MATH 304 Linear Algebra

Lecture 17: Euclidean structure in \mathbb{R}^n (continued). Orthogonal complement. Orthogonal projection.

Vectors: geometric approach



- A vector is represented by a directed segment.
- Directed segment is drawn as an arrow.
- Different arrows represent the same vector if they are of the same length and direction.

Notation: $\overrightarrow{AB} \ (= \overrightarrow{A'B'})$.

Linear structure: vector addition

Given vectors **a** and **b**, their sum $\mathbf{a} + \mathbf{b}$ is defined by the rule $\overrightarrow{AB} + \overrightarrow{BC} = \overrightarrow{AC}$.

That is, choose points A, B, C so that $\overrightarrow{AB} = \mathbf{a}$ and $\overrightarrow{BC} = \mathbf{b}$. Then $\mathbf{a} + \mathbf{b} = \overrightarrow{AC}$.



Linear structure: scalar multiplication

Let **v** be a vector and $r \in \mathbb{R}$. By definition, $r\mathbf{v}$ is a vector whose magnitude is |r| times the magnitude of **v**. The direction of $r\mathbf{v}$ coincides with that of **v** if r > 0. If r < 0 then the directions of $r\mathbf{v}$ and **v** are opposite.



Beyond linearity: Euclidean structure

Euclidean structure includes:

- length of a vector: $|\mathbf{x}|$,
- angle between vectors: θ ,
- dot product: $\mathbf{x} \cdot \mathbf{y} = |\mathbf{x}| |\mathbf{y}| \cos \theta$.



Vectors: algebraic approach

An *n*-dimensional coordinate vector is an element of \mathbb{R}^n , i.e., an ordered *n*-tuple (x_1, x_2, \ldots, x_n) of real numbers.

Let $\mathbf{a} = (a_1, a_2, \dots, a_n)$ and $\mathbf{b} = (b_1, b_2, \dots, b_n)$ be vectors, and $r \in \mathbb{R}$ be a scalar. Then, by definition,

$$\mathbf{a} + \mathbf{b} = (a_1 + b_1, a_2 + b_2, \dots, a_n + b_n),$$

$$r\mathbf{a} = (ra_1, ra_2, \dots, ra_n),$$

$$\mathbf{0} = (0, 0, \dots, 0),$$

$$-\mathbf{b} = (-b_1, -b_2, \dots, -b_n),$$

$$\mathbf{a} - \mathbf{b} = \mathbf{a} + (-\mathbf{b}) = (a_1 - b_1, a_2 - b_2, \dots, a_n - b_n),$$

Cartesian coordinates: geometric meets algebraic



Once we specify an origin O, each point A is associated a position vector \overrightarrow{OA} . Conversely, every vector has a unique representative with tail at O. Cartesian coordinates allow us to identify a line, a plane, and space with \mathbb{R} , \mathbb{R}^2 , and \mathbb{R}^3 , respectively.

Length and distance

Definition. The **length** of a vector $\mathbf{v} = (v_1, v_2, \dots, v_n) \in \mathbb{R}^n$ is $\|\mathbf{v}\| = \sqrt{v_1^2 + v_2^2 + \dots + v_n^2}.$

The **distance** between vectors/points **x** and **y** is $\|\mathbf{y} - \mathbf{x}\|$.

Properties of length: $\|\mathbf{x}\| \ge 0$, $\|\mathbf{x}\| = 0$ only if $\mathbf{x} = \mathbf{0}$ (positivity) $\|r\mathbf{x}\| = |r| \|\mathbf{x}\|$ (homogeneity) $\|\mathbf{x} + \mathbf{y}\| \le \|\mathbf{x}\| + \|\mathbf{y}\|$ (triangle inequality)

Scalar product

Definition. The scalar product of vectors $\mathbf{x} = (x_1, x_2, \dots, x_n)$ and $\mathbf{y} = (y_1, y_2, \dots, y_n)$ is $\mathbf{x} \cdot \mathbf{y} = x_1y_1 + x_2y_2 + \dots + x_ny_n$.

