

# MATHEMATICAL FOUNDATIONS OF DATA ANALYSIS

## UNIT V

### SINGULAR VALUE DE COMPOSITION OF A MATRIX

#### Definition: Singular Value Decomposition of a matrix:

A **Singular Value Decomposition (SVD)** of an  $m \times n$  matrix  $A$  of rank  $r$  is a factorization  $A = U\Sigma V^T$  where  $U$  and  $V$  are **orthogonal** and  $\Sigma = \begin{bmatrix} D & 0 \\ 0 & 0 \end{bmatrix}_{m \times n}$  in block form where  $D = \text{diag}(d_1, d_2, \dots, d_r)$  where each  $d_i > 0$ , and  $r \leq m$  and  $r \leq n$ .

**Note1 :** If  $A = U\Sigma V^T$  is any SVD for  $A$  as then:

1.  $r = \text{rank } A$ .
2. The numbers  $d_1, d_2, \dots, d_r$  are the singular values of  $A^T A$  in some order.

#### Note 2 :

Let  $A$  be a real  $m \times n$  matrix. Then:

1. The eigen values of  $A^T A$  and  $AA^T$  are **real and non-negative**.
2.  $A^T A$  and  $AA^T$  have the same set of **positive eigen values**.

#### Definition: Singular values of the matrix A

Let  $A$  be a real  $m \times n$  matrix. Let  $\lambda$  be an **eigenvalue of  $A^T A$** , with non zero eigenvectors  $q_i \in R^n$ . Then the **real numbers**  $\sigma_i = \sqrt{\lambda_i} = \|Aq_i\|$  for  $i = 1, 2, \dots, n$ , are called the **singular values of the matrix A**.

#### Definition: Singular matrix of A

Let  $A$  be a real,  $m \times n$  matrix of rank  $r$ , with **positive singular values**  $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_r > 0$  and  $\sigma_i = 0$  if  $i > r$ . Define:  $D_A = \text{diag}(\sigma_1, \sigma_2, \dots, \sigma_r)$  and  $\Sigma_A = \begin{bmatrix} D_A & 0 \\ 0 & 0 \end{bmatrix}_{m \times n}$  Here  $\Sigma_A$  is in **block form** and is called the **Singular matrix of A**.

**Definition:** Two subspaces associated with a matrix  $A$  having  $m$  rows and  $n$  columns.

$$\text{im } A = \{ Ax \mid x \in R^n \} \text{ and } \text{col } A = \text{span} \{ a \mid a \text{ is a column of } A \}.$$

Then **im A** is called the **image of A** (so named because of the linear transformation  $R^n \rightarrow R^m$  with  $x \rightarrow Ax$ ); and **col A** is called the **column space of A**.

Note :  $\text{im } A = \text{col } A$ .

#### Definition: Singular Value Decomposition (SVD) of A

**Definition:** Let  $A$  be a real  $m \times n$  matrix, and let  $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_r > 0$  be the positive **singular values of  $A$** . Then  $r$  is the **rank of  $A$**  and we have the factorization  $A = P \Sigma_A Q^T$  where  $P$  and  $Q$  are **orthogonal matrices**. The factorization  $A = P \Sigma_A Q^T$ , where  $P$  and  $Q$  are **orthogonal matrices**, is called a **Singular Value Decomposition (SVD) of  $A$** . This decomposition is not unique.

**Reference:**

[https://math.emory.edu/~lchen41/teaching/2020\\_Fall/Section\\_8-6.pdf](https://math.emory.edu/~lchen41/teaching/2020_Fall/Section_8-6.pdf)

### Procedure for finding Singular Value Decomposition (SVD) of the given matrix $A$

**Solution:**

Step 1: To find  $A^T A$

Step 2: To find Eigen values (Characteristic values) of  $A^T A$ .

$$\text{Use } |A^T A - \lambda I| = 0$$

Step 3: To find Eigen vectors (Characteristic vectors) Eigen vectors of  $A^T A$ , corresponding unit Eigen vectors  $q_1, q_2$  and  $q_3$ .

Use the Characteristic equations formula  $(A^T A - \lambda I)X = 0$  where  $X = \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}$

Step 4: To find orthogonal matrix  $Q = (q_1 \ q_2 \ q_3)$

Step 5: To find Singular values of  $A^T A$ .

