

## 1 Vectors

### 1.1 Linear Combination (Def. 1.4)

Let  $v_1, v_2, \dots, v_n \in \mathbb{R}^m$  and  $\lambda_1, \lambda_2, \dots, \lambda_n \in \mathbb{R}$ , then

$$\lambda_1 v_1 + \lambda_2 v_2 + \dots + \lambda_n v_n$$

is a linear combination of  $v_1, v_2, \dots, v_n$ .

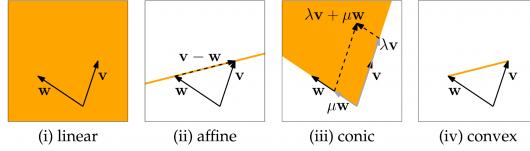
### 1.1.1 Special Linear Combinations (Def. 1.7)

A linear combination  $\lambda_1 v_1 + \lambda_2 v_2 + \dots + \lambda_n v_n$  is

(ii) *affine* if  $\lambda_1 + \lambda_2 + \dots + \lambda_n = 1$ ,

(iii) *conic* if  $\lambda_i \geq 0$  for  $i = 1, 2, \dots, n$ ,

(iv) *convex* if it is both affine and conic.



### 1.2 Euclidean Norm (Def. 1.11)

$$\|v\| := \sqrt{v \cdot v} = \sqrt{v_1^2 + v_2^2 + \dots + v_n^2}.$$

To normalize a vector, i.e. make it of length one, we can divide by the Euclidean norm:  $v' = v/\|v\|$ .

### 1.3 Dot Product and Angles (Def. 1.14)

The angle  $\alpha$  between two non-zero vectors  $v$  and  $w$  is

$$\cos(\alpha) = \frac{v \cdot w}{\|v\|\|w\|},$$

where  $-1 \leq \alpha \leq 1$ .

### 1.4 Prove Formula Defines a Scalar Product

Let  $A = \begin{bmatrix} 3 & -1 \\ -1 & 3 \end{bmatrix}$ . Prove that the following formula defines a scalar product in  $V = \mathbb{R}^2$ :

$$\langle x, y \rangle_A = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}, \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} \rangle_A = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}^T A \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}.$$

To be a scalar product, three conditions must be satisfied:

(i) **Symmetry:** Since  $A^T = A$ , the matrix is symmetric. Thus,

$$\langle x, y \rangle_A = x^T A y = (x^T A y)^T = y^T A^T x = y^T A x.$$

(ii) **Bilinearity:** Linearity in the first argument holds due to distributivity of matrix multiplication:

$$\begin{aligned} (\alpha x + \beta z)^T A y &= (\alpha x^T + \beta z^T) A y \\ &= \alpha x^T A y + \beta z^T A y. \end{aligned}$$

(iii) **Positive Definiteness:** We determine if  $A$  is Positive

Definite by checking its eigenvalues via  $\det(A - \lambda I) = 0$ :

$$\det \begin{bmatrix} 3 - \lambda & -1 \\ -1 & 3 - \lambda \end{bmatrix} = (3 - \lambda)^2 - 1 = \lambda^2 - 6\lambda + 8 = (\lambda - 4)(\lambda - 2).$$

The eigenvalues are  $\lambda_1 = 4$  and  $\lambda_2 = 2$ . Since all eigenvalues are strictly positive ( $\lambda_i > 0$ ),  $A$  is Positive Definite. By Prop 9.2.12, this implies:  $\langle x, x \rangle_A = x^T A x > 0 \quad \forall x \neq 0$ .

### 1.4.1 Cauchy-Schwarz (Lemma 1.12)

For any  $v, w \in \mathbb{R}^m$ :

$$|v^T w| \leq \|v\| \cdot \|w\| \implies -(\|v\| \cdot \|w\|) \leq v^T w \leq \|v\| \cdot \|w\|.$$

Equality holds if one is a scalar multiple of the other.

### 1.4.2 Triangle Inequality (Lemma 1.17)

Let  $v, w \in \mathbb{R}^m$ . Then:

$$\|v\| - \|w\| \leq \|v \pm w\| \leq \|v\| + \|w\|.$$

### 1.4.3 Orthogonal Vectors (Def. 1.15)

Let  $v, w \in \mathbb{R}^m$ .  $v$  and  $w$  are orthogonal if and only if

$$v \cdot w = 0,$$

i.e., the angle between them is  $\alpha = 90^\circ$ .

Note: If  $v$  and  $w$  are orthogonal, then  $\|v + w\|^2 = (v + w)^T(v + w) = v^T v + v^T w + w^T v + w^T w = \|v\|^2 + \|w\|^2$

### 1.5 Linear Independence (Cor. 1.23)

Let  $v_1, v_2, \dots, v_n \in \mathbb{R}^m$ . They are linearly independent if

- (i) none of the vectors is a linear combination of the other ones,
- (ii) there are no scalars  $\lambda_1, \lambda_2, \dots, \lambda_n$  besides  $0, 0, \dots, 0$  such that  $\sum_{j=1}^n \lambda_j v_j = 0$ ,
- (iii) none of the vectors is a linear combination of the previous ones.

Following, the columns of a matrix  $A$  are linearly independent if there is no  $x$  besides 0 such that  $Ax = 0$ .

### 1.6 Linear Dependence Example

Let  $u, v, w, z \in \mathbb{R}^2$ . Prove there exist non-zero scalars  $c_u, c_v, c_w, c_z$  such that  $c_u + c_v + c_w + c_z = 0$  and  $c_u u + c_v v + c_w w + c_z z = 0$ .

Define augmented vectors in  $\mathbb{R}^3$  by appending a 1, e.g.,  $u' = \begin{bmatrix} u_1 \\ u_2 \\ 1 \end{bmatrix}$ . Since there are 4 vectors in  $\mathbb{R}^3$ , they must be linearly dependent. The relation  $c_u u' + c_v v' + c_w w' + c_z z' = 0$  implies the vector sum is zero (first two coordinates) and the scalar sum is zero (last coordinate).

### 1.7 The Span (Def. 1.25)

Let  $v_1, v_2, \dots, v_n \in \mathbb{R}^m$ , their Span is defined as the set of all linear combinations, i.e.,

$$\text{Span}(v_1, v_2, \dots, v_n) := \left\{ \sum_{j=1}^n \lambda_j v_j : \lambda_j \in \mathbb{R} \forall j \in [n] \right\}.$$

### 1.8 Span Proof Example

Let  $v = \begin{bmatrix} v_1 \\ v_2 \end{bmatrix}$  and  $w = \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} \in \mathbb{R}^2$  be arbitrary and assume  $v \neq 0$  and  $w \neq \lambda v$ ,  $\forall \lambda \in \mathbb{R}$ . Show that  $\text{Span}(v, w) = \mathbb{R}^2$ .

To show this, prove that there are  $\lambda$  and  $\mu$  for each  $u \in \mathbb{R}^2$  such that  $u = \lambda v + \mu w$ , i.e.

$$\begin{bmatrix} u_1 \\ u_2 \end{bmatrix} = \lambda \begin{bmatrix} v_1 \\ v_2 \end{bmatrix} + \mu \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} \Rightarrow \begin{aligned} (1) u_1 &= \lambda v_1 + \mu w_1 \\ (2) u_2 &= \lambda v_2 + \mu w_2 \end{aligned}$$

Assume  $v_1 \neq 0$ , thus from (1) follows

$$\lambda = \frac{u_1 - \mu w_1}{v_1}.$$

Using this in (2) (assuming  $w_2 - \frac{v_2 w_1}{v_1} \neq 0$ ), we get

$$u_2 = \left( \frac{u_1 - \mu w_1}{v_1} \right) v_2 + \mu w_2 \Rightarrow \mu = \frac{u_2 - \frac{u_1 v_2}{v_1}}{w_2 - \frac{v_2 w_1}{v_1}}.$$

Thus, choosing  $\lambda$  and  $\mu$  is possible for all  $u \in \mathbb{R}^2$ .

### 2 Matrices (Def. 2.1)

An  $m \times n$  matrix is a rectangular array of numbers with  $m$  columns and  $n$  rows, i.e.,

$$A \in \mathbb{R}^{m \times n} := \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \dots & a_{mn} \end{bmatrix}.$$

### 2.5 Matrix-Matrix Multiplication (Def. 2.36)

For any two matrices  $A \in \mathbb{R}^{m \times k}$  and  $B \in \mathbb{R}^{k \times n}$ , the product  $AB \in \mathbb{R}^{m \times n}$  can also be understood in three ways:

#### 2.5.1 The Matrix Picture

$$\begin{bmatrix} -u_1- \\ -u_2- \\ \vdots \\ -u_m- \end{bmatrix} \begin{bmatrix} | & | & | \\ v_1 & v_2 & \dots & v_n \\ | & | & | \end{bmatrix} = \begin{bmatrix} u_1 \cdot v_1 & u_1 \cdot v_2 & \dots & u_1 \cdot v_n \\ u_2 \cdot v_1 & u_2 \cdot v_2 & \dots & u_2 \cdot v_n \\ \vdots & \vdots & \ddots & \vdots \\ u_m \cdot v_1 & u_m \cdot v_2 & \dots & u_m \cdot v_n \end{bmatrix}.$$

#### 2.5.2 The Row Picture

$$\begin{bmatrix} -u_1- \\ -u_2- \\ \vdots \\ -u_m- \end{bmatrix} B = \begin{bmatrix} -u_1 B- \\ -u_2 B- \\ \vdots \\ -u_m B- \end{bmatrix}.$$

#### 2.5.3 The Column Picture

$$A \begin{bmatrix} | & | & | \\ v_1 & v_2 & \dots & v_n \\ | & | & | \end{bmatrix} = \begin{bmatrix} | & | & | \\ Av_1 & Av_2 & \dots & Av_n \\ | & | & | \end{bmatrix}.$$

#### 2.5.4 Distributivity and Associativity (Lemma 2.42)

Let  $A, B, C$  and  $D$  be four matrices, then

(i)  $(A+B)C = AC + BC$  and  $(B+C)D = BD + CD$  (distributivity)

(ii)  $(AB)C = A(BC)$  (associativity)

Keep in mind, that MATRIX MULTIPLICATION IS NOT COMMUTATIVE.

### 2.6 CR' Decomposition $A = CR'$ (Theo. 2.46)

Let  $A \in \mathbb{R}^{m \times n}$  with rank  $r$ . Let  $C \in \mathbb{R}^{m \times r}$  be the submatrix of  $A$  containing all its independent columns. Then there exists a unique  $R' \in \mathbb{R}^{r \times n}$  such that  $A = CR'$ .

In other words,  $C$  describes the linearly independent columns, while  $R'$  ( $R$  from Gauss-Jordan Elimination, but without the zero rows) shows how to combine them to create  $A$ . For instance,

$$\begin{bmatrix} 1 & 2 & 0 & 3 \\ 2 & 4 & 1 & 4 \\ 3 & 6 & 2 & 5 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 2 & 1 \\ 3 & 2 \end{bmatrix} \begin{bmatrix} 1 & 2 & 0 & 3 \\ 0 & 0 & 1 & -2 \end{bmatrix}.$$

### 2.7 Linear Transformation (Def. 2.21)

Let  $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$  be a function.  $T$  is called a linear transformation if  $\forall v, w \in \mathbb{R}^n$  and  $\forall \lambda, \mu \in \mathbb{R}$ ,

$$T(\lambda v + \mu w) = \lambda T(v) + \mu T(w).$$

Let  $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$  is  $T$  a linear transformation?

