

# WEEK 9+10 SINGULAR DECOMPOSITION OF MATRICES

Notation If  $A$  is a complex matrix we will write

$$A^* = \bar{A}^T$$

For  $A$  a real matrix we put

$$A^* = A^T$$

$A$  is hermitian (symmetric) if  $A = A^*$ .

Example:  $A = \begin{pmatrix} 2+i & -3 \\ 1-i & 4+2i \\ i & 6+3i \end{pmatrix}$

$$A^* = \begin{pmatrix} 2-i & 1+i & -i \\ -3 & 4-2i & 6-3i \end{pmatrix}$$

Lemma Let  $A$  be a matrix  $k \times n$ .

Then  $AA^* \in \text{Mat}_{k \times k}(\mathbb{K})$  and  $A^*A \in \text{Mat}_{n \times n}(\mathbb{K})$  are hermitian matrices and their eigenvalues are  $\geq 0$ .

Proof:  $(AA^*)^* = (A^*)^* A^* = AA^*$

$$\langle AA^*x, x \rangle = \langle A^*x, A^*x \rangle \geq 0.$$

Lemma  $\ker A^*A = \ker A$

Proof : If  $x \in \ker A$ , then  $A^*Ax = A^*0 = 0$ ,  
i.e.  $x \in \ker A^*A$ .

If  $x \in \ker A^*A$ , then  $A^*Ax = 0$

$$\langle A^*Ax, x \rangle = 0$$

$$\langle Ax, Ax \rangle = 0$$

$$\|Ax\|^2 = 0$$

$$Ax = 0$$

i.e.  $x \in \ker A$ . ▣

Theorem on singular decomposition

Let  $A \in \text{Mat}_{k \times n}(\mathbb{K})$ . Then there are unitary (orthogonal) matrices  $P \in \text{Mat}_{k \times k}(\mathbb{K})$  and  $Q \in \text{Mat}_{n \times n}(\mathbb{K})$  such that

$$A = P S Q^*$$

where  $S = \left( \begin{array}{ccc|c} s_1 & & & 0 \\ & s_2 & & 0 \\ & & \ddots & \\ 0 & & & s_r \\ \hline & & & 0 \\ 0 & & & 0 \end{array} \right) \in \text{Mat}_{k \times n}(\mathbb{R})$

and  $s_1, \dots, s_r$  are  $\sqrt{\lambda_1}, \sqrt{\lambda_2}, \dots, \sqrt{\lambda_r}$  of positive eigenvalues of the matrix  $A^*A$ .

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Proof gives the way how to find this decomposition.

Consider  $\varphi : \mathbb{K}^n \rightarrow \mathbb{K}^k$ ,  $\varphi(x) = Ax$ .

Then  $\varphi^* \varphi : \mathbb{K}^n \rightarrow \mathbb{K}^n$ ,  $\varphi^* \varphi(x) = A^* A x$  is a selfadjoint operator with nonnegative eigenvalues. There is an orthonormal basis  $\alpha = (u_1, \dots, u_r, u_{r+1}, \dots, u_n)$  in  $\mathbb{K}^n$  formed from eigenvectors with eigenvalues

$$\lambda_1, \lambda_2, \dots, \lambda_r > 0 \text{ and } \lambda_{r+1} = \dots = \lambda_n = 0$$

Vectors  $\varphi(u_1), \dots, \varphi(u_r)$  are mutually ~~orthogonal~~ orthogonal and  $\|\varphi(u_i)\| = \sqrt{\lambda_i}$ .

$$\text{Put } v_i = \frac{\varphi(u_i)}{\sqrt{\lambda_i}} \quad 1 \leq i \leq r$$

and complete vector  $v_1, v_2, \dots, v_r$  into an orthonormal basis  $\beta$  of  $\mathbb{K}^k$ . Then

$$(\varphi)_{\beta, \alpha} = \left( \begin{array}{ccc|ccc} s_1 & & 0 & & & \\ & \ddots & & & & \\ & & s_r & & & \\ \hline & & & & & \\ & & & & & \\ & & & & & \end{array} \right) \begin{array}{l} \left. \vphantom{\begin{matrix} s_1 \\ \vdots \\ s_r \end{matrix}} \right\} r \\ \left. \vphantom{\begin{matrix} 0 \\ \vdots \\ 0 \end{matrix}} \right\} k-r \end{array} \in \text{Mat}_{k \times n}(\mathbb{K})$$

