

# MATH 4370/7370 – Linear Algebra and Matrix Analysis

## The Singular Value Decomposition

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# Outline

Singular values and the Singular value decomposition

Properties of Singular Values

Matrix norms and Singular values

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Matrix norms and Singular values

## Definition 5.1

Let  $A$  be a Hermitian matrix in  $\mathcal{M}_n$ . We say that  $A$  is **positive definite** if for all  $\mathbf{0} \neq \mathbf{x} \in \mathbb{C}^n$ ,  $\mathbf{x}^* A \mathbf{x} > 0$ . We say that  $A$  is **positive semidefinite** if for all  $\mathbf{x} \in \mathbb{C}^n$ ,  $\mathbf{x} \neq \mathbf{0}$ ,  $\mathbf{x}^* A \mathbf{x} \geq 0$

## Theorem 5.2

*Let  $A \in \mathcal{M}_n$  be a Hermitian matrix. Then*

- 1. for all  $\mathbf{x} \in \mathbb{C}^n$ ,  $\mathbf{x}^* A \mathbf{x} \in \mathbb{R}$*
- 2.  $\sigma(A) \subset \mathbb{R}$*
- 3.  $S^* A S$  is Hermitian for any  $S \in \mathcal{M}_n$*

## Theorem 5.3

*Each eigenvalue of a positive definite matrix (respectively positive semidefinite matrix) is positive (respectively nonnegative)*

### Proposition 5.4

*Let  $A$  be a positive semidefinite (respectively positive definite) matrix. Then  $\text{tr}(A)$ ,  $\det(A)$ , the principal minors of  $A$  are all nonnegative (respectively positive). Also,  $\text{tr}(A) = 0$  if and only if  $A = 0$*

### Theorem 5.5

*Let  $A \in \mathcal{M}_n$  be a positive semidefinite matrix and  $\mathbf{x} \in \mathbb{C}^n$ . Then*

$$\mathbf{x}^* A \mathbf{x} = 0 \iff A \mathbf{x} = \mathbf{0}$$

### Corollary 5.6

*Let  $A \in \mathcal{M}_n$  be a positive semidefinite matrix. Then  $A$  is positive definite if and only if  $A$  is nonsingular*

### Theorem 5.7 (Somewhat unrelated)

Let  $B \in \mathcal{M}_n$  be a Hermitian matrix,  $\mathbf{y} \in \mathbb{C}^n$ , and  $a \in \mathbb{R}$ . Let

$$A = \begin{pmatrix} B & \mathbf{y} \\ \mathbf{y}^* & a \end{pmatrix} \in \mathcal{M}_{n+1}$$

Then

$$\lambda_1(A) \leq \lambda_1(B) \leq \lambda_2(A) \leq \cdots \leq \lambda_n(A) \leq \lambda_n(B) \leq \lambda_{n+1}(A)$$

### Definition 5.8

The singular values of a matrix  $A$  are the (nonnegative) square roots of the eigenvalues of  $A^*A$

### Remark 5.9

$A^*A$  is positive semidefinite

### Theorem 5.10 (Zhang)

Let  $A \in \mathcal{M}_{mn}$  with nonzero singular values  $\sigma_1, \dots, \sigma_r$ . Then there exists  $U \in \mathcal{M}_m$  and  $V \in \mathcal{M}_n$  unitary such that

$$A = U \begin{pmatrix} D_r & 0 \\ 0 & 0 \end{pmatrix} V,$$

where  $\begin{pmatrix} D_r & 0 \\ 0 & 0 \end{pmatrix} \in \mathcal{M}_{mn}$  and  $D_r = \text{diag}(\sigma_1, \dots, \sigma_r)$



## Theorem 5.11 (H & J)

Let  $A \in \mathcal{M}_{nm}$ ,  $q = \min\{m, n\}$ . Assume that the rank of  $A$  is  $n$ . Then

1.  $\exists V \in M_n$  and  $W \in \mathcal{M}_m$  unitary matrices and  $\Sigma_q \in \mathcal{M}_q = \text{diag}(\sigma_1, \dots, \sigma_q)$  s.t.