Properties of scalar product:

 $\begin{array}{ll} \mathbf{x} \cdot \mathbf{x} \geq \mathbf{0}, & \mathbf{x} \cdot \mathbf{x} = \mathbf{0} \quad \text{only if } \mathbf{x} = \mathbf{0} & (\text{positivity}) \\ \mathbf{x} \cdot \mathbf{y} = \mathbf{y} \cdot \mathbf{x} & (\text{symmetry}) \\ (\mathbf{x} + \mathbf{y}) \cdot \mathbf{z} = \mathbf{x} \cdot \mathbf{z} + \mathbf{y} \cdot \mathbf{z} & (\text{distributive law}) \\ (r\mathbf{x}) \cdot \mathbf{y} = r(\mathbf{x} \cdot \mathbf{y}) & (\text{homogeneity}) \end{array}$

In particular, $\mathbf{x} \cdot \mathbf{y}$ is a **bilinear** function (i.e., it is both a linear function of \mathbf{x} and a linear function of \mathbf{y}).

Relations between lengths and scalar products:

$$\begin{aligned} \|\mathbf{x}\| &= \sqrt{\mathbf{x} \cdot \mathbf{x}} \\ |\mathbf{x} \cdot \mathbf{y}| &\leq \|\mathbf{x}\| \|\mathbf{y}\| \qquad \text{(Cauchy-Schwarz inequality)} \\ \|\mathbf{x} - \mathbf{y}\|^2 &= \|\mathbf{x}\|^2 + \|\mathbf{y}\|^2 - 2 \, \mathbf{x} \cdot \mathbf{y} \end{aligned}$$

By the Cauchy-Schwarz inequality, for any nonzero vectors $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$ we have

$$\cos \theta = \frac{\mathbf{x} \cdot \mathbf{y}}{\|\mathbf{x}\| \|\mathbf{y}\|}$$
 for some $0 \le \theta \le \pi$.

 θ is called the **angle** between the vectors **x** and **y**. The vectors **x** and **y** are said to be **orthogonal** (denoted **x** \perp **y**) if **x** \cdot **y** = 0 (i.e., if $\theta = 90^{\circ}$). **Problem.** Find the angle θ between vectors $\mathbf{x} = (2, -1)$ and $\mathbf{y} = (3, 1)$.

$$\mathbf{x} \cdot \mathbf{y} = 5, \quad \|\mathbf{x}\| = \sqrt{5}, \quad \|\mathbf{y}\| = \sqrt{10}.$$
$$\cos \theta = \frac{\mathbf{x} \cdot \mathbf{y}}{\|\mathbf{x}\| \|\mathbf{y}\|} = \frac{5}{\sqrt{5}\sqrt{10}} = \frac{1}{\sqrt{2}} \implies \theta = 45^{\circ}$$

Problem. Find the angle ϕ between vectors $\mathbf{v} = (-2, 1, 3)$ and $\mathbf{w} = (4, 5, 1)$. $\mathbf{v} \cdot \mathbf{w} = 0 \implies \mathbf{v} \perp \mathbf{w} \implies \phi = 90^{\circ}$

Orthogonality

Definition 1. Vectors $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$ are said to be **orthogonal** (denoted $\mathbf{x} \perp \mathbf{y}$) if $\mathbf{x} \cdot \mathbf{y} = 0$.

Definition 2. A vector $\mathbf{x} \in \mathbb{R}^n$ is said to be orthogonal to a nonempty set $Y \subset \mathbb{R}^n$ (denoted $\mathbf{x} \perp Y$) if $\mathbf{x} \cdot \mathbf{y} = 0$ for any $\mathbf{y} \in Y$.

Definition 3. Nonempty sets $X, Y \subset \mathbb{R}^n$ are said to be **orthogonal** (denoted $X \perp Y$) if $\mathbf{x} \cdot \mathbf{y} = 0$ for any $\mathbf{x} \in X$ and $\mathbf{y} \in Y$. Examples in \mathbb{R}^3 . • The line x = y = 0 is orthogonal to the line y = z = 0. Indeed, if $\mathbf{v} = (0, 0, z)$ and $\mathbf{w} = (x, 0, 0)$ then $\mathbf{v} \cdot \mathbf{w} = 0$.

