

## Orthogonal Complement :-

Let  $W$  be a subspace of  $\mathbb{R}^n$ . A vector  $v$  in  $\mathbb{R}^n$  is orthogonal to  $W$  if  $v$  is orthogonal to every vector in  $W$ . The set of all vectors that are orthogonal to  $W$  is called orthogonal complement of  $W$ , denoted  $W^\perp$ . That is

$$W^\perp = \{v \in \mathbb{R}^n : v \cdot w = 0 \text{ for all } w \in W\}$$

Note :-

- i) A vector  $x$  is in  $W^\perp$  iff  $x$  is orthogonal to every vector in a set that spans  $W$ .
- ii)  $W^\perp$  is a subspace of  $\mathbb{R}^n$ .
- iii)  $(W^\perp)^\perp = W$
- iv)  $W \cap W^\perp = \{0\}$
- v) If  $\{w_1, w_2, \dots, w_k\}$  spans  $W$  then  $z$  is in  $W^\perp$   
 $\Rightarrow w_1 \cdot z = w_2 \cdot z = \dots = w_k \cdot z = 0$

Since any  $w \in W$ , if we have to find  $z$  s.t.

$w_1 \cdot z = w_2 \cdot z = \dots = w_k \cdot z = 0$  mean we have to find the null space of  $W$ .

Hence, if  $A$  is an  $(m \times n)$  matrix, then the orthogonal complement of the row space of  $A$  is the null space of  $A$ . i.e.

$$(\text{Row } A)^\perp = \text{Null } A$$

$$\text{as } \text{Row } A^T = \text{Col } A$$

$$\therefore (\text{Col } A)^\perp = \text{Null } A^T$$

Orthogonal complement of column space of A is the null space of  $A^T$ .

Reason:- Every vector  $x$  that satisfies  $Ax=0$  is in the nullspace of  $A$ , and is perpendicular to every row of  $A$ . Thus  $x$  is also  $\perp$  to linear combination of rows of  $A$  and is thus  $\perp$  to every vector in the row space.

Problems:- ① Let  $w$  be the subspace spanned by the vectors  $\{w_1, w_2\}$ . Find a basis for  $w^\perp$  where  $w_1 = \begin{pmatrix} 2 \\ -1 \\ -2 \end{pmatrix}, w_2 = \begin{pmatrix} 4 \\ 0 \\ 0 \end{pmatrix}$

Solu<sup>n</sup>:-  $A = \begin{pmatrix} 2 & 4 \\ -1 & 0 \\ -2 & 0 \end{pmatrix}$  Now  $A^T = \begin{pmatrix} 2 & -1 & -2 \\ 4 & 0 & 0 \end{pmatrix} \xrightarrow{-2R_1 + R_2}$

$$\begin{pmatrix} 2 & -1 & -2 \\ 0 & -2 & 5 \end{pmatrix} \xrightarrow{\quad}$$

$$\begin{pmatrix} 1 & \frac{1}{2} & -1 \\ 0 & 1 & -5/2 \end{pmatrix} \xrightarrow{\quad} \begin{pmatrix} 1 & 0 & y_4 \\ 0 & 1 & -5/2 \end{pmatrix}$$

10:-  $y_1 = -\frac{1}{2}y_3$       basis =  $\text{span} \left( \begin{pmatrix} -1/2 \\ 5/2 \\ 1 \end{pmatrix} \right)$

 $y_2 = \frac{5}{2}y_3$

$$\text{null}(A^T) = \left\{ \begin{pmatrix} 1 \\ 0 \\ 4 \end{pmatrix} \right\} = \left( \begin{array}{c|cc} \text{col} & & \\ \hline \text{row} & & \\ A & & \end{array} \right)^T$$

⑩ Let  $w$  be a subspace spanned by  $u = (1, 2, 3, -1, 2)$  and  $v = (2, 4, 7, 2, -1)$ . Find a basis of the  $w^\perp$  of  $w$ .

Solu<sup>n</sup>

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Let  $w = (x, y, z, s, t)$

$$w \cdot u = x + 2y + 3z - s + 2t = 0$$

$$w \cdot v = 2x + 4y + 7z + 2s - t = 0$$

$$\text{Now } A = \begin{pmatrix} 1 & 2 & 3 & -1 & 2 \\ 2 & 4 & 7 & 2 & -1 \end{pmatrix} \rightarrow \begin{pmatrix} 1 & 2 & 3 & -1 & 2 \\ 0 & 0 & 1 & 4 & -5 \end{pmatrix}$$

then  $x + 2y + 3z - s + 2t = 0$   
 $z + 4s - 5t = 0$

$$\text{Let } s = a \quad t = b$$

$$z = 5a - 4b$$

$$y = c$$

$$\begin{aligned} x &= -2c - 3(5a - 4b) + b - 2a \\ &= -2c - 15a + 12b + b - 2a \\ &= -2c - 17a + 13b \end{aligned}$$

$$\begin{pmatrix} x \\ y \\ z \\ s \\ t \end{pmatrix} = a \begin{pmatrix} -17 \\ 0 \\ 5 \\ 1 \\ 0 \end{pmatrix} + b \begin{pmatrix} 13 \\ 0 \\ -4 \\ 0 \\ 1 \end{pmatrix} + c \begin{pmatrix} -2 \\ 1 \\ 0 \\ 0 \\ 0 \end{pmatrix}$$

$$\begin{aligned} \text{Basis} &= \text{span} \left\{ \begin{pmatrix} -17 \\ 0 \\ 5 \\ 1 \\ 0 \end{pmatrix}, \begin{pmatrix} 13 \\ 0 \\ -4 \\ 0 \\ 1 \end{pmatrix}, \begin{pmatrix} -2 \\ 1 \\ 0 \\ 0 \\ 0 \end{pmatrix} \right\} \\ &= \text{null}(A) = (\text{row } A)^\perp. \end{aligned}$$