$$\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_r > 0 = \sigma_{r+1} = \dots = \sigma_q$$

and

$$A \Sigma W$$

where

$$\Sigma = \begin{cases} \Sigma_1, & m = n \\ \begin{pmatrix} \Sigma_q & 0 \end{pmatrix} \in \mathcal{M}_{nm}, & m > n \\ \begin{pmatrix} \Sigma_q \\ 0 \end{pmatrix} \in \mathcal{M}_{nm}, & n > m \end{cases}$$

2. The parameters  $\sigma_1, \dots, \sigma_r$  are the positive square roots of the decreasingly ordered eigenvalues of  $A^*A$

### Remark 5.12

*Let  $A \in \mathcal{M}_{mn}$ . Then  $A, \bar{A}, A^T$ , and  $A^*$  have the same singular values*

### Remark 5.13

*Let  $A \in \mathcal{M}_n$  with singular values  $\sigma_1, \dots, \sigma_n$ , then*

$$\sigma_1 \dots \sigma_n = \det(A)$$

*and*

$$\sigma_1^2 + \dots + \sigma_n^2 = \operatorname{tr}(A^*A)$$

### Theorem 5.14

Let  $A \in \mathcal{M}_{nm}$ ,  $q = \min m, n$ , and  $\sigma_1 \geq \cdots \geq \sigma_q$  nonincreasingly ordered singular values of  $A$ . Define

$$\mathcal{A} = \begin{pmatrix} 0 & A \\ A^* & 0 \end{pmatrix}$$

to be a Hermitian matrix. Then the ordered eigenvalues of  $\mathcal{A}$  are

$$-\sigma_1 \leq \cdots \leq -\sigma_q \leq \underbrace{0 = \cdots = 0}_{|n-m|} \leq \sigma_q \leq \cdots \leq \sigma_1$$

### Theorem 5.15 (An interlacing result)

Let  $A \in \mathcal{M}_{nm}$ ,  $q = \min\{m, n\}$  and  $\hat{A}$  be the matrix obtained from  $A$  by deleting one row and one column. Let  $\sigma_1 \geq \dots \geq \sigma_q$  and  $\hat{\sigma}_1 \geq \dots \geq \hat{\sigma}_q$  be the nonsingular ordered singular values of  $A$  and  $\hat{A}$ , respectively, where  $\hat{\sigma}_q = 0$  if  $n \geq m$  and a column is deleted or if  $n \geq m$  and a row is deleted. Then

$$\sigma_1 \geq \hat{\sigma}_1 \geq \sigma_2 \geq \hat{\sigma}_2 \geq \dots \sigma_q \geq \hat{\sigma}_q.$$

### Theorem 5.16 (von Neumann)

Let  $A, B \in \mathcal{M}_{mn}$ ,  $q = \min\{m, n\}$ ,  $\sigma_1(A) \geq \dots \geq \sigma_q(A)$  and  $\sigma_1(B) \geq \dots \geq \sigma_q(B)$  the non-increasingly singular values of  $A$  and  $B$ , respectively. Then

$$\operatorname{Re} \operatorname{tr}(AB^*) \leq \sum_{i=1}^q \sigma_i(A) \sigma_i(B).$$

### Theorem 5.17

Let  $A \in \mathcal{M}_{nm}$ ,  $q = \min m, n$ , and  $\sigma_1 \geq \cdots \geq \sigma_q$  nonincreasingly ordered singular values of  $A$ , and  $\alpha = \{1, \dots, q\}$ . Then

$$\operatorname{Re tr}(A) \leq \sum_{i=1}^q \sigma_i$$

with equality if and only if  $A[\alpha]$  (principal leading submatrix of  $A$ ) is positive semidefinite and  $A$  has no nonzero entries outside  $A[\alpha]$ .

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- Let  $A \in \mathcal{M}_2$

$$\sigma_1, \sigma_2 = \frac{1}{2} \left( (\operatorname{tr} A^* A) \mp \sqrt{(\operatorname{tr} A^* A)^2 - 4|\det A|^2} \right)$$

- The nilpotent matrix

$$A = \begin{pmatrix} 0 & a_{12} & & \\ & \ddots & & \\ & & a_{n-1,n} & \\ & & & 0 \end{pmatrix}$$

has singular values  $0, |a_{12}|, \dots, |a_{n-1,n}|$ .

