

Singular Value Decomposition :→ ①

We know that every symmetric matrix A can be factored as $A = PDP^T$, where P is an orthogonal matrix and D is a diagonal matrix consisting of eigenvalues of A . If A is not symmetric, such a factorization is not possible. But again we know to factor a square matrix A as $A = PDP^T$, here P is simply an invertible matrix.

Not every matrix is diagonalizable, but with the help of SVD (Singular value decomposition), we will show that every matrix has a factorization of the form $A = P\mathcal{D}Q^T$, where P and Q are orthogonal matrices and \mathcal{D} is a diagonal matrix.

Singular Values of a Matrix :→

If A is an $m \times n$ matrix, the singular values of A are the square roots of the eigenvalues of A^TA and are denoted by $\sigma_1, \sigma_2, \dots, \sigma_n$. It is conventional to arrange the singular values so that

$$\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_n.$$

e.g.: Find the singular values of $A = \begin{bmatrix} 1 & 1 \\ 1 & 0 \\ 0 & 1 \end{bmatrix}$

Solu: $A^TA = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 1 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 1 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}$

$$\text{C.E.}: \lambda^2 - 4\lambda + 3 = 0 \Rightarrow \lambda_1 = 3 \quad \lambda_2 = 1$$

thus $\sigma_1 = \sqrt{3}$ and $\sigma_2 = \sqrt{1} = 1$ are the singular values of A .

Note → Since $[A]_{m \times n}$ and $A^T A \rightarrow$ symmetric and orthogonally diagonalizable.

$$\begin{aligned}\|A\mathbf{v}_i\|^2 &= (\mathbf{A}\mathbf{v}_i)^T \mathbf{A}\mathbf{v}_i = \mathbf{v}_i^T \mathbf{A}^T \mathbf{A}\mathbf{v}_i \\ &= \mathbf{v}_i^T \lambda_i \mathbf{v}_i \\ &= \lambda_i \quad (\mathbf{v}_i \text{ is a unit vector})\end{aligned}$$

So, the singular values of A are the lengths of the vectors $A\mathbf{v}_1, A\mathbf{v}_2, \dots, A\mathbf{v}_n$.

SVD : -

The decomposition of A involves an $n \times n$ diagonal matrix Σ of the form

$$\Sigma = \begin{bmatrix} D & 0 \\ 0 & 0 \end{bmatrix} \leftarrow m-91 \text{ rows}$$

\downarrow $n-91 \text{ columns}$

where D is an $n \times n$ diagonal matrix for some α not exceeding the smaller of m and n . If α equals m or n or both, some or all of the zero matrices do not appear.

Theorem: Let A be an $m \times n$ matrix with rank r . Then there exists an $n \times n$ matrix Σ for which the diagonal entries in Σ are the first r singular values of A , $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_r > 0$, and there exists an $m \times m$ orthogonal matrix U and an $n \times n$ orthogonal matrix V such that

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

ste:- i) A factorization of $A = U \Sigma V^T$ is called SVD of A . (3)

- ii) The columns of U are called the left singular vectors of A , and the columns of V are called right singular vectors of A .
- iii) The matrices U and V are not uniquely determined by A , but Σ must contain the singular values of A .

Example:- Find the singular value decomposition

$$\text{of } A = \begin{bmatrix} 4 & 11 & 14 \\ 8 & 7 & -2 \end{bmatrix}$$

Soluⁿ :- It is divided into three steps:

Step ①: Find an orthogonal diagonalization of $A^T A$.

$$A^T A = \begin{bmatrix} 4 & 8 \\ 11 & 7 \\ 14 & -2 \end{bmatrix} \begin{bmatrix} 4 & 11 & 14 \\ 8 & 7 & -2 \end{bmatrix} = \begin{bmatrix} 80 & 100 & 40 \\ 100 & 170 & 140 \\ 40 & 140 & 200 \end{bmatrix}$$

eigenvalues of $A^T A$ are: $\lambda_1 = 360$, $\lambda_2 = 90$, $\lambda_3 = 0$

& its corresponding eigenvectors are

$$v_1 = \begin{bmatrix} \frac{1}{\sqrt{3}} \\ \frac{2}{\sqrt{3}} \\ \frac{2}{\sqrt{3}} \end{bmatrix} \quad v_2 = \begin{bmatrix} -\frac{2}{\sqrt{3}} \\ -\frac{1}{\sqrt{3}} \\ \frac{2}{\sqrt{3}} \end{bmatrix} \quad v_3 = \begin{bmatrix} \frac{2}{\sqrt{3}} \\ -\frac{2}{\sqrt{3}} \\ \frac{1}{\sqrt{3}} \end{bmatrix}$$

as v_1 , v_2 and v_3 are already unit vectors
no need to normalize them.