(i) Show  $T(v + w) = T(v) + T(w)$  for all  $v, w \in \mathbb{R}^n$ .

(ii) Show  $T(\lambda v) = \lambda T(v)$  for all  $v \in \mathbb{R}^n$  and  $\lambda \in \mathbb{R}$ .

#### 2.7.1 $T = T_A$ (Theo. 2.26)

Let  $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$  be a linear transformation, there exists a unique  $A \in \mathbb{R}^{m \times n}$  such that  $T = T_A$ .

### 2.8 Rotation Matrix

In  $\mathbb{R}^{2 \times 2}$ , to rotate the  $xy$  plane counterclockwise around an angle  $\theta$  we use

$$R = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix}.$$

In  $\mathbb{R}^{3 \times 3}$ , there are three different rotation matrices, one for each axis:

$$R_x(\theta) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos \theta & -\sin \theta \\ 0 & \sin \theta & \cos \theta \end{bmatrix}$$

$$R_y(\theta) = \begin{bmatrix} \cos \theta & 0 & \sin \theta \\ 0 & 1 & 0 \\ -\sin \theta & 0 & \cos \theta \end{bmatrix}$$

$$R_z(\theta) = \begin{bmatrix} \cos \theta & -\sin \theta & 0 \\ \sin \theta & \cos \theta & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

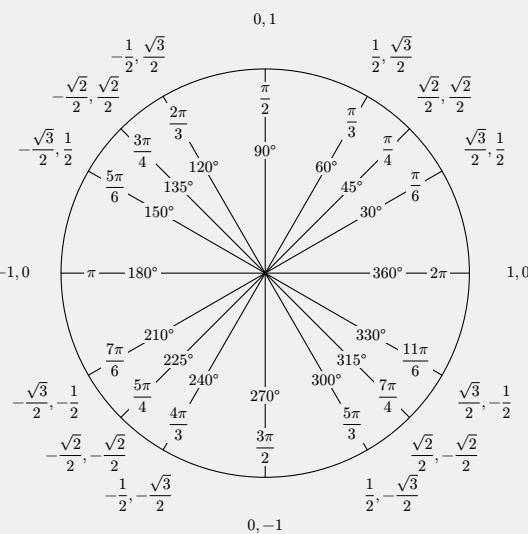
### 2.8.1 Composition of Rotations

Let  $R(\theta_1), R(\theta_2) \in \mathbb{R}^{2 \times 2}$  be two rotation matrices, then

$$R(\theta_1)R(\theta_2) = R(\theta_1 + \theta_2).$$

Moreover, for every  $R(\theta) \in \mathbb{R}^{2 \times 2}$ , there is some  $R(-\theta) \in \mathbb{R}^{2 \times 2}$  such that  $R(\theta)R(-\theta) = R(0) = I$ .

If we need to find an  $A \in \mathbb{R}^{2 \times 2}$  that satisfies  $A^k = I \iff k$  is a multiple of  $t$ , then  $A$  can be a rotation matrix with  $\theta = \frac{2\pi}{t}$ . For higher dimensions  $A \in \mathbb{R}^{n \times n}$ , the same principle applies if we embed the 2D rotation e.g. into the top left corner (like in  $R_z(\theta)$  above) and fill the rest of the diagonal with 1s. Below: left =  $\cos(\theta)$ , right =  $\sin(\theta)$ .



## 3 Linear Equations

A system of  $m$  linear equations in  $n$  variables,

$$\begin{aligned} a_{11}x_1 + a_{12}x_2 + \dots + a_{1n}x_n &= b_1 \\ a_{21}x_1 + a_{22}x_2 + \dots + a_{2n}x_n &= b_2 \\ &\vdots \\ a_{m1}x_1 + a_{m2}x_2 + \dots + a_{mn}x_n &= b_m. \end{aligned}$$

can be expressed using matrices in the shape  $Ax = b$ :

$$\begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \dots & a_{mn} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_m \end{bmatrix}.$$

### 3.1 Gauss Elimination

#### 3.1.1 Back Substitution

We can directly solve  $Ax = b$ , when  $A$  is an *upper triangular* matrix by solving the equations in reverse order.

$$\begin{bmatrix} 2 & 3 & 4 \\ 0 & 5 & 6 \\ 0 & 0 & 7 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} 19 \\ 17 \\ 14 \end{bmatrix} \quad \text{Solve for } x_3 \text{ first and then work your way up (backwards substitution).}$$

#### 3.1.2 Elimination

Transform  $Ax = b$  to  $Ux = c$ , where  $U$  is upper triangular, by performing

- (i) row exchanges,
- (ii) scalar multiplication,
- (iii) row subtraction.

$$\left[ \begin{array}{ccc|c} u_{11} & \dots & & c_1 \\ 0 & u_{22} & \dots & c_2 \\ 0 & 0 & \ddots & \vdots \\ 0 & 0 & \dots & u_{rr} & c_r \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 0 & c_m \end{array} \right]$$

Crucially,  $Ax = b$  and  $Ux = c$  have the same solutions (Lemma 3.2).

#### 3.1.3 Elimination and Permutation Matrices

Elimination and row exchanges requires matrices as *linear combinations of the rows* (multiply from the left).

$$\begin{array}{l} \text{row 2 minus } c \cdot \text{row 1} \\ E_{21} = \begin{bmatrix} 1 & 0 & 0 \\ -c & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}. \end{array} \quad \begin{array}{l} \text{exchange row 2 and row 3} \\ P_{23} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix}. \end{array}$$

### 3.2 Inverse Matrices (Def. 2.57)

Let  $M \in \mathbb{R}^{m \times m}$ ,  $M$  is invertible, if there exists an  $M^{-1} \in \mathbb{R}^{m \times m}$  such that

$$MM^{-1} = M^{-1}M = I.$$

For invertible matrices, the following holds

- (i) inverses are unique, i.e. if  $AM = MA = I$  and  $BM = MB = I$ ,  $A = B$  (Obs. 2.56),
- (ii) if  $A$  and  $B$  are invertible, then  $(AB)^{-1} = B^{-1}A^{-1}$  (the product of two invertible matrices is invertible too) (Lemma 2.59),
- (iii) if  $A$  is invertible, then  $(A^T)^{-1} = (A^{-1})^T$  (Lemma 2.60).

#### 3.2.1 Inverse Theo. (Lemma 2.53 / Theo. 3.8)

Let  $A \in \mathbb{R}^{m \times m}$ , the following is equivalent

- (i)  $A$  is invertible,
- (ii) For every  $b \in \mathbb{R}^m$ ,  $Ab = b$  has a unique solution  $x$ ,
- (iii) The columns of  $A$  are linearly independent.

#### 3.2.2 Example

Given  $A, B \in \mathbb{R}^{m \times m}$  such that  $AB = I$ , prove  $BA = I$ .

- (i) Show  $B$  has linearly independent columns: Let  $x \in \mathbb{R}^m$  such that  $Bx = 0$ , then

$$x = Ix = ABx = A0 = 0.$$

Hence by Obs. 2.5(ii), they are linearly independent.

- (ii) Show  $A$  also has linearly independent columns: Let  $y \in \mathbb{R}^m$  such that  $Ay = 0$ , then by Theorem 3.8 there is some  $x \in \mathbb{R}^m$  such that  $Bx = y$  (because  $B$  is invertible), then

$$y = Bx = B(Ix) = B(ABx) = B(Ay) = B0 = 0.$$

- (iii) Show  $BA - I = 0$ :

$$A(BA - I) = ABA - A = IA - A = 0.$$

Thus,  $BA = I$ .

#### 3.2.3 Inverse of a $2 \times 2$ matrix

Let  $A = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$ , then

$$A^{-1} = \frac{1}{ad - bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix} \quad (\text{if } ad - bc \neq 0).$$

#### 3.2.4 Inverse of an $n \times n$ matrix (easy way)

We compute  $A^{-1}$  by running Gauss-Jordan elimination on the augmented matrix  $[A \mid I]$ . If  $A$  reduces to  $I$ , the right side becomes  $A^{-1}$  (Theorem 3.19).

#### 3.2.4.1 Inverse Formula (Prop. 7.3.3)

Let  $A \in \mathbb{R}^{n \times n}$  with  $\det(A) \neq 0$ . Then

$$A^{-1} = \frac{1}{\det(A)} C^T,$$

where  $C$  is the matrix of *cofactors*, with entries  $C_{ij} = (-1)^{i+j} \det(A_{ij})$  (Def. 7.3.1). Here,  $A_{ij}$  is the  $(n-1) \times (n-1)$  submatrix obtained by removing row  $i$  and column  $j$  from  $A$ .

### 3.3 Gauss-Jordan Elimination

#### 3.3.1 Reduced Row Echelon Form (Def. 3.13)

Let  $M \in \mathbb{R}^{m \times n}$  with rank  $r$ ,  $M$  is in RREF, if

- (i) it contains the unit vectors  $e_0, \dots, e_r$  as its columns in ascending order,
- (ii) the columns in between contain values only up to the  $i$ -th row, where  $i$  refers to the index of the most recent unit vector.

#### 3.3.2 Solving $Ax = b$ (Theorem 3.20)

We add the following step to Gauss Elimination:

- (i) multiply each row with a pivot  $p$  with  $1/p \Rightarrow p = 1$
- (ii) eliminate any value above the pivot
- (iii) (at the end remove any zero-rows,  $R_0 \rightarrow R$ )

A solution to  $Ax = b$  exists if and only if  $b_i = 0$  for all zero-rows  $i > r$ ; then, a specific solution  $x$  is found by setting all free variables to 0 and each pivot variable  $x_{j_i} = b_i$ .

## 4 The Four Fundamental Subspaces

### 4.1 Vector Spaces (Def. 4.1)

A vector space is a triple  $(V, +, \cdot)$ , where

- (i)  $V$  is a set,
- (ii)  $+ : V \times V \rightarrow V$  a function (vector addition),
- (iii)  $\cdot : \mathbb{R} \times V \rightarrow V$  a function (scalar multiplication).

Such that they satisfy

- (i)  $v + w = w + v$  (commutativity)
- (ii)  $u + (v + w) = (u + v) + w$  (associativity)
- (iii) There is  $0$  such that  $v + 0 = v$  for all  $v$  (zero vector)
- (iv) There is  $-v$  such that  $v + (-v) = 0$  for all  $v$  (inverse)
- (v)  $1 \cdot v = v$  for all  $v$  (identity)
- (vi)  $(\lambda \cdot \mu)v = \lambda(\mu v)$  (compatibility in  $\mathbb{R}$ )
- (vii)  $\lambda(v + w) = \lambda v + \lambda w$  (distributivity over  $+$ )
- (viii)  $(\lambda + \mu)v = \lambda v + \mu v$  (distributivity over  $+$  in  $\mathbb{R}$ )

### 4.2 Subspaces (Def. 4.8) & Proof Strategy

A subset  $U \subseteq V$  is a *subspace* of vector space  $V$  if it satisfies these three conditions (standard checklist to prove  $U$  is a subspace):

- (i) Contains Zero:  $0 \in U$  (ensures  $U$  is non-empty).
- (ii) Closed under Addition:  $u + v \in U$  for all  $u, v \in U$ .
- (iii) Closed under Scaling:  $\lambda u \in U$  for all  $u \in U$  and  $\lambda \in \mathbb{R}$ .

