

MATH 430  
Advanced Linear Algebra

Session 36

# Singular Value Decomposition

So far: diagonalization of square matrices

•  $A \in M_{\mathbb{R}}^{n \times n}$  has  $n$  l.i. e-vectors  $\Rightarrow$

$A$  is diagonalizable.

$$Q = \begin{bmatrix} | & & | \\ v_1 & \dots & v_n \\ | & & | \end{bmatrix}$$

$$Q^{-1} A Q = \overset{D}{\begin{bmatrix} \lambda_1 & & \\ & \lambda_2 & \\ & & \dots & \\ & & & \lambda_n \end{bmatrix}}$$

$$A = Q D Q^{-1}$$

•  $A$  is self-adjoint or normal then

$$Q^* A Q = \overset{D}{\begin{bmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_n \end{bmatrix}}$$

$$A = Q D Q^*$$

$$Q^{-1} = Q^*$$

$Q$  - unitary

$A$  is similar to  $D$  (diagonal)

What if  $A \in M_{m \times n}$  where  $m \neq n$ ?

Can we find a decomposition of  $A$  into simpler matrices? Desire: use unitary matrices and diagonal matrices.

Let  $A_{m \times n}$  have rank  $= r$ ;  $r \leq \min(m, n)$

Singular Value Decomposition: A factorization

$$A_{m \times n} = U_{m \times m} \Sigma_{m \times n} V_{n \times n}^*$$

where  $U$  &  $V$  are unitary and  $\Sigma$  where  $\Sigma_{ij} = \begin{cases} \sigma_i & i = j \leq r \\ 0 & \text{otherwise} \end{cases}$

is called a singular value decomposition of  $A$ . SVD

Remark:  $U = V \Rightarrow A$  is self adjoint (real field)  
 or  $A$  is normal (complex field)

$$r < m < n : \quad [A]_{m \times n} = \begin{bmatrix} \overbrace{\sigma_1 \ \sigma_2 \ \dots \ \sigma_r}^{r} & & \\ & \underbrace{\hspace{10em}}_{m-r} & \\ & & \underbrace{\hspace{10em}}_{(n-r)} \end{bmatrix}_{m \times n}$$

$$r = n < m \quad [A]_{m \times n} = \begin{bmatrix} \sigma_1 & & & \\ \sigma_2 & & & \\ \vdots & \ddots & & \\ 0 & \dots & \sigma_r & \\ \vdots & \dots & \vdots & \\ 0 & \dots & 0 & \dots & 0 \end{bmatrix}$$

$\leftarrow n \quad \leftarrow n \quad \leftarrow m-r$

Theorem 6.26/6.27

The singular value decomposition exists for any matrix  $A \in M_{m \times n}$ .

Let  $A \in M_{m \times n}$ . Consider  $A^* A$ .

Note that  $A^* A$  is self-adjoint.

$$(A^* A)^* = A^* (A^*)^* = A^* A^*$$

Suppose we have the SVD:  $A = U \Sigma V^*$

$$U^* U = I$$

$$A^* A = (U \Sigma V^*)^* (U \Sigma V^*) = (V \Sigma^* U^*) (U \Sigma V^*)$$

$$A^* A = V \Sigma^* \Sigma V^* \rightarrow \text{diagonal}$$

$$\sum_{\substack{* \\ n \times m}} \sum_{\substack{m \times n \\ \text{matrix } W}} =$$

Assume  $\text{rank}(A) = r$

$$\left[ \begin{array}{ccc} \sigma_1 & & \\ & \sigma_2 & \\ & & \dots \\ & & & \sigma_r \\ & & & & 0 \dots 0 \end{array} \right]_{n \times n}$$

$$= \left[ \begin{array}{ccc} |\sigma_1|^2 & & \\ & |\sigma_2|^2 & \\ & & \dots \\ & & & |\sigma_r|^2 \\ & & & & 0 \dots 0 \end{array} \right]$$

Diagonal ←

$A^*A$  is diagonalizable by the unitary matrix  $V$ .

$$A^* A = V \left( \sum^* \sum^* \right) V^* = V D V^*$$

↘ diagonal

$\Rightarrow \sum^* \sum$  contains the e-values of  $A^* A$ .

