

$$=2px+\Lambda x$$

- 1 Transpose
- 2 Matrix as a Function
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# 1. Transpose

Given  $A = (a_{ij}), A^T := (a_{ji})$ 

## Proposition

Let A, B be matrices,  $\lambda \in \mathbb{R}$ .

- **2**  $(AB)^T = B^T A^T$
- **3**  $(A^T)^T = A$
- 4 If A is invertible, so is  $A^T$ , and  $(A^T)^{-1} = (A^{-1})^T$

A matrix A is called **symmetric** if  $A = A^T$ 

A matrix A is called **skew-symmetric** if  $A^T = -A \iff A + A^T = 0$ 

#### Remark

- A symmetric or skew-symmetric matrix is necessarily square.
- **2** For a skew-symmetric matrix, if i = j, then  $a_{ij} = 0$

## Example

$$A = \begin{pmatrix} 1 & -4 & -2 \\ 4 & 1 & 3 \\ 2 & -3 & 2 \end{pmatrix}$$
 is not skew-symmetric.

2. Matrix as a Function



An n imes m Matrix can be interpreted as a function  $F: M_{m imes p} o M_{n imes p}$ 

## **Property**

For  $M \in M_{n \times m}$ ,  $A, B \in M_{m \times p}$ ,  $\alpha, \beta \in \mathbb{R}$ We have  $M(\alpha A + \beta B) = \alpha MA + \beta MB$ 

#### Question

- 1 Do you know other function with such property?
- 2 Why we want such property?

3. Orthogonal Matrices and Orthonormal Vectors

A matrix  $A \in M_n(\mathbb{R})$  is called an orthogonal matrix iff  $A^T = A^{-1}$ 

## Properties.

- $I_n$  is an orthogonal matrix.
- If A and B are orthogonal matrices, then AB is also orthogonal.
- If A is an orthogonal matrix, then  $A^{-1}$  is also orthogonal matrix.
- If A is an orthogonal matrix, then  $det(A) = \pm 1$ .

## Examples.

► Rotation Matrix.

Rotation by  $\theta$  in  $\mathbb{R}^2$  is given by

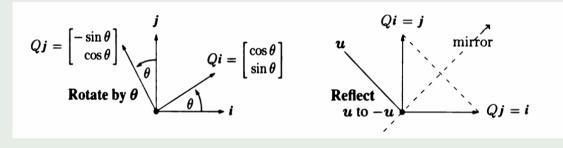
$$\begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix}.$$

► Reflection Matrix.

Reflect  $(x_1, x_2)$  across  $\theta/2$  in  $\mathbb{R}^2$  is given by

$$\begin{bmatrix} \cos \theta & \sin \theta \\ \sin \theta & -\cos \theta \end{bmatrix}.$$

You can treat such matrix as a function  $Q:\mathbb{R}^2 o \mathbb{R}^2$ 



Let  $\{v_1, \dots, v_k\} \in \mathbb{R}$  be a subset of k distinct vectors, then  $\{v_1, \dots, v_k\}$  is an orthogonal set of vectors if  $\langle v_i, v_i \rangle = 0$  for all  $1 \leq i, j \leq k$ ,  $i \neq j$ .

Also,  $\{q_1, \dots, q_k\}$  is an orthonormal set of vectors if it is an orthogonal set and all of its vectors are unit vectors (i.e.,  $||q_i|| = 1$  for  $i \le i \le k$ ).

#### Remark

Any set containing a single vector is orthogonal; any set containing a single unit vector is orthonormal.

## Example.

 $\bar{i},\bar{j},\bar{k}\in\mathbb{R}^3$ .