• The line x = y = 0 is orthogonal to the plane z = 0.

Indeed, if $\mathbf{v} = (0, 0, z)$ and $\mathbf{w} = (x, y, 0)$ then $\mathbf{v} \cdot \mathbf{w} = 0$.

• The line x = y = 0 is not orthogonal to the plane z = 1.

The vector $\mathbf{v} = (0, 0, 1)$ belongs to both the line and the plane, and $\mathbf{v} \cdot \mathbf{v} = 1 \neq 0$.

• The plane z = 0 is not orthogonal to the plane y = 0. The vector $\mathbf{v} = (1, 0, 0)$ belongs to both planes and $\mathbf{v} \cdot \mathbf{v} = 1 \neq 0$. **Proposition 1** If $X, Y \in \mathbb{R}^n$ are orthogonal sets then either they are disjoint or $X \cap Y = \{\mathbf{0}\}$.

 $\textit{Proof:} \quad \mathbf{v} \in X \cap Y \implies \mathbf{v} \perp \mathbf{v} \implies \mathbf{v} \cdot \mathbf{v} = \mathbf{0} \implies \mathbf{v} = \mathbf{0}.$

Proposition 2 Let V be a subspace of \mathbb{R}^n and S be a spanning set for V. Then for any $\mathbf{x} \in \mathbb{R}^n$

$$\mathbf{x} \perp S \implies \mathbf{x} \perp V.$$

Proof: Any $\mathbf{v} \in V$ is represented as $\mathbf{v} = a_1 \mathbf{v}_1 + \cdots + a_k \mathbf{v}_k$, where $\mathbf{v}_i \in S$ and $a_i \in \mathbb{R}$. If $\mathbf{x} \perp S$ then

$$\mathbf{x} \cdot \mathbf{v} = a_1(\mathbf{x} \cdot \mathbf{v}_1) + \cdots + a_k(\mathbf{x} \cdot \mathbf{v}_k) = 0 \implies \mathbf{x} \perp \mathbf{v}_k$$

Example. The vector $\mathbf{v} = (1, 1, 1)$ is orthogonal to the plane spanned by vectors $\mathbf{w}_1 = (2, -3, 1)$ and $\mathbf{w}_2 = (0, 1, -1)$ (because $\mathbf{v} \cdot \mathbf{w}_1 = \mathbf{v} \cdot \mathbf{w}_2 = 0$).

Orthogonal complement

Definition. Let $S \subset \mathbb{R}^n$. The **orthogonal** complement of *S*, denoted S^{\perp} , is the set of all vectors $\mathbf{x} \in \mathbb{R}^n$ that are orthogonal to *S*. That is, S^{\perp} is the largest subset of \mathbb{R}^n orthogonal to *S*.

Theorem 1 S^{\perp} is a subspace of \mathbb{R}^n .

Note that $S \subset (S^{\perp})^{\perp}$, hence $\operatorname{Span}(S) \subset (S^{\perp})^{\perp}$. **Theorem 2** $(S^{\perp})^{\perp} = \operatorname{Span}(S)$. In particular, for any subspace V we have $(V^{\perp})^{\perp} = V$.

Example. Consider a line $L = \{(x, 0, 0) \mid x \in \mathbb{R}\}$ and a plane $\Pi = \{(0, y, z) \mid y, z \in \mathbb{R}\}$ in \mathbb{R}^3 . Then $L^{\perp} = \Pi$ and $\Pi^{\perp} = L$.

Fundamental subspaces

Definition. Given an $m \times n$ matrix A, let $N(A) = \{ \mathbf{x} \in \mathbb{R}^n \mid A\mathbf{x} = \mathbf{0} \},$ $R(A) = \{ \mathbf{b} \in \mathbb{R}^m \mid \mathbf{b} = A\mathbf{x} \text{ for some } \mathbf{x} \in \mathbb{R}^n \}.$

R(A) is the range of a linear mapping $L : \mathbb{R}^n \to \mathbb{R}^m$, $L(\mathbf{x}) = A\mathbf{x}$. N(A) is the kernel of L.