Note that the e-values of  $A^* A$  are the squares (for real field) of the singular values of  $A$ .

What is  $V$  made up of?

The columns of  $V$  will be the orthonormal e-vectors of  $A^* A$ .

Example

Find the SVD of  $A = \begin{bmatrix} 1 & 1 & -1 \\ 1 & 1 & -1 \end{bmatrix}_{2 \times 3}$

$\text{rank}(A) = 1$

$A^*A = \begin{bmatrix} 1 & 1 & -1 \\ -1 & 1 & -1 \end{bmatrix} \begin{bmatrix} 1 & 1 & -1 \\ 1 & 1 & -1 \end{bmatrix} =$

$\begin{bmatrix} 2 & 2 & -2 \\ -2 & 2 & -2 \end{bmatrix}$

E-values of  $A^*A$  :  $\lambda_1 = 6, \lambda_2 = \lambda_3 = 0$

Singular values of  $A$  :  $\sigma_1 = \sqrt{6}$

$\Sigma_{2 \times 3} = \begin{bmatrix} \sqrt{6} & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$

Orthonormal e-vectors

$$V_1 = \begin{bmatrix} 1/\sqrt{3} \\ 1/\sqrt{3} \\ -1/\sqrt{3} \end{bmatrix}$$

$$\lambda_1 = 6$$

$$V_2 = \begin{bmatrix} 1/\sqrt{2} \\ -1/\sqrt{2} \\ 0 \end{bmatrix}$$

$$\lambda_2 = 0$$

$$V_3 = \begin{bmatrix} 1/\sqrt{6} \\ 1/\sqrt{6} \\ 2/\sqrt{6} \end{bmatrix}$$

$$\lambda_3 = 0$$

of  $A^* A$ :

$$A = \begin{bmatrix} u_{11} & u_{12} \\ u_{21} & u_{22} \\ u_{31} & u_{32} \end{bmatrix}$$

$$u = \begin{bmatrix} u_1 & u_2 \\ 1 & 1 \end{bmatrix}$$

$u = ?$   $u$  satisfies

$$A^* V = U \Sigma^* V$$

$$A V = U \Sigma$$

$$\Rightarrow A v_i = u_i \sigma_i \quad \sigma_i \neq 0$$

$$\Rightarrow u_i = \frac{1}{\sigma_i} A v_i$$

$$V = \begin{bmatrix} 1 & 1 & 1 \\ v_1 & v_2 & v_3 \\ 1 & 1 & 1 \end{bmatrix}$$

$$u_1 = \frac{1}{\sqrt{6}} \begin{bmatrix} 1 & 1 & -1 \\ 1 & 1 & -1 \\ -1 & 1 & -1 \end{bmatrix} \begin{bmatrix} 1/\sqrt{3} \\ 1/\sqrt{3} \\ -1/\sqrt{3} \end{bmatrix}$$

$$= \begin{bmatrix} 1/\sqrt{2} \\ 1/\sqrt{2} \end{bmatrix}$$

$$U = \begin{bmatrix} u_1 & u_2 \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & 1 \end{bmatrix} \quad ?$$

Extend  $\begin{bmatrix} \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \end{bmatrix}$  to an ONB of  $\mathbb{R}^2$   
 $u_1 \rightarrow \begin{bmatrix} \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \end{bmatrix}$

Can take  $u_2 = \begin{bmatrix} \frac{1}{\sqrt{2}} \\ -\frac{1}{\sqrt{2}} \end{bmatrix}$  Check  $\langle u_1, u_2 \rangle = 0$

Then  $U \Sigma U^* = A$