

# Linear Algebra

[KOMS119602] - 2022/2023

## 14.2 Matrix Decomposition: SVD

sumber: *Slide Perkuliahan Aljabar Linear dan Geometri - R. Munir ITB*

Dewi Sintiar

Computer Science Study Program  
Universitas Pendidikan Ganesha

# Learning objectives

After this lecture, you should be able to:

- explain the importance of singular value decomposition;
- perform singular value decomposition on a matrix.

# Matrix decomposition

**Decomposing matrix** means factoring a matrix into **product of matrices**

$$\text{Example: } A = P_1 \times P_2 \times \cdots \times P_k$$

## Matrix decomposition methods:

1. *LU*-decomposition (LU = Lower-Upper)
2. *QR*-decomposition (Q: orthogonal, R: upper-triangular)
3. **Singular value decomposition (SVD)**

# LU-decomposition

$$A = LU$$

The diagram shows the LU-decomposition of a matrix  $A$  into a lower triangular matrix  $L$  and an upper triangular matrix  $U$ . The equation  $A = LU$  is displayed at the top. Matrix  $L$  is a lower triangular matrix with ones on the diagonal and asterisks in the lower triangular region. Matrix  $U$  is an upper triangular matrix with zeros on the diagonal and asterisks in the upper triangular region.

**Example:**

$$\begin{bmatrix} 2 & -3 & -1 \\ 3 & 2 & -5 \\ 2 & 4 & -1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ \frac{3}{2} & 1 & 0 \\ \frac{1}{2} & \frac{11}{13} & 1 \end{bmatrix} \begin{bmatrix} 2 & -3 & -1 \\ 0 & \frac{13}{2} & -\frac{7}{2} \\ 0 & 0 & \frac{32}{13} \end{bmatrix}$$

# QR-decomposition

$$\mathbf{A} = \mathbf{Q} \mathbf{R}$$

$\mathbf{A} = \begin{bmatrix} | & | & | \\ \mathbf{a}_1 & \mathbf{a}_2 & \mathbf{a}_3 \\ | & | & | \end{bmatrix} = \underbrace{\begin{bmatrix} | & | & | \\ \mathbf{e}_1 & \mathbf{e}_2 & \mathbf{e}_3 \\ | & | & | \end{bmatrix}}_{\text{Orthogonal Unit vectors}} \underbrace{\begin{bmatrix} \mathbf{e}_1^T \cdot \mathbf{a}_1 & \mathbf{e}_1^T \cdot \mathbf{a}_2 & \mathbf{e}_1^T \cdot \mathbf{a}_3 \\ 0 & \mathbf{e}_2^T \cdot \mathbf{a}_2 & \mathbf{e}_2^T \cdot \mathbf{a}_3 \\ 0 & 0 & \mathbf{e}_3^T \cdot \mathbf{a}_3 \end{bmatrix}}_{\text{Upper Diagonal Matrix}}$

**Example:**

$$\begin{bmatrix} 1 & 4 \\ 2 & 3 \end{bmatrix} = \begin{bmatrix} \frac{1}{\sqrt{5}} & \frac{2}{\sqrt{5}} \\ \frac{2}{\sqrt{5}} & -\frac{1}{\sqrt{5}} \end{bmatrix} \begin{bmatrix} \sqrt{5} & 2\sqrt{5} \\ 0 & \sqrt{5} \end{bmatrix}$$

# Singular Value Decomposition

# Motivation of Singular Value Decomposition

In orthogonal diagonalization, a square  $n \times n$  matrix  $A$  can be decomposed into:

$$A = P^T D P$$

dimana:

- $P$  is an orthogonal matrix whose columns are eigenbases of  $A$  (so  $P^T = P^{-1}$ )

$$P = [p_1 \mid p_2 \mid \dots \mid p_n]$$

- $D$  is diagonal matrix, such that

$$D = P^{-1} A P$$

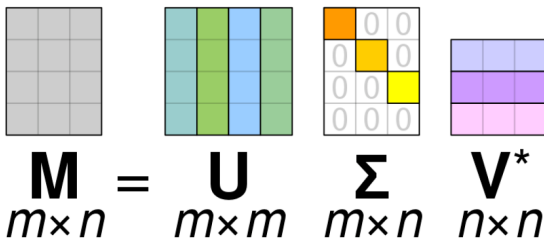
*How to factorize non-square  $m \times n$  matrix that do not have eigenvalues?*

# Singular Value Decomposition (SVD)

SVD is used to factorize non-square  $m \times n$  matrix into product of matrix  $U$ ,  $\Sigma$ , and  $V$ , such that:

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

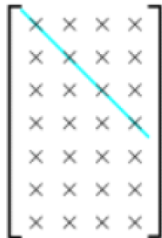
- $U$  is an orthogonal  $m \times m$  matrix
- $V$  is an orthogonal  $n \times n$  matrix
- $\Sigma$  is an  $m \times n$  matrix, whose elements in the *main diagonal* are singular values of  $A$ , and other elements are 0





## Main diagonal of a non-square matrix

**Main diagonal** of a non-square matrix  $A$  of size  $m \times n$ , is defined as entries  $a_{11}$  diagonally until  $a_{mm}$  (assuming that  $n > m$ ).



## Orthogonal matrix (revisited)

**Orthogonal matrix** is a matrix whose columns form a set of orthogonal vectors. ( $\mathbf{u}$  and  $\mathbf{v}$  are orthogonal if  $\mathbf{u} \cdot \mathbf{v} = 0$ ).