Step ②: Set up V and Σ .

Arrange the eigenvalues of $A^T A$ in decreasing order & find the singular values

$$\sigma_1 = 6\sqrt{10}, \quad \sigma_2 = 3\sqrt{10}, \quad \sigma_3 = 0,$$

The non zero singular values are the diagonal entries of Σ . The matrix Σ is the same size as A with D in its upper-left corner and 0's elsewhere

$$D = \begin{bmatrix} 6\sqrt{10} & 0 \\ 0 & 3\sqrt{10} \end{bmatrix} \quad \text{and} \quad \Sigma = [D \ 0] = \begin{bmatrix} 6\sqrt{10} & 0 & 0 \\ 0 & 3\sqrt{10} & 0 \end{bmatrix}$$

Step ③: Construct V : $V = [v_1 \ v_2 \ v_3]$

When A has rank r , the first r columns of V are the normalized vectors obtained from Av_1, \dots, Av_r

$$v_1 = \frac{1}{\sigma_1} Av_1 = \frac{1}{6\sqrt{10}} \begin{bmatrix} 18 \\ 6 \end{bmatrix} = \begin{bmatrix} 3/\sqrt{10} \\ 1/\sqrt{10} \end{bmatrix}$$

$$v_2 = \frac{1}{\sigma_2} Av_2 = \frac{1}{3\sqrt{10}} \begin{bmatrix} 3 \\ -9 \end{bmatrix} = \begin{bmatrix} \sqrt{10} \\ -3/\sqrt{10} \end{bmatrix}$$

Now singular value decomposition of A is

$$A = \begin{bmatrix} 3\sqrt{10} & \sqrt{10} \\ \sqrt{10} & -3\sqrt{10} \end{bmatrix} \begin{bmatrix} 6\sqrt{10} & 0 & 0 \\ 0 & 3\sqrt{10} & 0 \end{bmatrix} \begin{bmatrix} x_3 & y_3 & z_3 \\ -2y_3 & y_3 & y_3 \\ 2y_3 & -2y_3 & x_3 \end{bmatrix} \begin{matrix} \uparrow \\ V \\ \uparrow \\ \Sigma \\ \uparrow \\ VT \end{matrix}$$

① $A = \begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix} \rightarrow \text{Find SVD}$

Soluⁿ Step ①:- $A^T A = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}$

eigenvalues $\lambda_1 = 3$ & $\lambda_2 = 1$ & corresponding eigenvectors are $v_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}, v_2 = \begin{bmatrix} 1 \\ -1 \end{bmatrix}$

Since eigenvectors are orthogonal, so we will normalize it

$$V = [q_1 \ q_2] = \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & \frac{-1}{\sqrt{2}} \end{bmatrix} = \begin{bmatrix} \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix}$$

Step ② :- $\sigma_1 = \sqrt{3}$ and $\sigma_2 = 1$ (5)

So; $D = \begin{bmatrix} \sqrt{3} & 0 \\ 0 & 1 \end{bmatrix}$ and $\Sigma = \begin{bmatrix} D \end{bmatrix} = \begin{bmatrix} \sqrt{3} & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix}$

and $V = \begin{bmatrix} x_{\sqrt{2}} & x_{\sqrt{2}} \\ x_{\sqrt{2}} & x_{\sqrt{2}} \end{bmatrix}$

