

# LECTURE 3

## SINGULAR VALUE DECOMPOSITION (SVD)

Every matrix  $A \in \mathbb{C}^{n \times n}$  has an SVD of the form

$$\text{where } A = U \Sigma V^*$$

$U, V \in \mathbb{C}^{n \times n}$  are unitary matrices  
 $\Sigma$  is a diagonal matrix with nonnegative real entries along the diagonal.

( If  $A$  is real, SVD is of the form  
 $A = U \Sigma V^T$   
where  $U, V \in \mathbb{R}^{n \times n}$  are orthogonal. )

### EXAMPLE

$$\begin{bmatrix} 0.2 & 3.6 \\ 3.4 & 1.2 \end{bmatrix} = \underbrace{\begin{bmatrix} 1/\sqrt{2} & 1/\sqrt{2} \\ 1/\sqrt{2} & -1/\sqrt{2} \end{bmatrix}}_U \underbrace{\begin{bmatrix} 3\sqrt{2} & 0 \\ 0 & 2\sqrt{2} \end{bmatrix}}_\Sigma \underbrace{\begin{bmatrix} 0.6 & 0.8 \\ -0.8 & 0.6 \end{bmatrix}}_{V^T}$$

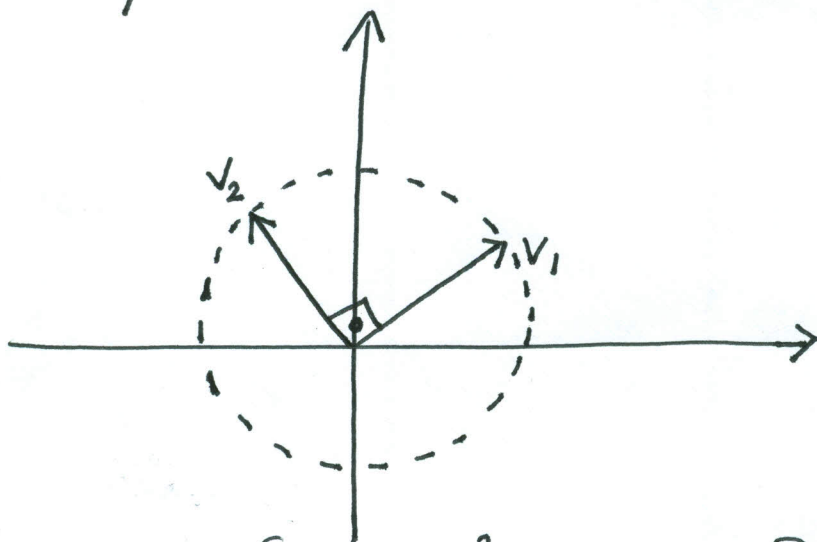
(Note that  $U^T U = V^T V = I$ )

Consider the SVD for a  $2 \times 2$  real matrix

$$A = \underbrace{\begin{bmatrix} u_1 & u_2 \end{bmatrix}}_U \underbrace{\begin{bmatrix} \sigma_1 & 0 \\ 0 & \sigma_2 \end{bmatrix}}_\Sigma \underbrace{\begin{bmatrix} v_1^T \\ v_2^T \end{bmatrix}}_V^T$$

$$u_1, u_2, v_1, v_2 \in \mathbb{R}^n \quad \text{s.t.} \quad u_1 \perp u_2 \quad \text{and} \quad v_1 \perp v_2 \\ \|v_1\|_2 = \|u_1\|_2 = \|u_2\|_2 = \|v_2\|_2 = 1$$

Set of unit vectors in  $\mathbb{R}^2$  (Unit Circle)



