MATH 311

Topics in Applied Mathematics I

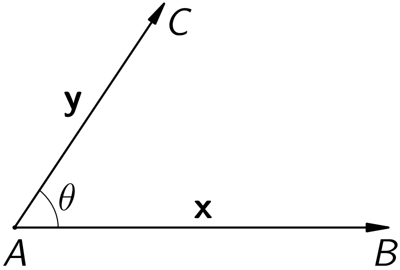
Lecture 24:
Orthogonal complement.

Beyond linearity: Euclidean structure

The vector space $\mathbb{R}^n$ is also a **Euclidean space**.

The Euclidean structure includes:

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



Length and distance

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

$$\|\mathbf{v}\| = \sqrt{v_1^2 + v_2^2 + \cdots + v_n^2}.$$

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

Properties of length:

$\|\mathbf{x}\| \geq 0$, $\|\mathbf{x}\| = 0$ only if $\mathbf{x} = \mathbf{0}$ (positivity)

$\|r\mathbf{x}\| = |r|\,\|\mathbf{x}\|$ (homogeneity)

$\|\mathbf{x} + \mathbf{y}\| \leq \|\mathbf{x}\| + \|\mathbf{y}\|$ (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

$$\boxed{\mathbf{x} \cdot \mathbf{y} = x_1 y_1 + x_2 y_2 + \cdots + x_n y_n.}$$

Alternative notation: $(\mathbf{x}, \mathbf{y})$ or $\langle \mathbf{x}, \mathbf{y} \rangle$.

Properties of scalar product:

$\mathbf{x} \cdot \mathbf{x} \geq 0$, $\mathbf{x} \cdot \mathbf{x} = 0$ only if $\mathbf{x} = \mathbf{0}$ (positivity)

$\mathbf{x} \cdot \mathbf{y} = \mathbf{y} \cdot \mathbf{x}$ (symmetry)

$(\mathbf{x} + \mathbf{y}) \cdot \mathbf{z} = \mathbf{x} \cdot \mathbf{z} + \mathbf{y} \cdot \mathbf{z}$ (distributive law)

$(r\mathbf{x}) \cdot \mathbf{y} = r(\mathbf{x} \cdot \mathbf{y})$ (homogeneity)

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 $\mathbf{y}$).

Angle

Cauchy-Schwarz inequality: $|\mathbf{x} \cdot \mathbf{y}| \leq \|\mathbf{x}\| \, \|\mathbf{y}\|$.

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

$$\cos\theta = \frac{\mathbf{x} \cdot \mathbf{y}}{\|\mathbf{x}\| \, \|\mathbf{y}\|} \quad \text{for a unique } \ 0 \leq \theta \leq \pi.$$

θ is called the **angle** between the vectors $\mathbf{x}$ and $\mathbf{y}$.

The vectors $\mathbf{x}$ and $\mathbf{y}$ are said to be **orthogonal** (denoted $\mathbf{x} \perp \mathbf{y}$) if $\mathbf{x} \cdot \mathbf{y} = 0$ (i.e., if $\theta = 90^{\mathrm{o}}$).

Orthogonality

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

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 $X \cap Y = \{\mathbf{0}\}$.

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

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

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

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

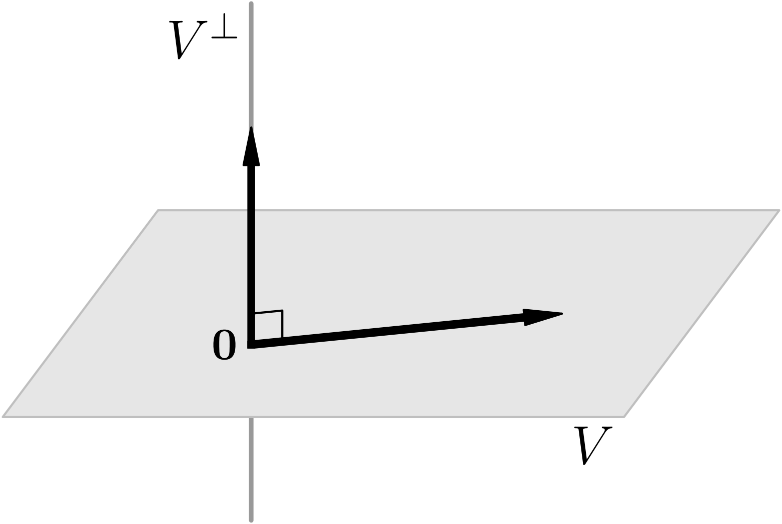
Definition. Let $S \subset \mathbb{R}^n$. The **orthogonal complement** of S, denoted $S^\perp$, is the set of all vectors $\mathbf{x} \in \mathbb{R}^n$ that are orthogonal to S. That is, $S^\perp$ is the largest subset of $\mathbb{R}^n$ orthogonal to S.

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

Note that $S \subset (S^\perp)^\perp$, hence $\mathrm{Span}(S) \subset (S^\perp)^\perp$.

Theorem 2 $(S^\perp)^\perp = \mathrm{Span}(S)$. 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 $\Pi^\perp = L$.


$V^{\perp}$
$\mathbf{0}$
V

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 $S^\perp = \mathrm{Span}(S)^\perp = R(A^T)^\perp$.

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

Proof: Pick a basis $\mathbf{v}_1, \dots, \mathbf{v}_k$ for V. Let A be the $k \times n$ matrix whose rows are vectors $\mathbf{v}_1, \dots, \mathbf{v}_k$. Then $V = R(A^T)$, hence $V^\perp = N(A)$. 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.

Problem. Let V be the plane spanned by vectors $\mathbf{v}_1 = (1, 1, 0)$ and $\mathbf{v}_2 = (0, 1, 1)$. Find $V^\perp$.

The orthogonal complement to V is the same as the orthogonal complement of the set $\{\mathbf{v}_1, \mathbf{v}_2\}$. A vector $\mathbf{u} = (x, y, z)$ belongs to the latter if and only if

$$\begin{cases} \mathbf{u} \cdot \mathbf{v}_1 = 0 \\ \mathbf{u} \cdot \mathbf{v}_2 = 0 \end{cases} \iff \begin{cases} x + y = 0 \\ y + z = 0 \end{cases}$$

Alternatively, the subspace V is the row space of the matrix

$$A = \begin{pmatrix} 1 & 1 & 0 \\ 0 & 1 & 1 \end{pmatrix},$$

hence $V^\perp$ is the nullspace of A.

The general solution of the system (or, equivalently, the general element of the nullspace of A) is $(t, -t, t)$ $= t(1, -1, 1)$, $t \in \mathbb{R}$. Thus $V^\perp$ is the straight line spanned by the vector $(1, -1, 1)$.