So we have

$$\begin{aligned} A &= (\varphi)_{\varepsilon_k, \varepsilon_n} = (\text{id})_{\varepsilon_k, \beta} (\varphi)_{\beta, \alpha} (\text{id})_{\alpha, \varepsilon_n} \\ &= P S Q^* \end{aligned}$$

Algorithm for finding singular decomposition.

Find eigenvalues and eigenvectors of  $A^*A$ . The orthonormal basis formed by eigenvectors gives the matrix  $Q = (u_1 u_2 \dots u_n)$ .

The ~~images~~ vectors  $Au_1, Au_2, \dots, Au_r$  are  $\neq \vec{0}$ , complete them into orthonormal basis

$$v_1 = \frac{Au_1}{\sqrt{\lambda_1}}, v_2 = \frac{Au_2}{\sqrt{\lambda_2}}, \dots, v_r = \frac{Au_r}{\sqrt{\lambda_r}}, v_{r+1}, \dots, v_k$$

Then  $P = (v_1, v_2, \dots, v_k)$ .

$$A = P \Sigma Q^*$$

Example  $A = \begin{pmatrix} 1 & 2 \\ 1 & 0 \\ 0 & 1 \end{pmatrix}$

$$A^*A = \begin{pmatrix} 2 & 2 \\ 2 & 5 \end{pmatrix} \quad \det \begin{pmatrix} 2-\lambda & 2 \\ 2 & 5-\lambda \end{pmatrix} = \lambda^2 - 7\lambda + 6$$

$$\lambda_{1,2} = 1, 6 \quad u_1 = \frac{1}{\sqrt{5}} \begin{pmatrix} 2 \\ -1 \end{pmatrix} \quad u_2 = \frac{1}{\sqrt{5}} \begin{pmatrix} 1 \\ 2 \end{pmatrix}$$

$$Q = \frac{1}{\sqrt{5}} \begin{pmatrix} 2 & 1 \\ -1 & 2 \end{pmatrix}$$

$$v_1 = \frac{Au_1}{\sqrt{1}} = \frac{1}{\sqrt{5}} \begin{pmatrix} 0 \\ 2 \\ -1 \end{pmatrix}$$

$$v_2 = \frac{Au_2}{\sqrt{6}} = \frac{1}{\sqrt{30}} \begin{pmatrix} 5 \\ 1 \\ 2 \end{pmatrix}$$

$$v_3 = \frac{1}{\sqrt{6}} \begin{pmatrix} -1 \\ 1 \\ 2 \end{pmatrix}$$

$$P = \begin{pmatrix} 0 & 5/\sqrt{30} & -1/\sqrt{6} \\ 2/\sqrt{5} & 1/\sqrt{30} & 4/\sqrt{6} \\ -1/\sqrt{5} & 2/\sqrt{30} & 2/\sqrt{6} \end{pmatrix}$$

$$A = P \begin{pmatrix} 1 & 0 \\ 0 & \sqrt{6} \\ 0 & 0 \end{pmatrix} Q^*$$

⑥

## PSEUDO INVERSE MATRIX

Inverse matrix to the matrix

$A \in \text{Mat}_{n \times n}(\mathbb{K})$  is  $A^{-1}$  such that

$$A A^{-1} = E \quad (\text{unit matrix})$$

$$A^{-1} A = E$$

If we have singular decomposition of  $A$

$$A = P S Q^*$$

where

$$S = \begin{pmatrix} s_1 & & 0 \\ & s_2 & \\ 0 & & \ddots \\ & & & s_n \end{pmatrix} \quad \text{where } s_i > 0.$$

Then

$$\begin{aligned} A^{-1} &= (P S Q^*)^{-1} = \\ &= (Q^*)^{-1} S^{-1} P^{-1} = \\ &= Q S^{-1} P^* \end{aligned}$$

Using this observation we can generalize the definition of inverse matrix.

