

## Lecture 10: Unitary Matrices and the SVD

- If  $A = (a_{ij})$  then  $A^T = (a_{ji})$  is the transpose of  $A$
- If  $A = (a_{ij})$  then  $A^* = (a_{ji}^*)$  is the conjugate transpose of  $A$ .
- $A$  is called symmetric if  $A^T = A$ .
- $A$  is called Hermitian if  $A^* = A$

Definition - A matrix  $A$  is called unitary if the columns of  $A$  are orthonormal with respect to the complex inner product

Example:

$$A = \begin{bmatrix} (1+i)/2 & (1-i)/2 \\ (1+i)/2 & (-1+i)/2 \end{bmatrix}$$

$$\vec{q}_1 = \begin{bmatrix} (1+i)/2 \\ (1+i)/2 \end{bmatrix}, \quad \vec{q}_2 = \begin{bmatrix} (1-i)/2 \\ (-1+i)/2 \end{bmatrix}$$

$$\Rightarrow \langle \vec{q}_1, \vec{q}_2 \rangle = (1+i)/2 \cdot (1+i)/2 + (1+i)/2 \cdot (-1-i)/2 \\ = \frac{1+i}{4} (1+i-1-i) \\ = 0$$

$$\langle \vec{q}_1, \vec{q}_1 \rangle = (1+i)/2 \cdot (1-i)/2 + (1+i)/2 \cdot (1-i)/2 \\ = \frac{1}{4} (1+1+1+1) \\ = 1$$

$$\langle \vec{q}_2, \vec{q}_2 \rangle = (1-i)/2 \cdot (1+i)/2 + (-1+i)/2 \cdot (-1-i)/2 \\ = \frac{1}{4} (1+1+1+1) \\ = 1$$

Therefore,  $\{\vec{q}_1, \vec{q}_2\}$  form an orthonormal set  $\Rightarrow A$  is unitary.

Theorem -  $A$  is unitary if and only if  $A^* = A^{-1}$ .

proof:

( $\Rightarrow$ ) If  $A$  is unitary then there exists orthonormal  $\{\vec{q}_1, \dots, \vec{q}_n\}$

such that

$$A = \left[ \vec{q}_1 \mid \dots \mid \vec{q}_n \right]$$

$$\Rightarrow A^* A = \begin{bmatrix} \vec{q}_1^* \\ \vdots \\ \vec{q}_n^* \end{bmatrix} \begin{bmatrix} \vec{q}_1 & \dots & \vec{q}_n \end{bmatrix}$$

$$= \begin{bmatrix} \vec{q}_1^* \vec{q}_1 & \vec{q}_1^* \vec{q}_2 & \dots & \vec{q}_1^* \vec{q}_n \\ \vdots & \vdots & \ddots & \vdots \\ \vec{q}_n^* \vec{q}_1 & \vec{q}_n^* \vec{q}_2 & \dots & \vec{q}_n^* \vec{q}_n \end{bmatrix}$$

$$= \begin{bmatrix} 1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & 1 \end{bmatrix} = I$$

The same is true for  $A \cdot A^*$ , i.e.,  $A \cdot A^* = I$ . Hence  $A^* = A^{-1}$ .

( $\Leftarrow$ ) If  $A^* = A^{-1}$  then if we let  $\vec{q}_i$  denote the columns of  $A$  then

$$A^* A = \begin{bmatrix} \vec{q}_1^* \\ \vdots \\ \vec{q}_n^* \end{bmatrix} \begin{bmatrix} \vec{q}_1 & \dots & \vec{q}_n \end{bmatrix}$$

Theorem - For all  $\vec{u}, \vec{v} \in \mathbb{C}^n$ ,

$$\langle \vec{u}, \vec{v} \rangle = \langle Q\vec{u}, Q\vec{v} \rangle$$

for the standard inner product.

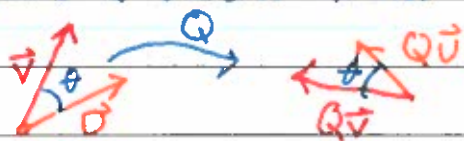
proof:

$$\langle Q\vec{u}, Q\vec{v} \rangle = (Q\vec{u})^* Q\vec{v}$$

$$= \vec{u}^* Q^* Q \vec{v}$$

$$= \vec{u}^* \vec{v} = \langle \vec{u}, \vec{v} \rangle$$

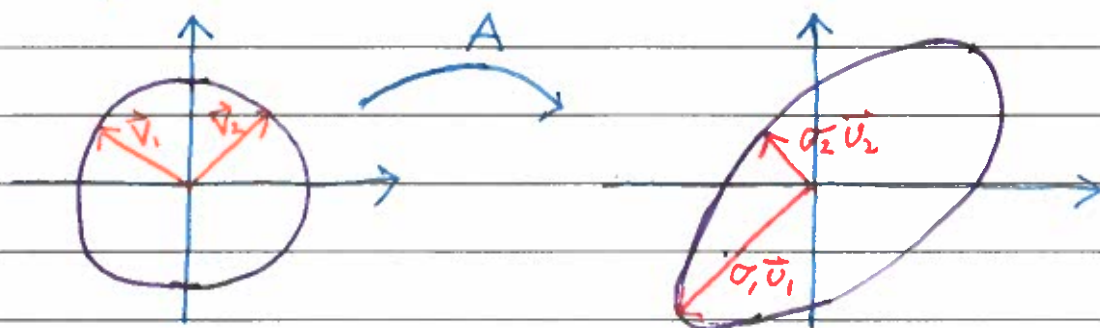
\* From this theorem it follows that angles and norms are preserved. ( $\|Q\vec{u}\| = \|\vec{u}\|$ )



## Singular Value Decomposition

- A matrix  $A \in M_{n \times n}(\mathbb{R})$  rotates and stretches vectors.

$\Rightarrow$  To figure out a matrix we can operate on the unit sphere in  $\mathbb{R}^n$



$$\Rightarrow \begin{matrix} [A] \\ A \end{matrix} \begin{matrix} [\vec{v}_1 | \dots | \vec{v}_n] \\ V \end{matrix} = \begin{matrix} [\sigma_1 | \dots | \sigma_n] \\ U \end{matrix} \begin{matrix} \begin{bmatrix} \sigma_1 & & 0 \\ & \ddots & \\ 0 & & \sigma_n \end{bmatrix} \\ \Sigma \end{matrix}$$

$$\Rightarrow \boxed{A = U \Sigma V^*} \rightarrow \text{SVD}$$

Theorem - Every matrix has an SVD and the singular values  $\sigma_1, \dots, \sigma_n$  are unique.

## Finding the SVD

$$\begin{aligned} - A^* A &= V \Sigma U^* U \Sigma V^* \\ &= V \Sigma^2 V^* \end{aligned}$$

$\Rightarrow \vec{v}_1, \dots, \vec{v}_n$  are eigenvectors of  $A^* A$

$\Rightarrow \sigma_1^2, \dots, \sigma_n^2$  are eigenvalues of  $A^* A$

$\Rightarrow \vec{u}_1 = A \vec{v}_1, \dots, \vec{u}_n = A \vec{v}_n$