}, \mathbf{x} \rangle \\ &= \langle \mathbf{x}, \mathbf{y} \rangle. \end{aligned}$$

□

4 Inner-Product of Matrices

4.1 Definition

Definition 4.1.1. The inner-product of matrices is defined as

$$\langle \mathbf{X}, \mathbf{Y} \rangle := \sum_{i=1}^m \sum_{j=1}^n X_{i,j} Y_{i,j} \quad (8)$$

where $\mathbf{X}, \mathbf{Y} \in \mathbb{R}^{m \times n}$.

4.2 Exercise

Exercise 2.10.2.

For $\forall \mathbf{X}, \forall \mathbf{Y} \in \mathbb{R}^{m \times n}$, derive the equalities:

$$\langle \mathbf{X}, \mathbf{Y} \rangle = \langle \mathbf{Y}, \mathbf{X} \rangle = \text{tr}(\mathbf{X}^T \mathbf{Y}) = \text{tr}(\mathbf{Y}^T \mathbf{X}) \quad (9)$$

Proof. Let $\mathbf{X}, \mathbf{Y} \in \mathbb{R}^{m \times n}$.

$$\langle \mathbf{X}, \mathbf{Y} \rangle = \sum_{i=1}^m \sum_{j=1}^n X_{i,j} Y_{i,j} = \sum_{i=1}^m \sum_{j=1}^n Y_{i,j} X_{i,j} = \langle \mathbf{Y}, \mathbf{X} \rangle$$

$$\begin{aligned}
tr(\mathbf{X}^T \mathbf{Y}) &= \sum_{j=1}^n (\mathbf{X}^T \mathbf{Y})_{j,j} \\
&= \sum_{j=1}^n \sum_{i=1}^m (\mathbf{X}^T)_{j,i} Y_{i,j} \\
&= \sum_{j=1}^n \sum_{i=1}^m X_{i,j} Y_{i,j} \\
&= \sum_{i=1}^m \sum_{j=1}^n X_{i,j} Y_{i,j} \\
&= \langle \mathbf{X}, \mathbf{Y} \rangle
\end{aligned}$$

$$\begin{aligned}
tr(\mathbf{Y}^T \mathbf{X}) &= \sum_{j=1}^n (\mathbf{Y}^T \mathbf{X})_{j,j} \\
&= \sum_{j=1}^n \sum_{i=1}^m (\mathbf{Y}^T)_{j,i} X_{i,j} \\
&= \sum_{j=1}^n \sum_{i=1}^m Y_{i,j} X_{i,j} \\
&= \sum_{i=1}^m \sum_{j=1}^n Y_{i,j} X_{i,j} \\
&= \langle \mathbf{Y}, \mathbf{X} \rangle
\end{aligned}$$

Therefore,

$$\langle \mathbf{X}, \mathbf{Y} \rangle = \langle \mathbf{Y}, \mathbf{X} \rangle = tr(\mathbf{X}^T \mathbf{Y}) = tr(\mathbf{Y}^T \mathbf{X}).$$

□

Exercise 2.10.5.

For $\forall a, \forall b \in \mathbb{R}, \forall \mathbf{X}, \forall \mathbf{Y} \in \mathbb{R}^{m \times n}$, show that

$$\langle a\mathbf{X}, b\mathbf{Y} \rangle = ab\langle \mathbf{X}, \mathbf{Y} \rangle. \quad (10)$$

Proof. Let $a, b \in \mathbb{R}$ and $\mathbf{X}, \mathbf{Y} \in \mathbb{R}^{m \times n}$.

$$\begin{aligned}
\langle a\mathbf{X}, b\mathbf{Y} \rangle &= \sum_{i=1}^m \sum_{j=1}^n aX_{i,j} bY_{i,j} \\
&= ab \sum_{i=1}^m \sum_{j=1}^n X_{i,j} Y_{i,j} \\
&= ab\langle \mathbf{X}, \mathbf{Y} \rangle
\end{aligned}$$

□

Exercise 2.10.7.

For $\forall \mathbf{X} \in \mathbb{R}^{m \times n}$, show that

$$\langle \mathbf{X}, \mathbf{E}_{i,j} \rangle = \text{tr}(\mathbf{X}^T, \mathbf{E}_{i,j}) = X_{i,j} \quad (11)$$

where $\mathbf{E}_{i,j}$ denotes an $m \times n$ matrix in which (i,j) th entry is one and all the others are zero.

