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EECS 16B  
Spring 2022  
Lecture 20  
3/31/2022 ✓

## LECTURE 20 : SVD

Given  $A \in \mathbb{R}^{m \times n}$  with rank =  $r$ , "outer product" form of SVD:

$$A = \sigma_1 \vec{u}_1 \vec{v}_1^\top + \dots + \sigma_r \vec{u}_r \vec{v}_r^\top = \sum_{i=1}^r \sigma_i \vec{u}_i \vec{v}_i^\top \quad (1)$$

where:

- $\vec{u}_1, \dots, \vec{u}_r$  are orthonormal in  $\mathbb{R}^m$
- $\vec{v}_1, \dots, \vec{v}_r$  " " " in  $\mathbb{R}^n$
- $\sigma_1 \geq \dots \geq \sigma_r$  are positive, real numbers.

Equivalently,

$$A = [\vec{u}_1 \dots \vec{u}_r] \begin{bmatrix} \sigma_1 & & \\ & \ddots & \\ & & \sigma_r \end{bmatrix} [\vec{v}_1^\top \dots \vec{v}_r^\top]^\top \quad \text{-- (2)}$$

$\underbrace{\vec{U}_r}_{m \times r, \text{ orthonormal columns}}$   
 $\vec{V}_r^\top : n \times r, \text{ orthonormal columns}$

look at  $(j, k)$  element:

$$A(j, k) = \sum_{i=1}^r \underbrace{U_r(j, i)}_{(\vec{u}_i)_j} \sigma_i \underbrace{V_r^\top(i, k)}_{= V_r(k, i)} \quad \text{from matrix multiplication}$$

since  $i$ th column  
 of  $U_r$  is  $\vec{u}_i$   $\doteq (\vec{v}_i)_k$

$$= \sum_{i=1}^r \sigma_i (\vec{u}_i)_j (\vec{v}_i)_k$$

$\left\{ \begin{array}{l} \text{this matches} \\ (j, k) \text{ entry} \\ \text{in (1); therefore} \\ (1) \text{ and (2)} \\ \text{are equivalent} \end{array} \right.$

Example 1:  $A = \begin{bmatrix} 4 & 4 \\ 3 & 3 \end{bmatrix}$   $r=1$

$$= \begin{bmatrix} 4 \\ 3 \end{bmatrix} [1 \ 1]$$

$$= 5\sqrt{2} \underbrace{\left(\frac{1}{5}\begin{bmatrix} 4 \\ 3 \end{bmatrix}\right)}_{\sigma_1} \underbrace{\left(\frac{1}{\sqrt{2}}\begin{bmatrix} 1 & 1 \end{bmatrix}\right)}_{\vec{U}_1^T}$$

If we change the signs of  $\vec{u}_1$  and  $\vec{v}_1$  simultaneously, length and outer product are the same  $\Rightarrow$  another SVD  
 $\Rightarrow$  SVD not unique!

How do we find a SVD in general? Will give a procedure to find SVD of  $A \in \mathbb{R}^{m \times n}$  from the evals/evecs of  $A^T A \in \mathbb{R}^{n \times n}$ .

Some facts about  $A^T A$ :

Claim 1:  $A^T A$  has real evals/evecs  $(\lambda_i, \vec{v}_i)$ ,  $i=1, \dots, n$ .

Proof from Spectral Thm because  $A^T A$  is symmetric:

$$(A^T A)^T = A^T (A^T)^T = A^T A.$$

Claim 2: Eval of  $A^T A$  are nonnegative.

Proof:  $A^T A \vec{v}_i = \lambda_i \vec{v}_i$

Multiply both sides from left by  $\vec{v}_i^T$ :

$$\vec{v}_i^T A^T A \vec{v}_i = \lambda_i \underbrace{\vec{v}_i^T \vec{v}_i}_{\|\vec{v}_i\|^2} \underbrace{(A \vec{v}_i)^T (A \vec{v}_i)}_{\|A \vec{v}_i\|^2} \Rightarrow \lambda_i = \frac{\|A \vec{v}_i\|^2}{\|\vec{v}_i\|^2} \geq 0$$

Claim 3: If  $\text{rank}(A) = r$ , then  $r$  eigenvalues of  $A^T A$  are strictly positive.

