

-1-

A **vector space**  $V$  over a field  $F$  has the operations of **addition** and **scalar multiplication**, and satisfies several basic laws. A vector space in a vector space is a **subspace**.

A vector  $v \in V$  is a **linear combination** of vectors of  $S \subseteq V$  if there exist a finite number of vectors  $u_1, u_2, \dots, u_n \in S$  and scalars  $a_1, a_2, \dots, a_n \in F$  such that

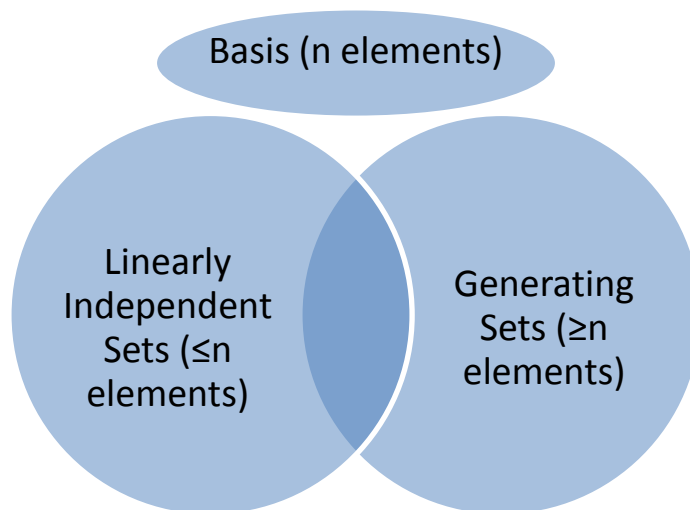
$$v = a_1 u_1 + \dots + a_n u_n.$$

If 0 can be nontrivially written in this form,  $S$  is **linearly dependent**. The set of all  $v$  in the above for is the subspace **generated** (spanned) by  $S$ .

A **basis**  $\beta$  for  $V$  is a linearly independent subset of  $V$  that generates  $V$ .

Replacement Theorem: (Simplified) Every linearly independent set can be made into a basis by adding elements.

Every basis for  $V$  contains the same number of vectors. The unique number of vectors in each basis is the **dimension** of  $V$  ( $\dim(V)$ ).



Every vector space has a basis.

-2-

For vector spaces  $V$  and  $W$  over  $F$ , a function  $T: V \rightarrow W$  is a **linear transformation** (homomorphism) if for all  $x, y \in V$  and  $c \in F$ ,

$$(a) T(x + y) = T(x) + T(y)$$

$$(b) T(cx) = cT(x)$$

The **null space** or kernel is the set of all vectors  $x$  in  $V$  such that  $T(x)=0$ .

$$N(T) = \{x \in V | T(x) = 0\}$$

The **range** or image is the subset of  $W$  consisting of all images of vectors in  $V$ .

$$R(T) = \{T(x) | x \in V\}$$

Both are subspaces. **nullity**( $T$ ) and **rank**( $T$ ) denote the dimensions of  $N(T)$  and  $R(T)$ , respectively.

Dimension Theorem: If  $V$  is finite-dimensional,  $\text{nullity}(T) + \text{rank}(T) = \dim(V)$

*Linear transformations (over finite-dimensional vector spaces) can be viewed as left-multiplication by matrices, so linear transformations under composition and their corresponding matrices under multiplication follow the same laws. This is a motivating factor for the definition of matrix multiplication.* Facts about matrices can be proved by using linear transformations, or vice versa.

Matrix product:

Let  $A$  be a  $m \times n$  and  $B$  be a  $n \times p$  matrix. The product  $AB$  is the  $m \times p$  matrix with entries

$$(AB)_{ij} = \sum_{k=1}^n A_{ik} B_{kj}, 1 \leq i \leq m, 1 \leq j \leq p$$

Interpretation of the product  $AB$ :

1. Row picture: Each row of  $A$  multiplies the whole matrix  $B$ .
2. Column picture:  $A$  is multiplied by each column of  $B$ . Each column of  $AB$  is a linear combination of the columns of  $A$ , with the coefficients of the linear combination being the entries in the column of  $B$ .
3. Row-column picture:  $C_{ij}$  is the dot product of row  $i$  of  $A$  and column  $j$  of  $B$ .

The matrix representation of T in  $\beta = \{v_1, \dots, v_n\}$  and  $\gamma$  is  $A = [T]_{\beta}^{\gamma}$ . Load the coordinates of  $T(v_i)$  into the  $i$ th column.  $[I_V]_{\beta}^{\gamma}$  changes  $\beta$ -coordinates to  $\gamma$ -coordinates. So:

$$[T]_{\gamma} = [I_V]_{\gamma}^{\beta} [T]_{\beta} [I_V]_{\beta}^{\gamma}$$

$$B = Q A Q^{-1}$$

Linear transformations T, U	Matrices A, B
$\text{rank}(TU) \leq \min(\text{rank}(T), \text{rank}(U))$	$\text{rank}(AB) \leq \min(\text{rank}(A), \text{rank}(B))$

