

1. Define subspaces.

Let  $V$  be a vector space over a field  $F$ . A non-empty subset  $W$  of  $V$  is called subspace of  $V$  if  $W$  itself is a vector space over  $F$  under the operations of  $V$ .

2. Prove that the intersection of two sub-spaces of a vector space is a subspace.

Sol: Let  $A$  and  $B$  be two subspaces of a vector space  $V$  over a field  $F$ .

We claim that  $A \cap B$  is a subspace of  $V$ .

Clearly,  $0 \in A \cap B$  and hence  $A \cap B$  is not empty. Now, let  $u, v \in A \cap B$  and  $\alpha, \beta \in F$

Then,  $u, v \in A$  and  $u, v \in B$

$\therefore \alpha u + \beta v \in A$  and  $\alpha u + \beta v \in B$  [ $A, B$  are subspaces]

$\therefore \alpha u + \beta v \in A \cap B$

Hence  $A \cap B$  is a subspace of  $V$ .

3. Let  $V$  be a vector space over a field  $F$ .

Let  $A$  and  $B$  be subspaces of  $V$  then

$$\frac{A+B}{A} \cong \frac{B}{A \cap B}$$

Sol: W.K.T,  $A+B$  is a subspace of  $V$  containing  $A$ .

Hence  $\frac{A+B}{A}$  is also a vector space over  $F$ .

(2)

An element of  $\frac{A+B}{A}$  is of the form  $A+(a+b)$  where  $a \in A$  and  $b \in B$ . But  $A+a = A$

Hence an element of  $\frac{A+B}{A}$  is of the form  $A+b$ .

Now, consider  $f: B \rightarrow \frac{A+B}{A}$  defined by  $f(b) = A+b$ .

Clearly  $f$  is onto.

$$\text{Also } f(b_1 + b_2) = A + (b_1 + b_2)$$

$$= (A+b_1) + (A+b_2)$$

$$= f(b_1) + f(b_2)$$

$$\text{and } f(\alpha b_1) = A + \alpha b_1$$

$$= \alpha(A+b_1)$$

$$= \alpha f(b_1)$$

Hence  $f$  is a linear transformation.

Let  $K$  be the kernel of  $f$ .

Then,  $K = \{b \mid b \in B, A+b = A\}$

Now,  $A+b = A$  iff  $b \in A$ . Hence  $K = A \cap B$

$$\therefore \frac{B}{A \cap B} \cong \frac{A+B}{A}$$

\* Define Homomorphism.

Let  $V$  and  $W$  be vector space over a field  $F$ .

A mapping  $T: V \rightarrow W$  is called homomorphism.

if

$$a) T(u+v) = T(u) + T(v) \text{ and}$$

$$b) T(\alpha u) = \alpha T(u) \text{ where } \alpha \in F \text{ and } u, v \in V.$$

(3)

5. Let  $V$  be a vector space over  $F$ . A non-empty subset  $W$  of  $V$  is a subspace of  $V$  iff  $W$  is closed with respect to vector addition and scalar multiplication in  $V$ .

Proof: Let  $W$  is a subspace of  $V$ .

Then  $W$  itself is a vector space and hence  $W$  is closed with respect to vector addition and scalar multiplication.

Conversely, let  $W$  be a non-empty subset of  $V$  such that  $u, v \in W \Rightarrow u+v \in W$  and  $u \in W$  and  $\alpha \in F \Rightarrow \alpha u \in W$ .

We prove that  $W$  is a subspace of  $V$ .

Since  $W$  is non-empty, there exists an element  $u \in W$ .

$$0u = 0 \in W$$

$$\text{Also } v \in W \Rightarrow (-1)v = -v \in W$$

Thus  $W$  contains  $0$  and the additive inverse of each of its elements.

Hence  $W$  is an additive subgroup of  $V$ .

$$\text{Also } u \in W \text{ and } \alpha \in F \Rightarrow \alpha u \in W.$$

Since the elements of  $W$  are the elements of  $V$  the other axioms of a vector space are true in  $W$ .

$\therefore$  Hence  $W$  is a subspace of  $V$ .

1. Any subset of linearly independent set is linearly independent.

Sol: Let  $V$  be a vector space over a field  $F$ .