### 4.3 Example

Let  $V$  be a vector space and  $U, W$  subspaces of  $V$ . Show that  $U \cup W$  is a subspace of  $V \iff U \subseteq W$  or  $W \subseteq U$ .

$\Leftarrow$ : Assume  $U \subseteq W$ , then  $U \cup W = W$ , which is a subspace of  $V$  by assumption. (Analogous for  $W \subseteq U$ ).

$\Rightarrow$ : Assume  $U \cup W$  is a subspace of  $V$  and  $W \not\subseteq U$ , then there is some  $w \in W \setminus U$ . Let  $u \in U$  be arbitrary, then  $w + u \in W \cup U$ . If  $w + u \in U$ , then  $w$  also  $\in U$  (bc of additivity, but this is not possible bc we said  $w \in W \setminus U$ ). Thus  $w + u \in W$  must hold, and bc of additivity,  $u \in W$ . So we started with an arbitrary  $u \in U$  and proved it must land in  $W$ , as in  $u \in W$ . Thus,  $U \subseteq W$ . Intuition: Union of two subspaces is only a subspace if one is contained in the other (think x-y-axes).

### 4.4 Bases and Dimensions

#### 4.4.1 Basis (Def. 4.18)

Let  $V$  be a vector space. A subset  $B \subseteq V$  is called a *basis* of  $V$  if  $B$  is linearly independent and  $\text{Span}(B) = V$ .

#### 4.4.2 Dimensions (Def. 4.25)

Let  $V$  be a finitely generated vector space. Then  $\dim(V) = |B|$ , for any basis  $B \subseteq V$ . Moreover, the size of all bases of a vector space is equal (Theo. 4.24).

### 4.5 Example

Let  $V \subseteq \mathbb{R}^m$ , what is the dimension of  $V$ ?

- (i) Find a basis of  $V$ ,
- (ii) show it is a basis (linearly independent & span is  $V$ ),
- (iii) dimension is the cardinality of the base.

#### 4.5.1 Steinitz Exchange Lemma (Lemma 4.23)

Let  $V$  be a vector space,  $F \subseteq V$  a finite set of linearly independent vectors, and  $G \subseteq V$  a finite set of vectors with  $\text{Span}(G) = V$ . Then

- (i)  $|F| \leq |G|$ ,
- (ii) there is some subset  $E \subseteq G$  with  $|E| = |G| - |F|$  such that  $\text{Span}(F \cup E) = V$ .

### 4.6 The Column Space of $A$ (Def. 2.9)

Let  $A \in \mathbb{R}^{m \times n}$ . The *column space* of  $A$  is the span of its columns,

$$C(A) := \{Ax : x \in \mathbb{R}^n\} \subseteq \mathbb{R}^m.$$

The set of all vectors you can get by combining the columns of the matrix. For a matrix transformation  $Ab = b$ , the column space is the set of all possible output vectors  $b$  for which a solution  $x$  exists.

#### 4.6.1 Basis of $C(A)$ (Theo. 4.31)

The basis of  $C(A)$  is the set of its *linearly independent columns*, and hence  $\dim(C(A)) = \text{rank}(A)$ . These can be calculated using Gauss-Jordan ( $C$  matrix of  $A = CR'$ ).

#### 4.7 The Row Space of $A$ (Def. 2.14)

Let  $A \in \mathbb{R}^{m \times n}$ . The *row space* of  $A$  is the span of its rows,

$$R(A) := \{A^T x : x \in \mathbb{R}^m\} = C(A^T) \subseteq \mathbb{R}^n.$$

It tells about the fundamental, independent equations in a system. If a new equation is a combination of existing rows, it's in the row space. I.e. if a vector satisfies this new equation, it's in the row space.

For example, let  $A \Rightarrow R = \begin{bmatrix} 1 & 0 & 2 \\ 0 & 1 & 0 \end{bmatrix}$ , with row vectors  $r_1 = [1, 0, 2]$  and  $r_2 = [0, 1, 0]$ . A linear combination of these is:

$$c_1[1, 0, 2] + c_2[0, 1, 0] = [c_1, c_2, 2c_1]$$

The row space is the set of vectors  $(x, y, z) \in \mathbb{R}^3$  satisfying  $z = 2x$  (one less free variable  $\Rightarrow$  a plane through the origin).

#### 4.7.1 Basis of $R(A)$ (Theo. 4.32)

The basis of  $R(A)$  is the set of its *linearly independent rows*, and hence  $\dim(R(A)) = \dim(C(A)) = \text{rank}(A)$ . These correspond to the first  $r$  rows of  $A$  in REF, where  $r$  is the rank of  $A$ .

So  $R(A) = R(R') = C(R'^T)$  with  $R$  from CR decomposition.

#### 4.8 Bases in $A = CR'$ (Theo. 3.18)

Let  $A = CR'$ , then the columns of  $C$  form a basis of  $C(A)$  and the rows of  $R'$  form a basis of  $R(A)$ .

So  $C(A) = C(C)$  and  $R(A) = R(R') = C(R'^T)$ .

#### 4.9 The Nullspace of $A$ (Def. 2.17)

Let  $A \in \mathbb{R}^{m \times n}$ . The *nullspace* of  $A$  is the set of all solutions to  $Ax = 0$ ,

$$N(A) := \{x \in \mathbb{R} : Ax = 0\} \subseteq \mathbb{R}^n.$$

#### 4.9.1 Basis of $N(A)$ (Theo. 4.36)

We can calculate a basis of  $N(A)$ , by converting  $A$  to  $R'$  in RREF through Gauss-Jordan and then solving  $R'x = 0$  with the *special cases* where  $x_i = 1$  for every  $i = 1, \dots, n$  for every linearly dependent column in  $R'$ .

For example,  $A \in \mathbb{R}^{2 \times 4}$ ,

(i) convert  $A \rightarrow R'$  through Gauss-Jordan,

(ii) solve  $R'x = 0$  with special cases (per special case: set one free variable (one variable of the **dependent** columns) e.g.  $x_2 = 1$ , the other free variables to 0), solve for  $x$

$$\underbrace{\begin{bmatrix} 1 & 2 & 0 & 3 \\ 0 & 0 & 1 & -2 \end{bmatrix}}_{A \text{ in RREF }= R'} \underbrace{\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}}_x = 0 \text{ with } x = \underbrace{\begin{bmatrix} x_1 \\ 1 \\ x_3 \\ 0 \end{bmatrix}}_{\text{special cases}} \text{ and } \underbrace{\begin{bmatrix} x_1 \\ 0 \\ x_3 \\ 1 \end{bmatrix}}_{\text{special cases}}.$$

(iii) The solutions  $x_1, \dots, x_n$  form a Basis of  $N(R')$ ,

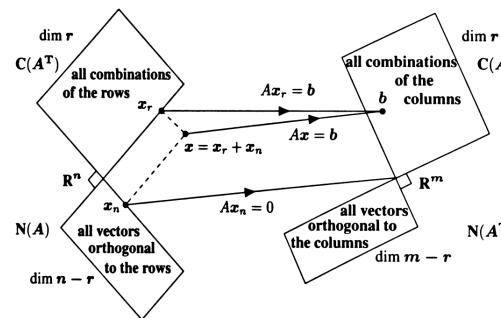
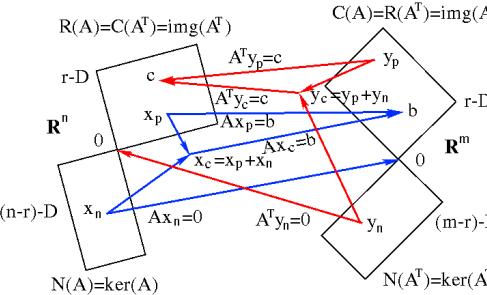
$$x_1 = \begin{bmatrix} -2 \\ 1 \\ 0 \\ 0 \end{bmatrix}, x_2 = \begin{bmatrix} -3 \\ 0 \\ 2 \\ 1 \end{bmatrix} \Rightarrow \{x_1, x_2\} \text{ is a basis of } N(R).$$

(iv) Any basis of  $N(R')$  is also a basis of  $N(A)$  (Lemma 3.3).

Following,  $\dim(N(A)) = n - \text{rank}(A)$  (Theo. 4.36).

For  $A \in \mathbb{R}^{m \times n}$ :

subspace	$C(A)$	$R(A)$	$N(A)$	$N(A^T)$
dimensions	$r$	$r$	$n - r$	$m - r$
subspace of	$\mathbb{R}^m$	$\mathbb{R}^n$	$\mathbb{R}^n$	$\mathbb{R}^m$



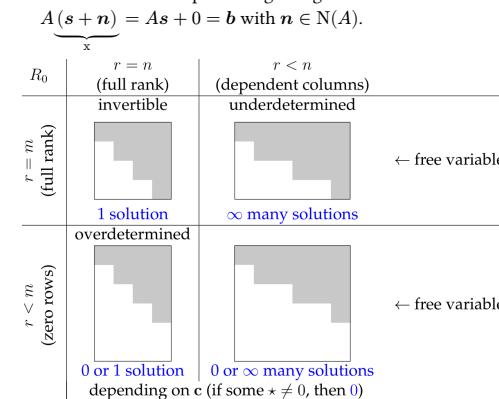
#### 4.10 The Solution Space of $Ax = b$ (Def. 4.37)

Let  $A \in \mathbb{R}^{m \times n}$ , and  $b \in \mathbb{R}^m$ , then *solution space* of  $Ax = b$  is the set

$$\text{Sol}(A, b) := \{x \in \mathbb{R}^n : Ax = b\} \subseteq \mathbb{R}^n.$$

For any  $Ax = b$  we have three options, 1. no solutions, 2. one solution and 3. infinite solutions.

- (i) If  $A$  is not invertible and  $b \notin C(A)$  then no solution exists.
- (ii) If  $A$  is invertible  $\Rightarrow N(A) = \{0\}$  then exactly one solution exists.
- (iii) If  $A$  is not invertible, but  $b \in C(A)$ , then  $\exists s$  and we can shift the non-trivial nullspace using  $s$  to get infinite solutions:  
 $A(s + n) = As + 0 = b$  with  $n \in N(A)$ .



#### 4.10.1 Sol. Space is shifted Nullspace (Theo. 4.38)

Let  $A \in \mathbb{R}^{m \times n}$  and  $b \in \mathbb{R}^m$ . Let  $s$  some solution for  $x$  to  $Ax = b$ , then

$$\text{Sol}(A, b) = \{s + n : n \in N(A)\}.$$

## 5 Orthogonality

#### 5.1 Orthogonal Subspaces (Def. 5.1.1)

Two subspaces  $V$  and  $W$  are *orthogonal* if for all  $v \in V$  and  $w \in W$ ,  $v^T w = 0$ .

More specifically, this also holds for the bases, i.e., let  $v_1, \dots, v_k$  be a basis of  $V$  and  $w_1, \dots, w_l$  be a basis of  $W$ .  $V$  and  $W$  are orthogonal if and only if  $v_i \cdot w_j = 0 \forall i \in [k]$  and  $j \in [l]$  (Lemma 5.1.2).