Note

$$\| \alpha_1 v_1 + \alpha_2 v_2 \|_2 = 1$$

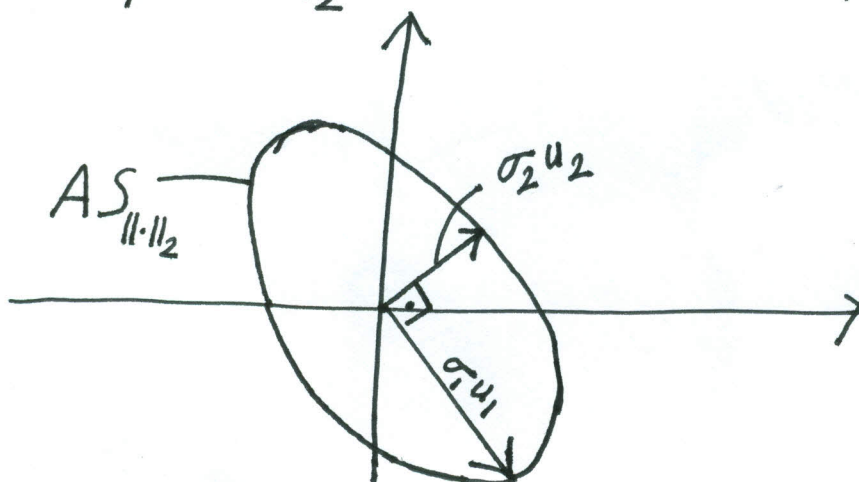
$$\iff \sqrt{\alpha_1^2 + \alpha_2^2} = 1$$

$$S_{\|\cdot\|_2} = \{ v \in \mathbb{R}^2 : \|v\|_2 = 1 \}$$

~~$$= \{ v \in \mathbb{R}^2 : \alpha_1 v_1 + \alpha_2 v_2 = 1 \}$$~~

$$= \{ \alpha_1 v_1 + \alpha_2 v_2 \in \mathbb{R}^2 : \alpha_1, \alpha_2 \in \mathbb{R} \text{ s.t. } \| \alpha_1 v_1 + \alpha_2 v_2 \|_2 = 1 \}$$

Image of  $S_{\|\cdot\|_2}$  under the transformation



$$x \rightarrow Ax$$

Note that

$$Av_1 = \sigma_1 u_1$$

$$Av_2 = \sigma_2 u_2$$

$$A(\alpha_1 v_1 + \alpha_2 v_2) = \alpha_1 A v_1 + \alpha_2 A v_2 \\ = \alpha_1 \sigma_1 v_1 + \alpha_2 \sigma_2 v_2$$

i.e.

$$A S_{\|\cdot\|_2} = \{A v \in \mathbb{R}^2 : \|v\|_2 = 1\} \\ = \{A(\alpha_1 v_1 + \alpha_2 v_2) \in \mathbb{R}^2 : \|\alpha_1 v_1 + \alpha_2 v_2\|_2 = 1\} \\ = \{\alpha_1 (\sigma_1 u_1) + \alpha_2 (\sigma_2 u_2) \in \mathbb{R}^2 : \|\alpha_1 v_1 + \alpha_2 v_2\|_2 = 1\}$$

In  $\mathbb{R}^2$   
 $(S_{\|\cdot\|_2})$  Unit Circle with axes  $v_1, v_2$   $\xrightarrow{A \in \mathbb{R}^{2 \times 2}}$  Ellipse with  $(A S_{\|\cdot\|_2})$  semi-axes  $\sigma_1 u_1, \sigma_2 u_2$

In  $\mathbb{C}^n$   
 Unit  $n$ -Sphere with axes  $v_1, v_2, \dots, v_n$   $\xrightarrow{A \in \mathbb{C}^{n \times n}}$  Ellipsoid with semi-axes  $\sigma_1 u_1, \dots, \sigma_n u_n$

### DEFINITION OF SINGULAR VALUES AND VECTORS

SVD for a  $2 \times 2$  matrix

$$A = \underbrace{\begin{bmatrix} u_1 & u_2 \end{bmatrix}}_U \underbrace{\begin{bmatrix} \sigma_1 & 0 \\ 0 & \sigma_2 \end{bmatrix}}_\Sigma \underbrace{\begin{bmatrix} v_1^* \\ v_2^* \end{bmatrix}}_{V^*}$$