Use the formula  $\sigma_i = \sqrt{\lambda_i}$   $i = 1, 2, 3$ .  $\sigma_i$  is called the Singular value of the matrix  $A^T A$

Step 6: To find rank of the given matrix  $A$

Step 7: To find singular matrix of  $A$  denoted by  $\Sigma_A$

$$\Sigma_A = \begin{pmatrix} D_A & 0 \\ 0 & 0 \end{pmatrix} \text{ Where } D_A = \text{diag}(\sigma_1 \ \sigma_2 \ \sigma_3 \ \dots)$$

Step 8: To find  $2 \times 2$  Orthogonal matrix  $P = (p_1 \ p_2)$  where  $p_1$  and  $p_2$  are normalisers of  $Aq_1$  and  $Aq_2$  respectively.

Step 9: Singular Value Decomposition (SVD) of  $A$  is obtained by using the formula

$$A = P \Sigma_A Q^T$$

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**Problem:**

**Find Singular Value Decomposition (SVD) for the matrix**  $A = \begin{pmatrix} 1 & 0 & 1 \\ -1 & 1 & 0 \end{pmatrix}$

**Solution:**

Let the given matrix be  $A = \begin{pmatrix} 1 & 0 & 1 \\ -1 & 1 & 0 \end{pmatrix}$

**Step 1: To find  $A^T A$**

$$A^T A = \begin{pmatrix} 1 & -1 \\ 0 & 1 \\ 1 & 0 \end{pmatrix} \begin{pmatrix} 1 & 0 & 1 \\ -1 & 1 & 0 \end{pmatrix} = \begin{pmatrix} 2 & -1 & 1 \\ -1 & 1 & 0 \\ 1 & 0 & 1 \end{pmatrix}$$

**Step 2: To find Eigen values (Characteristic values) of  $A^T A$**

$$|A^T A - \lambda I| = 0$$

$$\Rightarrow \left| \begin{pmatrix} 2 & -1 & 1 \\ -1 & 1 & 0 \\ 1 & 0 & 1 \end{pmatrix} - \lambda \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \right| = 0$$

$$\Rightarrow \left| \begin{pmatrix} 2-\lambda & -1 & 1 \\ -1 & 1-\lambda & 0 \\ 1 & 0 & 1-\lambda \end{pmatrix} \right| = 0$$

$$\Rightarrow (2-\lambda)(1-\lambda)(1-\lambda) - (1-\lambda) - (1-\lambda) = 0$$

$$\Rightarrow (1-\lambda) [(2-\lambda)(1-\lambda) - 1 - 1] = 0$$

$$\Rightarrow (1-\lambda) [\lambda^2 - 3\lambda + 2 - 2] = 0$$

$$\Rightarrow (1-\lambda) [\lambda^2 - 3\lambda] = 0$$

$$\Rightarrow (1-\lambda)(\lambda-3)\lambda = 0$$

$$\Rightarrow \lambda = 3, \lambda = 1 \text{ and } \lambda = 0$$

**Let  $\lambda_1 = 3$   $\lambda_2 = 1$  and  $\lambda_3 = 0$**

**Step 3: To find Eigen vectors (Characteristic vectors) Eigen vectors of  $A^T A$ , corresponding unit Eigen vectors  $q_1$ ,  $q_2$  and  $q_3$ .**

Characteristic equations is  $(A^T A - \lambda I)X = 0$  where  $X = \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}$

$$\Rightarrow (A^T A - \lambda I)X = 0$$

$$\Rightarrow \begin{pmatrix} 2-\lambda & -1 & 1 \\ -1 & 1-\lambda & 0 \\ 1 & 0 & 1-\lambda \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}$$

$$(2-\lambda)x_1 - x_2 + x_3 = 0$$

$$-x_1 + (1 - \lambda)x_2 + 0x_3 = 0$$

$$x_1 + 0x_2 + (1 - \lambda)x_3 = 0$$

Put  $\lambda = 3$  in the above first two equations we get

$$-x_1 - x_2 + x_3 = 0$$

$$-x_1 - 2x_2 + 0x_3 = 0$$

$$\frac{x_1}{0+2} = \frac{x_2}{-1-0} = \frac{x_3}{0-1}$$

$$\Rightarrow \frac{x_1}{2} = \frac{x_2}{-1} = \frac{x_3}{-1}$$

$x_2$	$x_3$	$x_1$	$x_2$
-1	1	-1	-1
-2	0	-1	0

Therefore Eigen vector corresponding to the Eigen value  $\lambda = 3$  is  $\begin{pmatrix} 2 \\ -1 \\ -1 \end{pmatrix}$