Ques. 1(i) Find the orthogonal complement of  $w^\perp$  of  $w$  and give a basis for  $w^\perp$  Answer

$$\text{Solu}^n \quad w = \left\{ \begin{pmatrix} x \\ y \end{pmatrix} : 2x - y = 0 \right\}$$

$$\begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} x \\ 2x \end{pmatrix} = \begin{pmatrix} 1 \\ 2 \end{pmatrix} \cdot n$$

(22)

Now  $v = \begin{pmatrix} a \\ b \end{pmatrix}$   $v \cdot w = 0$   
 $\Rightarrow a+2b=0$

then  $\begin{pmatrix} a \\ b \end{pmatrix} = \begin{pmatrix} -2b \\ b \end{pmatrix} = b \begin{pmatrix} -2 \\ 1 \end{pmatrix}$   $\Rightarrow a = -2b$

so basis for  $w^\perp = \text{span} \left\{ \begin{pmatrix} -2 \\ 1 \end{pmatrix} \right\}$  Answer

(iv)  $W = \left\{ \begin{pmatrix} x \\ y \\ z \end{pmatrix} : 2x-y+3z=0 \right\}$

$$\begin{pmatrix} x \\ y \\ z \end{pmatrix} = \begin{pmatrix} x \\ 2x+3z \\ z \end{pmatrix} = x \begin{pmatrix} 1 \\ 2 \\ 0 \end{pmatrix} + z \begin{pmatrix} 0 \\ 3 \\ 1 \end{pmatrix}$$

$\downarrow w_1 \quad \downarrow w_2$

say  $v = \begin{pmatrix} a \\ b \\ c \end{pmatrix} \in W^\perp$   $w_1 \cdot v = 0 \Rightarrow a+2b=0$   
 $\Rightarrow w_2 \cdot v = 0 \Rightarrow 3b+c=0$

Now let  $c=t$ ,  $b=-\frac{t}{3}$ ,  $a=\frac{2}{3}t$

basis for  $w^\perp = \text{span} \left\{ \begin{bmatrix} 2 \\ -1 \\ 3 \end{bmatrix} \right\}$  Ans

(v)  $W = \left\{ \begin{pmatrix} x \\ y \\ z \end{pmatrix}, x=t, y=-t, z=3t \right\}$

$$\begin{pmatrix} x \\ y \\ z \end{pmatrix} = t \begin{pmatrix} 1 \\ -1 \\ 3 \end{pmatrix}$$

$\downarrow w_1$

Let  $v = \begin{pmatrix} a \\ b \\ c \end{pmatrix} \in W^\perp$

(23)

$$W: w_1 \cdot v = 0 \Rightarrow a - b + 3c = 0$$

$$c = t, b = 2t, a = 2t - 3t = -t$$

basis for  $W^\perp = \text{span} \left\{ \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix}, \begin{pmatrix} -3 \\ 0 \\ 1 \end{pmatrix} \right\}$  (Answer)

Problems:- i) Find bases for the row space and null space of A. Verify that every vector in  $\text{row}(A)$  is orthogonal to every vector in  $\text{null}(A)$ .

$$A = \begin{bmatrix} 1 & -1 & 3 \\ 5 & 2 & 1 \\ 0 & 1 & -2 \\ -1 & 1 & 1 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & -1 & 3 \\ 0 & 7 & -14 \\ 0 & 1 & -2 \\ 0 & -2 & 4 \end{bmatrix} \rightarrow$$

$$\begin{bmatrix} 1 & -1 & 3 \\ 0 & 1 & -2 \\ 0 & 1 & -2 \\ 0 & 1 & -2 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & -1 & 3 \\ 0 & 1 & -2 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & -2 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

$$\text{row}(A) = \text{Span} \{ u_1, u_2 \}$$

$$u_1 = (1, 0, 1) \quad \text{and} \quad u_2 = (0, 1, -2) \quad \Theta$$

$$\text{null}(A) = \begin{aligned} x+z &= 0 \\ y-2z &= 0 \end{aligned}$$

$$z = t, \quad y = 2t$$

$$\text{null}(A) = \text{span} \left\{ \begin{pmatrix} 1 \\ 2 \\ 1 \end{pmatrix} \right\} \text{ and } v = \begin{pmatrix} 1 \\ 2 \\ 1 \end{pmatrix}$$

①

$$v \cdot u_1 = -1 - 2 + 3 = 0$$

$$v \cdot u_2 = 0 + 2 - 2 = 0$$

(2u)

To show  $(\text{Row } A)^\perp = \text{null } A$ , it is enough to show that every  $u$  of  $\text{Row}(A)$  is orthogonal to  $v$ .

$$\rightarrow \text{col}(A) = \text{Span} \left\{ \begin{pmatrix} 1 \\ 5 \\ 0 \\ -1 \end{pmatrix}, \begin{pmatrix} 3 \\ -1 \\ 1 \\ -2 \end{pmatrix} \right\}$$

$$u_1 = \begin{pmatrix} 1 \\ 5 \\ 0 \\ -1 \end{pmatrix} \text{ and } u_2 = \begin{pmatrix} 3 \\ -1 \\ 1 \\ -2 \end{pmatrix}$$

$$\text{Null space of } A^T = \left\{ \begin{pmatrix} 5 \\ 1 \\ 7 \\ 0 \end{pmatrix}, \begin{pmatrix} -3 \\ 2 \\ 0 \\ 2 \end{pmatrix} \right\}$$