#### 5.2 Orthogonal Complement (Def. 5.1.5)

Let  $V$  be a subspace of  $\mathbb{R}^n$ , the *orthogonal complement* to  $V$  is defined as

$$V^\perp := \{w \in \mathbb{R}^n : w^T v = 0 \text{ for all } v \in V\}.$$

#### 5.3 Double Complement (Lemma 5.1.8)

Let  $V$  be a subspace of  $\mathbb{R}^n$ . Then:  $V = (V^\perp)^\perp$

#### 5.4 Orthogonal Decomp. (Theo. 5.1.7)

Let  $V, W$  be subspaces of  $\mathbb{R}^n$ , then these are equivalent

- (i)  $W = V^\perp$ ,
- (ii)  $\dim(V) + \dim(W) = n$ ,
- (iii) Every  $u \in \mathbb{R}^n$  can be written as  $u = v + w$  with  $v \in V$  and  $w \in W$ .

#### 5.5 Intersection of Orthogonal Subspaces (Cor. 5.1.4)

Let  $V$  and  $W$  be orthogonal subspaces. Then their intersection is trivially only at the origin:

$$V \cap W = \{0\}$$

#### 5.6 Orthogonal Matrix Subspaces (Cor. 5.1.9 & Lemma 5.1.10)

Let  $A \in \mathbb{R}^{m \times n}$ , then

- (i)  $N(A) = C(A^T)^\perp$ , also  $N(A) = N(A^T A)$ ,
- (ii)  $C(A^T) = N(A)^\perp$ , also  $C(A^T) = C(A^T A)$ .

#### 5.7 Decomp. of the Sol. Space (Theo. 6.2.2)

Let  $A \in \mathbb{R}^{m \times n}$  and  $b \in \mathbb{R}^m$ .  $\text{Sol}(A, b) = x_1 + N(A)$  with  $x_1 \in R(A)$  such that  $Ax_1 = b$ .

## 6 Projections

#### 6.1 Projection (Def. 5.2.1)

The projection of a vector  $b \in \mathbb{R}^m$  on a subspace  $S$  is the point in  $S$  closest to  $b$ :

$$\text{proj}_S(b) = \underset{p \in S}{\text{argmin}} \|b - p\|$$

#### 6.2 Normal Equations (Lemma 5.2.3)

The projection of  $b$  on  $S = C(A)$  is well defined and given by  $p = Ax$ , where  $\hat{x}$  satisfies the *normal equations*:

$$A^T A \hat{x} = A^T b$$

#### 6.3 Projection Matrix (Theo. 5.2.5)

Let  $S$  be a subspace of  $\mathbb{R}^m$  and  $A$  be a matrix with columns that are a basis of  $S$ . The projection of  $b \in \mathbb{R}^m$  on  $S$  is given by

$$\text{proj}_S(b) = Pb \text{ with } P = A(A^T A)^{-1} A^T = Q Q^T.$$

Moreover,

- (i)  $A^T A$  is invertible  $\Leftrightarrow A$  has linearly independent columns (Lemma 5.2.4),
- (ii) if  $A$  has linearly independent columns, then  $A^T A$  is square, invertible and symmetric.

#### 6.3.1 Remark 5.2.6

For any projection matrix  $P$  and corresponding subspace  $S$ ,

$$(i) P^2 = \left( A(A^T A)^{-1} A^T \right)^2 = A(A^T A)^{-1} \overset{I}{\cancel{A^T A}} (A^T A)^{-1} A^T = A(A^T A)^{-1} A^T = P$$

$$(ii) \text{proj}_{S^\perp}(b) = b - Pb = (I - P)b.$$

#### 6.4 Matrix for Reflection Through a Plane

To find the matrix  $B$  representing a reflection through a plane  $P$  passing through the origin:

- (i) **Find the normal vector  $v$**  from the plane equation  $(ax + by + cz = 0 \Rightarrow v = \begin{bmatrix} a \\ b \\ c \end{bmatrix})$ .  $v$  is orthogonal to the plane.
- (ii) **Normalize it** to get the unit normal vector  $n = \frac{v}{\|v\|}$ .
- (iii) **Apply the reflection formula:**  $B = I - 2nn^T$

Note: This formula works because  $nn^T$  is the projection onto the normal, i.e.  $I - nn^T$  would be the projection onto the plane. Subtracting it twice reflects the vector across the plane.

## 7 Linear Regression

#### 7.1 Least Squares Approximation (Section 6.1)

A linear regression through the data points  $(t_1, b_1), (t_2, b_2), \dots, (t_m, b_m)$  can be expressed in algebraic terms as minimizing the sum of the squared errors (where  $\alpha_0$  is the intercept, and  $\alpha_1$  the slope),

$$\min_{\alpha_0, \alpha_1} \left\| b - A \underbrace{\begin{bmatrix} \alpha_0 \\ \alpha_1 \end{bmatrix}}_{\alpha} \right\|^2, \text{ where } b = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_m \end{bmatrix} \text{ and } A = \begin{bmatrix} 1 & t_1 \\ 1 & t_2 \\ \vdots & \vdots \\ 1 & t_m \end{bmatrix}.$$

To minimize error, the error vector must be orthogonal to columns of  $A$ , so the minimizer satisfies the **normal equations** (Fact 6.1.1):

$$A^T(b - A\alpha) = 0$$

$$A^T A \alpha = A^T b \text{ ("normal equation", Gauss-J. [ } A^T A \mid A^T b ] )$$

$$\alpha = (A^T A)^{-1} A^T b$$

$$\begin{bmatrix} \alpha_0 \\ \alpha_1 \end{bmatrix} = \left[ \sum_{k=1}^m t_k \sum_{k=1}^m t_k^2 \right]^{-1} \left[ \sum_{k=1}^m b_k t_k \right].$$

Moreover, the columns of the  $m \times 2$  matrix  $A$  are linearly dependent  $\Leftrightarrow t_i = t_j$  for all  $i \neq j$  (Lemma 6.1.2).

#### 7.2 Remark 6.1.3

If the columns of  $A$  are pairwise orthogonal (which corresponds to  $\sum_{k=1}^m t_k = 0$ ), then  $A^T A$  is a diagonal matrix and we can further simplify the expression,

$$\begin{bmatrix} \alpha_0 \\ \alpha_1 \end{bmatrix} = \begin{bmatrix} \frac{1}{m} & 0 \\ 0 & \frac{1}{\sum_{k=1}^m t_k^2} \end{bmatrix} \begin{bmatrix} \sum_{k=1}^m b_k \\ \sum_{k=1}^m t_k b_k \end{bmatrix} = \begin{bmatrix} \frac{1}{m} \sum_{k=1}^m b_k \\ \frac{\sum_{k=1}^m t_k b_k}{\sum_{k=1}^m t_k^2} \end{bmatrix}$$

### 7.3 Least Squares Example

Find  $a, b \in \mathbb{R}$  for the function  $f(x) = ax^2 + b$  that minimizes the squared error for the data points  $(-1, 2), (0, 1)$ , and  $(1, 3)$ .

We set up the system  $Ax \approx y$  where unknowns are  $x = \begin{bmatrix} b \\ a \end{bmatrix}$  corresponding to basis functions 1 and  $x^2$ :

$$A = \begin{bmatrix} 1 & (-1)^2 \\ 1 & 0^2 \\ 1 & 1^2 \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & 1 \\ 1 & 1 \end{bmatrix}, \quad y = \begin{bmatrix} 2 \\ 1 \\ 3 \end{bmatrix}.$$

Solve via normal equations  $A^T Ax = A^T y$ :

$$A^T A = \begin{bmatrix} 3 & 2 \\ 2 & 2 \end{bmatrix}, \quad A^T y = \begin{bmatrix} 6 \\ 5 \end{bmatrix} \Rightarrow \begin{bmatrix} 3 & 2 \\ 2 & 2 \end{bmatrix} \begin{bmatrix} b \\ a \end{bmatrix} = \begin{bmatrix} 6 \\ 5 \end{bmatrix}.$$

Row reduction or substitution yields  $b = 1$  and  $a = \frac{3}{2}$ .

## 8 Orthonormal Bases

### 8.1 Orthonormal Vectors (Def. 6.3.1)

Vectors  $q_1, \dots, q_n \in \mathbb{R}^m$  are orthonormal if they are orthogonal and have norm 1, i.e., if for all  $i, j \in [n]$

$$q_i^T q_j = \begin{cases} 1 & \text{if } i = j \\ 0 & \text{otherwise.} \end{cases}$$

### 8.2 Orthogonal Matrix (Def. 6.3.3)

A square matrix  $Q \in \mathbb{R}^{n \times n}$  is orthogonal when  $Q^T Q = I$ . Then  $QQ^T = I$  and the columns of  $Q$  form an orthonormal basis of  $\mathbb{R}^n$ .

Additionally, orthogonal matrices preserve norm and dot product, i.e.,

$$\|Qx\| = \|x\| \text{ and } (Qx)^T (Qy) = x^T y,$$

for all  $x, y \in \mathbb{R}^n$  (Prop. 6.3.6).

If  $A$  and  $B$  are orthogonal, then so is  $AB$ .

### 8.3 Gram-Schmidt (Alg. 6.3.8)

Given  $n$  linearly independent vectors  $a_1, \dots, a_n$  that span  $S$ ,  $q_1, \dots, q_n$  can be constructed as follows:

- (i)  $q_1 = \frac{a_1}{\|a_1\|}$
- (ii) For  $k = 2, \dots, n$ ,

$$q_{k'} = a_k - \sum_{i=1}^{k-1} \frac{(a_i^T q_i)}{R_{ik}} q_i \rightarrow q_k = \frac{q_{k'}}{\|q_{k'}\|}.$$

The vectors  $q_1, \dots, q_n$  form an orthonormal basis of  $S$  (Theorem 6.3.9).

Note: An upper triangular  $n \times n$  matrix with non-zero diagonals that does not yield the canonical basis after the Gram-Schmidt process is  $-I$ .

### 8.4 QR-Decomposition (Def. 6.3.10)

Let  $A \in \mathbb{R}^{m \times n}$  with linearly independent columns.

$$A = QR$$

where  $Q$  is an  $m \times n$  matrix with orthonormal columns and  $R$  is an upper triangular matrix given by  $R = Q^T A$ . Use Gram-Schmidt on the columns of  $A$  to get  $Q$ .

### 8.5 Projections with QR (Fact 6.3.12)

- (i) Any projection on  $C(A)$  can also be done by  $Q$ , as  $C(A) = C(Q)$ , following  $\text{proj}_{C(A)}(b) = Q(Q^T Q)^{-1} Q^T b = QQ^T b$ .
- (ii) The normal equation can be re-written as

$$A^T A \hat{x} = A^T b$$

$$R^T R \hat{x} = R^T Q^T b \quad (R^T \text{ is invertible})$$

$$R \hat{x} = Q^T b. \quad (\text{useful for least squares})$$

$$A \hat{x} = QQ^T b$$

## 9 Pseudoinverses

### 9.1 Full Column Rank (Def. 6.4.1)

For any  $A \in \mathbb{R}^{m \times n}$  with  $\text{rank}(A) = n$ ,  $A_{\text{left}}^+ = (A^T A)^{-1} A^T$  is a left inverse,  $\Rightarrow A^+ A = I$ .