Let  $S = \{v_1, v_2, \dots, v_n\}$  be a linearly independent set.

Let  $S'$  be a subset of  $S$  without loss of generality we take  $S' = \{v_1, v_2, \dots, v_k\}$  where  $k \leq n$ .

Suppose  $S'$  is a linearly dependent set. Then there exists  $\alpha_1, \alpha_2, \dots, \alpha_k$  in  $F$  not all zero such that  $\alpha_1 v_1 + \alpha_2 v_2 + \dots + \alpha_k v_k = 0$

$$\text{Hence } \alpha_1 v_1 + \alpha_2 v_2 + \dots + \alpha_k v_k + 0v_{k+1} + \dots + 0v_n = 0$$

is a non-trivial linear combination giving the zero vector.

Hence  $S$  is a linearly dependent set which is a contradiction.

Hence  $S'$  is a linearly independent.

2. Let  $T: V \rightarrow W$  be a linear transformation.

Then  $\dim V = \text{rank } T + \text{nullity } T$ .

Proof: w.k.T  $V/\text{Ker } T = T(V)$

$$\dim V - \dim(\text{Ker } T) = \dim(T(V))$$

$$\dim V - \text{nullity } T = \text{rank } T$$

$$\dim V = \text{nullity } T + \text{rank } T$$

3. Define dimension. (5)

Let  $V$  be a finite dimensional vector space over a field  $F$ . The number of elements in any basis of  $V$  is called the dimension of  $V$  and is denoted by  $\dim V$ .

4. Any set containing a linearly dependent is also linearly dependent.

Proof: Let  $V$  be a vector space. Let  $S$  be a linearly dependent set. Let  $S' \subset S$ .

If  $S'$  is linearly independent  $S$  is also linearly independent.

By the theorem: Any subset of a linearly independent set is linearly independent which is a contradiction.

Hence  $S'$  is a linearly dependent.

5. Define rank and nullity.

Let  $T: V \rightarrow W$  be a linear transformation.

Then the dimension of  $T(V)$  is called the rank of  $T$ . The dimension of  $\ker T$  is called the nullity of  $T$ .

UNIT-III

1.  $V_n(\mathbb{C})$  is a complex inner product space with inner product defined by.

$$\langle x, y \rangle = x_1 \bar{y}_1 + x_2 \bar{y}_2 + \dots + x_n \bar{y}_n \quad \text{where } \textcircled{6}$$

$$x = (x_1, x_2, \dots, x_n) \text{ and } y = (y_1, y_2, \dots, y_n)$$

soln: let  $x, y, z \in V_n(\mathbb{C})$  and  $\alpha \in \mathbb{C}$

$$\begin{aligned} \text{i) } \langle x+y, z \rangle &= (x_1 + y_1) \bar{z}_1 + (x_2 + y_2) \bar{z}_2 + \dots + (x_n + y_n) \bar{z}_n \\ &= (x_1 \bar{z}_1 + x_2 \bar{z}_2 + \dots + x_n \bar{z}_n) + (y_1 \bar{z}_1 + y_2 \bar{z}_2 + \dots + y_n \bar{z}_n) \\ &= \langle x, z \rangle + \langle y, z \rangle \end{aligned}$$

$$\begin{aligned} \text{ii) } \langle \alpha x, y \rangle &= \alpha x_1 \bar{y}_1 + \alpha x_2 \bar{y}_2 + \dots + \alpha x_n \bar{y}_n \\ &= \alpha (x_1 \bar{y}_1 + x_2 \bar{y}_2 + \dots + x_n \bar{y}_n) \\ &= \alpha \langle x, y \rangle \end{aligned}$$

$$\text{iii) } \langle y, x \rangle = \overline{y_1 x_1 + y_2 x_2 + \dots + y_n x_n}$$

$$\begin{aligned} &= \overline{y_1 x_1} + \overline{y_2 x_2} + \dots + \overline{y_n x_n} \\ &= x_1 \bar{y}_1 + x_2 \bar{y}_2 + \dots + x_n \bar{y}_n \\ &= \langle x, y \rangle \end{aligned}$$

$$\begin{aligned} \text{iv) } \langle x, x \rangle &= x_1 \bar{x}_1 + \dots + x_n \bar{x}_n \\ &= |x_1|^2 + |x_2|^2 + \dots + |x_n|^2 \geq 0 \end{aligned}$$

and  $\langle x, x \rangle = 0 \iff x = 0$

## 2. Define orthogonality.

Let  $V$  be an inner product space

and let  $x, y \in V$ .  $x$  is said to be orthogonal to  $y$  if  $\langle x, y \rangle = 0$