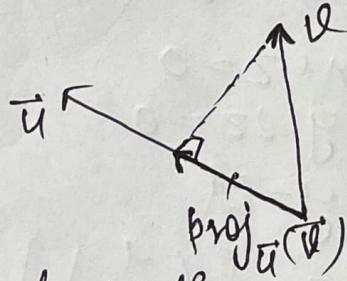
$$\text{clearly } (\text{col } A)^\perp = \text{null } A^T \quad \underline{\text{Proved}}$$

### Orthogonal Projection :-

In  $\mathbb{R}^2$ , the projection of  $\vec{v}$  onto  $\vec{u}$  is defined as

$$\text{proj}_{\vec{u}}(\vec{v}) = \left( \frac{\vec{u} \cdot \vec{v}}{\vec{u} \cdot \vec{u}} \right) \vec{u} = \left( \frac{\vec{u} \cdot \vec{v}}{\|\vec{u}\|^2} \right) \vec{u}$$

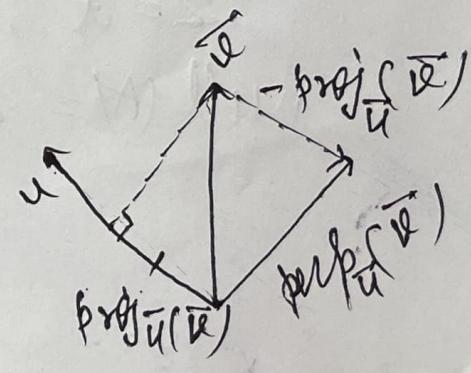
Geometrically:



Now orthogonal projection :-

$$\Rightarrow \text{perp}_{\vec{u}}(\vec{v}) = \vec{v} - \text{proj}_{\vec{u}}(\vec{v})$$

$$\vec{v} = \text{proj}_{\vec{u}}(\vec{v}) + \text{perp}_{\vec{u}}(\vec{v})$$



Definition - Let  $W$  be a subspace of  $\mathbb{R}^n$  and let  $\{u_1, u_2, \dots, u_k\}$  be orthogonal basis for  $W$ . For any vector  $v$  in  $\mathbb{R}^n$ , the orthogonal projection of  $v$  onto  $W$  is defined as

$$\text{proj}_W(v) = \left( \frac{u_1 \cdot v}{u_1 \cdot u_1} \right) u_1 + \dots + \left( \frac{u_k \cdot v}{u_k \cdot u_k} \right) u_k \quad (1)$$

The orthogonal to  $W$  is the vector component of  $v$

$$\text{perp}_W(v) = v - \text{proj}_W(v)$$

eq<sup>n</sup> (1) can be rewritten as

$$\text{proj}_W(v) = \text{proj}_{u_1}(v) + \dots + \text{proj}_{u_k}(v)$$

Question Let  $W$  be the plane in  $\mathbb{R}^3$  with equation

$x - y + 2z = 0$  and let  $v = \begin{bmatrix} 3 \\ 1 \\ 2 \end{bmatrix}$ . Find the orthogonal projection of  $v$  onto  $W$  and the components of  $v$  orthogonal to  $W$ .

Solu<sup>n</sup> - Orthogonal basis for  $W = \{u_1, u_2\}$  where

$$u_1 = \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} \text{ and } u_2 = \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}$$

Now orthogonal projection of  $v$  onto  $W$  is

$$\begin{aligned} \text{proj}_W(v) &= \text{proj}_{u_1}(v) + \text{proj}_{u_2}(v) \\ &= \left( \frac{u_1 \cdot v}{u_1 \cdot u_1} \right) u_1 + \left( \frac{u_2 \cdot v}{u_2 \cdot u_2} \right) u_2 \\ &= \frac{2}{2} \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} + \frac{(-3+1+2)}{3} \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix} \end{aligned}$$

$$= \frac{2}{2} \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} - \frac{2}{3} \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 5/3 \\ 1/3 \\ -2/3 \end{bmatrix}$$

and component of  $v$  orthogonal to  $w$

$$\text{perp}_w(v) = v - \text{proj}_w(v)$$

$$= \begin{bmatrix} 3 \\ -1 \\ 2 \end{bmatrix} - \begin{bmatrix} 5/3 \\ 1/3 \\ -2/3 \end{bmatrix} = \begin{bmatrix} 4/3 \\ -4/3 \\ 8/3 \end{bmatrix}$$

- Note: 1) It is easy to see that  $\text{proj}_w(v)$  is in  $W$ , since it satisfies the eq<sup>n</sup> of plane.  
 2) It is equally easy to see that  $\text{perp}_w(v)$  is orthogonal to  $W$ , since it is a scalar multiple of the normal vector  $\begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$  to  $W$ .

→ If we let  $W = \text{span}(u)$ , then  $w = \text{proj}_u(v)$  is in  $W$  and  $w^\perp = \text{perp}_u(v)$  is in  $w^\perp$ . We therefore have a way of decomposing  $v$  into the sum of two vectors, one from  $W$  and other orthogonal to  $W$ , namely

$$v = w + w^\perp$$

formally;

### The Orthogonal Decomposition Theorem :-

Let  $W$  be a subspace of  $\mathbb{R}^n$  and let  $v$  be a vector in  $\mathbb{R}^n$ . Then there are unique vectors  $w$  in  $W$  and  $w^\perp$  in  $W^\perp$  such that

$$\boxed{v = w + w^\perp}$$

Eg: from previous example  $\boxed{w + w^\perp = v}$

(Answer)

## QR Factorization

①

If  $A$  is an  $m \times n$  matrix with linearly independent columns ( $m \geq n$ ), then applying the Gram-Schmidt Process to these columns yields a very useful factorization of  $A$  into the product of a matrix  $Q$  with orthonormal columns and an upper triangular matrix  $R$ . This is QR factorization, and it has applications in solving the equations and finding the eigenvalues.

