

Recall: every real  $m \times n$  matrix  $A$  has a singular value decomposition (SVD):

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

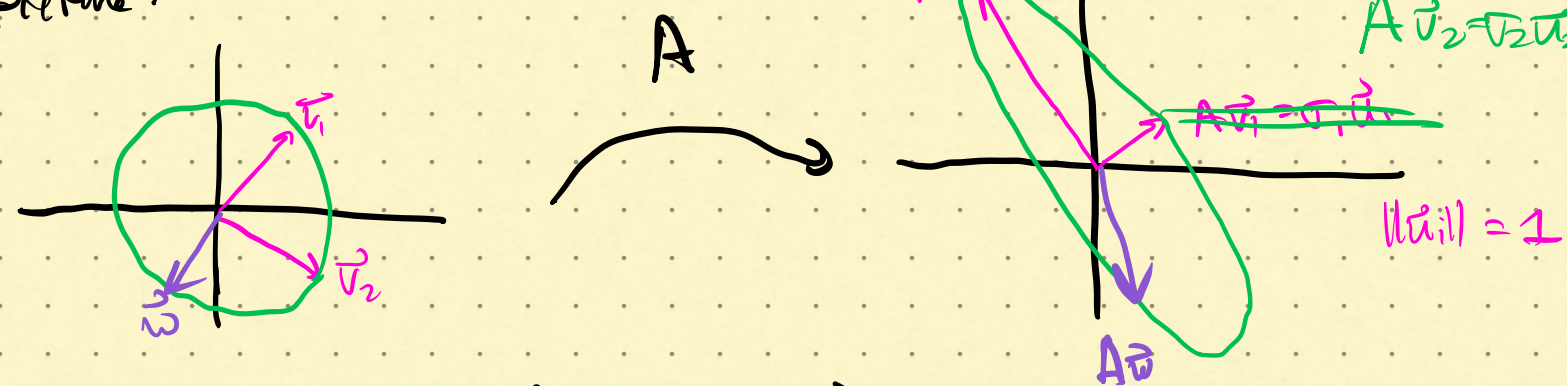
$m \times n$   $\swarrow$   $\nearrow$   $m \times m$   $\swarrow$   $\nearrow$   $n \times n$   
 orthogonal  $m \times m$   $\swarrow$   $\nearrow$   $n \times n$   
 "almost" diagonal

$$\Sigma = \begin{bmatrix} \sigma_1 & & & \\ & \sigma_2 & & \\ & & \ddots & \\ & & & \sigma_m \\ & & & & 0 \dots 0 \end{bmatrix} \quad (n \leq m)$$

OR  $\Sigma = \begin{bmatrix} \sigma_1 & & & 0 & \dots & 0 \\ & \ddots & & & & \\ & & \sigma_m & & & \\ & & & 0 & \dots & 0 \end{bmatrix}$   
 $(m \leq n)$   
 $\sigma_1 \geq \sigma_2 \geq \dots \geq 0$   
 "singular values"

For simplicity, let's assume  $n \leq m$

Pictorial:



Let's prove that  $A \vec{v}_i = \sigma_i \vec{u}_i$ :

$$A = U \Sigma V^T \rightsquigarrow AV = U \Sigma \underbrace{V^T V}_{= I_n}$$

$$\rightsquigarrow A [\vec{v}_1, \dots, \vec{v}_n] = [\vec{u}_1, \dots, \vec{u}_m] \begin{bmatrix} \sigma_1 & & & \\ & \ddots & & \\ & & \sigma_m & \\ & & & 0 \dots 0 \end{bmatrix} = [\sigma_1 \vec{u}_1, \dots, \sigma_n \vec{u}_n]$$

$$\Rightarrow A \vec{v}_i = \sigma_i \vec{u}_i \text{ for all } i$$

Note: From the picture, we can tell how  $A$  affects lengths. I.e. if  $\|\vec{w}\|=1$ ,  $\sigma_2 \leq \|A\vec{w}\| \leq \sigma_1$   
 In general, if  $\vec{w} \in \mathbb{R}^n$  with  $\|\vec{w}\|=1$ , then  $\sigma_n \leq \|A\vec{w}\| \leq \sigma_1$

Pf Given SVD  $A = U \Sigma U^T$   $U = [\vec{u}_1, \dots, \vec{u}_m]$

$V = [\vec{v}_1, \dots, \vec{v}_n]$

Note: the  $\vec{v}_i$  are a basis of  $\mathbb{R}^n$  ( $V$  is invertible)