Proof: First note that null spaces of  $A$  and  $A^T A$  are the same:  $N(A) = N(A^T A)$  because

$$(i) \quad N(A) \subseteq N(A^T A)$$

$$A\vec{v} = 0 \Rightarrow A^T \underbrace{A\vec{v}}_{=0} = 0$$

$$(ii) \quad N(A^T A) \subseteq N(A)$$

$$A^T A \vec{v} = 0 \Rightarrow \underbrace{\vec{v}^T A^T A \vec{v}}_{\substack{\text{multiply} \\ \text{from left} \\ \text{by } \vec{v}^T}} = (A\vec{v})^T (A\vec{v}) = \|A\vec{v}\|^2 = 0$$

$$\|A\vec{v}\| = 0$$

$$\text{From (i) and (ii): } N(A) = N(A^T A).$$

$$A\vec{v} = 0$$

$$\text{Rank}(A) = r \Rightarrow \dim N(A) = n-r = \dim N(A^T A)$$

$$A \in \mathbb{R}^{m \times n}$$

$\uparrow$   
is A,  
Rank/Nullity  
Thm

$A^T A$  is  $n \times n$ , has  $n-r$  dim. null space.

Elements of  $N(A^T A)$  are eigenvectors of  $A^T A$  (for eigenvalue = 0, repeated  $n-r$  times).

Claim 2 said  $n, \geq 0$  eigenvalues.  $n-r$  of them are = 0.  
 $\Rightarrow$  remaining  $r$  eigenvalues of  $A^T A$  are strictly positive.

SVD Procedure for  $A \in \mathbb{R}^{m \times n}$ ,  $\text{rank}=r$  (using  $A^T A$ ):

Step 1) Find orthogonal matrix  $V$  diagonalizing  $A^T A$ :  
(exists by Spectral Thm)

$$V^T (A^T A) V = \begin{bmatrix} \lambda_1 & & & & 0 \\ & \ddots & & & \\ & & \lambda_r & & \\ 0 & & & \ddots & \\ 0 & & & & 0 \end{bmatrix}_{n-r}$$

$\lambda_1, \dots, \lambda_r$   
are eigenvalues  
of  $A^T A$

and make sure to put evals in decreasing order:

$$\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_r > 0.$$

Step 2) For  $i=1, \dots, r$ , pick  $i$ th column  $\vec{V}_i$  of  $V$  (which is eigenvector of  $A^T A$  for eval  $\lambda_i$ ) and let

$$\sigma_i = \sqrt{\lambda_i}, \quad \vec{U}_i = \frac{1}{\sigma_i} A \vec{V}_i.$$

↳ singular value of  $A$  are square roots of eigenvalues of  $A^T A$

Example 2:  $A = \begin{bmatrix} 4 & 4 \\ -3 & 3 \end{bmatrix} \quad r=2$

$$A^T A = \begin{bmatrix} 4 & -3 \\ 4 & 3 \end{bmatrix} \begin{bmatrix} 4 & 4 \\ -3 & 3 \end{bmatrix} = \begin{bmatrix} 25 & 7 \\ 7 & 25 \end{bmatrix}$$

$$2I - A^T A = \begin{bmatrix} 2-25 & -7 \\ -7 & 2-25 \end{bmatrix} \rightarrow \det = (2-25)^2 - 7^2 = 0$$

$$2-25 = -7$$

$$\lambda_{1,2} = 25 \pm 7$$

$$\lambda_1 = 32 \quad \lambda_1 I - A^T A = \begin{bmatrix} 7 & -7 \\ -7 & 7 \end{bmatrix} \quad \vec{V}_1 = \frac{1}{\sqrt{12}} \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

$$\lambda_2 = 18 \quad \lambda_2 I - A^T A = \begin{bmatrix} -7 & -7 \\ -7 & -7 \end{bmatrix} \quad \vec{V}_2 = \frac{1}{\sqrt{12}} \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

Step 2:

$$\sigma_1 = \sqrt{\lambda_1} = \sqrt{32} = 4\sqrt{2} \quad \vec{U}_1 = \frac{1}{\sigma_1} A \vec{V}_1 = \frac{1}{4\sqrt{2}} \frac{1}{\sqrt{2}} \begin{bmatrix} 8 \\ 0 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

$$\sigma_2 = \sqrt{\lambda_2} = \sqrt{18} = 3\sqrt{2} \quad \vec{U}_2 = \frac{1}{\sigma_2} A \vec{V}_2 = \frac{1}{3\sqrt{2}} \frac{1}{\sqrt{2}} \begin{bmatrix} 0 \\ -6 \end{bmatrix}$$

$$= \begin{bmatrix} 0 \\ -1 \end{bmatrix}$$

$$A = 4\sqrt{2} \underbrace{\begin{bmatrix} 1 \\ 0 \end{bmatrix}}_{\sigma_1} \underbrace{\frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \end{bmatrix}}_{\vec{U}_1^T} + 3\sqrt{2} \underbrace{\begin{bmatrix} 0 \\ -1 \end{bmatrix}}_{\sigma_2} \underbrace{\frac{1}{\sqrt{2}} \begin{bmatrix} 1 & -1 \end{bmatrix}}_{\vec{U}_2^T}$$