Theorem:- If  $A$  is an  $m \times n$  matrix with linearly independent columns, then  $A$  can be formed and factored as  $A = QR$ , where  $Q$  is an  $m \times n$  matrix whose columns form an orthonormal basis for  $\text{Col } A$  and  $R$  is an  $n \times n$  upper triangular invertible matrix with positive entries on its diagonal.

Example:- Find a QR factorization of  $A = \begin{bmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 1 & 1 & 1 \end{bmatrix}$

Solu<sup>n</sup>:- An orthogonal basis for  $\text{Col } A = \{v_1, v_2, v_3\}$  is  
 $v_1 = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}, v_2 = \begin{bmatrix} -3 \\ 1 \\ 1 \end{bmatrix}, v_3 = \begin{bmatrix} 0 \\ -2/3 \\ 1/3 \end{bmatrix}$

Now normalize  $v_1, v_2$  and  $v_3$

$$Q = \begin{bmatrix} \frac{1}{2} & -\frac{3}{\sqrt{12}} & 0 \\ \frac{1}{2} & \frac{1}{\sqrt{12}} & -\frac{2}{\sqrt{12}} \\ \frac{1}{2} & \frac{1}{\sqrt{12}} & \frac{1}{\sqrt{12}} \\ \frac{1}{2} & \frac{1}{\sqrt{12}} & \frac{1}{\sqrt{12}} \end{bmatrix} = [q_1, q_2, q_3]$$

as  $A = QR$  for some upper triangular matrix.  
 To find  $R$ , we use the fact that  $Q$  has orthonormal columns and, hence  $Q^T Q = I$ , thus

$$\begin{aligned} A &= QR \\ Q^T A &= Q^T QR \\ Q^T A &= IR \\ &= R \end{aligned}$$

thus,  $R = Q^T A = \begin{bmatrix} \frac{1}{2} & Y_2 & \frac{1}{2} & Y_2 \\ -3\sqrt{2} & Y_{12} & Y_{12} & Y_{12} \\ 0 & -2\sqrt{6} & Y_6 & Y_6 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$

$$= \begin{bmatrix} 2 & \frac{3}{2} & 1 \\ 0 & 3\sqrt{2} & 2\sqrt{2} \\ 0 & 0 & 2\sqrt{6} \end{bmatrix}$$

Question:- Find QR factorization of  $A = \begin{bmatrix} 1 & 2 & 2 \\ -1 & 1 & 2 \\ -1 & 0 & 1 \\ 1 & 1 & 2 \end{bmatrix}$

## Orthogonal Diagonalization of Symmetric Matrices:

As we know, not all square matrices are diagonalizable. The situation changes if we restrict our attention to real symmetric matrices. All the eigenvalues of a real symmetric matrix are real, and such matrix is always diagonalizable.

$$\text{Eg: } A = \begin{bmatrix} 1 & 2 \\ 2 & -2 \end{bmatrix}$$

E-Values:  $-3, 2$

$\Rightarrow$  diagonalizable

$$B = \begin{bmatrix} 6 & -2 & -1 \\ -2 & 6 & -1 \\ -1 & -1 & 5 \end{bmatrix}$$

E-Values:  $8, 6, 3$

$\Rightarrow$  diagonalizable

$$\begin{aligned} \text{C.E.} &= -\lambda^3 + 17\lambda^2 \\ &\quad - 90\lambda + 144 \\ &= -(\lambda - 8)(\lambda - 6) \\ &\quad (\lambda - 3) \end{aligned}$$

Def: A square matrix is orthogonally diagonalizable (3)  
if there exists an orthogonal matrix  $Q$  and a  
diagonal matrix  $D$  such that  $Q^T A Q = D$ .

e.g.  $A = \begin{bmatrix} 1 & 2 \\ 2 & -2 \end{bmatrix}$

$$C.E. = \lambda^2 + \lambda - 6 = (\lambda + 3)(\lambda - 2)$$

E.V. for  $\lambda = -3$   $\begin{bmatrix} -1 \\ -2 \end{bmatrix} = v_1$

$\lambda = 2$   $\begin{bmatrix} 2 \\ 1 \end{bmatrix} = v_2$

thus  $P = \begin{bmatrix} 1 & 2 \\ -2 & 1 \end{bmatrix}$ . Since  $v_1$  &  $v_2$  are ortho-  
-gonal, thus

$$u_1 = \frac{v_1}{\|v_1\|} = \begin{bmatrix} \frac{1}{\sqrt{5}} \\ \frac{-2}{\sqrt{5}} \end{bmatrix} \quad u_2 = \frac{v_2}{\|v_2\|} = \begin{bmatrix} \frac{2}{\sqrt{5}} \\ \frac{1}{\sqrt{5}} \end{bmatrix}$$

and then  $Q = [u_1 \ u_2] = \begin{bmatrix} \frac{1}{\sqrt{5}} & \frac{2}{\sqrt{5}} \\ \frac{-2}{\sqrt{5}} & \frac{1}{\sqrt{5}} \end{bmatrix}$

