

# Matrix Operations

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In what follows,  $A \in \mathbb{R}^{m \times n}$ ,  $B \in \mathbb{R}^{n \times p}$  and  $x, y \in \mathbb{R}^n$ .

1. Compute the following, giving conditions on  $m, n, p$  for the formulas to be well-defined. When the result is a matrix, give its value at position  $(i, j)$ . When it is a vector, give its value at position  $i$ .

- $AB$
- $x^T A$
- $x^T y$
- $xy^T$
- $y^T Ax$
- $Tr(A^T A)$

2. Show that

- $(AB)^T = B^T A^T$
- $(AB)^{-1} = B^{-1} A^{-1}$
- $(A^T)^{-1} = (A^{-1})^T$
- The *trace* operator  $A \rightarrow Tr(A)$  is a *linear operator* on  $\mathbb{R}^{m \times n}$ .
- $Tr(AB) = Tr(BA)$ .

3. Given a matrix  $A \in \mathbb{R}^{n \times n}$  and a vector  $r \in \mathbb{R}^n$ , how to multiply each row of  $A$  by the elements of  $r$ ?

4. Given  $x_i \in \mathbb{R}^d$ ,  $i = 1, \dots, n$ , how to compute the mean of  $\{\|x_i - x_j\|_2; i, j = 1, \dots, n\}$  in Python, without a loop?

# Gradients

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1. Let  $A \in \mathbb{R}^{m \times n}$ . In the following, give the function's output dimension and compute the gradient:

- $\nabla_x (xA), \quad x \in \mathbb{R}$
- $\nabla_x (Ax), \quad x \in \mathbb{R}^n$

- $\nabla_{\mathbf{x}} (\mathbf{y}^T A \mathbf{x}), \nabla_{\mathbf{y}} (\mathbf{y}^T A \mathbf{x}), \quad \mathbf{x}, \mathbf{y} \in \mathbb{R}^n$
- $\nabla_{\mathbf{x}} (\mathbf{x}^T A \mathbf{x}), \quad \mathbf{x} \in \mathbb{R}^n$
- $\nabla_{\mathbf{x}} \|\mathbf{y} - A \mathbf{x}\|_2^2, \quad \mathbf{x} \in \mathbb{R}^n$
- $\nabla_X \text{Tr}(A^T X), \quad X \in \mathbb{R}^{m \times n}$

2. Compute the following gradients using the chain rule:

- $\nabla_z Ax(z)$
- $\nabla_z y(z)^T Ax(z)$

## Symmetric matrices

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### Reminders

**Def (Eigenvector Equation).** Let  $A \in \mathbb{R}^n$ . If  $Au = \lambda u$  with  $\lambda \in \mathbb{R}$  and  $u \in \mathbb{R}^n$ , then  $\lambda$  is called an *eigenvalue* of  $A$  and  $u$  an *eigenvector*.

**Def (Orthogonal matrix).**  $U \in \mathbb{R}^n$  is orthogonal  $\iff U$  is invertible and  $U^{-1} = U^T$ .

**Spectral theorem.** Any (real) symmetric matrix  $A \in \mathbb{R}^{n \times n}$  can be decomposed as

$$A = U \Lambda U^T$$

where  $U$  is an orthogonal matrix and  $\Lambda = \text{diag}(\lambda_1, \dots, \lambda_n)$ .

### Exercises

1. Show that for an orthogonal matrix  $U$ ,

$$u_i^T u_j = \begin{cases} 1 & \text{if } i = j \\ 0 & \text{otherwise} \end{cases}$$

2. Let  $A \in \mathbb{R}^{n \times n}$  a (real) symmetric matrix and  $A := U \Lambda U^T$  with  $U$  orthogonal and  $\Lambda = \text{diag}(\lambda_1, \dots, \lambda_n)$ . Show that the columns of  $U$  are eigenvectors of  $A$  and  $\lambda_i, i = 1, \dots, n$  are eigenvalues.

3. Let  $A = U \Lambda U^T$  a symmetric matrix. Show that:

- $A$  is invertible  $\iff \lambda_i \neq 0, \forall i$
- $A^{-1} = U \Lambda^{-1} U^T$  with  $\Lambda^{-1} = \text{diag}(\lambda_1^{-1}, \dots, \lambda_n^{-1})$
- $\text{Tr}(A) = \sum_i \lambda_i, \text{Tr}(A^{-1}) = \sum_i \lambda_i^{-1}$

# Positive semi-definite matrices

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## Reminders

**Def (Positive (semi-)definite matrix).** Let  $A \in \mathbb{R}^{n \times n}$ .

$$\begin{aligned} A \text{ p.s.d.} &\iff x^T A x \geq 0, \forall x \in \mathbb{R}^n \\ A \text{ p.d.} &\iff x^T A x > 0, \forall x \in \mathbb{R}^n \end{aligned}$$

## Exercises

1. Let  $A \in \mathbb{R}^{n \times n}$ . Show that
  - a.  $A$  p.s.d. and symmetric  $\iff A$  has  $n$  eigenvalues  $\lambda_i \geq 0$
  - b.  $A$  p.d. and symmetric  $\iff A$  has  $n$  eigenvalues  $\lambda_i > 0$
2. Let  $X \in \mathbb{R}^{n \times p}$ ,  $\lambda > 0$ . Prove that  $M = X^T X + \lambda I_p$  is invertible.  
*Hint: Prove that the eigenvalues of  $M$  are larger than  $\lambda$ .*
3. For any general  $X \in \mathbb{R}^{m \times n}$ , show that
  - a.  $X^T X$  and  $X X^T$  are symmetric, p.s.d.
  - b. the non-zero eigenvalues of  $X^T X$  and  $X X^T$  are the same, that are  $\{\sigma_i^2, \sigma_i \neq 0, i = 1, \dots, \min(m, n)\}$  where  $\sigma_i$ 's are singular values of  $X$