Justification of the Procedure: Do  $\vec{U}_i, \vec{U}_j, \sigma_i$  resulting from procedure satisfy the following?

- $\sum_{i=1}^r \sigma_i \vec{U}_i \vec{U}_i^T = A$
- $\vec{U}_1, \dots, \vec{U}_r$  orthonormal
- $\vec{U}_1, \dots, \vec{U}_r$  " → true by Step 1 of procedure
- $\sigma_1, \dots, \sigma_r$  real and positive → true by Step 2:  $\sigma_i = \sqrt{\lambda_i}$

$$\vec{U}_i^T \vec{U}_j = \left( \frac{1}{\sigma_i} A \vec{V}_i \right)^T \left( \frac{1}{\sigma_j} A \vec{V}_j \right) = \frac{1}{\sigma_i \sigma_j} \underbrace{\vec{V}_i^T A^T A \vec{V}_j}_{= \lambda_j \vec{V}_j} = \lambda_j$$

$$= \frac{\lambda_j}{\sigma_i \sigma_j} \underbrace{\vec{V}_i^T \vec{V}_j}_{= \begin{cases} 0 & i \neq j \\ 1 & i=j \end{cases}} = \begin{cases} 0 & i \neq j \\ \frac{\lambda_j}{\sigma_i \sigma_j} & i=j \end{cases}$$

$$\vec{U}_i^T \vec{U}_j = \begin{cases} 0 & i \neq j \\ \frac{\lambda_j}{\sigma_i^2} & i=j \end{cases}$$

First bullet:

$$\sum_{i=1}^r \sigma_i \vec{u}_i \vec{v}_i^\top = A$$

?

Note:  $\vec{u}_i \vec{v}_i^\top = \underbrace{\left( \frac{1}{\sigma_i} A \vec{v}_i \right)}_{\vec{u}_i \text{ by Step 2}} \vec{v}_i^\top = \frac{1}{\sigma_i} A \vec{v}_i \vec{v}_i^\top$

Therefore,

$$\sum_{i=1}^r \sigma_i \vec{u}_i \vec{v}_i^\top = \sum_{i=1}^r A \vec{v}_i \vec{v}_i^\top = A \sum_{i=1}^r \vec{v}_i \vec{v}_i^\top \quad \text{-- (3)}$$

Recall  $V$  orthogonal  $V^\top V = VV^\top = I$

$$\underbrace{[\vec{v}_1 \dots \vec{v}_n]}_{\sum_{i=1}^r \vec{v}_i \vec{v}_i^\top} \underbrace{[\vec{v}_1^\top \dots \vec{v}_n^\top]}_{V^\top}$$

$$\sum_{i=1}^r \vec{v}_i \vec{v}_i^\top = I$$

$$\Rightarrow A \sum_{i=1}^r \vec{v}_i \vec{v}_i^\top = A \quad \text{-- (4)}$$

Note, for  $i > r$ ,  $\vec{v}_i$  eigenvector of  $A^\top A$  corresponding to a zero eigenvalue:

$$A \vec{v}_i = 0 \Rightarrow A \sum_{i=r+1, \dots, n} \vec{v}_i \vec{v}_i^\top = 0$$

multiply from right by  $V^\top$

$$\sum_{i=r+1, \dots, n} \vec{v}_i \vec{v}_i^\top = 0$$

$$\Rightarrow \sum_{i=r+1}^n A \vec{v}_i \vec{v}_i^\top = 0 \Rightarrow A \sum_{i=r+1}^n \vec{v}_i \vec{v}_i^\top = 0 \quad \text{-- (5)}$$

Subtract (5) from (4):  $A \sum_{i=1}^r \vec{v}_i \vec{v}_i^\top = A \quad \text{-- (6)}$

and substitute (6) in (3):  $\sum_{i=1}^r \sigma_i \vec{u}_i \vec{v}_i^\top = A$ .