

**Adjacency matrix of a graph:** Square matrix with  $a_{ij} = 1$  when there is an edge from node  $i$  to node  $j$ ; otherwise  $a_{ij} = 0$ ,  $A = A^T$  for an undirected graph.

**Affine Transformation:**  $T(v) = Av + v_0$  = linear transformation plus shift.

**Back substitution:** Upper triangular systems are solved in reverse order  $x_n$  to  $x_1$ .

**Basis for  $V$ :** Independent vectors  $v_1, \dots, v_n$  whose linear combinations give every  $v$  in  $V$ . A vector space has many bases.

**Block matrix:** A matrix can be partitioned into matrix blocks, by cuts between rows and/or between columns, **Block multiplication** of  $AB$  is allowed if the block shapes permit (the columns of  $A$  and rows of  $B$  must be matching blocks).

**Cayley-Hamilton Theorem:**  $p(\lambda) = \det(A - \lambda I) = \text{zero matrix}$ .

**Change of basis matrix  $M$ :** The old basis vectors  $v_i$  are combinations  $\sum m_{ij} w_i$  of the new basis vectors. The coordinates of  $c_1 v_1 + \dots + c_n v_n = d_1 w_1 + \dots + d_n w_n$  are related by  $d = Mc$ . (For  $n = 2$  set  $v_1 = m_{11} w_1 + m_{21} w_2$ ,  $v_2 = m_{12} w_1 + m_{22} w_2$ .)

**Characteristic equation:**  $\det(A - \lambda I) = 0$ . The  $n$  roots are the eigenvalues of  $A$ .

**Cholesky factorization:**  $A = CC^T = (L\sqrt{D})(L\sqrt{D})^T$  for positive eigenvalues of  $A$ .

**Circulant matrix  $C$ :** Constant diagonals wrap around as in cyclic shift  $S$ . Every Circulant is  $c_0 I + c_1 S + \dots + c_{n-1} S_{n-1}$ .  $Cx = \text{convolution } c * x$ . Eigenvectors in  $F$ .

**Cofactor  $C_{ij}$ :** Remove row  $i$  and column  $j$ ; multiply the determinant by  $(-1)^{i+j}$

**Column picture of  $Ax = b$ :** The vector  $b$  becomes a combination of the columns of  $A$ . The system is solvable only when  $b$  is in the column space  $C(A)$ .

**Column space  $C(A)$ :** consists of all linear combinations of the columns. The combinations are all possible vectors  $Ax$ .

**Commuting matrices  $AB = BA$ :** If diagonalizable, they share  $n$  eigenvectors.

**Companion matrix:** Put  $c_1, \dots, c_n$  in row  $n$  and put  $n - 1$  1's along diagonal 1. Then

$$\det(A - \lambda I) = \pm (c_1 + c_2 \lambda + c_3 \lambda^2 + \dots)$$

**Complete solution:**  $x = x_p + x_n$  to  $Ax = b$ .  $\left( \text{Particular } x_p \right) + \left( x_n \text{ in nullspace} \right)$

**Complex conjugate:**  $\bar{z} = a - ib$  for any complex number  $z = a + ib$ . Then

$$z\bar{z} = |z|^2 \Rightarrow (a - ib)(a + ib) = a^2 + b^2$$

**Covariance matrix  $\Sigma$ :** When random variables  $x_i$  have mean = average value = 0, their covariances

$\sum_{ij}$  are the averages of  $x_i x_j$ . With means  $\bar{x}_i$ , the matrix  $\Sigma = \text{mean of } (x - \bar{x})(x - \bar{x})^T$  is positive (semi) definite; it is diagonal if the  $x_i$  are independent.