Since  $Q$  is an orthogonal matrix, then  $Q^T = Q^{-1}$

$$\begin{aligned} \text{then } Q^T A Q &= \begin{bmatrix} \frac{1}{\sqrt{5}} & \frac{2}{\sqrt{5}} \\ \frac{-2}{\sqrt{5}} & \frac{1}{\sqrt{5}} \end{bmatrix} \begin{bmatrix} 1 & 2 \\ 2 & -2 \end{bmatrix} \begin{bmatrix} \frac{1}{\sqrt{5}} & \frac{2}{\sqrt{5}} \\ \frac{-2}{\sqrt{5}} & \frac{1}{\sqrt{5}} \end{bmatrix} \\ &= \begin{bmatrix} \frac{1}{\sqrt{5}} - \frac{4}{\sqrt{5}} & \frac{2}{\sqrt{5}} + \frac{4}{\sqrt{5}} \\ \frac{2}{\sqrt{5}} + \frac{2}{\sqrt{5}} & \frac{4}{\sqrt{5}} - \frac{2}{\sqrt{5}} \end{bmatrix} \begin{bmatrix} \frac{1}{\sqrt{5}} & \frac{2}{\sqrt{5}} \\ \frac{-2}{\sqrt{5}} & \frac{1}{\sqrt{5}} \end{bmatrix} \\ &= \begin{bmatrix} \frac{-3}{\sqrt{5}} & \frac{6}{\sqrt{5}} \\ \frac{4}{\sqrt{5}} & \frac{2}{\sqrt{5}} \end{bmatrix} \begin{bmatrix} \frac{1}{\sqrt{5}} & \frac{2}{\sqrt{5}} \\ \frac{-2}{\sqrt{5}} & \frac{1}{\sqrt{5}} \end{bmatrix} = \begin{bmatrix} -3 & 0 \\ 0 & 2 \end{bmatrix} = D \end{aligned}$$

Hence, A is orthogonally diagonalizable.

Theorem: - ① An  $n \times n$  matrix A is orthogonally diagonalizable if and only if A is a symmetric matrix.

② If A is symmetric matrix, then any 2 eigenvectors corresponding to distinct eigenvalues of A are orthogonal.

Example:-  $A = \begin{bmatrix} 2 & 1 & 1 \\ 1 & 2 & 1 \\ 1 & 1 & 2 \end{bmatrix}$

$$\text{C.E. : } -\lambda^3 + 6\lambda^2 - 9\lambda + 4 = -(\lambda-4)(\lambda-1)^2$$

thus eigenvalues are 1, 1, 4.

$$\text{Now } E_4 = \text{span} \left( \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \right) \text{ and } E_1 = \text{span} \left( \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} \right)$$

clearly  $\begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \cdot \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix} = 0$  and  $\begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \cdot \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} = 0$

$\Rightarrow E_4$  is orthogonal to every vector in  $E_1$ .

Note: ①  $\begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix} \cdot \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix} = 1$ . Thus, eigenvectors corresponding to the same eigenvalue need not to be orthogonal.

## The Spectral Theorem :-

(5)

The set of eigenvalues of a matrix is called spectrum and the spectral theorem is given below as:

Theorem: An  $n \times n$  matrix  $A$  is orthogonally diagonalizable if and only if  $A$  is symmetric matrix.

Example:-  $A = \begin{bmatrix} 2 & 1 & 1 \\ 1 & 2 & 1 \\ 1 & 1 & 2 \end{bmatrix}$

$$E_4 = \text{span} \left( \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \right) \text{ and } E_1 = \text{span} \left( \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \right)$$

Now orthonormal vectors

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

Now  $Q$  is orthogonal matrix

$$\Rightarrow Q^T = Q^{-1}$$

$$\text{Now } Q^T A Q = \begin{bmatrix} 4 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad \underline{\text{Answer}}$$

$\Rightarrow A$  is orthogonally diagonalizable.

## Spectral Decomposition :-

The spectral theorem allows us to write a real symmetric matrix  $A$  in the form  $A = Q D Q^T$ , where  $Q$  is orthogonal and  $D$  is diagonal.

The diagonal entries of  $D$  are just the eigenvalues of  $A$ , and if columns of  $Q$  are orthonormal vectors  $q_1, q_2, \dots, q_n$ , then we have

$$\begin{aligned} A &= QDQ^T = [q_1, \dots, q_n] \begin{bmatrix} \lambda_1 & 0 & 0 & \cdots & 0 \\ 0 & \ddots & & & 0 \\ 0 & & \ddots & & 0 \\ & & & \ddots & \lambda_n \\ 0 & & & & 0 \end{bmatrix} \begin{bmatrix} q_1^T \\ q_2^T \\ \vdots \\ q_n^T \end{bmatrix} \\ &= [\lambda_1 q_1, \dots, \lambda_n q_n] \begin{bmatrix} q_1^T \\ q_2^T \\ \vdots \\ q_n^T \end{bmatrix} \\ &= \lambda_1 q_1 q_1^T + \lambda_2 q_2 q_2^T + \cdots + \lambda_n q_n q_n^T \end{aligned}$$

This is called the spectral decomposition of  $A$ .  $\textcircled{1}$

- Note
- i) Each of the terms  $\lambda_i q_i q_i^T$  is a rank 1 matrix
  - ii)  $q_i q_i^T$  is actually the matrix of the projection onto the subspace spanned by  $q_i$ .
  - iii) eq  $\textcircled{1}$  is sometimes referred to as the projection form of the spectral theorem.