## Proposition

Given vectors  $q_i \in \mathbb{R}^n$ ,  $i = 1, \dots, m$  such that

$$\langle q_i,q_j
angle = q_i^{\mathsf{T}}q_j = \delta_{ij} = \left\{egin{array}{ll} 1, & i=j, \ 0, & i
eq j, \end{array} 
ight. (\delta_{ij}: \mathit{Kronecker})$$

then we call the set of vectors  $\{q_i\}$  orthonormal, and

## Proof

$$Q^TQ = \left[ egin{array}{cccc} -&q_1^T&-\ ‐ &\ -&q_m^T&- \end{array} 
ight] \left[ egin{array}{cccc} |&&&|\ q_1&...&q_m \ |&&&| \end{array} 
ight] = \left[ egin{array}{cccc} q_1^Tq_1&...&q_1^Tq_m \ dash &\ddots ‐ \ q_m^Tq_1&...&q_m^Tq_m \end{array} 
ight] = I_m$$

### **Proposition**

Let 
$$Q = egin{bmatrix} | & | & | & | \ \mathbf{q}_1 & \mathbf{q}_2 & \cdots & \mathbf{q}_n \ | & | & | \end{bmatrix} \in M_n(\mathbb{R}),$$

where  $\{\mathbf{q}_1, \mathbf{q}_2, \dots, \mathbf{q}_n\}$  is a set of orthonormal vectors in  $\mathbb{R}^n$ .

Then Q is an orthogonal matrix,  $Q^T = Q^{-1}$ .

We verify that  $QQ^T = I_n$  and  $Q^TQ = I_n$ .

#### Exercise

Determine whether the following matrices are orthogonal matrices

$$\left[\begin{array}{cc} \frac{\sqrt{3}}{2} & -\frac{1}{2} \\ \frac{1}{2} & \frac{\sqrt{3}}{2} \end{array}\right].$$

$$\left[\begin{array}{cc} 1 & 1 \\ 1 & -1 \end{array}\right].$$

### Proposition

The orthogonal matrices are precisely the matrices that preserve the inner product in  $\mathbb{R}^n$  i.e.,  $\forall x, y \in \mathbb{R}^n$ ,  $\langle x, y \rangle = \langle Ax, Ay \rangle$  or  $x^T y = (Ax)^T Ay$ .

#### Proof.

If A is orthogonal, i.e., 
$$A^{-1} = A^T$$
, then  $A^T A = I_n$ , so  $(Ax)^T (Ay) = x^T A^T Ay = x^T I_n y = x^T y$ .

## Magnitude of Determinant and Column Norms:

- $\bullet |\det(A)| = 1.$
- Column vectors  $\mathbf{q}_i$  have unit norm:  $||\mathbf{q}_i|| = 1$ .
- *Implication:* The transformation represented by A is a rotation or a reflection.

#### Defining Property and Its Consequences:

- $A^TA = I_n$  (which means  $A^{-1} = A^T$ ).
- The original note mentions this "has very good symmetric properties."
- Implications include:
  - Preservation of inner products (hence, lengths and angles are preserved:  $\langle Ax, Ay \rangle = \langle x, y \rangle$ ).
  - The inverse  $A^{-1}$  is easy to compute (it's just the transpose  $A^{T}$ ).

### **3** Applications in Data Processing:

• Effective in removing redundant information from data

4. Kernel and Image



• Given matrix  $A \in M_{m \times n}(\mathbb{R})$ . The kernel, or nullspace of A, is defined as

$$\ker A = \mathcal{N}(A) = \{x \in \mathbb{R}^n \mid Ax = \mathbf{0}\} \subseteq \mathbb{R}^n$$

where  $A: \mathbb{R}^n \to \mathbb{R}^n$ .

• The image of A, or column space, is defined as

$$\operatorname{im} A = C(A) = \{ y \in \mathbb{R}^m \mid \exists x \in \mathbb{R}^n, y = Ax \}$$
$$= \{ Ax \mid x \in \mathbb{R}^n \}$$

(The image is a subspace of  $\mathbb{R}^m$ ).