Proof. Let $\mathbf{X} \in \mathbb{R}^{m \times n}$. Recall (9). It leads

$$\langle \mathbf{X}, \mathbf{E}_{i,j} \rangle = \text{tr}(\mathbf{X}^T, \mathbf{E}_{i,j}).$$

Furthermore, since $(\mathbf{E}_{i,j})_{k,l} = \begin{cases} 1 & (k=i, l=j) \\ 0 & (k \neq i \text{ or } l \neq j), \end{cases}$

$$\begin{aligned} \langle \mathbf{X}, \mathbf{E}_{i,j} \rangle &= \sum_{k=1}^m \sum_{l=1}^n X_{k,l} (\mathbf{E}_{i,j})_{k,l} \\ &= X_{i,j}. \end{aligned}$$

Therefore, we get (11). \square

5 Frobenius Norm

5.1 Definition

Definition 5.1.1. The Frobenius norm of a matrix $\mathbf{X} \in \mathbb{R}^{m \times n}$ is defined as

$$\|\mathbf{X}\|_F := \sqrt{\langle \mathbf{X}, \mathbf{X} \rangle}.$$

5.2 Exercise

Exercise 2.11.3.

For $\forall \mathbf{X} \in \mathbb{R}^{m \times n}$, show that

$$\|\mathbf{X}\|_F \geq 0.$$

Proof. Let $\mathbf{X} \in \mathbb{R}^{m \times n}$, and $k \in \mathbb{N}_m, l \in \mathbb{N}_n$.

$$\|\mathbf{X}\|_F = \sqrt{\sum_{i=1}^m \sum_{j=1}^n X_{i,j}^2} \geq \sqrt{X_{k,l}^2} = |X_{k,l}| \geq 0$$

Thus, it follows that

$$\|\mathbf{X}\|_F \geq 0.$$

\square

Exercise 2.11.5.

Let $\mathbf{X}, \mathbf{Y} \in \mathbb{R}^{m \times n}$. Derive the equality:

$$\|\mathbf{X} + \mathbf{Y}\|_F^2 = \|\mathbf{X}\|_F^2 + \|\mathbf{Y}\|_F^2 + 2\langle \mathbf{X}, \mathbf{Y} \rangle. \quad (12)$$

Proof. Let $\mathbf{X}, \mathbf{Y} \in \mathbb{R}^{m \times n}$.

$$\begin{aligned} \|\mathbf{X} + \mathbf{Y}\|_F^2 &= \langle \mathbf{X} + \mathbf{Y}, \mathbf{X} + \mathbf{Y} \rangle \\ &= \sum_{i=1}^m \sum_{j=1}^n (X_{i,j} + Y_{i,j})^2 \\ &= \sum_{i=1}^m \sum_{j=1}^n (X_{i,j}^2 + Y_{i,j}^2 + 2X_{i,j}Y_{i,j}) \\ &= \sum_{i=1}^m \sum_{j=1}^n X_{i,j}^2 + \sum_{i=1}^m \sum_{j=1}^n Y_{i,j}^2 + 2 \sum_{i=1}^m \sum_{j=1}^n X_{i,j}Y_{i,j} \\ &= \langle \mathbf{X}, \mathbf{X} \rangle + \langle \mathbf{Y}, \mathbf{Y} \rangle + 2\langle \mathbf{X}, \mathbf{Y} \rangle \\ &= \sqrt{\langle \mathbf{X}, \mathbf{X} \rangle}^2 + \sqrt{\langle \mathbf{Y}, \mathbf{Y} \rangle}^2 + 2\langle \mathbf{X}, \mathbf{Y} \rangle \\ &= \|\mathbf{X}\|_F^2 + \|\mathbf{Y}\|_F^2 + 2\langle \mathbf{X}, \mathbf{Y} \rangle \end{aligned} \quad (13)$$

□

Exercise 2.11.7.