$\rightarrow$  we can write  $\vec{w} = c_1 \vec{v}_1 + \dots + c_n \vec{v}_n$

The fact that  $\|\vec{w}\|=1$  will put a restriction on the  $c_i$ :

$$1 = \|\vec{w}\| = \sqrt{\vec{w} \cdot \vec{w}} = \sqrt{(c_1 \vec{v}_1 + \dots + c_n \vec{v}_n) \cdot (c_1 \vec{v}_1 + \dots + c_n \vec{v}_n)}$$

$$= \sqrt{c_1 \vec{v}_1 \cdot c_1 \vec{v}_1 + c_2 \vec{v}_2 \cdot c_2 \vec{v}_2 + \dots}$$

$c_1^2 \underbrace{\vec{v}_1 \cdot \vec{v}_1}_1 + c_2^2 \underbrace{\vec{v}_2 \cdot \vec{v}_2}_1 + \dots$

$\vec{v}_i$  are an ONB



$$= \sqrt{c_1^2 + c_2^2 + \dots + c_n^2}$$

OTOH,  $A \vec{w} = c_1 A \vec{v}_1 + \dots + c_n A \vec{v}_n$   
 $= c_1 \sigma_1 \vec{u}_1 + \dots + c_n \sigma_n \vec{u}_n$

$$\|A \vec{w}\| = \sqrt{(c_1 \sigma_1 \vec{u}_1 + \dots + c_n \sigma_n \vec{u}_n) \cdot (c_1 \sigma_1 \vec{u}_1 + \dots + c_n \sigma_n \vec{u}_n)}$$

$\sigma_n \leq$

$\vec{u}_i$  are an ONB

$$= \sqrt{c_1^2 \sigma_1^2 + \dots + c_n^2 \sigma_n^2}$$

$\leq \sigma_1$

we know  $\sigma_i^2 \leq \sigma_1^2$

1

$$\Rightarrow \|A \vec{w}\| \leq \sqrt{c_1^2 \sigma_1^2 + c_2^2 \sigma_1^2 + \dots + c_n^2 \sigma_1^2} = \sigma_1 \sqrt{c_1^2 + \dots + c_n^2} = \sigma_1$$

Similarly,  $\sigma_n \leq \|A\|$ .

Computing SVD: Given  $A$ , how do we actually

find  $U, \Sigma, V$ ?

$$\text{Given } A = U \Sigma V^T \rightsquigarrow A^T A = V \Sigma^T \Sigma V^T \\ = V \begin{bmatrix} \sigma_1^2 & & \\ & \ddots & \\ & & \sigma_n^2 \end{bmatrix} V^T$$

diagonalization of  $A^T A$ !

$\Rightarrow$  cols of  $V$  are eigenvectors of  $A^T A$ . Eigenvalues of  $A^T A$  are  $\sigma_1^2, \dots, \sigma_n^2$ .

Exc Find SVD of  $A = \begin{bmatrix} 2 & 3 \\ 0 & 2 \end{bmatrix}$  (or at least  $\Sigma, V$ ).  
(Feel free to use a calc. to find eigenvectors)

Ans:  $A^T A = \begin{bmatrix} 4 & 6 \\ 6 & 13 \end{bmatrix}$ .

eigenvectors:  $\begin{bmatrix} -2 \\ 1 \end{bmatrix}, \lambda = 1$ ;  $\begin{bmatrix} 1 \\ 2 \end{bmatrix}, \lambda = 16$

$$\sigma_1 = \sqrt{16} = 4, \quad \sigma_2 = 1$$

$$\vec{v}_1 = \frac{1}{\sqrt{5}} \begin{bmatrix} 1 \\ 2 \end{bmatrix}$$

$$\vec{v}_2 = \frac{1}{\sqrt{5}} \begin{bmatrix} -2 \\ 1 \end{bmatrix}$$

$$\text{so } V = \frac{1}{\sqrt{5}} \begin{bmatrix} 1 & -2 \\ 2 & 1 \end{bmatrix}$$

need  $V$  to be orthonormal!

To find  $\vec{u}_i$ :

$$A \vec{v}_i = \sigma_i \vec{u}_i$$

$$\begin{bmatrix} 2 & 3 \\ 0 & 2 \end{bmatrix} \cdot \frac{1}{\sqrt{5}} \begin{bmatrix} 1 \\ 2 \end{bmatrix} = 4 \cdot \vec{u}_1$$

$$\begin{bmatrix} 8/\sqrt{5} \\ 4/\sqrt{5} \end{bmatrix}$$

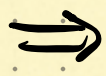


$$\vec{u}_1 = \begin{bmatrix} 2/\sqrt{5} \\ 1/\sqrt{5} \end{bmatrix}$$

Similarly,

$$A\vec{v}_2 = \sigma_2$$

$$\vec{u}_2$$



$$\vec{u}_2 = \begin{bmatrix} -1/\sqrt{5} \\ 2/\sqrt{5} \end{bmatrix}$$