### 9.2 Full Row Rank (Def. 6.4.3)

For any  $A \in \mathbb{R}^{m \times n}$  with  $\text{rank}(A) = m$ ,  $A_{\text{right}}^+ = A^T (AA^T)^{-1}$  is a right inverse,  $\Rightarrow AA^+ = I$ .

### 9.3 All Matrices (Def. 6.4.7)

For any  $R \in \mathbb{R}^{m \times n}$  with rank  $r$  and CR-decomposition  $A = CR$ ,

$$\begin{aligned} A^+ &= (CR)^+ = R^+ C^+ \\ &= R^T (RR^T)^{-1} (C^T C)^{-1} C^T \\ &= R^T (C^T A R^T)^{-1} C^T. \end{aligned}$$

### 9.4 Pseudoinverses with rank $r$ (Prop. 6.4.9)

For  $A \in \mathbb{R}^{m \times n}$  with rank  $r$ , let  $S \in \mathbb{R}^{m \times r}$  and  $T \in \mathbb{R}^{r \times n}$ , such that  $A = ST$ , then  $A^+ = T^+ S^+$ .

### 9.5 Optimization Properties (Lemma 6.4.8)

Given  $A \in \mathbb{R}^{m \times n}$  and  $b \in \mathbb{R}^m$ , the vector  $\hat{x} = A_{\text{left}}^+ b$  is the unique solution to the problem:

$$\begin{aligned} \min_{x \in \mathbb{R}^n} \|x\|_2 \text{ subject to } A^T Ax = A^T b \\ x = (A^T A)^{-1} A^T b \end{aligned}$$

In words:  $A_{\text{left}}^+ b$  is the solution to the least squares problem with the smallest norm.

### 9.6 Properties of $A^+$ (Theo. 6.4.10)

- (i)  $AA^+ A = A$
- (ii)  $A^+ AA^+ = A^+$ . Proof: see below.
- (iii)  $A_{\text{left}}^+$  is symmetric & the projection matrix on  $C(A)$ .
- (iv)  $A_{\text{right}}^+$  is symmetric & the projection matrix on  $C(A^T)$ .
- (v)  $(A^T)^+ = (A^+)^T$ . Proof: see below.

### 9.7 Proof of Pseudoinverse Properties

- (i) Prove that if  $\text{rank}(A) = \text{rank}(B) = n$ , we have  $(AB)^+ = B^+ A^+$ .

$C(AB) = C(A)$  (as  $\text{rank}(B) = n$  implies that  $C(B) = \mathbb{R}^n$ ). Then using Prop. 6.4.9 we get  $(AB)^+ = B^+ A^+$ .

- (ii) Prove that  $A^+ AA^+ = A^+$ .

$$A^+ AA^+ = (CR)^+ CR(CR)^+ = R^+ (C^+ C) (RR^+)^- C^+ = R^+ C^+ = A^+.$$

- (iii) Prove that  $(A^T)^+ = (A^+)^T$ .

prove for full row & column rank separately, then use Prop. 6.4.9 to get  $(A^T)^+ = (C^T)^+ (R^T)^+ = (C^+)^T (R^+)^T = (R^+ C^+)^T = (A^+)^T$ .

- (iv) Prove that  $A^+ A$  is symmetric and that it is the projection matrix for the subspace  $C(A^T)$ .

projection matrix:  $A^+ A = (CR)^+ CR = R^+ C^+ CR = R^T (RR^T)^{-1} R. \quad (C(A^T) = C(R^T))$   
symmetric:  $(A^+ A)^T = (R^T (RR^T)^{-1} R)^T = R^T ((RR^T)^{-1})^T R = R^T (RR^T)^{-1} R = A^+ A$ .

### 10 Certificate of Unsolvability (Theo 6.2.4)

Let  $A \in \mathbb{R}^{m \times n}$  and  $b \in \mathbb{R}^m$ . The system of linear equations has no solution iff there exists non-zero vector  $z$  s.t.:

$$\begin{aligned} \{x \in \mathbb{R}^n \mid Ax = b\} &= \emptyset \\ \Leftrightarrow \{z \in \mathbb{R}^m \mid A^T z = 0, b^T z = 1\} &\neq \emptyset \end{aligned}$$

### 10.1 Parametric Solvability Example

For  $A = \begin{bmatrix} 2 & 1 \\ 1 & 3 \\ 0 & 2 \end{bmatrix}$  and  $B = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix}$ . Find  $b_i$  s.t.  $Ax + By = c$  is solvable for all  $c$ .

We know  $Ax + By = c$  is solvable for all  $c$  iff the only solution to  $\begin{bmatrix} A^T \\ B^T \end{bmatrix} z = 0$  is with  $z = 0$ .

$$\begin{bmatrix} 2 & 1 & 0 \\ 1 & 3 & 2 \\ 0 & 2 & 3 \end{bmatrix} \begin{bmatrix} z_1 \\ z_2 \\ z_3 \end{bmatrix} = 0 \Rightarrow \begin{cases} 2z_1 + z_2 = 0 \\ z_1 + 3z_2 + 2z_3 = 0 \\ b_1 z_1 + b_2 z_2 + b_3 z_3 = 0 \end{cases} = 0$$

$$\Rightarrow \begin{cases} 2z_1 = -z_2 \\ z_1 + 3z_2 = -2z_3 \end{cases} \Rightarrow z_1 = -\frac{1}{2}z_2, \quad z_3 = -\frac{5}{4}z_2$$

Sub. into row 3:  $b_1(-\frac{1}{2}z_2) + b_2 z_2 + b_3(-\frac{5}{4}z_2) = 0$ .

$$\left(-\frac{1}{2}b_1 + b_2 - \frac{5}{4}b_3\right)z_2 = 0$$

A non-zero  $z$  can only exist if  $(-\frac{1}{2}b_1 + b_2 - \frac{5}{4}b_3) = 0$ , which would mean  $Ax + By = c$  is not solvable. But we want it to be solvable, so we must force  $z$  to be 0, which is only possible if  $-\frac{1}{2}b_1 + b_2 - \frac{5}{4}b_3 \neq 0 \Rightarrow -2b_1 + 4b_2 - 5b_3 \neq 0$ .

### 10.2 The Algebraic Certificate

The vector  $z$  serves as a "certificate" that  $Ax = b$  is impossible. If both  $x$  and  $z$  existed, we would reach the following contradiction:

$$0 = 0^T x = (z^T A)x = z^T (Ax) = z^T b = 1$$

### 10.3 Characterizing Solvability

- **Row Independence:** If the rows of  $A$  are linearly independent, then  $A^T z = 0$  only has the trivial solution  $z = 0$ . Since  $b^T 0 = 0 \neq 1$ , a certificate  $z$  can never exist. Therefore,  $Ax = b$  always has a solution for every  $b$ .
- **Linear Independence:** A vector  $b$  is linearly independent from the columns of  $A$  if and only if  $Ax = b$  has no solution, which can be verified by finding the certificate  $z$ .

To find  $z$ , use Gaussian elimination (RREF) on the augmented matrix:

$$\begin{bmatrix} A^T \\ b^T \end{bmatrix} z = \begin{bmatrix} 0 \\ 1 \end{bmatrix}.$$

### 10.4 The Set of All Solutions (Theorem 6.2.2)

If the system is solvable, the set of all solutions is a shifted copy of the nullspace:

$$\{x \in \mathbb{R}^n \mid Ax = b\} = x_r + N(A)$$

where  $x_r$  is the unique vector in the row space  $R(A) = C(A^T)$  such that  $Ax_r = b$ . This uniqueness is guaranteed because  $A$  acts injectively on its row space (Lemma 6.2.1).

Every solution  $x$  is a mix of two orthogonal parts:

$$x = \underbrace{x_r}_{\text{Row Space (unique)}} + \underbrace{x_n}_{\text{Nullspace (any)}}$$

- (i) **The "Pure" Solution ( $x_r$ ):** There is exactly one solution living entirely in the Row Space (the "Active Zone" of  $A$ ). This is the solution with the shortest length because it contains no "waste" (Lemma 6.4.5).
- (ii) **The "Invisible" Noise ( $x_n$ ):** You can add any vector  $x_n$  from the Nullspace to  $x_r$  without changing the result. Why? Because the matrix is blind to it:

$$A(x_r + x_n) = Ax_r + Ax_n = b + 0 = b$$

### 11 Determinant (Def. 7.2.3)

Let  $A \in \mathbb{R}^{n \times n}$ , the determinant  $\det(A)$  is defined as

$$\det(A) = \sum_{\sigma \in \Pi_n} \text{sgn}(\sigma) \prod_{i=1}^n A_{i,\sigma(i)},$$

where  $\Pi_n$  is the set of all permutations of  $n$  elements. Moreover,

$$\det(I) = 1 \quad (\text{Prop. 7.2.4})$$

$$\text{If } A \in \mathbb{R}^{1 \times 1}, \det(A) = A \quad (\text{Def. 7.2.3})$$

$$\det(A^T) = \det(A) \quad (\text{Theo. 7.2.5})$$

$$\text{If } A \text{ is triangular, } \det(A) = \prod_{k=1}^n A_{kk} \quad (\text{Prop. 7.2.4})$$

$$\text{If } A \text{ is orthogonal, } \det(A) = 1 \text{ or } -1 \quad (\text{Prop. 7.2.4})$$

$$A \text{ is invertible if and only if } \det(A) \neq 0 \quad (\text{Theo. 7.2.6})$$

$$\text{If } \det(A) \neq 0, \det(A^{-1}) = \frac{1}{\det(A)} \quad (\text{Theo. 7.2.6})$$

$$\text{Given some } B \in \mathbb{R}^{n \times n}, \det(AB) = \det(A) \cdot \det(B) \quad (\text{Theo. 7.2.6})$$

$$\bullet \det(A + B) \neq \det(A) + \det(B)$$

$$\bullet \text{If any two rows are equal, then } \det(A) = 0.$$

$$\bullet \text{If } A \text{ has a row of zeros, then } \det(A) = 0.$$

$$\bullet \text{If any Eigenvalue of } A \text{ is 0, then } \det(A) = 0.$$

$$\bullet \text{If we swap the rows of } A \rightarrow B \text{ once, then } \det(B) = -\det(A) \quad (\text{Prop. 7.3.6})$$

$$\bullet \text{The determinant is a linear function of each row separately.}$$

$$\bullet \text{If a single row of } A \text{ is multiplied by some scalar } t, \text{ then } \det(A') = t \cdot \det(A).$$

$$\bullet \text{If the whole matrix is multiplied by } t \text{ (i.e. all n rows are multiplied by } t\text{), then } \det(t \cdot A) = t^n \cdot \det(A). \text{ Proof:}$$

$$\det(t \cdot A) = \sum_{\sigma \in \Pi_n} \text{sgn}(\sigma) \prod_{i=1}^n (t \cdot a_{i,\sigma(i)}) = \dots = t^n \sum_{\sigma \in \Pi_n} \text{sgn}(\sigma) \prod_{i=1}^n a_{i,\sigma(i)} = t^n \det(A).$$

$$\bullet \text{If a row of } A \text{ is replaced by the sum of itself and a multiple of another row, the determinant stays unchanged.}$$

$$\bullet \det(Q) \in \{1, -1\}, \text{ because } Q^T Q = I \text{ and } \det(Q^T Q) = \det(Q^T) \det(Q) = \det(I) = \det(Q)^2 = 1, \text{ so } \det(Q) \in \{1, -1\}.$$

## 11.1 Determinant of a $2 \times 2$ Matrix

Let  $A = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$ , then  $\det(A) = ad - bc$ .