**Cramer's Rule for  $Ax = b$ :**  $B_j$  has  $b$  replacing column  $j$  of  $A$ , and  $x_j = \frac{|B_j|}{|A|}$ .

**Cross product  $u \times v$  in  $\mathbf{R}^3$ :** Vector perpendicular to  $u$  and  $v$ , length  $\|u\|\|v\|\sin\theta$  = parallelogram area, computed as the “determinant” of  $\begin{bmatrix} i & j & k; & u_1 & u_2 & u_3; & v_1 & v_2 & v_3 \end{bmatrix}$

**Diagonal matrix  $D$ :**  $d_{ij} = 0$  if  $i \neq j$ . **Block diagonal:** zero outside square blocks  $D_{ij}$ .

**Dimension of a vector space:**  $\dim(V)$  = number of vectors in any basis for  $V$ .

**Dot Product:**  $x^T y = x_1 y_1 + \dots + x_n y_n$ . Complex dot product is  $\bar{x}^T y$ . Perpendicular vectors have zero dot product.  $(AB)_{ij} = (\text{row } i \text{ of } A) \cdot (\text{column } j \text{ of } B)$

**Echelon matrix  $U$ :** The first nonzero entry (the pivot) in each row comes after the pivot in the previous row. All zero rows come last.

**Eigenvalue  $\lambda$  and eigenvector  $x$ :**  $Ax = \lambda x$  with  $x \neq 0$  so  $\det(A - \lambda I) = 0$

**Elimination:** A sequence of row operations that reduces  $A$  to an upper triangular  $U$  or to the reduced form  $R = \text{rref}(A)$ . Then  $A = LU$  with multipliers  $\ell_{ij}$  in  $L$ , or  $PA = LU$  with row exchanges in  $P$ , or  $EA = R$  with an invertible  $E$ .

**Factorization:**  $A = LU$ . If elimination takes  $A$  to  $U$  without row exchanges, then the lower triangular  $L$  with multipliers  $\ell_{ij}$  (and  $\ell_{ii} = 1$ ) brings  $U$  back to  $A$ .

**Fibonacci numbers:** 0, 1, 1, 2, 3, 5, ... satisfy  $F_n = F_{n-1} + F_{n-2} = \frac{\lambda_1^n - \lambda_2^n}{\lambda_1 - \lambda_2}$ . Growth rate  $\lambda_1 = \frac{1+\sqrt{5}}{2}$  is

the largest eigenvalue of the Fibonacci matrix  $\begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix}$

**Four Fundamental subspaces of  $A$**  =  $C(A)$ ,  $N(A)$ ,  $C(A^T)$ ,  $N(A^T)$ .

**Free Columns of  $A$ :** Columns without pivots; combinations of earlier columns.

**Free variables**  $x_i$ : Column  $i$  has no pivot in elimination. We can give the  $n - r$  free variables any values, the  $Ax = b$  determines the  $r$  pivot variables (if solvable!).

**Full column rank**  $r = n$ . Independent columns,  $N(A) = \{0\}$ , no free variables.

**Full row rank**  $r = m$ . Independent rows, at least one solution to  $Ax = b$ , column space is all of  $\mathbf{R}^m$ . Full rank means full column rank or full column rank or full row rank.

**Fundamental Theorem**: the nullspace  $N(A)$  and row space  $C(A^T)$  are orthogonal complements (perpendicular subspaces of  $\mathbf{R}^n$  with dimensions  $r$  and  $n - r$ ) from  $Ax = 0$ . Applied to  $A^T$ , the column space  $C(A)$  is the orthogonal complement of  $N(A^T)$ .

**Independent vectors**:  $v_1, \dots, v_n$ . No combination  $c_1 v_1 + \dots + c_n v_n = \text{zero vector}$  unless all  $c_i = 0$ . If the  $v$ 's are the columns of  $A$ , the only solution to  $Ax = 0$  is  $x = 0$ .

**Least squares solution**  $\hat{x}$ : The vector  $\hat{x}$  that minimizes the error  $\|e\|^2$  solves  $A^T A \hat{x} = A^T b$ . Then  $e = b - A\hat{x}$  is orthogonal to all columns of  $A$ .