$\iff$

$$A \begin{bmatrix} v_1 & v_2 \end{bmatrix} = \begin{bmatrix} u_1 & u_2 \end{bmatrix} \begin{bmatrix} \sigma_1 & 0 \\ 0 & \sigma_2 \end{bmatrix} \text{ and } \begin{bmatrix} u_1^* \\ u_2^* \end{bmatrix} A = \begin{bmatrix} \sigma_1 & 0 \\ 0 & \sigma_2 \end{bmatrix} \begin{bmatrix} v_1^* \\ v_2^* \end{bmatrix} \quad (3)$$



$$(1) \quad A v_1 = \sigma_1 u_1 \quad \longleftrightarrow \quad u_1^* A = \sigma_1 v_1^*$$

and

$$(2) \quad A v_2 = \sigma_2 u_2 \quad u_2^* A = \sigma_2 v_2^*$$

$\sigma_1, \sigma_2$  are called singular values

$u_1, u_2$  are called the associated left singular vectors

$v_1, v_2$  are called the associated right singular vectors

DEFN (Singular Values and Vectors)

Suppose that the equations

$$A v_i = \sigma_i u_i \quad \text{and} \quad u_i^* A = \sigma_i v_i^*$$

hold for some  $u_i, v_i \in \mathbb{C}^n$  and  $\sigma_i \geq 0$ .

Then

(i)  $\sigma_i$  is called a singular value of  $A$

(ii)  $u_i, v_i$  are called the left and right singular vectors associated with  $\sigma_i$ , respectively.

e.g.

$$\begin{bmatrix} 0.2 & 3.6 \\ 3.4 & 1.2 \end{bmatrix} \underbrace{\begin{bmatrix} 0.6 \\ 0.8 \end{bmatrix}}_{v_1} = \underbrace{3\sqrt{2}}_{\sigma_1} \underbrace{\begin{bmatrix} 1/\sqrt{2} \\ 1/\sqrt{2} \end{bmatrix}}_{u_1}$$

$$\begin{bmatrix} 1/\sqrt{2} & 1/\sqrt{2} \end{bmatrix} \begin{bmatrix} 0.2 & 3.6 \\ 3.4 & 1.2 \end{bmatrix} = 3\sqrt{2} \begin{bmatrix} 0.6 & 0.8 \end{bmatrix}$$

$\sigma_1$  is called a singular value

$u_1 = \begin{bmatrix} 1/\sqrt{2} \\ 1/\sqrt{2} \end{bmatrix}$  and  $v_1 = \begin{bmatrix} 0.6 \\ 0.8 \end{bmatrix}$  are the associated left and right singular vectors (4)

## PROOF OF EXISTENCE OF SVD

Suppose that  $\sigma_1 = \|A\|_2$  and  $u_1, v_1 \in \mathbb{C}^n$  be such that

$$A v_1 = \sigma_1 u_1.$$

(there exist such  $u_1, v_1 \in \mathbb{C}^n$  since the maximization  $\sigma_1 = \max_{\|x\|=1} \|Ax\|$  is over a compact set and  $\|Ax\|$  is continuous)

Now form the sets  $\{u_1, \dots, u_n\}$  and  $\{v_1, \dots, v_n\}$  that are orthonormal in  $\mathbb{C}^n$ .