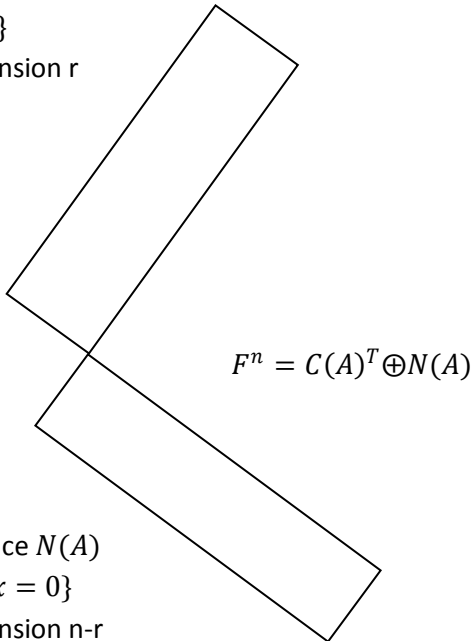
-3-

Fundamental Theorem of Linear Algebra (Part 1):

Dimensions of the Four Subspaces: A is  $m \times n$ ,  $\text{rank}(A)=r$  (If the field is complex, replace  $A^T$  by  $A^*$ .)

Row space  $C(A^T)$

- $\{A^T y\}$
- Dimension r



Nullspace  $N(A)$

- $\{x | Ax = 0\}$
- Dimension  $n-r$

Column space  $C(A)$

- $\{Ax\}$
- Dimension r

$$F^m = C(A) \oplus N(A^T)$$

Left nullspace  $N(A^T)$

- $\{y | A^T y = 0\}$
- Dimension  $m-r$

The **determinant** (denoted  $|A|$  or  $\det(A)$ ) is a function from the set of square matrices to the field  $F$ , satisfying the following conditions:

1. The determinant of the  $n \times n$  identity matrix is 1, i.e.  $\det(I) = 1$ .
2. If two rows of  $A$  are equal, then  $\det(A) = 0$ , i.e. the determinant is alternating.
3. The determinant is a linear function of each row separately, i.e. it is  $n$ -linear. That is, if  $a_1, \dots, a_n, u, v$  are rows with  $n$  elements,

$$\det \begin{pmatrix} a_1 \\ \vdots \\ a_{r-1} \\ u + kv \\ a_{r+1} \\ \vdots \\ a_n \end{pmatrix} = \det \begin{pmatrix} a_1 \\ \vdots \\ a_{r-1} \\ u \\ a_{r+1} \\ \vdots \\ a_n \end{pmatrix} + k \det \begin{pmatrix} a_1 \\ \vdots \\ a_{r-1} \\ v \\ a_{r+1} \\ \vdots \\ a_n \end{pmatrix}$$

*These properties completely characterize the determinant.*

**Cofactor Expansion:** Recursive, useful with many zeros, perhaps with induction.

(Row)

$$\det(A) = \sum_{j=1}^n a_{ij} C_{ij} = \sum_{j=1}^n a_{ij} (-1)^{i+j} \det(M_{ij})$$

(Column)

$$\det(A) = \sum_{i=1}^n a_{ij} C_{ij} = \sum_{i=1}^n a_{ij} (-1)^{i+j} \det(M_{ij})$$

where  $M_{ij}$  is  $A$  with the  $i$ th row and  $j$ th column removed.

Cramer's Rule:

If  $A$  is a  $n \times n$  matrix and  $\det(A) \neq 0$  then  $Ax = b$  has the unique solution given by

$$x_i = \frac{\det(B_i)}{\det(A)}, 1 \leq i \leq n$$

Where  $B_i$  is  $A$  with the  $i$ th column replaced by  $b$ . If  $\det(A) = 0$ , then  $A$  is singular (has no inverse).

-5-

Let  $T$  be a linear operator (or matrix) on  $V$ . A nonzero vector  $v \in V$  is an **eigenvector** of  $T$  if there exists a scalar  $\lambda$ , called the **eigenvalue**, such that  $T(v) = \lambda v$ . The **eigenspace** of  $\lambda$  is the set of all eigenvectors corresponding to  $\lambda$ :  $E_\lambda = \{x \in V | T(x) = \lambda x\}$ .

The **characteristic polynomial** of a matrix  $A$  is  $\det(A - \lambda I)$ . The zeros of the polynomial are the eigenvalues of  $A$ . For each eigenvalue solve  $Av = \lambda v$  to find linearly independent eigenvectors that span the eigenspace.

If there are  $n$  linearly independent eigenvectors,  $T(A)$  is diagonalizable:

$$[T]_\gamma = [I_V]_\gamma^\beta [T]_\beta [I_V]_\beta^\gamma$$
$$A = Q\Lambda Q^{-1}$$

Where  $\Lambda = [T]_\beta$  is a diagonal matrix.

Applications to recursive sequences, probability (Markov chains).

-6-

The **incidence matrix** of a graph:  $A$  has a row and column for each vertex, and  $A_{ij} = 1$  if vertices  $i$  and  $j$  are connected by an edge, and 0 otherwise.

The incidence matrix  $A$  for a family of subsets  $\{S_1, \dots, S_n\}$  containing elements  $\{x_1, \dots, x_m\}$  has  $A_{ij} = \begin{cases} 1 & \text{if } x_i \in S_j \\ 0 & \text{if } x_i \notin S_j \end{cases}$ . Exploring  $AA^T$  and using properties of ranks, determinants, linear dependency, etc. may give conclusions about the sets. Working in the field  $\mathbb{Z}_2$  on problems dealing with parity may help.