Example: Find the spectral decomposition of the given matrix  $A = \begin{bmatrix} 7 & 2 \\ 2 & 4 \end{bmatrix}$

Solu<sup>n</sup>-

$$\text{C.E. : } \lambda^2 - 11\lambda + 24 = 0 \Rightarrow \lambda = 8, 3$$

eigenvector corresponding to  $\lambda = 8$  is  $\begin{bmatrix} 2 \\ 1 \end{bmatrix} = v_1$ ,  
 $\lambda = 3$  is  $\begin{bmatrix} -1 \\ 1 \end{bmatrix}$  or  $\begin{bmatrix} 1 \\ 2 \end{bmatrix} = v_2$

as  $v_1$  &  $v_2$  are orthogonal.

$$\Rightarrow Q = [q_1, q_2] = \begin{bmatrix} \frac{2}{\sqrt{5}} & \frac{1}{\sqrt{5}} \\ \frac{1}{\sqrt{5}} & \frac{2}{\sqrt{5}} \end{bmatrix} \rightarrow \text{orthogonal matrix.}$$

$$\text{Now } q_1 q_1^T = \begin{bmatrix} \frac{2}{\sqrt{5}} \\ \frac{1}{\sqrt{5}} \end{bmatrix} \begin{bmatrix} \frac{2}{\sqrt{5}} & \frac{1}{\sqrt{5}} \end{bmatrix} = \begin{bmatrix} \frac{4}{5} & \frac{2}{5} \\ \frac{2}{5} & \frac{1}{5} \end{bmatrix} \quad (7)$$

$$q_2 q_2^T = \begin{bmatrix} \frac{1}{\sqrt{5}} \\ \frac{2}{\sqrt{5}} \end{bmatrix} \begin{bmatrix} \frac{1}{\sqrt{5}} & \frac{2}{\sqrt{5}} \end{bmatrix} = \begin{bmatrix} \frac{1}{5} & \frac{2}{5} \\ -\frac{2}{5} & \frac{4}{5} \end{bmatrix}$$

$$\text{So: } \lambda_1 q_1 q_1^T + \lambda_2 q_2 q_2^T = 8 \begin{bmatrix} \frac{4}{5} & \frac{2}{5} \\ \frac{2}{5} & \frac{1}{5} \end{bmatrix} + 3 \begin{bmatrix} \frac{1}{5} & \frac{2}{5} \\ -\frac{2}{5} & \frac{4}{5} \end{bmatrix} \\ = \begin{bmatrix} 7 & 2 \\ 2 & 4 \end{bmatrix} = A$$

Note :- Spectral decomposition expresses a symmetric matrix A explicitly in terms of eigenvalues & eigenvectors. This gives us a way of constructing a matrix with given eigenvalues and orthonormal eigenvectors.

Example :- Find a  $2 \times 2$  matrix with eigenvalues  $\lambda_1 = 3$  and  $\lambda_2 = -2$  and its corresponding eigenvectors

$$v_1 = \begin{bmatrix} 3 \\ 4 \end{bmatrix} \text{ and } v_2 = \begin{bmatrix} -4 \\ 3 \end{bmatrix}$$

$$\text{Solu}^{\gamma}: \text{ Now } q_1 = \begin{bmatrix} \frac{3}{5} \\ \frac{4}{5} \end{bmatrix} \quad q_2 = \begin{bmatrix} -\frac{4}{5} \\ \frac{3}{5} \end{bmatrix}$$

with the help of spectral decomposition:

$$\begin{aligned} A &= \lambda_1 q_1 q_1^T + \lambda_2 q_2 q_2^T = \\ &= 3 \begin{bmatrix} \frac{3}{5} \\ \frac{4}{5} \end{bmatrix} \begin{bmatrix} \frac{3}{5} & \frac{4}{5} \end{bmatrix} + (-2) \begin{bmatrix} -\frac{4}{5} \\ \frac{3}{5} \end{bmatrix} \begin{bmatrix} -\frac{4}{5} & \frac{3}{5} \end{bmatrix} \\ &= 3 \begin{bmatrix} \frac{9}{25} & \frac{12}{25} \\ \frac{12}{25} & \frac{16}{25} \end{bmatrix} - 2 \begin{bmatrix} \frac{16}{25} & -\frac{12}{25} \\ -\frac{12}{25} & \frac{9}{25} \end{bmatrix} = \begin{bmatrix} -\frac{1}{5} & \frac{12}{5} \\ \frac{12}{5} & \frac{6}{5} \end{bmatrix} \end{aligned}$$

Answe<sup>r</sup>

## Quadratic forms :-

Until now, our attention in the course has focused only on linear equations, except for the sums of squares when computing  $\mathbf{x}^T \mathbf{x}$ . Such sums and more general expressions, called quadratic forms, occurs frequently in applications of linear Algebra to engineering.

An expression of the form

$$ax^2 + by^2 + cz^2 \quad \text{--- (i)}$$

is called a quadratic form in  $x$  and  $y$ . Similarly

$$ax^2 + by^2 + cz^2 + dxy + exz + fyz \quad \text{--- (ii)}$$

is a quadratic form in  $x, y$  and  $z$ .

Note - i) A quadratic form is the sum of terms, each of which has total degree two in the variables.

ii)  $5x^2 - 3y^2 + 2xy$  is a quadratic form, but  $x^2 + y^2 + z$  is not.

Definition :- A quadratic form in  $n$  variables is a function  $f: \mathbb{R}^n \rightarrow \mathbb{R}$  of the form

$$f(\mathbf{x}) = \mathbf{x}^T \mathbf{A} \mathbf{x}$$

where  $\mathbf{A}$  is symmetric  $n \times n$  matrix and  $\mathbf{x}$  in  $\mathbb{R}^n$ . We refer to  $\mathbf{A}$  as the matrix associated with  $f$ .