Let  $\tilde{U} = [u_1 \ u_2 \ \dots \ u_n]$  and  $\tilde{V} = [v_1 \ v_2 \ \dots \ v_n]$ .  
Then

$$\begin{aligned} \tilde{U}^* A \tilde{V} &= \begin{bmatrix} u_1^* \\ \vdots \\ u_n^* \end{bmatrix} [A v_1 \ A v_2 \ \dots \ A v_n] \\ &= \begin{bmatrix} u_1^* \\ \vdots \\ u_n^* \end{bmatrix} [\sigma_1 u_1 \ A v_2 \ \dots \ A v_n] \\ &= \begin{bmatrix} \sigma_1 & w^* \\ 0 & \tilde{A} \end{bmatrix} \end{aligned}$$

where  $w \in \mathbb{C}^n$  and  $\tilde{A} \in \mathbb{C}^{(n-1) \times (n-1)}$ .



Noting that  $\|\tilde{U}^* A \tilde{V}\|_2 = \|A\|_2$  (By unitary invariance)

$$\begin{aligned} \sigma_1 = \|\tilde{U}^* A \tilde{V}\|_2 &\geq \left\| \begin{bmatrix} \sigma_1 & w^* \\ 0 & \tilde{A} \end{bmatrix} \begin{bmatrix} \sigma_1 \\ w \end{bmatrix} / \left\| \begin{bmatrix} \sigma_1 \\ w \end{bmatrix} \right\|_2 \right\|_2 \\ &= \frac{\left\| \begin{bmatrix} \sigma_1 & w^* \\ 0 & \tilde{A} \end{bmatrix} \begin{bmatrix} \sigma_1 \\ w \end{bmatrix} \right\|_2}{\left\| \begin{bmatrix} \sigma_1 \\ w \end{bmatrix} \right\|_2} \\ &\geq \frac{\sigma_1^2 + w^* w}{\left\| \begin{bmatrix} \sigma_1 \\ w \end{bmatrix} \right\|_2} = \left\| \begin{bmatrix} \sigma_1 \\ w \end{bmatrix} \right\|_2 \end{aligned}$$

Therefore  $w = 0$  implying

$$\tilde{U}^* A \tilde{V} = \begin{bmatrix} \sigma_1 & 0 \\ 0 & \tilde{A} \end{bmatrix}.$$

Now the proof follows by induction on the size of  $A$ . Suppose for all  $(n-1) \times (n-1)$  matrices there are singular value decompositions. In particular let

$$\tilde{A} = \hat{U} \hat{\Sigma} \hat{V}^*$$

be an SVD of  $\tilde{A}$ . Then

$$\tilde{U}^* A \tilde{V} = \begin{bmatrix} 1 & 0 \\ 0 & \hat{U} \end{bmatrix} \begin{bmatrix} \sigma_1 & 0 \\ 0 & \hat{\Sigma} \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & \hat{V}^* \end{bmatrix}$$

$\iff$

$$A = \underbrace{\tilde{U} \begin{bmatrix} 1 & 0 \\ 0 & \tilde{U} \end{bmatrix}}_{(\text{Unitary}) U} \underbrace{\begin{bmatrix} \sigma_1 & 0 \\ 0 & \hat{\Sigma} \end{bmatrix}}_{\Sigma} \underbrace{\begin{bmatrix} 1 & 0 \\ 0 & \hat{V}^* \end{bmatrix}}_{V^* (\text{Unitary})} \tilde{V}^*$$

Therefore  $A$  has an SVD. □

### EXAMPLE

Consider

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

2-norm of  $A$

$$\sigma_1 = \|A\|_2 = \max_{\|x\|_2=1} \|Ax\|_2$$

$$= \max_{\|x\|_2=1} \left\| \begin{bmatrix} x_1 - x_2 \\ x_1 + x_2 \end{bmatrix} \right\|_2$$

$$= \max_{\|x\|_2=1} \sqrt{(x_1 - x_2)^2 + (x_1 + x_2)^2}$$

$$= \max_{\|x\|_2=1} \sqrt{2x_1^2 + 2x_2^2} = \sqrt{2}$$

Also

$$\begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix} \underbrace{\begin{bmatrix} 1/\sqrt{2} \\ 1/\sqrt{2} \end{bmatrix}}_{v_1} = \sqrt{2} \underbrace{\begin{bmatrix} 0 \\ 1 \end{bmatrix}}_{u_1}$$

