

5 Vectors and Spans

Definition 1 (Row vector). For $n \in \mathbb{N}$ and $x_1, x_2, \dots, x_n \in \mathbb{R}$ an n -tuple or row vector is defined by (x_1, x_2, \dots, x_n) . Two row vectors (x_1, x_2, \dots, x_n) and (y_1, y_2, \dots, y_n) are equal if and only if $x_i = y_i$ for $i = 1, 2, \dots, n$.

Definition 2 ((Column) vector). For $n \in \mathbb{N}$ and $x_1, x_2, \dots, x_n \in \mathbb{R}$ a (column) vector is defined by

$$\begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} = (x_1, x_2, \dots, x_n)^T.$$

We denote $(x_1, x_2, \dots, x_n)^T$ by \mathbf{x} and $\underbrace{(0, 0, \dots, 0)^T}_{n \text{ times}}$ by $\mathbf{0}$. The last vector is also called the origin.

Definition 3 (EUCLIDEAN space). The n -dimensional EUCLIDEAN space \mathbb{R}^n is

$$\mathbb{R}^n = \underbrace{\mathbb{R} \times \mathbb{R} \times \dots \times \mathbb{R}}_{n \text{ times}} = \left\{ (x_1, x_2, \dots, x_n)^T : x_1, x_2, \dots, x_n \in \mathbb{R} \right\}.$$

Definition 4 (Vector addition & scalar multiplication). Let $\mathbf{x} = (x_1, x_2, \dots, x_n)^T, \mathbf{y} = (y_1, y_2, \dots, y_n)^T \in \mathbb{R}^n$. Then

- $\mathbf{x} + \mathbf{y} = (x_1 + y_1, x_2 + y_2, \dots, x_n + y_n)^T$ (vector addition),
- for $s \in \mathbb{R}$: $s \cdot \mathbf{x} = (sx_1, sx_2, \dots, sx_n)^T$ (scalar multiplication). The dot \cdot is usually omitted.

Theorem 5 (vector-space axioms). The n -dimensional EUCLIDEAN space \mathbb{R}^n together with vector addition and scalar multiplication fulfills the so-called vector-space axioms. Let $x, y, z \in \mathbb{R}^n$ and $s, t \in \mathbb{R}$.

V1: $x + y = y + x$.

V2: $(x + y) + z = x + (y + z)$.

$$V3: \mathbf{0} = x - x = 0 \cdot x.$$

$$V4: s(x + y) = sx + sy.$$

$$V5: (s + t) \cdot x = sx + tx.$$

$$V6: x = 1x = \mathbf{0} + x.$$

Definition 6 (scalar product). The scalar product of two column vectors $\mathbf{x} = (x_1, x_2, \dots, x_n)^T$ and $\mathbf{y} = (y_1, y_2, \dots, y_n)^T$ is defined as

$$\mathbf{x} \cdot \mathbf{y} = \sum_{k=1}^n x_k y_k = x_1 y_1 + x_2 y_2 + \dots + x_n y_n.$$

The dot \cdot is usually omitted.

Definition 7 (Length of a vector). The length of a vector $\mathbf{x} \in \mathbb{R}^n$ is

$$|\mathbf{x}| = \sqrt{x_1^2 + x_2^2 + \dots + x_n^2}.$$

Definition 8 (Distance of points). The distance between $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$ is

$$\text{dist}(\mathbf{x}, \mathbf{y}) = |\mathbf{x} - \mathbf{y}|.$$

Theorem 9 (Properties of scalar product & length). If $\mathbf{x}, \mathbf{y}, \mathbf{z} \in \mathbb{R}^n$ and $s \in \mathbb{R}$, then

$$(i) (s\mathbf{x})\mathbf{y} = s(\mathbf{x}\mathbf{y}),$$

$$(ii) \mathbf{x}\mathbf{y} = \mathbf{y}\mathbf{x},$$

$$(iii) (\mathbf{x} + \mathbf{y})\mathbf{z} = \mathbf{x}\mathbf{z} + \mathbf{y}\mathbf{z},$$

$$(iv) |\mathbf{x}| \geq 0 \text{ and } |\mathbf{x}| = 0 \text{ if and only if } \mathbf{x} = \mathbf{0},$$

$$(v) |s\mathbf{x}| = |s||\mathbf{x}|,$$

$$(vi) |\mathbf{x}\mathbf{y}| \leq |\mathbf{x}||\mathbf{y}|,$$

$$(vii) ||\mathbf{x}| - |\mathbf{y}|| \leq |\mathbf{x} + \mathbf{y}| \leq |\mathbf{x}| + |\mathbf{y}|.$$

Definition 10 (Orthogonality). Two vectors $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$ are orthogonal or perpendicular, denoted by $\mathbf{x} \perp \mathbf{y}$, if $\mathbf{x}\mathbf{y} = 0$.