*If  $P$  is an orthogonal matrix, then  $P^{-1} = P^T$ .*

**Proof.**

Vectors  $v_1, v_2, \dots, v_n$  of  $Q$  are orthogonal:

$$v_i^T v_j = \begin{cases} 0 & \text{if } i \neq j \\ 1 & \text{if } i = j \end{cases}$$

Let  $P = [v_1 \mid v_2 \mid \dots \mid v_n]$ , then:

$$P^T \cdot P = \begin{bmatrix} v_1^T \\ v_2^T \\ \vdots \\ v_n^T \end{bmatrix} [v_1 \mid v_2 \mid \dots \mid v_n] = \begin{bmatrix} v_1^T v_1 & \cdots & v_1^T v_n \\ v_2^T v_1 & \cdots & v_2^T v_n \\ \cdots & \ddots & \cdots \\ v_n^T v_1 & \cdots & v_n^T v_n \end{bmatrix} = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \cdots & \cdots & \ddots & \cdots \\ 0 & 0 & \cdots & 1 \end{bmatrix}$$



## Example

Are the following matrices orthogonal?

- $P = \begin{bmatrix} 1/3 & 2/3 & -2/3 \\ -2/3 & 2/3 & 1/3 \\ 2/3 & 1/3 & 2/3 \end{bmatrix}$

- $Q = \begin{bmatrix} 3/7 & 2/7 & 6/7 \\ -6/7 & 3/7 & 2/7 \\ 2/7 & 6/7 & -3/7 \end{bmatrix}$

## Singular values

Let  $A$  be an  $m \times n$  matrix. If  $\lambda_1, \lambda_2, \dots, \lambda_n$  be the eigenvalues of  $A^T A$ , then:

$$\tau_1 = \sqrt{\lambda_1}, \tau_2 = \sqrt{\lambda_2}, \dots, \tau_n = \sqrt{\lambda_n}$$

are called the **singular values** of  $A$ .

*In this case, we assume that  $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_n \geq 0$ , so that  $\tau_1 \geq \tau_2 \geq \dots \geq \tau_n \geq 0$ .*

### Theorem

*Orthogonally diagonalizable matrices have positive eigenvalues If  $A$  is an  $m \times n$  matrix, then:*

- $A^T A$  is orthogonally diagonalizable*
- The eigenvalues of  $A^T A$  are non-negative*

## Example

Given matrix  $A = \begin{bmatrix} 1 & 1 \\ 0 & 1 \\ 1 & 0 \end{bmatrix}$

## Example

Given matrix  $A = \begin{bmatrix} 1 & 1 \\ 0 & 1 \\ 1 & 0 \end{bmatrix}$

**Solution:**

$$B = A^T A = \begin{bmatrix} 1 & 0 & 1 \\ 1 & 1 & 0 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 0 & 1 \\ 1 & 0 \end{bmatrix} = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}$$

Solve the characteristic equation:

$$\det(\lambda I - B) = 0 \Leftrightarrow \begin{vmatrix} \lambda - 2 & -1 \\ -1 & \lambda - 2 \end{vmatrix} = 0 \Leftrightarrow (\lambda - 2)(\lambda - 2) - 1 = 0$$

This gives  $\lambda^2 - 4\lambda + 3 = 0 \Leftrightarrow (\lambda - 3)(\lambda - 1) = 0$

The eigenvalues pf  $AA^T$  are  $\lambda_1 = 3$  and  $\lambda_2 = 1$ .

Hence:

$$\tau_1 = \sqrt{3} \quad \text{and} \quad \tau_2 = \sqrt{1} = 1$$

## Decomposing matrix $A_{m \times n}$ into products of $U$ , $\Sigma$ , and $V$

1. Untuk vektor singular kiri, hitung nilai-nilai eigen dari  $AA^T$ .
2. Tentukan vektor-vektor eigen  $\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_m$  yang berkoresponden dengan nilai-nilai eigen dari  $AA^T$ . Normalisasi vektor eigen-nya sehingga diperoleh:

$$U = \left[ \frac{\mathbf{u}_1}{|\mathbf{u}_1|} \mid \frac{\mathbf{u}_2}{|\mathbf{u}_2|} \mid \dots \mid \frac{\mathbf{u}_m}{|\mathbf{u}_m|} \right]$$

3. Untuk vektor singular kiri, hitung nilai-nilai eigen dari  $A^T A$ .
4. Tentukan vektor-vektor eigen  $\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_m$  yang berkoresponden dengan nilai-nilai eigen dari  $A^T A$ . Normalisasi vektor eigen-nya sehingga diperoleh:

$$V = \left[ \frac{\mathbf{v}_1}{|\mathbf{v}_1|} \mid \frac{\mathbf{v}_2}{|\mathbf{v}_2|} \mid \dots \mid \frac{\mathbf{v}_m}{|\mathbf{v}_m|} \right]$$

5. Bentuklah matriks  $\Sigma$  berukuran  $m \times n$  dengan elemen-elemen diagonalnya adalah *nilai-nilai singular* dari matriks  $A$  (yaitu  $\tau_1 = \sqrt{\lambda_1}, \tau_2 = \sqrt{\lambda_2}, \dots, \tau_n = \sqrt{\lambda_n}$ ) dari besar ke kecil.
6. Maka:  $A = U\Sigma V^T$

# Example

Given matrix:

$$A = \begin{bmatrix} 3 & 1 & 1 \\ -1 & 3 & 1 \end{bmatrix}$$

Find the Singular Value Decomposition of  $A$ .



## Example

Given matrix:

$$A = \begin{bmatrix} 3 & 1 & 1 \\ -1 & 3 & 1 \end{bmatrix}$$

Find the Singular Value Decomposition of  $A$ .

*For the solution, check the pdf file.*

# Applications of Singular Value Decomposition

- Image and video compression
- Image processing
- Machine learning
- Computer vision
- Digital watermarking
- ...?
- ...?