## 11.2 Det. through Co-Factors

### 11.2.1 Co-Factors (Def. 7.3.1)

Let  $A \in \mathbb{R}^{n \times n}$ , for each  $1 \leq i, j \leq n$ , let  $\mathcal{A}_{ij}$  denote the matrix obtained by removing the  $i$ -th row and  $j$ -th column from  $A$ . The co-factors or  $A$  are  $C_{ij} = (-1)^{i+j} \det(\mathcal{A}_{ij})$ .

### 11.2.2 Determinant (Prop. 7.3.2)

We can then rewrite the determinant of  $A$  as

$$\det(A) = \sum_{j=1}^n A_{ij} C_{ij}, \quad \text{for some } 1 \leq i \leq n$$

As in, make a  $+ - + \dots$  grid, pick a row or column and calculate  $\pm A_{ij} \det(\dots)$  for that whole row or column recursively.

## 11.3 Cramer's Rule (Prop. 7.3.5)

Let  $A \in \mathbb{R}^{n \times n}$ , such that  $\det(A) \neq 0$  and  $b \in \mathbb{R}^n$ . Then the solution  $x \in \mathbb{R}^n$  for  $Ax = b$  is given by

$$x_j = \frac{\det(\mathcal{B}_j)}{\det(A)},$$

where  $\mathcal{B}_j$  is the matrix obtained by replacing the  $j$ -th column of  $A$  with  $b$ .

## 11.4 Linearity of the Determinant (Prop. 7.3.7)

The determinant is linear in each row or each column, i.e.,

$$\left| \begin{array}{c} -\alpha_0 a_0^T + \alpha_1 a_1^T \\ -a_2^T \\ \vdots \\ -a_n^T \end{array} \right| = \alpha_0 \left| \begin{array}{c} -a_0^T \\ -a_2^T \\ \vdots \\ -a_n^T \end{array} \right| + \alpha_1 \left| \begin{array}{c} -a_1^T \\ -a_2^T \\ \vdots \\ -a_n^T \end{array} \right|.$$

## 11.5 Example

Let  $v_1, v_2, u_1, u_2 \in \mathbb{R}^n$  and  $M \in \mathbb{R}^{(n-2) \times n}$  be arbitrary and consider the four  $n \times n$  matrices

$$A = \begin{bmatrix} -v_1^T \\ -u_1^T \\ M \end{bmatrix}, B = \begin{bmatrix} -v_2^T \\ -u_2^T \\ M \end{bmatrix},$$

$$C = \begin{bmatrix} -v_2^T \\ -u_1^T \\ M \end{bmatrix}, D = \begin{bmatrix} -v_2^T \\ -u_2^T \\ M \end{bmatrix}$$

as well as the following  $n \times n$  matrix

$$E = \begin{bmatrix} -(v_1 - v_2)^T \\ -(u_1 - u_2)^T \\ M \end{bmatrix}.$$

Find a formula for  $\det(E)$  in terms of  $\det(A)$ ,  $\det(B)$ ,  $\det(C)$  and  $\det(D)$ .

Use Prop. 7.3.7 to get

$$\begin{aligned} \det(A) - \det(B) &= \det \begin{bmatrix} -v_1^T \\ -u_1^T \\ M \end{bmatrix} - \det \begin{bmatrix} -v_2^T \\ -u_2^T \\ M \end{bmatrix} \\ &= \det \begin{bmatrix} -v_1^T \\ -(u_1 - u_2)^T \\ M \end{bmatrix} \end{aligned}$$

and

$$\begin{aligned} \det(C) - \det(D) &= \det \begin{bmatrix} -v_2^T \\ -u_1^T \\ M \end{bmatrix} - \det \begin{bmatrix} -v_2^T \\ -u_2^T \\ M \end{bmatrix} \\ &= \det \begin{bmatrix} -v_2^T \\ -(u_1 - u_2)^T \\ M \end{bmatrix} \end{aligned}$$

together this gives us

$$\begin{aligned} \det \begin{bmatrix} -v_1^T \\ -(u_1 - u_2)^T \\ M \end{bmatrix} - \det \begin{bmatrix} -v_2^T \\ -(u_1 - u_2)^T \\ M \end{bmatrix} \\ = \det \begin{bmatrix} -(v_1 - v_2)^T \\ -(u_1 - u_2)^T \\ M \end{bmatrix}. \end{aligned}$$

Hence,  $\det(E) = \det(A) - \det(B) - (\det(C) - \det(D))$ .

## 12 Eigenvalues/vectors (Def. 8.2.1)

Let  $A \in \mathbb{R}^{n \times n}$ ,  $\lambda \in \mathbb{C}$  is an eigenvalue of  $A$  and  $v \in \mathbb{C}^n \setminus \{0\}$  is the associated eigenvector of  $A$ , if

$$Av = \lambda v.$$

To calculate eigenvalue/vector pairs, we use Lemma 8.2.3:

- (i)  $\det(A - \lambda I) = 0 \iff \lambda$  is an eigenvalue of  $A$ ,
- (ii)  $v$  is an eigenvector of  $A$  (associated with  $\lambda$ )  $\iff v \in N(A - \lambda I)$  and  $v \neq 0$ .

Every matrix  $A \in \mathbb{R}^{n \times n}$  has an eigenvalue (Theo. 8.2.5).

## 12.1 Eigenvector Recurrence in "Closed Form"

Consider the sequence of numbers given by  $a_0 = 1$ ,  $a_1 = 1$  and  $a_n = -a_{n-1} + 6a_{n-2}$  for  $n \geq 2$ . Find  $\alpha, \beta \in \mathbb{R}$  such that  $a_n = \frac{4}{5}\alpha^n + \frac{1}{5}\beta^n$  for all  $n \in \mathbb{N}_0$ . Prove your answer.

- (i) Define sequence algebraically: Let  $v_n = \begin{bmatrix} a_{n+1} \\ a_n \end{bmatrix}$ . We translate the recurrence  $a_n = -a_{n-1} + 6a_{n-2}$  into matrix form.

$$\underbrace{\begin{bmatrix} a_n \\ a_{n-1} \end{bmatrix}}_v = \underbrace{\begin{bmatrix} -1 & 6 \\ 1 & 0 \end{bmatrix}}_A \underbrace{\begin{bmatrix} a_{n-1} \\ a_{n-2} \end{bmatrix}}_v$$

Note: Since  $v_0 = \begin{bmatrix} a_1 \\ a_0 \end{bmatrix}$  has  $a_0$  at the bottom, our target  $a_n$  (which we'll need later) will always correspond to the **bottom component** of  $v_n$ . This is more clear if we shift the above stated matrix equation:

$$\underbrace{\begin{bmatrix} a_{n+1} \\ a_n \end{bmatrix}}_v = \underbrace{\begin{bmatrix} -1 & 6 \\ 1 & 0 \end{bmatrix}}_A \underbrace{\begin{bmatrix} a_n \\ a_{n-1} \end{bmatrix}}_v$$

- (iii) Find the corresponding eigenvectors  $v_i \in N(A - \lambda_i I)$ :

$$(A - \lambda_i I)v_i = 0$$

$$\begin{bmatrix} -3 & 6 \\ 1 & -2 \end{bmatrix} \begin{bmatrix} (v_1)_1 \\ (v_1)_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \implies v_1 = \begin{bmatrix} 2 \\ 1 \end{bmatrix},$$

$$\begin{bmatrix} 2 & 6 \\ 1 & 3 \end{bmatrix} \begin{bmatrix} (v_2)_1 \\ (v_2)_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \implies v_2 = \begin{bmatrix} -3 \\ 1 \end{bmatrix},$$

- (iv) Express  $v_0$  as a linear combination  $c_1 v_1 + c_2 v_2$ : We solve the system for the initial vector  $v_0 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$ :

$$c_1 \begin{bmatrix} 2 \\ 1 \end{bmatrix} + c_2 \begin{bmatrix} -3 \\ 1 \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \implies \begin{cases} 2c_1 - 3c_2 = 1 \\ c_1 + c_2 = 1 \end{cases}$$

From the second equation,  $c_1 = 1 - c_2$ . Substituting into the first:

$$2(1 - c_2) - 3c_2 = 1$$

$$2 - 5c_2 = 1 \implies 5c_2 = 1 \implies c_2 = \frac{1}{5}$$

Then,  $c_1 = 1 - \frac{1}{5} = \frac{4}{5}$ . Thus:

$$\begin{bmatrix} a_1 \\ a_0 \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \frac{4}{5}v_1 + \frac{1}{5}v_2$$

(v) Rewrite  $v_n = \begin{bmatrix} a_{n+1} \\ a_n \end{bmatrix} = A^n v_0$  as

$$v_n = A^n \left( \frac{4}{5}v_1 + \frac{1}{5}v_2 \right) = \frac{4}{5}A^n v_1 + \frac{1}{5}A^n v_2$$

$$= \frac{4}{5}\lambda_1^n v_1 + \frac{1}{5}\lambda_2^n v_2 = \frac{4}{5}2^n \begin{bmatrix} 2 \\ 1 \end{bmatrix} + \frac{1}{5}(-3)^n \begin{bmatrix} -3 \\ 1 \end{bmatrix}.$$

(vi) Consider second component:  $a_n = \frac{4}{5} \cdot 2^n \cdot 1 + \frac{1}{5} \cdot (-3)^n \cdot 1$ .

## 12.2 Reverse Diagonalization Example

Construct a square matrix  $B$  with eigenvalues 0, 1, 2, such that  $B$  is not a diagonal matrix.

Let  $A$  be the diagonal matrix with 0, 1, 2 on its diagonals and let

$$V = \begin{bmatrix} 1 & & & \\ e_1 + e_2 & e_1 - e_2 & & e_3 \\ & & 1 & \\ & & & 1 \end{bmatrix}, \text{ then } B = VAV^{-1}. \text{ Ensure } \det(V) \neq 0.$$

## 12.3 Quadratic Formula (for finding $\lambda$ )

To find zeros of  $ax^2 + bx + c = 0$  are given by

$$x = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}.$$

## 12.4 Special Eigenvalues

- (i) If  $\lambda$  and  $v$  are an eigenvalue-eigenvector pair of  $A$ , then  $\lambda^k$  and  $v$  are one for  $A^k$ . Induction Proof:  $A^k v = A(A^{k-1}v) = A(\lambda^{k-1}v) = \lambda^{k-1}(Av) = \lambda^k v$  (Prop. 8.3.1).
- (ii) Let  $A$  be invertible, if  $\lambda$  and  $v$  are an eigenvalue-eigenvector pair of  $A$ , then  $\frac{1}{\lambda}$  and  $v$  are an eigenvalue-eigenvector pair of  $A^{-1}$ . Proof:  $Av = \lambda v \iff v = A^{-1}(\lambda v) \iff \lambda A^{-1}v = v \iff A^{-1}v = \frac{1}{\lambda}v$  (works since  $\lambda \neq 0$ ) (Prop. 8.3.1).
- (iii) Let  $A \in \mathbb{R}^{n \times n}$ , the eigenvalues of  $A$  are the same ones as of  $A^T$ . Proof:  $\det(A - zI) = \det((A - zI)^T) = \det(A^T - zI)$  (Lemma 8.3.5).
- (iv) Let  $Q \in \mathbb{R}^{n \times n}$  be an orthogonal matrix, if  $\lambda$  is an eigenvalue of  $Q$ , then  $|\lambda| = 1$ . Proof:  $\|v\|^2 = \|Qv\|^2 = \|\lambda v\|^2 = |\lambda| \cdot \|v\|^2$  (Prop. 8.2.7).
- (v) Let  $A \in \mathbb{R}^{n \times n}$ , if  $(\lambda, v)$  is an eigenvalue-eigenvector pair of  $A$ , then  $(\bar{\lambda}, \bar{v})$  is an eigenvalue-eigenvector pair of  $A$  too. Thus, if  $\lambda \in \mathbb{C}$  is an eigenvalue of  $A$ , then  $\bar{\lambda}$  is also an eigenvalue of  $A$  (Lemma 8.2.8). Proof: See "Eigenvalues of Sym. Matrices (Cor. 9.2.2)" in the middle of the next page.
- (vi) Let  $P \in \mathbb{R}^{n \times n}$  be a projection matrix, then  $P$  has two distinct eigenvalues, 0 and 1 (every single one of the  $n$  eigenvalues is either 0 or 1) and a complete set of eigenvectors (Prop. 9.1.6).
- (vii) Let  $D \in \mathbb{R}^{n \times n}$  be a diagonal matrix, then its eigenvalues are its diagonal entries and the standard basis  $(e_1, e_2, \dots, e_n)$  is a complete set of eigenvectors of  $D$  (Example 9.1.4).