### 3. Schwarz's equality.

The inequality is trivially true when  $x=0$  or  $y=0$ . Hence let  $x \neq 0$  and  $y \neq 0$ .

$$\text{Consider } z = y - \frac{\langle y, x \rangle}{\|x\|^2} x$$

Then,  $0 \leq \langle z, z \rangle$

$$= \langle y - \frac{\langle y, x \rangle}{\|x\|^2} x, y - \frac{\langle y, x \rangle}{\|x\|^2} x \rangle$$

$$= \langle y, y \rangle - \frac{\langle y, x \rangle \langle y, x \rangle}{\|x\|^2} - \frac{\langle y, x \rangle \langle x, y \rangle}{\|x\|^2}$$

$$+ \frac{\langle y, x \rangle \langle y, x \rangle}{\|x\|^2 \|x\|^2} - \langle x, x \rangle$$

$$= \|y\|^2 - \frac{\langle y, x \rangle \langle y, x \rangle}{\|x\|^2} - \frac{\langle y, x \rangle \langle x, y \rangle}{\|x\|^2} + \frac{\langle y, x \rangle \langle y, x \rangle}{\|x\|^2}$$

$$= \|y\|^2 - \frac{2\langle x, y \rangle \langle x, y \rangle}{\|x\|^2}$$

$$\therefore 0 \leq \|x\|^2 \|y\|^2 - 4|\langle x, y \rangle|^2$$

$\therefore |\langle x, y \rangle| \leq \|x\| \|y\|$  is a Schwarz's inequality.

4. Let  $V$  be a finite dimensional inner product space. Let  $W$  be a subspace of  $V$ . Then  $(W^\perp)^\perp = W$ .

For let  $w \in W$ . Then for any  $u \in W^\perp$ ,  $\langle w, u \rangle = 0$ .

Hence  $w \in (W^\perp)^\perp$ . Thus  $w \in (W^\perp)^\perp \rightarrow \textcircled{1}$

Now by theorem  $V = W \oplus W^\perp$

$$\text{also } V = W^\perp \oplus (W^\perp)^\perp$$

Hence  $\dim W = \dim (W^\perp)^\perp \rightarrow \textcircled{2}$

From  $\textcircled{1}$  &  $\textcircled{2}$  we get  $W = (W^\perp)^\perp$

5. If  $S$  is any subset of  $V$  then  $S^\perp$  is a subspace of  $V$ . (9)

*Soln:* Clearly  $0 \in S^\perp$ , and hence  $S^\perp \neq \emptyset$ .

Now, let  $x, y \in S^\perp$  and  $\alpha, \beta \in F$ .

Then  $\langle x, u \rangle = \langle y, u \rangle = 0 \quad \forall u \in S$ .

$\langle \alpha x + \beta y, u \rangle = \alpha \langle x, u \rangle + \beta \langle y, u \rangle = 0 \quad \forall u \in S$ .

$\alpha x + \beta y \in S^\perp$ . Hence  $S^\perp$  is a subspace of  $V$ .

#### UNIT - IV

1. Let  $A$  be an  $m \times n$  matrix,  $B$  an  $n \times p$  matrix and  $C$  a  $p \times q$  matrix. Then  $A(BC) = (AB)C$ .

*Soln:* Let  $A = (a_{ij})$ ,  $B = (b_{ij})$  and  $C = (c_{ij})$ . Let us find the  $r$ <sup>th</sup> entry in  $A(BC)$ .

