

## Lecture 24

### Consequences of the $\perp$ Decomp Theorem!

Cor : If  $W \subset \mathbb{R}^n$  is a subspace then

$$i) \dim W + \dim W^\perp = n$$

$$ii) (W^\perp)^\perp = W$$

### 5.3 Matrix Transposes

Def : If  $A = (a_{ij})$  =  $m \times n$  matrix, then the transpose is the  $n \times m$  matrix  $A^T$  whose  $ij$ -entry is  $a_{ji}$ .

Ex  $A = \begin{bmatrix} 1 & 0 & 7 \\ -2 & 1 & 4 \end{bmatrix}, A^T = \begin{bmatrix} 1 & -2 \\ 0 & 1 \\ 7 & 4 \end{bmatrix}$

i.e. rows of  $A$  are cols of  $A^T$  and vice versa.

Why transposes :  $\vec{v}, \vec{w} \in \mathbb{R}^n \rightarrow \vec{v} \cdot \vec{w} = \vec{v}^\perp \vec{w}$

Prop : If  $A = m \times n$  matrix then  $\forall \vec{v} \in \mathbb{R}^n$  and  $\vec{w} \in \mathbb{R}^m$  we have  $\vec{v} \cdot (A\vec{w}) = (A^T\vec{v}) \cdot \vec{w}$

Proof : Observe

$$\begin{aligned} \vec{v} \cdot (A\vec{w}) &= \vec{v} (w_1 \vec{a}_1 + \dots + w_n \vec{a}_n) \\ &= w_1 (\vec{v} \cdot \vec{a}_1) + \dots + w_n (\vec{v} \cdot \vec{a}_n) \end{aligned}$$

$$= \vec{w} \cdot \begin{pmatrix} \vec{v} \cdot \vec{a}_1 \\ \vdots \\ \vec{v} \cdot \vec{a}_n \end{pmatrix} = \vec{w} \cdot (A^T \vec{v}) = (A^T \vec{v}) \cdot \vec{w} \quad \blacksquare$$

Def : A matrix  $A$  is symmetric if  $A^T = A$

Eg. Identity matrix and zero matrices are symmetric

E.g.  $\begin{bmatrix} 1 & 4 & -5 \\ 4 & 2 & 0 \\ -5 & 0 & 3 \end{bmatrix}$  is symmetric

• Symmetric implies  $n \times n$  (i.e. square)

Properties of transposes : Suppose  $A$  and  $B$  are (compatibly-sized) matrices and  $c \in \mathbb{R}$  is a scalar then:

- $(A^T)^T = A$
- $(cA)^T = cA^T$
- $(A+B)^T = A^T + B^T$
- $(AB)^T = B^T A^T$

Proof  $(AB)^T = B^T A^T$  :

• From proposition, we have  $\forall$  (compatibly-sized) vectors  $\vec{v}$  and  $\vec{w}$  that

On the one hand :  $\vec{v} \cdot [(AB)\vec{w}] = [(AB)^T \vec{v}] \cdot \vec{w}$

But On the other hand:-

$$\begin{aligned} & \vec{v} \cdot (AB\vec{w}) \\ &= \vec{v} \cdot [A(B\vec{w})] \\ &= (A^T \vec{v}) \cdot (B\vec{w}) \\ &= (B^T A^T \vec{v}) \cdot \vec{w} \\ \rightarrow & (AB)^T = B^T A^T \end{aligned}$$

Questions: If  $A, B$  are  $n \times n$  symmetric matrices :

- Is  $A+B$  symmetric? Yes
- Is  $AB$  symmetric? No

Observe:  $A = [\vec{a}_1 \dots \vec{a}_n]$  and then take  $A^T A$ , then  $A^T A$  is symmetric matrix with  
ij - entry  $= \vec{a}_i \cdot \vec{a}_j$

Ex  $A = \begin{bmatrix} 1 & 2 \\ 0 & 1 \\ 1 & 4 \end{bmatrix}$

$$A^T A = \begin{bmatrix} 1 & 0 & 1 \\ 2 & 1 & 4 \end{bmatrix} \begin{bmatrix} 1 & 2 \\ 0 & 1 \\ 1 & 4 \end{bmatrix} = \begin{bmatrix} 2 & 6 \\ 6 & 21 \end{bmatrix}$$

- So if  $\vec{a}_1, \dots, \vec{a}_n$  is ortho-normal set of vectors then  $A^T A = I$ .

Def:  $m \times n$  matrix is orthogonal if  $A^T A = I$  i.f.f. columns of  $A$  form an  $\perp$ -normal set

Ex

$$\text{rotation matrices} = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix} = \perp \text{ matrix}$$

Identity in any dimension :  $\perp$  matrix

Rmk: If  $A: n \times n$  is an  $\perp$  matrix then  $A$  is invertible and  $A^{-1} = A^T$

Questions: Are sums and products of  $\perp$  matrices also  $\perp$  matrices?

Idea:  $n \times n$   $\perp$  matrix is like an  $n$ -dimensional rotation. (or reflection)

Cor : If  $A$  is an  $m \times n$  matrix, then  $\forall \vec{v}, \vec{w} \in \mathbb{R}^n$  we have :

$$(A\vec{v}) \cdot (A\vec{w}) = \vec{v} \cdot \vec{w}$$

Proof:  $(A\vec{v}) \cdot (A\vec{w}) = (A^T A \vec{v}) \cdot \vec{w} = \vec{v} \cdot \vec{w}$  because  $A^T A = I$

Cor : If  $A$  is an  $m \times n$  orthogonal matrix and  $\vec{v}, \vec{w} \in \mathbb{R}^n$ , then

- $\|A\vec{v}\| = \|\vec{v}\|$
- $\text{angle}(A\vec{v}, A\vec{w}) = \text{angle}(\vec{v}, \vec{w})$

Prop : Suppose  $W \subset \mathbb{R}^n$  is a subspace with orthonormal basis  $\{\vec{u}_1, \dots, \vec{u}_k\}$ . Let  $Q = [\vec{u}_1 \dots \vec{u}_k]$

Then  $\forall \vec{v} \in \mathbb{R}^n$  we have :

$$\text{proj}_W(\vec{v}) = Q Q^T \vec{v}$$

i.e.  $[\text{proj}_W] = Q Q^T$