(viii) Let  $T \in \mathbb{R}^{n \times n}$  be a triangular matrix, then its eigenvalues are its diagonal entries, however,  $T$  might not have a complete set of eigenvectors (Example 9.1.5).

(ix)  $A + (k \cdot I) \iff$  adding  $k$  to all eigenvalues of  $A$ . Eigenvectors stay the same. Proof:  $Av = \lambda v \implies (A + kI)v = (Av) + kIv = \lambda v + kv = (\lambda + k)v$

(x) If matrix  $A$  has an eigenvalue  $\lambda$ , then the matrix  $cA$  (where  $c$  is a scalar number) has the eigenvalue  $c\lambda$ . Proof:  $(cA)v = c(Av) = c(\lambda v) = (c\lambda)v$ .

(xi) For  $A \in \mathbb{R}^{n \times 2}$ ,  $\lambda_1, \lambda_2 = m \pm \sqrt{m^2 - p}$ ,  $m = \frac{a+d}{2}$ ,  $p = \det(A)$

## 12.5 Important Words Of Caution

- (i) Even though the eigenvalues of  $A$  and  $A^T$  are the same, the eigenvectors are not!
- (ii) The eigenvalues of  $A + B$  are not the sum of the eigenvalues of  $A$  and the eigenvalues of  $B$ !
- (iii) The eigenvalues of  $AB$  are not the product of the eigenvalues of  $A$  and the eigenvalues of  $B$ !
- (iv) Gaussian Elimination does not preserve eigenvalues and eigenvectors!

## 12.6 Distinct Eigenvalues (Theo. 8.3.3)

Let  $A \in \mathbb{R}^{n \times n}$  with  $n$  distinct, real eigenvalues, then there is a basis of  $\mathbb{R}^n$  made up of eigenvectors of  $A$ . We also say that  $A$  has a complete set of eigenvectors (Def. 9.1.3).

## 12.7 Complex Numbers

Complex numbers are of the form  $z = (a + ib) \in \mathbb{C}$  with  $a, b \in \mathbb{R}$  and  $i^2 = -1$ . The following operations are defined:

- (i)  $(a + ib) + (x + iy) = (a + x) + i(b + y)$ .
- (ii)  $(a + ib) \cdot (x + iy) = (ax - by) + i(ay + bx)$ .
- (iii)  $(a + ib) \cdot (a - ib) = a^2 + b^2$ .
- (iv)  $\frac{a+ib}{x+iy} = \frac{(a+ib)(x-iy)}{(x^2+y^2)} = \left( \frac{ax+by}{x^2+y^2} \right) + i \left( \frac{bx-ay}{x^2+y^2} \right)$ .
- (v)  $|z| = \sqrt{a^2 + b^2}$  (modulus).
- (vi)  $a + ib = a - ib$ .
- (vii)  $|z|^2 = z\bar{z}$ .
- (viii)  $\overline{z_1 + z_2} = \overline{z_1} + \overline{z_2}$ .
- (ix)  $\frac{1}{z} = \frac{\bar{z}}{|z|^2}$ .

A complex number  $z = (a + ib) \in \mathbb{C}$  can be written as  $z = re^{i\theta}$  where  $r = \sqrt{a^2 + b^2}$  and  $\theta = \tan^{-1}(\frac{b}{a})$ .

## 12.7.1 Complex Matrices/Vectors

Let  $A \in \mathbb{C}^{m \times n}$ , the conjugate transpose  $A^* = \bar{A}^T$ .

Given  $v \in \mathbb{C}^n$ , we have

$$\|v\|^2 = v^* v = \bar{v}^T v = \sum_{i=1}^n \bar{v}_i v_i = \sum_{i=1}^n |v_i|^2.$$

The dot-product in  $\mathbb{C}^n$  is given by  $\langle v, w \rangle = \bar{w}^* v$ .

## 12.8 Fund. Theorem of Algebra (Cor. 8.1.3)

Any degree  $n \geq 1$  polynomial  $P(z) = \alpha_n z^n + \dots + a_1 z + a_0$  with  $a_n \neq 0$  has  $n$  zeros:  $\lambda_1, \dots, \lambda_n \in \mathbb{C}$  such that

$$P(z) = \alpha_n(z - \lambda_1)(z - \lambda_2) \dots (z - \lambda_n).$$

The number of times  $\lambda \in \mathbb{C}$  appears in this expression is called the *algebraic multiplicity* of the zero (i.e. of the  $P(\lambda) = 0$ ). This guarantees that an  $n \times n$  matrix always has exactly  $n$  eigenvalues (if you count repeats and complex eigenvalues).

## 12.9 Geometric Multiplicity

Let  $A \in \mathbb{R}^{n \times n}$  with eigenval  $\lambda_i$ , we call the dim of  $N(A - \lambda_i I)$  the *geometric multiplicity* of  $\lambda_i$ . Number of lin. indep. eigenvects for  $\lambda_i$ .

## 12.10 Characteristic Polynomial

Let  $A \in \mathbb{R}^{m \times n}$ , the *characteristic polynomial* of  $A$  is

$$P(z) = (-1)^n \det(A - zI) = (z - \lambda_1)(z - \lambda_2)\dots(z - \lambda_n) \\ = z^n + \left( -\sum_{i=1}^n \lambda_i \right) z^{n-1} + \underbrace{\sum_{k=1}^{n-2} b_k z^k}_{-\text{Tr}(A)} + (-1)^n \underbrace{\sum_{i=1}^n \lambda_i}_{(-1)^n \det(A)}$$

## 12.11 Trace and Determinant (Lemma 8.3.6)

Let  $A \in \mathbb{R}^{n \times n}$  and  $\lambda_1, \dots, \lambda_n$  its  $n$  eigenvalues, then

$$\text{Tr}(A) = \sum_{i=1}^n \lambda_i \text{ and } \det(A) = \prod_{i=1}^n \lambda_i.$$

Following (Lemma 8.3.7), for matrices  $A, B$  and  $C \in \mathbb{R}^{n \times n}$ ,

- (i)  $\text{Tr}(AB) = \sum_{i=1}^n \sum_{j=1}^n A_{ij}B_{ji} = \sum_{j=1}^n \sum_{i=1}^n B_{ji}A_{ij} = \text{Tr}(BA)$ .
- (ii)  $\text{Tr}(A(BC)) = \text{Tr}((BC)A) = \text{Tr}((CA)B)$ .

## 12.12 Diagonalization (Theo. 9.1.1)

Let  $A \in \mathbb{R}^{n \times n}$  be a matrix with a complete set of eigenvectors.

Let  $V = \begin{bmatrix} | & | & | \\ v_1 & \dots & v_n \\ | & | & | \end{bmatrix} \in \mathbb{R}^{n \times n}$  be the matrix whose columns are the eigenvectors, and  $\Lambda \in \mathbb{R}^{n \times n}$  the matrix whose diagonal entries are the eigenvalues ( $\Lambda_{ii} = \lambda_i$  for all  $i \in [n]$ ), then

$$A = V\Lambda V^{-1} \implies A^k = V\Lambda^k V^{-1}$$

$$AV = V\Lambda$$

$$[Av_1, Av_2, \dots, Av_n] = [\lambda_1 v_1, \lambda_2 v_2, \dots, \lambda_n v_n]$$

## 12.13 Diagonalizable Matrix (Def. 9.1.2)

A matrix  $A \in \mathbb{R}^{n \times n}$  is said to be *diagonalizable*, if there are  $n$  independent eigenvectors (complete set of eigenvectors), and thus there exists an invertible matrix  $V$ , such that  $V^{-1}AV = \Lambda$ , where  $\Lambda$  is a diagonal matrix. "Can we flatten  $A$  into a diagonal matrix?"

## 12.14 Complete Set of Eigenvectors (Lemma 9.1.11)

A matrix has a complete set of eigenvectors if all its eigenvalues are real and the geometric multiplicities are the same as the algebraic multiplicities, for all of its eigenvalues.

If given a matrix  $A \in \mathbb{R}^{n \times n}$ , we can build a basis of  $\mathbb{R}^n$  with eigenvectors of  $A$  (the eigenvectors are linearly independent), we say that  $A$  has a *complete set of eigenvectors* (Def. 9.1.3).

## 12.15 Similar Matrices (Def. 9.1.7)

Two matrices  $A$  and  $B \in \mathbb{R}^{n \times n}$  are *similar*, if exists an invertible matrix  $S$ , such that  $B = S^{-1}AS$ . (Or  $B = SAS^{-1}$ , doesn't matter).

Similar matrices have the same eigenvalues, Trace and Determinant.

*Proof:*  $Av = \lambda v \iff \lambda S^{-1}v = S^{-1}Av = S^{-1}ASS^{-1}v = B(S^{-1}v)$

Similar matrices are clones of each other. They represent the exact same linear transformation, just viewed from a different coordinate system ( $S$  is a change of basis matrix).

## 12.16 Characteristic Polynomial Example

Assume that  $A, B \in \mathbb{R}^{n \times n}$  are similar, prove that their characteristic polynomials are equal.

As  $A$  and  $B$  are similar, there exists a matrix  $S$  such that  $B = S^{-1}AS$ . Recall that  $\det(S)\det(S^{-1}) = 1$ . Thus,  $\det(A - zI) = \det(S^{-1})\det(A - zI)\det(S) = \det(S^{-1}(A - zI)S) = \det(S^{-1}AS - zS^{-1}IS) = \det(B - zI)$ .

## 12.17 Spectral Theorem (Theo. 9.2.1)

Any symmetric matrix  $A \in \mathbb{R}^{n \times n}$  has  $n$  real eigenvalues and an orthonormal basis consisting of its eigenvectors.