Let  $q_1$  be the unit Eigen vector corresponding to the Eigen value  $\lambda = 3$ .

$$q_1 = \begin{pmatrix} \frac{2}{\sqrt{6}} \\ \frac{1}{\sqrt{6}} \\ -\frac{1}{\sqrt{6}} \\ \frac{1}{\sqrt{6}} \\ -\frac{1}{\sqrt{6}} \end{pmatrix} = \frac{1}{\sqrt{6}} \begin{pmatrix} 2 \\ -1 \\ -1 \\ 1 \\ -1 \end{pmatrix} \text{ the length of this vector is } \sqrt{2^2 + (-1)^2 + (-1)^2} = \sqrt{6}$$

Next Put  $\lambda = 1$  in the above first two equations we get

$$1x_1 - x_2 + x_3 = 0$$

$$-x_1 + 0x_2 + 0x_3 = 0$$

$$\frac{x_1}{0+0} = \frac{x_2}{-1-0} = \frac{x_3}{0-1}$$

$$\Rightarrow \frac{x_1}{0} = \frac{x_2}{-1} = \frac{x_3}{-1} \Rightarrow \frac{x_1}{0} = \frac{x_2}{1} = \frac{x_3}{1}$$

$x_2$	$x_3$	$x_1$	$x_2$
-1	1	1	-1
0	0	-1	0

Therefore Eigen vector corresponding to the Eigen value  $\lambda = 1$  is  $\begin{pmatrix} 0 \\ 1 \\ 1 \end{pmatrix}$

Let  $q_2$  be the unit Eigen vector corresponding to the Eigen value  $\lambda = 1$ .

$$\text{Therefore } q_2 = \begin{pmatrix} \frac{0}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \end{pmatrix} = \frac{1}{\sqrt{2}} \begin{pmatrix} 0 \\ 1 \\ 1 \end{pmatrix} \text{ the length of this vector is } \sqrt{0^2 + (1)^2 + (1)^2} = \sqrt{2}$$

Next Put  $\lambda = 0$  in the above first two equations we get

$$2x_1 - x_2 + x_3 = 0$$

$$-x_1 + 1x_2 + 0x_3 = 0$$

$x_2$	$x_3$	$x_1$	$x_2$
-1	1	2	-1
1	0	-1	1

$$\frac{x_1}{0-1} = \frac{x_2}{-1-0} = \frac{x_3}{2-1}$$

$$\Rightarrow \frac{x_1}{-1} = \frac{x_2}{-1} = \frac{x_3}{1}$$

Therefore Eigen vector corresponding to the Eigen value  $\lambda = 0$  is  $\begin{pmatrix} -1 \\ -1 \\ 1 \end{pmatrix}$

Let  $q_3$  be the unit Eigen vector corresponding to the Eigen value  $\lambda = 0$ .

Therefore  $q_3 = \begin{pmatrix} -\frac{1}{\sqrt{3}} \\ \frac{-1}{\sqrt{3}} \\ \frac{1}{\sqrt{3}} \end{pmatrix}$  the length of this vector is  $\sqrt{(-1)^2 + (-1)^2 + (1)^2} = \sqrt{3}$

**Step 4: To find orthogonal matrix  $Q = (q_1 \ q_2 \ q_3)$**

The orthogonal matrix  $Q$  is

$$Q = [q_1 \ q_2 \ q_3] = \begin{pmatrix} \frac{2}{\sqrt{6}} & 0 & -\frac{1}{\sqrt{3}} \\ -\frac{1}{\sqrt{6}} & \frac{1}{\sqrt{2}} & \frac{-1}{\sqrt{3}} \\ -\frac{1}{\sqrt{6}} & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{3}} \end{pmatrix}$$

By taking  $\frac{1}{\sqrt{6}}$  outside we get  $Q = \frac{1}{\sqrt{6}} \begin{pmatrix} 2 & 0 & -\sqrt{2} \\ -1 & \sqrt{3} & -\sqrt{2} \\ 1 & \sqrt{3} & \sqrt{2} \end{pmatrix}$

**Step 5: To find Singular values of  $A^T A$ .**

Use the formula  $\sigma_i = \sqrt{\lambda_i}$   $i = 1, 2, 3$ .  $\sigma_i$  is called the Singular value of the matrix  $A^T A$ .