The  $r$ <sup>th</sup> row in  $A$  is  $a_{r1}, a_{r2}, \dots, a_{rn}$ . The  $s$ <sup>th</sup> column in  $BC$  consists of the elements  $\sum_{j=1}^n b_{1j}c_{js}$ ,  $\dots$ ,  $\sum_{j=1}^n b_{nj}c_{js}$ . Hence, the  $r$ <sup>th</sup> entry in  $A(BC)$

$$\begin{aligned} & \text{is } a_{r1} \sum_{j=1}^n b_{1j}c_{js} + \dots + a_{rn} \sum_{j=1}^n b_{nj}c_{js} \\ & = \sum_{i=1}^n a_{ri} \sum_{j=1}^p b_{ij}c_{js} = \sum_{i=1}^n \sum_{j=1}^p a_{ri} b_{ij}c_{js} \end{aligned}$$

Let us now find the  $r$ <sup>th</sup> entry in  $(AB)C$ .

The  $r$ <sup>th</sup> row in  $AB$  is  $\sum_{i=1}^n a_{ri}b_{i1}, \sum_{i=1}^n a_{ri}b_{i2}, \dots, \sum_{i=1}^n a_{ri}b_{ip}$ .

The  $s$ <sup>th</sup> column in  $C$  is  $c_{1s}, c_{2s}, \dots, c_{ps}$ .

Hence the  $r$ <sup>th</sup> entry in  $(AB)C$  is

$$\begin{aligned} & (\sum_{i=1}^n a_{ri}b_{i1})c_{1s} + (\sum_{i=1}^n a_{ri}b_{i2})c_{2s} + \dots + (\sum_{i=1}^n a_{ri}b_{ip})c_{ps} \\ & = \sum_{i=1}^n \sum_{j=1}^p a_{ri} b_{ij} c_{js} \end{aligned}$$

Thus  $A(BC) = (AB)C$ .

2. Let  $A$  and  $B$  be two  $m \times n$  matrices. Then (9)

$$i) (A^T)^T = A \quad ii) (A+B)^T = A^T + B^T$$

$$i) \text{ The } (i, j)^{\text{th}} \text{ entry of } (A^T)^T = (j, i)^{\text{th}} \text{ entry of } A^T \\ = (i, j)^{\text{th}} \text{ entry of } A$$

$$\therefore (A^T)^T = A$$

$$ii) \text{ The } (i, j)^{\text{th}} \text{ entry of } (A+B)^T$$

$$= (j, i)^{\text{th}} \text{ entry of } A+B$$

$$= (j, i)^{\text{th}} \text{ entry of } A + (j, i)^{\text{th}} \text{ entry of } B$$

$$= (j, i)^{\text{th}} \text{ entry of } A^T + (j, i)^{\text{th}} \text{ entry of } B^T$$

$$= (j, i)^{\text{th}} \text{ entry of } (A^T + B^T)$$

$$\therefore (A+B)^T = A^T + B^T$$

3. A square matrix  $A$  is symmetric iff  $A = A^T$ .

Proof: Let  $A$  be a symmetric matrix.

Then the  $(i, j)^{\text{th}}$  entry of  $A = (j, i)^{\text{th}}$  entry of  $A$

$$= (i, j)^{\text{th}} \text{ entry of } A^T$$

$$\text{Hence } A = A^T$$

Conversely let  $A = A^T$

Then  $(i, j)^{\text{th}}$  entry of  $A = (i, j)^{\text{th}}$  entry of  $A^T$

$$= (j, i)^{\text{th}} \text{ entry of } A$$

Hence  $A$  is symmetric

4. Let  $A$  be any square matrix of order  $n$ . Then

$$(\text{adj } A)A = A(\text{adj } A) = |A|I$$

where  $I$  is the identity matrix of order  $n$ .

soln: The  $(i, j)^{th}$  element of  $(A(\text{adj } A))$  (10)

$$= \sum_{k=1}^n a_{ik} A_{jk}$$

$$= \begin{cases} |A| & \text{if } i=j \\ 0 & \text{if } i \neq j \end{cases}$$

$$A(\text{adj } A) = \begin{vmatrix} |A| & 0 & \dots & 0 \\ 0 & |A| & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & |A| \end{vmatrix} = |A| I$$

Similarly  $(\text{adj } A)A = |A| I$

Hence  $(\text{adj } A)A = A(\text{adj } A) = |A| I$

5. Define Elementary matrix.

A matrix obtained from the identity matrix by applying a single elementary row or column operation is called an elementary matrix.

$$\text{WRT} - \Sigma$$

1. Define characteristics matrix.

Let  $A$  be any square matrix of order  $n$  and let  $I$  be the identity matrix of order  $n$ . Then the matrix polynomial given by  $A - \lambda I$  is called the characteristics matrix of  $A$ .