Also, N(A) is the nullspace of the matrix A while R(A) is the column space of A. The row space of A is $R(A^{T})$.

The subspaces $N(A), R(A^T) \subset \mathbb{R}^n$ and $R(A), N(A^T) \subset \mathbb{R}^m$ are **fundamental subspaces** associated to the matrix A.

Theorem $N(A) = R(A^T)^{\perp}$, $N(A^T) = R(A)^{\perp}$. That is, the nullspace of a matrix is the orthogonal complement of its row space.

Proof: The equality $A\mathbf{x} = \mathbf{0}$ means that the vector \mathbf{x} is orthogonal to rows of the matrix A. Therefore $N(A) = S^{\perp}$, where S is the set of rows of A. It remains to note that $S^{\perp} = \operatorname{Span}(S)^{\perp} = R(A^{\top})^{\perp}$.

Corollary Let V be a subspace of \mathbb{R}^n . Then dim $V + \dim V^{\perp} = n$.

Proof: Pick a basis $\mathbf{v}_1, \ldots, \mathbf{v}_k$ for V. Let A be the $k \times n$ matrix whose rows are vectors $\mathbf{v}_1, \ldots, \mathbf{v}_k$. Then $V = R(A^T)$ and $V^{\perp} = N(A)$. Consequently, dim V and dim V^{\perp} are rank and nullity of A. Therefore dim $V + \dim V^{\perp}$ equals the number of columns of A, which is n.

Orthogonal projection

Theorem 1 Let V be a subspace of \mathbb{R}^n . Then any vector $\mathbf{x} \in \mathbb{R}^n$ is uniquely represented as $\mathbf{x} = \mathbf{p} + \mathbf{o}$, where $\mathbf{p} \in V$ and $\mathbf{o} \in V^{\perp}$.

In the above expansion, \mathbf{p} is called the **orthogonal projection** of the vector \mathbf{x} onto the subspace V.

Theorem 2 $\|\mathbf{x} - \mathbf{v}\| > \|\mathbf{x} - \mathbf{p}\|$ for any $\mathbf{v} \neq \mathbf{p}$ in V.

Thus $\|\mathbf{o}\| = \|\mathbf{x} - \mathbf{p}\| = \min_{\mathbf{v} \in V} \|\mathbf{x} - \mathbf{v}\|$ is the **distance** from the vector \mathbf{x} to the subspace V.

Orthogonal projection onto a vector

Let
$$\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$$
, with $\mathbf{y} \neq \mathbf{0}$.

Then there exists a unique decomposition $\mathbf{x} = \mathbf{p} + \mathbf{o}$ such that \mathbf{p} is parallel to \mathbf{y} and \mathbf{o} is orthogonal to \mathbf{y} .



 $\mathbf{p} =$ orthogonal projection of \mathbf{x} onto \mathbf{y}

Orthogonal projection onto a vector

Let $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$, with $\mathbf{y} \neq \mathbf{0}$. Then there exists a unique decomposition $\mathbf{x} = \mathbf{p} + \mathbf{o}$ such that \mathbf{p} is parallel to \mathbf{y} and \mathbf{o} is orthogonal to \mathbf{y} .

We have $\mathbf{p} = \alpha \mathbf{y}$ for some $\alpha \in \mathbb{R}$. Then

$$0 = \mathbf{o} \cdot \mathbf{y} = (\mathbf{x} - \alpha \mathbf{y}) \cdot \mathbf{y} = \mathbf{x} \cdot \mathbf{y} - \alpha \mathbf{y} \cdot \mathbf{y}$$

$$\implies \alpha = \frac{\mathbf{x} \cdot \mathbf{y}}{\mathbf{y} \cdot \mathbf{y}} \implies \mathbf{p} = \frac{\mathbf{x} \cdot \mathbf{y}}{\mathbf{y} \cdot \mathbf{y}} \mathbf{y}$$

Problem. Find the distance from the point $\mathbf{x} = (3, 1)$ to the line spanned by $\mathbf{y} = (2, -1)$.