Example :- Write the quadratic form associated with the matrices

$$\mathbf{A} = \begin{bmatrix} 2 & -3 \\ -3 & 5 \end{bmatrix}$$

$$\mathbf{B} = \begin{bmatrix} 4 & 0 \\ 0 & 3 \end{bmatrix}$$

$$\mathbf{C} = \begin{bmatrix} 3 & -2 \\ -2 & 7 \end{bmatrix}$$

L<sup>n</sup>: for matrix A

$$x^T Ax = [x_1 \ x_2] \begin{bmatrix} 2 & -3 \\ -3 & 5 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = 2x_1^2 + 5x_2^2 - 6x_1x_2$$

(3)

for matrix B

$$x^T Ax = [x_1 \ x_2] \begin{bmatrix} 4 & 0 \\ 0 & 3 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = 4x_1^2 + 3x_2^2$$

for matrix C

$$x^T Ax = [x_1 \ x_2] \begin{bmatrix} 3 & -2 \\ -2 & 7 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = 3x_1^2 - 4x_1x_2 + 7x_2^2$$

Answer

Example ②: i) Find the matrix associated with the quadratic form

$$\text{i)} f(x_1, x_2, x_3) = 2x_1^2 - x_2^2 + 5x_3^2 + 6x_1x_2 - 3x_1x_3$$

$$\text{ii)} f(x_1, x_2, x_3) = 5x_1^2 + 3x_2^2 + 2x_3^2 - x_1x_2 + 8x_2x_3$$

Solu<sup>n</sup> → The coefficients of  $x_i^2$  go on the diagonal of A.

To make A symmetric, the coefficients of  $x_i x_j$  for  $i \neq j$  must be split b/w  $(i, j)$  and  $(j, i)$  entries in A.

thus i)  $A = \begin{bmatrix} 2 & 3 & -\frac{3}{2} \\ 3 & 1 & 0 \\ -\frac{3}{2} & 0 & 5 \end{bmatrix}$

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

Example ③: Let  $Q(x) = x_1^2 - 8x_1x_2 - 5x_2^2$ . Compute the value of  $Q(x)$  for  $x = \begin{bmatrix} -3 \\ 1 \end{bmatrix}, \begin{bmatrix} 2 \\ -2 \end{bmatrix}$  and  $\begin{bmatrix} 1 \\ -3 \end{bmatrix}$ .

Solu<sup>n</sup> →  $Q(-3, 1) = (-3)^2 - 8(-3)(1) - 5(1)^2 = 28$

$$Q(2, -2) = 16 = (2)^2 - 8(2)(-2) - 5(-2)^2$$

$$Q(1, -3) = 1^2 - 8(1)(-3) - 5(-3)^2 = -20$$

Answer

In some cases, quadratic forms are easier to use when they have no cross-product terms, i.e. when the matrix of the quadratic form is a diagonal matrix. Fortunately, the cross-product term can be eliminated by making a suitable change of variables.

Let  $f(x) = x^T A x$  be a quadratic form in  $n$  variables, with  $A$  a symmetric  $n \times n$  matrix. By the spectral theorem, there is a diagonal matrix  $Q$  that diagonalizes  $A$ ; i.e.  $Q^T A Q = D$ , where  $D$  is a diagonal matrix displaying the eigenvalues of  $A$ . Now set  $x = Qy$  or, equivalently  $y = Q^{-1}x = Q^T x$ . Substitute this into the quadratic form yields

$$\begin{aligned} x^T A x &= (Qy)^T A (Qy) \\ &= y^T Q^T A Q y \\ &= y^T D y \quad (\text{as } Q^T A Q = D) \end{aligned}$$

which is a quadratic form without cross-product term. Thus

$$y^T D y = \lambda_1 y_1^2 + \dots + \lambda_n y_n^2$$

This process is called diagonalizing a quadratic form.

### The Principal Axes Theorem :-

Every quadratic form can be diagonalized; i.e. Let  $A$  be an  $n \times n$  symmetric matrix, then there is an orthogonal change of variables,  $x = Qy$ , that transforms the quadratic form  $x^T A x$  into a quadratic form  $y^T D y$  with no cross-product term.

- ste :-
- The columns of  $Q$  in the theorem are called the principal axes of the quadratic form  $x^T A x$ .
  - The vector  $y$  is the coordinate vector of  $x$  relative to the orthonormal basis of  $\mathbb{R}^n$  given by these principal axes.

Example :- Find a change of variables that transforms the quadratic form

$$f(x_1, x_2) = 5x_1^2 + 4x_1x_2 + 2x_2^2$$

into one with no cross-product terms.

Solu<sup>n</sup> :- The matrix of  $f$  is  $A = \begin{bmatrix} 5 & 2 \\ 2 & 2 \end{bmatrix}$

$$\text{C.E. : } \lambda^2 - 7\lambda + 6 = 0$$

$$\Rightarrow \lambda_1 = 6 \quad \& \quad \lambda_2 = 1$$

E.V. corresponding to  $\lambda = 6$  is  $\begin{bmatrix} 2 \\ 1 \end{bmatrix} = v_1$   
 $\lambda = 1$  is  $\begin{bmatrix} 1 \\ -2 \end{bmatrix} = v_2$

clearly  $v_1$  &  $v_2$  are orthogonal.

$$\text{Now } Q = [q_1, q_2] = \begin{bmatrix} \frac{2}{\sqrt{5}} & \frac{1}{\sqrt{5}} \\ \frac{1}{\sqrt{5}} & \frac{-2}{\sqrt{5}} \end{bmatrix} \text{ and } D = \begin{bmatrix} 6 & 0 \\ 0 & 1 \end{bmatrix}$$

then  $Q^T A Q = D$ . The change of variables  $x = Qy$  where

$$x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \text{ and } y = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}$$

$$\text{converts } f \text{ into } f(y) = f(y_1, y_2) = [y_1, y_2] \begin{bmatrix} 6 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}$$

Note :- The original quadratic form  $x^T A x$  and the new one  $y^T D y$  are equal in the following sense.  
 Suppose we want to evaluate,