**Length**  $\|x\|$ : Square root of  $x^T x$  (Pythagoras in  $n$  dimensions).

**Linear combination**  $cv + dw$  or  $\sum c_j v_j$ . Vector addition and scalar multiplication.

**Linear Transformation  $T$** : Each vector  $v$  in the input space transforms to  $T(v)$  in the output space, and linearity requires  $T(cv + dw) = cT(v) + dT(w)$ .

**Linearly dependent**  $v_1, \dots, v_n$ . A combination other than all  $c_i = 0$  gives  $\sum c_i v_i = 0$

**Linearly independent** when the only solution to  $Ax = 0$  is  $x = 0$ . **No other combination**  $Ax$  of the columns gives the zero vector.

**Nullspace** of  $A$  consists of all solutions to  $Ax = 0$ . These solution vectors  $x$  are in  $\mathbf{R}^n$ . The Nullspace containing all solutions is denoted by  $N(A)$  or  $NS(A)$ .  $\{\vec{x} \in \mathbf{R}^n \mid Ax = 0\}$  is the nullspace of  $A$ ,  $NS(A)$  (Can also be called **Kernel** of  $A$ :  $Ker(A)$ )

**Particular solution**  $x_p$  Any solution to  $Ax = b$ ; often  $x_p$  has free variables = 0.

**Permutation matrix  $P$** . There are  $n!$  orders of  $1, \dots, n$ ; the  $n!$   $P$ 's have the rows of  $I$  in those orders.  $PA$  puts the rows of  $A$  in the same order.  $P$  is a product of row exchanges  $P_{ij}$ ;  $P$  is *even* or *odd* ( $\det P = 1$  or  $-1$ ) based on the number of exchanges.

**Pivot columns of  $A$** : Columns that contain pivots after row reduction; not combinations of earlier columns. The pivot columns are a basis for the column space.

**Pivot  $d$ :** The diagonal entry (first nonzero) when a row is used in elimination.

**Rank** of a matrix  $A$  ( $m$  by  $n$ ) is the number of **nonzero rows** in the row-reduced echelon form of  $A$ . (it is the number of pivot).  $\text{rank}(A) = r$

**Reduced Row Echelon Form (rref):** is a matrix ( $R$ ) with each pivot column has only one nonzero entry (the pivots which is always 1).

**Row space**  $C(A^T)$  = all combinations of rows of  $A$ . Column vectors by convention.

**Schwarz inequality**  $|v \cdot w| = \|v\| \cdot \|w\|$ : Then  $\left| v^T A w \right|^2 \leq (v^T A v)(w^T A w)$  if  $A = C^T C$

**Singular matrix  $A$ :** A square matrix that has no inverse:  $\det(A) = 0$ .

**Spanning set  $v_1, \dots, v_m$  for  $V$ :** Every vector in  $V$  is a combination of  $v_1, \dots, v_m$ .

**Subspace:** of a vector space is a set of vectors (including 0) that satisfies two requirements: if  $v$  and  $w$  are vectors in the subspace and  $c$  is any scalar, then  $v + w$  is in the subspace and  $cv$  is in the subspace

**Symmetric matrix  $A$ :** The transpose is  $A^T = A$ , and  $a_{ij} = a_{ji}$ .  $A^{-1}$  is also symmetric. All matrices of the form  $R^T R$ ,  $LDL^T$  and  $Q\Lambda Q^T$  are symmetric. Symmetric matrices have real eigenvalues in  $\Lambda$  and orthonormal eigenvectors in  $Q$ .

**Trace of  $A$ :** = sum of diagonal entries = sum of eigenvalues of  $A$ .  $\text{Tr}(AB) = \text{Tr}(BA)$ .

**Transpose matrix  $A^T$ :** Entries  $A_{ij}^T = A_{ji}$ .  $A^T$  is  $n$  by  $m$ ,  $A^T A$  is square, symmetric, positive semi-definite. The transposes of  $AB$  and  $A^{-1}$  are  $B^T A^T$  and  $(A^T)^{-1}$