### 12.17.1 Diagonalization for Symmetric Matrices (Cor. 9.2.2)

For any symmetric matrix  $A \in \mathbb{R}^{n \times n}$ , there exists an *orthogonal* matrix  $V \in \mathbb{R}^{n \times n}$  (whose columns are the eigenvectors of  $A$ ) and a diagonal matrix  $\Lambda$  whose entries are the eigenvalues of  $A$ , such that

$$A = V\Lambda V^T \text{ and } V^TV = I.$$

(This is also called the *eigendecomposition*). Normalize  $V$ !

## 12.18 Spectral Construction Example

Find matrix  $A$  with these given *orthonormal* eigenvectors

$$v_1 = \frac{1}{9} \begin{bmatrix} 1 \\ 8 \\ -4 \\ -4 \end{bmatrix}, v_2 = \frac{1}{9} \begin{bmatrix} -4 \\ 4 \\ 7 \\ 4 \end{bmatrix}, v_3 = \frac{1}{9} \begin{bmatrix} 8 \\ 1 \\ 1 \\ 4 \end{bmatrix}$$

and corresponding eigenvalues  $\lambda_1 = 1, \lambda_2 = -1, \lambda_3 = 0$ .

Let  $V$  be the  $3 \times 3$  matrix with  $v_1, v_2, v_3$  as its columns and  $D$  the diagonal matrix with  $\lambda_1, \lambda_2, \lambda_3$  on its diagonal, then  $A = VDV^T$ . Note that for  $V^{-1} = V^T$  to work,  $V$  needs to be normed!

## 12.19 Eigenvalues of Sym. Matrices (Cor. 9.2.4)

The rank of a real symmetric matrix  $A$  is the number of non-zero eigenvalues (counting repetitions).

For general  $n \times n$  (non-symmetric) matrices, the rank is  $n$  minus the dimension of the nullspace, so it is  $n$  minus the geometric multiplicity of  $\lambda = 0$ . Since symmetric matrices always have a complete set of eigenvalues and eigenvectors, the geometric multiplicities are always the same as the algebraic multiplicities (Remark 9.2.5).

Every symmetric matrix has only real eigenvalues (Lemma 9.2.8).

*Proof:*  $\bar{\lambda}\|v\|^2 = \bar{\lambda}v^*v = (\lambda v)^*v = (Av)^*v = v^*A^*v = v^*(\lambda v) = \lambda\|v\|^2 \implies \bar{\lambda} = \lambda$  only holds if  $\lambda \in \mathbb{R}$ .

## 12.20 Rayleigh Quotient (Prop. 9.2.10)

Let  $A \in \mathbb{R}^{n \times n}$  be a symmetric matrix, the *Rayleigh Quotient*, defined for  $x \in \mathbb{R}^n \setminus \{0\}$ , as

$$R(x) = \frac{x^T Ax}{x^T x},$$

attains its max at  $R(v_{\max}) = \lambda_{\max}$  and its min at  $R(v_{\min}) = \lambda_{\min}$ , where  $\lambda_{\max}$  and  $\lambda_{\min}$  are the max and min eigenvalues of  $A$  and  $v_{\max}$  and  $v_{\min}$  their eigenvectors. Useful because it allows to plug in any vector  $x$  and get back a number that's like a *weighted average* of the eigenvalue contained in that vector. Measures "how much" the matrix stretches that specific direction  $x$ .

## 12.21 Positive (Semi)-Definite (Def. 9.2.11)

A symmetric matrix  $A \in \mathbb{R}^{n \times n}$  is said to be *positive semidefinite* (PSD) if all its eigenvalues are  $\geq 0$  and *positive definite* they are  $> 0$ . Moreover, (as per Prop. 9.2.12)  $A$  is

- (i) PSD  $\iff x^T Ax \geq 0$  for all  $x \in \mathbb{R}^n$ ,
- (ii) PD  $\iff x^T Ax > 0$  for all  $x \in \mathbb{R}^n \setminus \{0\}$ .

- Given two matrices  $A$  and  $B$  that are PSD (PD), their sum is also PSD (PD), i.e. they are closed under taking addition.
- A diagonal dominant matrix (diagonal entries are greater than the absolute sum of rest of the row's elements) is always PSD!
- Matrix is PSD/PD  $\implies$  all diagonal entries are  $\geq 0 > 0$  Proof: Choose  $x = e_i$  in equations (i), (ii) to get the diagonal entry  $A_{ii}$  only. (But the other way " $\Leftarrow$ " doesn't hold!)

## 12.22 Gram Matrix (Def. 9.2.13)

Let  $V \in \mathbb{R}^{m \times n}$ , the Gram matrix of  $V$  is the inner product of the columns of  $V$ , i.e.,  $G = V^TV$ .

Sometimes  $VV^T$  is also called a Gram matrix of  $V$  (the inner product of the rows) (Remark 9.2.14).

## 12.23 Gram and Eigenvalues (Prop. 9.2.15)

Let  $A \in \mathbb{R}^{m \times n}$ , the non-zero eigenvalues of  $A^TA$  are the same as the ones of  $AA^T$ . Both matrices are symmetric and PSD.

*Proof:*  $x^T A^T A x = (Ax)^T (Ax) = \|Ax\|^2 \geq 0$ .

## 12.24 Cholesky Decomposition (Prop. 9.2.16)

Every symmetric, PSD matrix  $M$  is a gram matrix of an *upper triangular* matrix  $C$ , i.e.,  $M = C^TC$ .

### 12.24.1 Calculating the Cholesky Decomposition

- (i) Let  $M$  be symmetric and PSD (PSD because we later do  $\sqrt{\lambda}$ ), the eigendecomposition (Cor. 9.2.2) gives us  $M = V\Lambda V^T$
- (ii) We build  $\Lambda^{\frac{1}{2}}$  by taking the square root of each entry of  $\Lambda$ , following,  $M = (V\Lambda^{\frac{1}{2}})(V\Lambda^{\frac{1}{2}})^T$  ( $\sqrt{\text{neg}}$  wouldn't work).
- (iii) We then take the QR decomposition  $(V\Lambda^{\frac{1}{2}})^T = QR$ , following,  $M = (QR)^T(QR) = R^T Q^T QR = R^T R = C^TC$ . We set  $(V\Lambda^{\frac{1}{2}})^T = QR$ , s.t.  $C = R$  is *upper triangular*.

## 13 Singular Value Decomposition (Def. 9.3.1)

Let  $A \in \mathbb{R}^{m \times n}$ . There exists orthogonal matrices  $U \in \mathbb{R}^{m \times m}$  and  $V \in \mathbb{R}^{n \times n}$  such that

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

where  $\Sigma \in \mathbb{R}^{m \times n}$  is a diagonal matrix whose entries  $\Sigma_{ii} = \sigma_i$  are non-negative and ordered in descending order. Moreover,

- (i)  $U^T U = V^T V = I$ .
- (ii)  $\sigma_1 \geq \dots \geq \sigma_{\min\{m,n\}} \geq 0$ .
- (iii) The columns of  $U$  are called the *left singular vectors* and are orthonormal  $\implies U$  has full column rank.
- (iv) The columns of  $V$  are called the *right singular vectors* and are orthonormal  $\implies V$  has full column rank.
- (v) The diagonal entries of  $\Sigma$  are called the *singular values*. The singular values of a matrix  $A$  are the square roots of the eigenvalues of the symmetric matrix  $A^T A$  or  $AA^T$ .

### 13.1 Existence of SVD (Theo. 9.3.3)

Every matrix  $A \in \mathbb{R}^{m \times n}$  has a SVD.

As in, every linear transformation is diagonal when viewed in the bases of the singular vectors.

where  $U_r$  and  $V_r$  contain the first  $r$  left/right singular vectors respectively and  $\Sigma_r$  contains the first  $r$  singular values (which are strictly positive).  $V_r$  full col-rank,  $V_r^T$  full row-rank,  $U_r$  full col-rank.

## 13.3 Calculating the SVD (Section 9.3)

Let  $A \in \mathbb{R}^{m \times n}$  and  $A = U\Sigma V^T$  be its SVD, then

$$AA^T = U(\Sigma^T)U^T \text{ and } A^T A = V(\Sigma^T\Sigma)V^T.$$

In other words, the SVD of  $A$  can be calculated by

- (i) Taking the eigendecomposition of  $AA^T$  or  $A^T A$ .
- (ii)  $U$  = orthogonal eigenvector matrix of  $AA^T$ ,
- (iii)  $V$  = orthogonal eigenvector matrix of  $A^T A$ ,
- (iv) singular values =  $\sqrt{\text{eigenvalues of } AA^T \text{ or } A^T A}$ . Only if  $A$  is real & *symmetric*, singular values of  $A$  =  $|\text{eigenvalues}|$  of  $A$ .
- (v)  $\Sigma$  = descending ordered square roots of eigenvalues of  $AA^T$  or  $A^T A$ , they are equal.  $\sigma_1$  is the largest,  $\sigma_n$  the smallest.
- (vi)  $AA^T, A^T A$  are PSD, thus eigenvalues  $\geq 0 \implies$  sing. values  $\geq 0$ .
- (vii) If  $A$  is invertible, then  $A^{-1} = (U\Sigma V^T)^{-1} = V^T \Sigma^{-1} U^{-1} = V \Sigma^{-1} U^T$  (as  $V^T V = I, U^T U = I$ )

## 13.4 Rank $r$ Matrices (Prop. 9.3.4)

Let  $A \in \mathbb{R}^{m \times n}$  with rank  $r$  and  $\sigma_1, \dots, \sigma_r$  be the non-zero singular values of  $A$ ,  $u_1, \dots, u_r$  the corresponding left singular vectors and  $v_1, \dots, v_r$  the corresponding right singular vectors. Then  $A = \sum_{k=1}^r \sigma_k u_k v_k^T$ .

## 14 Vector and Matrix Norms

### 14.1 Vector Norms

For  $1 \leq p \leq \infty$ , the  $l_p$  norm is given by

$$\|x\|_p = \left( \sum_{i=1}^n |x_i|^p \right)^{\frac{1}{p}},$$

for  $p < \infty$ , and  $\|x\|_\infty = \max_i |x_i|$ .

In particular let  $\|x\|_p$  for  $p = 1$  denote the *Manhattan distance*.

### 14.1.1 Relations (Prop. 10.0.1)

For all  $x \in \mathbb{R}^n$ ,  $\|x\|_2 \leq \|x\|_1 \leq \sqrt{n}\|x\|_2$

### 14.2 Matrix Norms (Def. 10.0.2)

Let  $A \in \mathbb{R}^{m \times n}$  then consider

$$\text{Frobenius norm} \quad \|A\|_F := \sqrt{\sum_{i=1}^m \sum_{j=1}^n A_{ij}^2}$$

$$\text{operator/spectral norm} \quad \|A\|_{op} := \max_{x \in \mathbb{R}^n \text{ s.t. } \|x\|=1} \|Ax\|$$

### 14.2.1 Properties with Singular Values (Prop. 10.0.3)

Given singular values  $\sigma_1 \geq \dots \geq \sigma_{\min\{m,n\}}$  of  $A$ :

$$(i) \|A\|_F^2 = \text{Tr}(A^T A) = \sum_i \sigma_i^2$$

$$(ii) \|A\|_{op} = \sigma_1$$

$$(iii) \|A\|_{op} \leq \|A\|_F \leq \sqrt{\min\{m, n\}} \|A\|_{op}$$

## 15 Surjectivity, Injectivity, Bijectivity