Step ③ :- $U_1 = \frac{1}{\sigma_1} Av_1 = \frac{1}{\sqrt{3}} \begin{bmatrix} 1 & 1 \\ 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_{\sqrt{2}} \\ x_{\sqrt{2}} \end{bmatrix} = \begin{bmatrix} \frac{2\sqrt{6}}{\sqrt{3}} \\ \frac{x_{\sqrt{6}}}{\sqrt{3}} \\ \frac{x_{\sqrt{6}}}{\sqrt{3}} \end{bmatrix}$

$$U_2 = \frac{1}{\sigma_2} Av_2 = \frac{1}{1} \begin{bmatrix} 1 & 1 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} -x_{\sqrt{2}} \\ x_{\sqrt{2}} \end{bmatrix} = \begin{bmatrix} 0 \\ -x_{\sqrt{2}} \\ x_{\sqrt{2}} \end{bmatrix}$$

~~No singular value decomposition of A is~~

~~Now V should be a 3×3 matrix, but we are getting only 2 vectors, so we will extend $\{U_1, U_2\}$ to an orthonormal basis for \mathbb{R}^3 .~~

~~say $\{U_1, U_2, e_3\}$ is linearly independent.~~

Apply the Gram-Schmidt Process:

$$U_3 = \begin{bmatrix} -x_{\sqrt{3}} \\ x_{\sqrt{3}} \\ x_{\sqrt{3}} \end{bmatrix}$$

So; $V = \begin{bmatrix} \frac{2\sqrt{6}}{\sqrt{3}} & 0 & -x_{\sqrt{3}} \\ \frac{x_{\sqrt{6}}}{\sqrt{3}} & \frac{x_{\sqrt{2}}}{\sqrt{3}} & x_{\sqrt{3}} \\ \frac{x_{\sqrt{6}}}{\sqrt{3}} & \frac{x_{\sqrt{2}}}{\sqrt{3}} & x_{\sqrt{3}} \end{bmatrix}$

So; $A = \begin{bmatrix} \frac{2\sqrt{6}}{\sqrt{3}} & 0 & -x_{\sqrt{3}} \\ \frac{x_{\sqrt{6}}}{\sqrt{3}} & \frac{x_{\sqrt{2}}}{\sqrt{3}} & x_{\sqrt{3}} \\ \frac{x_{\sqrt{6}}}{\sqrt{3}} & \frac{x_{\sqrt{2}}}{\sqrt{3}} & x_{\sqrt{3}} \end{bmatrix} \begin{bmatrix} \sqrt{3} & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x_{\sqrt{2}} & x_{\sqrt{2}} \\ -x_{\sqrt{2}} & x_{\sqrt{2}} \end{bmatrix}$ (Ans.)

(6)

$$\textcircled{11} \quad A = \begin{bmatrix} 1 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \text{ find SVD.}$$

$$\text{Ans: } A = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \sqrt{2} & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} \frac{\sqrt{2}}{2} & \frac{\sqrt{2}}{2} & 0 \\ 0 & 0 & 1 \\ -\frac{\sqrt{2}}{2} & \frac{\sqrt{2}}{2} & 0 \end{bmatrix} = U \Sigma V^T$$

$$\begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \\ \frac{\partial f}{\partial z} \end{bmatrix} = \begin{bmatrix} \partial f \\ \partial y \\ \partial z \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}^{-1} = \sqrt{2} A^{-\frac{1}{2}} = \sqrt{2}$$

$$\begin{bmatrix} 0 \\ \partial f \\ \partial y \\ \partial z \end{bmatrix} = \begin{bmatrix} \partial f \\ \partial y \\ \partial z \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}^{-1} = \sqrt{2} A^{\frac{1}{2}} = \sqrt{2}$$

in the first part we take the gradient
 and we get two sets of black U with
 four N's and we have the other 2 plus extra
 one red row denoted by the
 two rows which is for left, right
 second three rows are right

$$\begin{bmatrix} \partial f \\ \partial y \\ \partial z \end{bmatrix} = \sqrt{2}$$

$$\begin{bmatrix} \partial f & 0 & \partial f \\ \partial y & \partial f & \partial y \\ \partial z & \partial y & \partial z \end{bmatrix} = U \Sigma V^T$$

$$\begin{bmatrix} \partial f & 0 & \partial f \\ \partial y & \partial f & \partial y \\ \partial z & \partial y & \partial z \end{bmatrix} = U \Sigma V^T$$