A function  $f: A \rightarrow B$  is called injective, if

$$\forall x_1, x_2 \in A, f(x_1) = f(x_2) \implies x_1 = x_2$$
  
i.e.,  $\forall x_1, x_2 \in A, x_1 \neq x_2 \implies f(x_1) \neq f(x_2)$ 

## Proposition

Given  $A \in M_{m \times n}(\mathbb{R})$ , i.e.,  $A : \mathbb{R}^n \to \mathbb{R}^m$ then, A is injective  $\iff \ker A = N(A) = \{0\}$ 

#### Proof

 $(\Rightarrow)$  Assume A is injective, that is,

 $\forall x_1, x_2 \in \mathbb{R}^n, Ax_1 = Ax_2 \implies x_1 = x_2.$ 

Take  $v \in \ker A$ , i.e., Av = 0. We also know that A0 = 0, hence Av = A0. By injectivity of

A, v = 0. Therefore ker  $A = \{0\}$ .

 $(\Leftarrow)$  Conversely, suppose  $\ker A = \{0\}$ .

Take  $v_1, v_2 \in \mathbb{R}^n$ , s.t.  $Av_1 = Av_2$ . We want to show that  $v_1 = v_2$ . Indeed, we have

 $A(v_1 - v_2) = 0$ , but ker  $A = \{0\}$ , hence  $v_1 - v_2 = 0$ . So  $v_1 = v_2$ .

## Proposition

Given  $A \in M_{m \times n}(\mathbb{R})$ ,  $\ker(A) = \ker(A^T A)$ 

#### Proof

$$(\subseteq)$$
 Take  $x \in \ker(A)$ , i.e.,  $Ax = 0$ . So  $(A^TA)x = A^T(Ax) = A^T0 = 0$ . So  $x \in \ker(A^TA)$ .

$$(\supseteq)$$
 Take  $x \in \ker(A^T A)$ , i.e.,  $A^T A x = 0$ . So  $x^T A^T A x = x^T 0 = 0$ .

$$(Ax)^T Ax = ||Ax||^2 = 0. \implies Ax = 0 \implies x \in \ker A.$$

$$(v_1^2 + v_2^2 + \cdots + v_n^2 = 0 \implies v_i = 0)$$

5. Projection Matrix

A matrix  $P \in M_n(\mathbb{R})$  is a projection matrix, if  $P^2 = P$ . It is called an orthogonal projection, if  $P = P^T$ .

## Example

For an orthonormal matrix Q

- $(QQ^T)^T = (Q^T)^T Q^T = QQ^T$
- $(QQ^T)^2 = (QQ^T)(QQ^T) = Q(Q^TQ)Q^T = QI_kQ^T = QQ^T$

 $QQ^T: \mathbb{R}^n \to \mathbb{R}^n$  is a projection

## Proposition

A projection matrix P is an orthogonal projection if

 $\ker P \perp \operatorname{im} P$ 

i.e.,  $\forall x \in \ker P$ ,  $\forall y \in \operatorname{im} P$ ,

$$\langle x, y \rangle = x^T y = 0 \in \mathbb{R}$$

#### Exercise

Show that  $\ker P \perp \operatorname{im} P$  if  $P = P^T$ 

## Example

$$\{q_1, q_2\} = \left\{ \begin{pmatrix} 1/\sqrt{2} \\ 1/\sqrt{2} \\ 0 \end{pmatrix}, \begin{pmatrix} 1/\sqrt{2} \\ -1/\sqrt{2} \\ 0 \end{pmatrix} \right\}$$

$$Q = \begin{bmatrix} 1/\sqrt{2} & 1/\sqrt{2} \\ 1/\sqrt{2} & -1/\sqrt{2} \\ 0 & 0 \end{bmatrix}, \quad Q^T = \begin{bmatrix} 1/\sqrt{2} & 1/\sqrt{2} & 0 \\ 1/\sqrt{2} & -1/\sqrt{2} & 0 \end{bmatrix}$$

$$QQ^T = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{pmatrix} x \\ y \\ z \end{pmatrix} = \begin{pmatrix} x \\ y \\ 0 \end{pmatrix}$$

- 1 VV255, Lecture Notes 24SU, Runze Cai
- 2 VV255 RC2, Jiayue Huang, et al
- 3 Introduction to Linear Algebra, Sixth Edition, Gilbert Strang



Thank you and Enjoy your Summer Semester!