Definition 11 (Linear combination). Let $\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_m \in \mathbb{R}^n$ and $\lambda_1, \lambda_2, \dots, \lambda_m \in \mathbb{R}$. Then

$$\mathbf{w} = \lambda_1 \mathbf{v}_1 + \lambda_2 \mathbf{v}_2 + \dots + \lambda_m \mathbf{v}_m$$

is called a linear combination of $\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_m$.

Definition 12 (Span). Let $\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_m \in \mathbb{R}^n$. The span of $\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_m$, denoted by $\text{span}(\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_m)$, is the set of all linear combinations of $\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_m$, i.e.

$$\text{span}(\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_m) = \{ \mathbf{w} = \lambda_1 \mathbf{v}_1 + \lambda_2 \mathbf{v}_2 + \dots + \lambda_m \mathbf{v}_m \in \mathbb{R}^n : \lambda_1, \lambda_2, \dots, \lambda_m \in \mathbb{R} \}.$$

Theorem 13. Let $\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_m \in \mathbb{R}^n$. Then the set $U = \text{span}(\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_m)$ is a subspace of \mathbb{R}^n , i.e. it fulfills

S1: $\mathbf{0} \in U$.

S2: If $x, y \in U$, then $x + y \in U$.

S3: If $s \in \mathbb{R}$ and $x \in U$, then $sx \in U$.

Definition 14 (Linear (in-)dependence). A set $\{ \mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_m \} \subset \mathbb{R}^n$ of vectors is called linearly independent if

$$\lambda_1 \mathbf{v}_1 + \lambda_2 \mathbf{v}_2 + \dots + \lambda_m \mathbf{v}_m = \mathbf{0} \implies \lambda_1 = \lambda_2 = \dots = \lambda_m = 0.$$

I.e. the only possibility to represent $\mathbf{0} \in \mathbb{R}^n$ as a linear combination of $\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_m$ is choosing all coefficients $\lambda_1, \lambda_2, \dots, \lambda_m$ equal to 0.

Definition 15 (Basis, Dimension). A linearly independent set $\{ \mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_m \} \subset \mathbb{R}^n$ with $\text{span}(\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_m) = U$ resp. \mathbb{R}^n is called basis of U resp. \mathbb{R}^n . The number m is called the dimension of U . (If $\text{span}(\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_m) = \mathbb{R}^n$, then $m = n$.)

Theorem 16. Let $\{ \mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_m \} \subset \mathbb{R}^n$ and $U \subseteq \mathbb{R}^n$ a subspace. The following assertions are equivalent:

- $\{ \mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_m \}$ is a minimal spanning set of U .
- $\{ \mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_m \}$ is a maximal linearly independent set of vectors of U .
- Every $\mathbf{u} \in U$ has a unique expression as linear combination of $\{ \mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_m \}$.
- $\{ \mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_m \}$ is a basis of U .

Definition 17. Let a $(m \times n)$ matrix A be given. Then the set of solutions of the homogenous system $S(A, \mathbf{0})$ is called the kernel of A .

Theorem 18 (Structure of the solution set of a homogenous system). The set of solutions of a homogenous system of linear equations is a span of linearly independent vectors.

Theorem 19 (Structure of the solution set of an inhomogenous system). Let \mathbf{x}_{sp} be a (special) solution of an inhomogenous system of linear equations and let S_{hom} denote the set of all solutions of the corresponding homogenous system. Then the set of solutions of the inhomogenous system is given by

$$S = \{ \mathbf{x} = \mathbf{x}_{sp} + \mathbf{x}_{hom} : \mathbf{x}_{hom} \in S_{hom} \},$$

i.e. one gets all solutions of the inhomogenous system by adding all solutions of the homogenous system to one solution of the inhomogenous system.