$f(x) = x^T A x$  at  $x = \begin{bmatrix} -1 \\ 3 \end{bmatrix}$ . We have

$$f(-1, 3) = 5(-1)^2 + 4(-1)(3) + 2(3)^2 = 11$$

$$f(y_1, y_2) = \cancel{y_1^2 + y_2^2} = 6y_1^2 + y_2^2 = 6\left(\frac{1}{\sqrt{5}}\right)^2 + \left(\frac{-2}{\sqrt{5}}\right)^2$$

$$\text{where } \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = y = Q^T x = \frac{1}{\sqrt{5}} \begin{bmatrix} 2 & 1 \\ 1 & -2 \end{bmatrix} \begin{bmatrix} 1 \\ 3 \end{bmatrix}^T = \begin{bmatrix} \frac{1}{\sqrt{5}} \\ -\frac{2}{\sqrt{5}} \end{bmatrix}$$

Answer

Exercise :-  $f(x_1, x_2) = x_1^2 + 5x_2^2 - 8x_1x_2$

Ans :-  $f(y_1, y_2) = 3y_1^2 - 7y_2^2$

Classification of Quadratic forms :-

A quadratic form  $f(x) = x^T A x$  is classified as one of the following :

- i) positive definite if  $f(x) > 0 \quad \forall x \neq 0$ .
- ii) positive semidefinite if  $f(x) \geq 0 \quad \forall x$ .
- iii) negative definite if  $f(x) < 0 \quad \forall x \neq 0$ .
- iv) negative semidefinite if  $f(x) \leq 0 \quad \forall x$ .
- v) indefinite if  $f(x)$  takes on both positive & negative values.

Note :- A symmetric matrix  $A$  is called positive definite, positive semidefinite, negative definite, negative semidefinite or indefinite if the associated quadratic form  $f(x) = x^T A x$  has corresponding property.

Quadratic form and eigenvalues :-

Let  $A$  be an  $n \times n$  symmetric matrix. The quadratic form  $f(x) = x^T A x$  is of  $A$

- a.)  $\text{pos def}$  iff all eigenvalues are  $\text{pos}$ .
- b.)  $\text{pos semi-def}$  iff all the eigenvalues of  $A$  are  $\text{nonnegative}$ .
- c.)  $\text{neg def}$  iff all of the eigenvalues of  $A$  are  $\text{negative}$ .
- d.)  $\text{neg semi-def}$  iff all of the eigenvalues of  $A$  are  $\text{nonpositive}$ .
- e.)  $\text{indefinite}$  iff  $A$  has both positive and negative eigenvalues.

Example:- classify the following quadratic forms

i)  $f(x, y, z) = 3x^2 + 3y^2 + 3z^2 - 2xy - 2xz - 2yz$

ii)  $f(x, y, z) = 3x^2 + 2y^2 + z^2 + xy + 4yz$

Solu<sup>n</sup>. i)  $A = \begin{bmatrix} 3 & -1 & -1 \\ -1 & 3 & -1 \\ -1 & -1 & 3 \end{bmatrix}$

it has eigenvalues 1, 4, 4

$\Rightarrow$  positive definite quadratic form.

ii)  $A = \begin{bmatrix} 3 & 2 & 0 \\ 2 & 2 & 2 \\ 0 & 2 & 1 \end{bmatrix}$

it has eigenvalues 5, 2, -1.

$\Rightarrow$  indefinite quadratic form.

Answer

## 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  $\Sigma$  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  $\alpha$  not exceeding the smaller of  $m$  and  $n$ . If  $\alpha$  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  $\Sigma$  for which the diagonal entries in  $\Sigma$  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  $\Sigma$  must contain the singular values of  $A$ .

Example:- Find the singular value decomposition of  $A = \begin{bmatrix} 4 & 11 & 14 \\ 8 & 7 & -2 \end{bmatrix}$

Solu<sup>n</sup> :- 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

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

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

Step ②: Set up  $V$  and  $\Sigma$ .

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

Solu<sup>n</sup> 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 :-  $U_1 = \frac{1}{\sigma_1} Av_1 = \frac{1}{\sqrt{3}} \begin{bmatrix} 1 & 1 \\ 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_{\sqrt{2}} \\ x_{\sqrt{2}} \end{bmatrix} = \begin{bmatrix} \frac{2\sqrt{6}}{\sqrt{3}} \\ \frac{x_{\sqrt{6}}}{\sqrt{3}} \\ \frac{x_{\sqrt{6}}}{\sqrt{3}} \end{bmatrix}$

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

~~Now singular value decomposition of A is~~

~~Now~~ Now  $V$  should be a  $3 \times 3$  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.)

$$\textcircled{11} \quad A = \begin{bmatrix} 1 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \text{ find SVD.} \quad \textcircled{6}$$

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

$$\begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \\ \frac{\partial f}{\partial z} \end{bmatrix} = \begin{bmatrix} \partial f \\ \partial y \\ \partial z \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}^{-1} = \sqrt{2} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}^{-1} = \sqrt{2} \mathbf{I}_2 = \mathbf{0}$$

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

After substituting into relevant rows  
 we see that  $\mathbf{u}_1$  and  $\mathbf{u}_2$  will be  
 linearly independent and  
 form basis since  $\mathbf{u}_1$  is the first column of  $\mathbf{U}$   
 and  $\mathbf{u}_2$  is the second column of  $\mathbf{U}$ .

$$\begin{bmatrix} \partial f \\ \partial y \\ \partial z \end{bmatrix} = \mathbf{0}$$

$$\begin{bmatrix} \partial f & 0 & \partial f \\ \partial y & \partial f & \partial y \\ \partial z & \partial y & \partial z \end{bmatrix} = \mathbf{U}^{-1} \Sigma$$

$$\begin{bmatrix} \partial f & 0 & \partial f \\ \partial y & \partial f & \partial y \\ \partial z & \partial y & \partial z \end{bmatrix} = \mathbf{U}^{-1} \Sigma$$