Let  $\tilde{V} = \begin{bmatrix} 1/\sqrt{2} & 1/\sqrt{2} \\ 1/\sqrt{2} & -1/\sqrt{2} \end{bmatrix}$ ,  $\tilde{U} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$

$$\tilde{U}^T A \tilde{V} = \begin{bmatrix} \sqrt{2} & 0 \\ 0 & \sqrt{2} \end{bmatrix}$$

Therefore SVD of A

$$A = \underbrace{\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}}_{\tilde{U}} \underbrace{\begin{bmatrix} \sqrt{2} & 0 \\ 0 & \sqrt{2} \end{bmatrix}}_{\Sigma} \underbrace{\begin{bmatrix} 1/\sqrt{2} & 1/\sqrt{2} \\ 1/\sqrt{2} & -1/\sqrt{2} \end{bmatrix}}_{\tilde{V}^T}$$

### SVD OF RECTANGULAR MATRICES

Every rectangular matrix  $A \in \mathbb{C}^{m \times n}$  (with  $m \geq n$ ) has a reduced SVD of the form

$$A = \hat{U} \hat{\Sigma} \hat{V}^*$$

$$\begin{array}{c} \boxed{\phantom{A}} \\ m \times n \end{array} = \begin{array}{c} \boxed{\phantom{A}} \\ m \times n \end{array} \begin{array}{c} \boxed{\phantom{A}} \\ n \times n \end{array} \begin{array}{c} \boxed{\phantom{A}} \\ n \times n \end{array}$$

where

$\hat{U} \in \mathbb{C}^{m \times n}$  has orthonormal columns  
 $\hat{V} \in \mathbb{C}^{n \times n}$  has orthonormal columns  
 $\hat{\Sigma} \in \mathbb{R}^{n \times n}$  is diagonal with nonnegative entries



# EXAMPLE

$$\begin{bmatrix} 3 & 4 \\ 6 & 8 \\ 9 & 12 \end{bmatrix} = \underbrace{\begin{bmatrix} \frac{1}{\sqrt{14}} & \frac{-5}{\sqrt{27}} \\ 2/\sqrt{14} & 1/\sqrt{27} \\ 3/\sqrt{14} & 1/\sqrt{27} \end{bmatrix}}_U \underbrace{\begin{bmatrix} 5\sqrt{14} & 0 \\ 0 & 0 \end{bmatrix}}_{\Sigma} \underbrace{\begin{bmatrix} 3/5 & 4/5 \\ -4/5 & 3/5 \end{bmatrix}}_V$$

Same definition - scalar  $\sigma$  satisfying  
for singular value  
 $Av = \sigma u$  and  $u^*A = \sigma v^*$   
for some  $u \in \mathbb{C}^m$ ,  $v \in \mathbb{C}^n$  applies.

Same geometric interpretation

Unit  $n$ -sphere with axes  $v_1, \dots, v_n$  (lies in  $\mathbb{C}^n$ )  $\xrightarrow{A \in \mathbb{C}^{m \times n}}$  Ellipsoid with semi-axes  $\sigma_1 u_1, \dots, \sigma_n u_n$  (lies in  $\mathbb{C}^m$ )  
applies.

Every rectangular matrix  $A \in \mathbb{C}^{m \times n}$  (with  $m \geq n$ ) also has a full SVD of the form

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

(Can be obtained from reduced SVD by appending cols to  $\hat{U}$  so that  $U$  is unitary, appending  $(m-n)$  0 zero rows to  $\hat{\Sigma}$ )

where  $U \in \mathbb{C}^{m \times m}$ ,  $V \in \mathbb{C}^{n \times n}$  are unitary  
 $\Sigma \in \mathbb{R}^{m \times n}$  is diagonal with nonnegative entries