2. Show that matrix  $A = \begin{bmatrix} 2 & -3 & 1 \\ 3 & 1 & 5 \\ 5 & 2 & -4 \end{bmatrix}$  satisfies the eqn

$$A(A - I)(A + 2I) = 0$$

The characteristic polynomial of A is

$$|A - \lambda I| = \begin{vmatrix} 2-\lambda & -3 & 1 \\ 3 & 1-\lambda & 3 \\ -5 & 0 & -4-\lambda \end{vmatrix}$$

$$= -\lambda^3 - \lambda^2 + 2\lambda$$

By Cayley-Hamilton theorem,  $A^3 - A^2 + 2A = 0$

$$\text{(i.e.) } A^3 + A^2 - 2A = 0 \quad \text{Hence } A(A^2 + A - 2I) = 0$$

$$\therefore A(A+2I)(A-I) = 0$$

3. Verify Cayley-Hamilton's theorem for the

$$\text{matrix } A = \begin{pmatrix} 1 & 2 \\ 4 & 3 \end{pmatrix}$$

The characteristic eqn of A is  $|A - \lambda I| = 0$

$$\begin{vmatrix} 1-\lambda & 2 \\ 4 & 3-\lambda \end{vmatrix} = 0 \Rightarrow \begin{pmatrix} 1-\lambda & 2 \\ 4 & 3-\lambda \end{pmatrix} = 0$$

$$\therefore (1-\lambda)(3-\lambda) - 8 = 0$$

$$\lambda^2 - 4\lambda - 5 = 0$$

We have  $A^2 - 4A - 5I = 0$

$$\text{Now, } A^2 = \begin{pmatrix} 1 & 2 \\ 4 & 3 \end{pmatrix} \begin{pmatrix} 1 & 2 \\ 4 & 3 \end{pmatrix}$$

$$= \begin{pmatrix} 9 & 8 \\ 16 & 17 \end{pmatrix}$$

$$4A = \begin{pmatrix} 4 & 8 \\ 16 & 12 \end{pmatrix}$$

$$5I = \begin{pmatrix} 5 & 0 \\ 0 & 5 \end{pmatrix}$$

$$A^2 - 4A - 5I = \begin{pmatrix} 9 & 8 \\ 16 & 17 \end{pmatrix} - \begin{pmatrix} 4 & 8 \\ 16 & 12 \end{pmatrix} - \begin{pmatrix} 5 & 0 \\ 0 & 5 \end{pmatrix} = 0$$

Hence Cayley Hamilton's theorem is verified. (12)

4. The eigen value of  $A$  and its transpose  $A^T$  are the same.

Proof: It is enough if we prove  $A$  and  $A^T$  have the same characteristics polynomial.

Since for any square  $M$ ,  $|M| = |M^T|$  we have,

$$|A - \lambda I| = |(A - \lambda I)^T| = |A^T - (\lambda I)^T| = |A^T - \lambda I|$$

Hence the result.

5. Find the sum of the square of eigen value of

$$A = \begin{pmatrix} 3 & 1 & 4 \\ 0 & 2 & 6 \\ 0 & 0 & 5 \end{pmatrix}$$

Soln:-

Let,  $\lambda_1, \lambda_2, \lambda_3$  be the eigen value of  $A$ .

$$A^2 = \begin{pmatrix} 3 & 1 & 4 \\ 0 & 2 & 6 \\ 0 & 0 & 5 \end{pmatrix} \begin{pmatrix} 3 & 1 & 4 \\ 0 & 2 & 6 \\ 0 & 0 & 5 \end{pmatrix} = \begin{pmatrix} 9 & 5 & 38 \\ 0 & 4 & 42 \\ 0 & 0 & 25 \end{pmatrix}$$

Sum of the eigen value of  $A^2$  } = Trace of  $A^2$

$$= 9 + 4 + 25$$

$$(ie) \lambda_1^2 + \lambda_2^2 + \lambda_3^2 = 38$$

Sum of the square of the eigen values of  $A = 38$ .