### Theorem 5.18

Let  $A_1, A_2, \dots \in \mathcal{M}_{nm}$  given (infinite) sequence with  $\lim_{k \rightarrow \infty} A_k = A$  (entrywise). Let  $q = \min(m, n)$ . Let  $\sigma_1(A) \geq \dots \geq \sigma_q(A)$  and  $\sigma_1(A_k) \geq \dots \geq \sigma_q(A_k)$  be the non-increasingly ordered singular values of  $A$  and  $A_k$ , respectively (for all  $k$ ). Then

$$\lim_{k \rightarrow \infty} \sigma_i(A_k) = \sigma_i(A)$$



## Theorem 5.19

Let  $A \in \mathcal{M}_n$  where  $n = \text{rank } A$

1.  $A = A^T$  if and only if there exists  $U \in \mathcal{M}_n$  unitary and a nonnegative diagonal matrix  $\Sigma$  such that  $A = U\Sigma U^T$ . Then the diagonal entries of  $\Sigma$  are the singular values of  $A$
2. If  $A = -A^T$ , then  $n$  is even and there exists  $U \in \mathcal{M}_n$  unitary and positive real scalars  $s_1, \dots, s_{r/2}$  such that

$$U \left( \begin{pmatrix} 0 & s_1 \\ -s_1 & 0 \end{pmatrix} \oplus \dots \oplus \begin{pmatrix} 0 & s_{r/2} \\ -s_{r/2} & 0 \end{pmatrix} \right) U^T$$

The non-zero singular values of  $A$  are  $s_1, s_1, \dots, s_{r/2}, s_{r/2}$ . Conversely, any matrix of the above form is skew-symmetric

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Let  $V = \mathcal{M}_{mn}(\mathbb{C})$  with Frobenius inner product

$$\langle A, B \rangle_F = \text{tr}(B^* A)$$

The norm derived from the Frobenius inner product is

$$\|A\|_2 = (\text{tr}(A^* A))^{1/2}$$

is the  $\ell$ -2 norm (or Frobenius norm)

The spectral norm  $\|\cdot\|$  defined on  $\mathcal{M}_n$  by

$$\|A\|_2 = \sigma_1(A),$$

where  $\sigma_1(A)$  is the largest singular value of  $A$  is induced by the  $\ell_2$  norm on  $\mathbb{C}^n$ .  
Indeed, from the singular value decomposition theorem, let

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

be a singular value decomposition of  $A$ , where  $V, W$  unitary,  $\Sigma = \text{diag}(\sigma_1, \dots, \sigma_n)$  and  $\sigma_1 \geq \dots \geq \sigma_n \geq 0$  are the non-increasingly ordered singular values of  $A$

From unitary invariance and monotonicity of the Euclidean norm, we say that

$$\begin{aligned}\max_{\|x\|_1} \|Ax\|_1 &= \max_{\|x\|_1} \|V\Sigma W^*\|_2 \\ &= \max_{\|x\|_2} \|\Sigma W^*x\|_2 \\ &= \max_{\|Wy\|_2=1} \|\Sigma y\|_2 \\ &= \max_{\|y\|_2} \|\Sigma y\|_2 \\ &\leq \max_{\|y\|_2} \|\sigma_1 y\|_2 \\ &= \sigma_1 \max_{\|y\|_2} \|y\|_2 \\ &= \sigma_1\end{aligned}$$

Since  $\|\Sigma y\|_2 = \sigma_1$  for  $y = e_1$ ,

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

We could have used

$$\begin{aligned}\max_{\|x\|_2=1} \|Ax\|_2^2 &= \max_{\|x\|_2=1} x^* A^* A x \\ &= \lambda_{\max}(A^* A) \\ &= \sigma_1(A)\end{aligned}$$

### Proposition 5.20

*For all  $U, V \in \mathcal{M}_n$  unitary matrices, we have  $\|UAV\|_2 = \|A\|_2$*

# References I