$$\sigma_1 = \sqrt{\lambda_1} = \sqrt{3} \quad \sigma_2 = \sqrt{\lambda_2} = \sqrt{1} = 1 \quad \sigma_3 = \sqrt{\lambda_3} = \sqrt{0} = 0$$

**Step 6: To find rank of the given matrix A**

$$A = \begin{pmatrix} 1 & 0 & 1 \\ -1 & 1 & 0 \end{pmatrix}. \text{ Here order of A is } 2 \times 3. \text{ Therefore Rank of A, } \rho(A) \leq 2$$

$$\text{Now, } \begin{vmatrix} 1 & 0 \\ -1 & 1 \end{vmatrix} = 1 \neq 0. \text{ Therefore } \rho(A) = 2.$$

**Step 7: To find singular matrix of A denoted by  $\Sigma_A$**

$$\Sigma_A = \begin{pmatrix} D_A & 0 \\ 0 & 0 \end{pmatrix} \text{ Where } D_A = \mathbf{diag}(\sigma_1 \ \sigma_2 \ \sigma_3) = \mathbf{diag}(\sqrt{3} \ 1 \ 0)$$

Since the Rank of A is 2, we consider only two singular values  $\sigma_1$  and  $\sigma_2$ . Therefore Singular matrix of A is

$$\Sigma_A = \begin{pmatrix} \sigma_1 & 0 & 0 \\ 0 & \sigma_2 & 0 \end{pmatrix} = \begin{pmatrix} \sqrt{3} & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix}$$

**Step 8:** To find  $2 \times 2$  Orthogonal matrix  $P = (\mathbf{p}_1 \ \mathbf{p}_2)$  where  $\mathbf{p}_1$  and  $\mathbf{p}_2$  are normalisers of  $Aq_1$  and  $Aq_2$  respectively.

$$\text{Now } Aq_1 = \begin{pmatrix} 1 & 0 & 1 \\ -1 & 1 & 0 \end{pmatrix} \begin{pmatrix} \frac{2}{\sqrt{6}} \\ -\frac{1}{\sqrt{6}} \\ -\frac{1}{\sqrt{6}} \end{pmatrix} = \begin{pmatrix} \frac{3}{\sqrt{6}} \\ -\frac{3}{\sqrt{6}} \end{pmatrix} = \frac{3}{\sqrt{6}} \begin{pmatrix} 1 \\ -1 \end{pmatrix}$$

$$\mathbf{p}_1 = \text{Normaliser of } Aq_1 = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 \\ -1 \end{pmatrix} = \begin{pmatrix} \frac{1}{\sqrt{2}} \\ -\frac{1}{\sqrt{2}} \end{pmatrix}$$

$$\text{Now } Aq_2 = \begin{pmatrix} 1 & 0 & 1 \\ -1 & 1 & 0 \end{pmatrix} \frac{1}{\sqrt{2}} \begin{pmatrix} 0 \\ 1 \\ 1 \end{pmatrix} = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 \\ 1 \end{pmatrix}$$

$$\mathbf{p}_2 = \text{Normaliser of } Aq_2 = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 \\ 1 \end{pmatrix} = \begin{pmatrix} \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \end{pmatrix}$$

Therefore **Orthogonal matrix**

$$P = (\mathbf{p}_1 \ \mathbf{p}_2) = \begin{pmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ -\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{pmatrix} = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 & 1 \\ -1 & 1 \end{pmatrix}$$

**Step 9:** Singular Value Decomposition (SVD) for A is obtained by using the formula

$$\begin{aligned} A &= P \Sigma_A Q^T = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 & 1 \\ -1 & 1 \end{pmatrix} \begin{pmatrix} \sqrt{3} & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix} \frac{1}{\sqrt{6}} \begin{pmatrix} 2 & 0 & -\sqrt{2} \\ -1 & \sqrt{3} & -\sqrt{2} \\ 1 & \sqrt{3} & \sqrt{2} \end{pmatrix}^T \\ &= \frac{1}{\sqrt{2}} \begin{pmatrix} 1 & 1 \\ -1 & 1 \end{pmatrix} \begin{pmatrix} \sqrt{3} & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix} \frac{1}{\sqrt{6}} \begin{pmatrix} 2 & -1 & 1 \\ 0 & \sqrt{3} & \sqrt{3} \\ -\sqrt{2} & -\sqrt{2} & \sqrt{2} \end{pmatrix} \end{aligned}$$