Def If  $A \in \text{Mat}_{k+n}(\mathbb{K})$ , then the pseudoinverse  $A^{(-1)}$  to  $A$  is

$$A^{(-1)} = \underbrace{Q}_{n \times n} \underbrace{\begin{pmatrix} D^{-1} & 0 \\ 0 & 0 \end{pmatrix}}_{n \times k} \underbrace{P^*}_{k \times k} \in \text{Mat}_{n \times k}(\mathbb{K})$$

⑦

if

$$A = P \begin{pmatrix} D & 0 \\ 0 & 0 \end{pmatrix} Q^*$$

$\underbrace{\hspace{10em}}_{k+k} \quad \underbrace{\hspace{10em}}_{k+n} \quad \underbrace{\hspace{10em}}_{n+n}$

## Properties of pseudoinverses

① If  $A$  is invertible, then

$$A^{(-1)} = A^{-1}$$

~~② If  $x \in \mathbb{R}^m$ , then  $A^{(-1)}Ax$  is an orthogonal projection of  $x$  into  $\ker A$ .~~

② If  $x \in \mathbb{R}^m$  then  $A^{(-1)}Ax$  is an orthogonal projection of  $x$  into  $\ker A$ .

$$\textcircled{3} \quad (A^{(-1)})^{(-1)} = A.$$

④  $A^{(-1)}A$  and  $AA^{(-1)}$  are selfadjoint.

⑤ It holds

$$AA^{(-1)}A = A,$$

$$A^{(-1)}AA^{(-1)} = A^{(-1)}$$

⑧

⑥ Important

$$A^{(-1)} = (A^* A)^{(-1)} A^*$$

Consequence If  $A^* A$  is invertible,

then

$$A^{(-1)} = (A^* A)^{-1} \cdot A^*$$

and we can compute  $A^{(-1)}$  without looking for a singular decomposition.

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## APPROXIMATION OF SOLUTIONS OF LIN. EQUATIONS

Let  $A$  be a matrix  $k \times n$ . Consider the system of equations

$$Ax = b \quad x \in \mathbb{K}^n, b \in \mathbb{K}^k$$

If  $\text{rank}(A|b) > \text{rank}(A)$

the system has no solution. In this case we want to find  $x \in \mathbb{K}^n$  such that  $\|Ax - b\|$  is minimal. ~~It means,~~

Thm The function  $\|Ax - b\|$  takes its minimum in  $x = A^{(-1)} b$ .



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Example

We have a system

$$x_1 + 2x_2 = 3$$

$$x_1 = 7$$

$$x_2 = 5$$

This system has no solution. Nevertheless, we are looking for  $x$  such that

$$(x_1 + 2x_2 - 3)^2 + (x_1 - 7)^2 + (x_2 - 5)^2$$

is minimal. The solution is

$$A^{(-1)} b = \begin{pmatrix} 1/6 & 5/6 & -1/3 \\ 1/3 & -1/3 & 1/3 \end{pmatrix} \begin{pmatrix} 3 \\ 7 \\ 5 \end{pmatrix}$$
$$= \begin{pmatrix} 28/6 \\ 1/3 \end{pmatrix}$$

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## Polar decomposition of matrices

Every square matrix  $A \in \text{Mat}_{n \times n}(\mathbb{K})$  can be written in the form

$$A = R \cdot U$$

where  $R$  is selfadjoint and positive semidefinite and  $U$  is a orthonormal or unitary. If  $A$  is invertible,

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the decomposition is unique and

$$U = A \left( \sqrt{AA^*} \right)^{-1}$$

Proof:  $A = PSQ^*$  is a singular decomposition. From here

$$A = \underbrace{PSP^*}_R \underbrace{PQ^*}_U \quad \begin{array}{l} \text{orthogonal or} \\ \text{unitary} \end{array}$$

*self-adjoint*