For $\forall \mathbf{X}, \forall \mathbf{Y} \in \mathbb{R}^{m \times n}$, show that

$$\|\mathbf{X} + \mathbf{Y}\|_F \leq \|\mathbf{X}\|_F + \|\mathbf{Y}\|_F. \quad (14)$$

Proof. Let $\mathbf{X}, \mathbf{Y} \in \mathbb{R}^{m \times n}, t \in \mathbb{R}$. Consider the function

$$\begin{aligned} f(t) &= \|\mathbf{X} + t\mathbf{Y}\|_F \\ &= \langle \mathbf{X} + t\mathbf{Y}, \mathbf{X} + t\mathbf{Y} \rangle \\ &= \sum_{i=1}^m \sum_{j=1}^n (X_{i,j} + tY_{i,j})^2 \\ &= \sum_{i=1}^m \sum_{j=1}^n (X_{i,j}^2 + t^2Y_{i,j}^2 + 2tX_{i,j}Y_{i,j}) \\ &= \sum_{i=1}^m \sum_{j=1}^n X_{i,j}^2 + t^2 \sum_{i=1}^m \sum_{j=1}^n Y_{i,j}^2 + 2t \sum_{i=1}^m \sum_{j=1}^n X_{i,j}Y_{i,j} \\ &= \langle \mathbf{X}, \mathbf{X} \rangle + t^2 \langle \mathbf{Y}, \mathbf{Y} \rangle + 2t \langle \mathbf{X}, \mathbf{Y} \rangle \\ &= \|\mathbf{Y}\|_F^2 t^2 + 2\langle \mathbf{X}, \mathbf{Y} \rangle t + \|\mathbf{X}\|_F^2 \geq 0. \end{aligned}$$

Then, the quadratic equation

$$\|\mathbf{Y}\|_{\mathbb{F}}^2 t^2 + 2\langle \mathbf{X}, \mathbf{Y} \rangle t + \|\mathbf{X}\|_{\mathbb{F}}^2 = 0$$

has at most one solution. This implies that its discriminant must be less or zero, that is

$$(2\langle \mathbf{X}, \mathbf{Y} \rangle)^2 - 4\|\mathbf{Y}\|_{\mathbb{F}}^2 \|\mathbf{X}\|_{\mathbb{F}}^2 \leq 0.$$

Hence

$$\begin{aligned} 4\langle \mathbf{X}, \mathbf{Y} \rangle^2 &\leq 4\|\mathbf{X}\|_{\mathbb{F}}^2 \|\mathbf{Y}\|_{\mathbb{F}}^2 \\ \langle \mathbf{X}, \mathbf{Y} \rangle^2 &\leq \|\mathbf{X}\|_{\mathbb{F}}^2 \|\mathbf{Y}\|_{\mathbb{F}}^2. \end{aligned}$$

It follows that

$$-\|\mathbf{X}\|_{\mathbb{F}} \|\mathbf{Y}\|_{\mathbb{F}} \leq \langle \mathbf{X}, \mathbf{Y} \rangle \leq \|\mathbf{X}\|_{\mathbb{F}} \|\mathbf{Y}\|_{\mathbb{F}}.$$

This also implies

$$\langle \mathbf{X}, \mathbf{Y} \rangle \leq \|\mathbf{X}\|_{\mathbb{F}} \|\mathbf{Y}\|_{\mathbb{F}}.$$

Therefore, recall (12),

$$\begin{aligned} \|\mathbf{X} + \mathbf{Y}\|_{\mathbb{F}} &= \sqrt{\|\mathbf{X}\|_{\mathbb{F}}^2 + \|\mathbf{Y}\|_{\mathbb{F}}^2 + 2\langle \mathbf{X}, \mathbf{Y} \rangle} \\ &\leq \sqrt{\|\mathbf{X}\|_{\mathbb{F}}^2 + \|\mathbf{Y}\|_{\mathbb{F}}^2 + 2\|\mathbf{X}\|_{\mathbb{F}} \|\mathbf{Y}\|_{\mathbb{F}}} \\ &= \sqrt{(\|\mathbf{X}\|_{\mathbb{F}} + \|\mathbf{Y}\|_{\mathbb{F}})^2} \\ &= \|\mathbf{X}\|_{\mathbb{F}} + \|\mathbf{Y}\|_{\mathbb{F}}. \end{aligned}$$

□