Consider the decomposition $\mathbf{x} = \mathbf{p} + \mathbf{o}$, where \mathbf{p} is parallel to \mathbf{y} while $\mathbf{o} \perp \mathbf{y}$. The required distance is the length of the orthogonal component \mathbf{o} .

$$\mathbf{p} = \frac{\mathbf{x} \cdot \mathbf{y}}{\mathbf{y} \cdot \mathbf{y}} \mathbf{y} = \frac{5}{5} (2, -1) = (2, -1),$$

$$\mathbf{o} = \mathbf{x} - \mathbf{p} = (3, 1) - (2, -1) = (1, 2), \quad ||\mathbf{o}|| = \sqrt{5}.$$

Problem. Find the point on the line y = -x that is closest to the point (3, 4).

The required point is the projection **p** of $\mathbf{v} = (3, 4)$ on the vector $\mathbf{w} = (1, -1)$ spanning the line y = -x.

$$\mathbf{p} = rac{\mathbf{v} \cdot \mathbf{w}}{\mathbf{w} \cdot \mathbf{w}} \mathbf{w} = rac{-1}{2} (1, -1) = \left(-rac{1}{2}, rac{1}{2}
ight)$$

Problem. Let Π be the plane spanned by vectors $\mathbf{v}_1 = (1, 1, 0)$ and $\mathbf{v}_2 = (0, 1, 1)$. (i) Find the orthogonal projection of the vector $\mathbf{x} = (4, 0, -1)$ onto the plane Π . (ii) Find the distance from \mathbf{x} to Π .

We have $\mathbf{x} = \mathbf{p} + \mathbf{o}$, where $\mathbf{p} \in \Pi$ and $\mathbf{o} \perp \Pi$. Then the orthogonal projection of \mathbf{x} onto Π is \mathbf{p} and the distance from \mathbf{x} to Π is $\|\mathbf{o}\|$.

We have $\mathbf{p} = \alpha \mathbf{v}_1 + \beta \mathbf{v}_2$ for some $\alpha, \beta \in \mathbb{R}$. Then $\mathbf{o} = \mathbf{x} - \mathbf{p} = \mathbf{x} - \alpha \mathbf{v}_1 - \beta \mathbf{v}_2$.

$$\begin{cases} \mathbf{o} \cdot \mathbf{v}_1 = \mathbf{0} \\ \mathbf{o} \cdot \mathbf{v}_2 = \mathbf{0} \end{cases} \iff \begin{cases} \alpha(\mathbf{v}_1 \cdot \mathbf{v}_1) + \beta(\mathbf{v}_2 \cdot \mathbf{v}_1) = \mathbf{x} \cdot \mathbf{v}_1 \\ \alpha(\mathbf{v}_1 \cdot \mathbf{v}_2) + \beta(\mathbf{v}_2 \cdot \mathbf{v}_2) = \mathbf{x} \cdot \mathbf{v}_2 \end{cases}$$

$$\mathbf{x}=(4,0,-1)$$
, $\mathbf{v}_1=(1,1,0)$, $\mathbf{v}_2=(0,1,1)$

$$\begin{cases} \alpha(\mathbf{v}_1 \cdot \mathbf{v}_1) + \beta(\mathbf{v}_2 \cdot \mathbf{v}_1) = \mathbf{x} \cdot \mathbf{v}_1 \\ \alpha(\mathbf{v}_1 \cdot \mathbf{v}_2) + \beta(\mathbf{v}_2 \cdot \mathbf{v}_2) = \mathbf{x} \cdot \mathbf{v}_2 \end{cases}$$
$$\iff \begin{cases} 2\alpha + \beta = 4 \\ \alpha + 2\beta = -1 \end{cases} \iff \begin{cases} \alpha = 3 \\ \beta = -2 \end{cases}$$

$$\mathbf{p} = 3\mathbf{v}_1 - 2\mathbf{v}_2 = (3, 1, -2)$$

 $\mathbf{o} = \mathbf{x} - \mathbf{p} = (1, -1, 1)$
 $\|\mathbf{o}\| = \sqrt{3}$