MATH 311

Topics in Applied Mathematics I

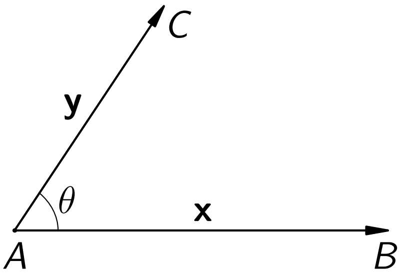
Lecture 24:
Orthogonal complement.
Orthogonal projection.

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 $\mathbf{x}$ and $\mathbf{y}$ 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

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

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

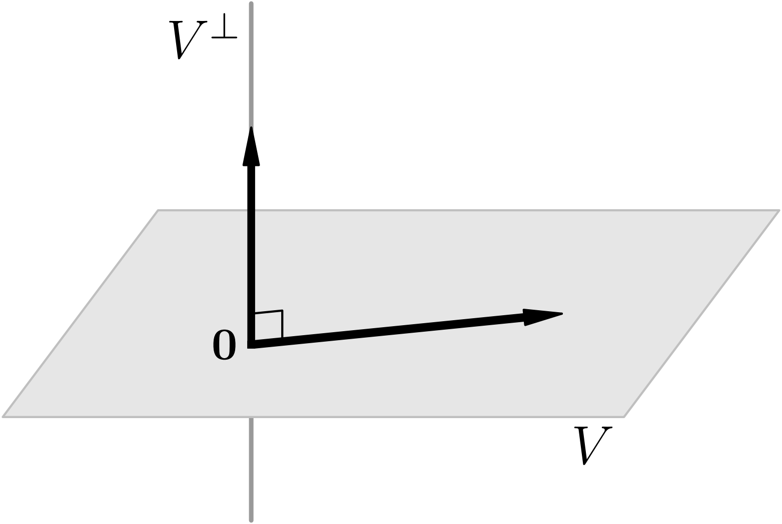
Definition. Let $S \subset \mathbb{R}^n$. The **orthogonal complement** of S, denoted $S^\perp$, is the set of all vectors $\mathbf{x} \in \mathbb{R}^n$ that are orthogonal to S. That is, $S^\perp$ is the largest subset of $\mathbb{R}^n$ orthogonal to S.

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

Theorem For any matrix A, the nullspace $N(A)$ is the orthogonal complement of the row space of A.

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 $S^\perp = \mathrm{Span}(S)^\perp = \{\text{row space of } A\}^\perp$.

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 is the row space of A, 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 $(1, -1, 1)$.

Orthogonal projection

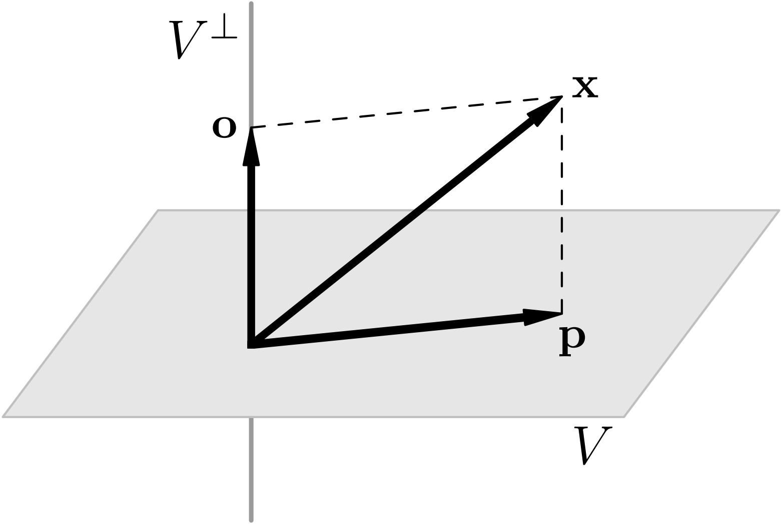
Theorem 1 Let V be a subspace of $\mathbb{R}^n$. Then any vector $\mathbf{x} \in \mathbb{R}^n$ is uniquely represented as $\mathbf{x} = \mathbf{p} + \mathbf{o}$, where $\mathbf{p} \in V$ and $\mathbf{o} \in V^\perp$.

Idea of the proof: Let $\mathbf{v}_1, \dots, \mathbf{v}_k$ be a basis for V and $\mathbf{w}_1, \dots, \mathbf{w}_m$ be a basis for $V^\perp$. Then $\mathbf{v}_1, \dots, \mathbf{v}_k, \mathbf{w}_1, \dots, \mathbf{w}_m$ is a linearly independent set. Hence it is a basis for $\mathbb{R}^n$.

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

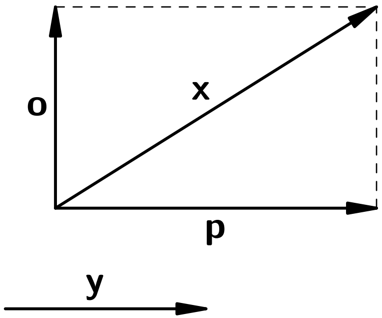
Theorem 2 $\|\mathbf{x} - \mathbf{v}\| > \|\mathbf{x} - \mathbf{p}\|$ for any $\mathbf{v} \neq \mathbf{p}$ in V.

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.


$V^\perp$
$\mathbf{x}$
$\mathbf{o}$
$\mathbf{p}$
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

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

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

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

$$\mathbf{p} = \frac{\mathbf{v} \cdot \mathbf{w}}{\mathbf{w} \cdot \mathbf{w}}\,\mathbf{w} = \frac{-1}{2}\,(1, -1) = \left(-\frac{1}{2}, \frac{1}{2}\right).$$