MATH 304

Lecture 18:
Orthogonal complement (continued).

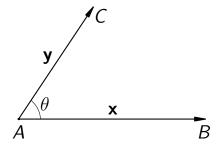
Linear Algebra

Orthogonal complement (continued).
Orthogonal projection.
Least squares problems.

Euclidean structure

Euclidean structure in \mathbb{R}^n includes:

- length of a vector: |x|,
- ullet angle between vectors: heta,
- 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 $\|\mathbf{v}\| = \sqrt{v_1^2 + v_2^2 + \dots + v_n^2}$.

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

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

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

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

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

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 $\mathbf{y} \in Y$.

Orthogonal complement

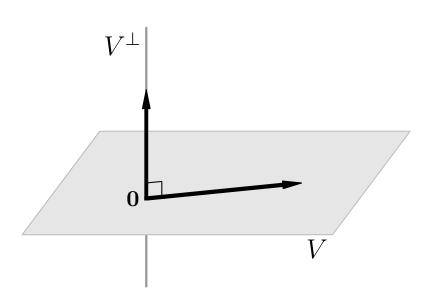
Definition. Let $S \subset \mathbb{R}^n$. The **orthogonal** complement of S, denoted S^{\perp} , is the set of all vectors $\mathbf{x} \in \mathbb{R}^n$ that are orthogonal to S.

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

- (ii) $\operatorname{Span}(S)^{\perp} = S^{\perp}$.
- (iii) $(S^{\perp})^{\perp} = \operatorname{Span}(S)$.

Theorem 2 If V is a subspace of \mathbb{R}^n , then

- (i) $(V^{\perp})^{\perp} = V$,
- (ii) $V \cap V^{\perp} = \{0\}.$



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

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

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

Orthogonal projection

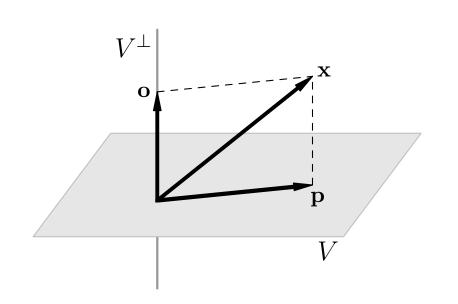
Theorem 1 Let V be a subspace of \mathbb{R}^n . Then any vector $\mathbf{x} \in \mathbb{R}^n$ is uniquely represented as $\mathbf{x} = \mathbf{p} + \mathbf{o}$, where $\mathbf{p} \in V$ and $\mathbf{o} \in V^{\perp}$.

Idea of the proof: Let $\mathbf{v}_1, \ldots, \mathbf{v}_k$ be a basis for V and $\mathbf{w}_1, \ldots, \mathbf{w}_m$ be a basis for V^{\perp} . Then $\mathbf{v}_1, \ldots, \mathbf{v}_k, \mathbf{w}_1, \ldots, \mathbf{w}_m$ 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.

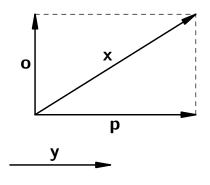
Thus $\|\mathbf{o}\| = \|\mathbf{x} - \mathbf{p}\| = \min_{\mathbf{v} \in V} \|\mathbf{x} - \mathbf{v}\|$ is the **distance** from the vector \mathbf{x} to the subspace V.



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

$$\implies \alpha = \frac{\mathbf{x} \cdot \mathbf{y}}{\mathbf{y} \cdot \mathbf{y}} \implies \left[\mathbf{p} = \frac{\mathbf{x} \cdot \mathbf{y}}{\mathbf{y} \cdot \mathbf{y}} \mathbf{y} \right]$$

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} .

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

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

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.

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

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 $\mathbf{o} = \mathbf{x} - \mathbf{p} = \mathbf{x} - \alpha \mathbf{v}_1 - \beta \mathbf{v}_2$.

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

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

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

$$\iff \begin{cases} 2\alpha + \beta = 4 \\ \alpha + 2\beta = -1 \end{cases} \iff \begin{cases} \alpha = 3 \\ \beta = -2 \end{cases}$$

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

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

 $\|\mathbf{o}\| = \sqrt{3}$

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 x to Π .

Alternative solution: 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 $\|\mathbf{o}\|$.

Notice that ${\bf o}$ is the orthogonal projection of ${\bf x}$ onto the orthogonal complement Π^\perp . In the previous lecture, we found that Π^\perp is the line spanned by the vector ${\bf y}=(1,-1,1)$. It follows that

$$\mathbf{o} = \frac{\mathbf{x} \cdot \mathbf{y}}{\mathbf{y} \cdot \mathbf{y}} \mathbf{y} = \frac{3}{3} (1, -1, 1) = (1, -1, 1).$$

Then $\mathbf{p} = \mathbf{x} - \mathbf{o} = (4, 0, -1) - (1, -1, 1) = (3, 1, -2)$ and $\|\mathbf{o}\| = \sqrt{3}$.

Overdetermined system of linear equations:

$$\begin{cases} x + 2y = 3 \\ 3x + 2y = 5 \\ x + y = 2.09 \end{cases} \iff \begin{cases} x + 2y = 3 \\ -4y = -4 \\ -y = -0.91 \end{cases}$$

No solution: inconsistent system

Assume that a solution (x_0, y_0) does exist but the system is not quite accurate, namely, there may be some errors in the right-hand sides.

Problem. Find a good approximation of (x_0, y_0) .

One approach is the **least squares fit**. Namely, we look for a pair (x, y) that minimizes the sum $(x + 2y - 3)^2 + (3x + 2y - 5)^2 + (x + y - 2.09)^2$.

Least squares solution

System of linear equations:

$$\begin{cases} a_{11}x_1 + a_{12}x_2 + \dots + a_{1n}x_n = b_1 \\ a_{21}x_1 + a_{22}x_2 + \dots + a_{2n}x_n = b_2 \\ \dots \\ a_{m1}x_1 + a_{m2}x_2 + \dots + a_{mn}x_n = b_m \end{cases} \iff A\mathbf{x} = \mathbf{b}$$

For any $\mathbf{x} \in \mathbb{R}^n$ define a **residual** $r(\mathbf{x}) = \mathbf{b} - A\mathbf{x}$.

The **least squares solution** \mathbf{x} to the system is the one that minimizes $||r(\mathbf{x})||$ (or, equivalently, $||r(\mathbf{x})||^2$).

$$||r(\mathbf{x})||^2 = \sum_{i=1}^m (a_{i1}x_1 + a_{i2}x_2 + \cdots + a_{in}x_n - b_i)^2$$

Let A be an $m \times n$ matrix and let $\mathbf{b} \in \mathbb{R}^m$.

Theorem A vector $\hat{\mathbf{x}}$ is a least squares solution of the system $A\mathbf{x} = \mathbf{b}$ if and only if it is a solution of the associated **normal system** $A^T A \mathbf{x} = A^T \mathbf{b}$.

Proof: $A\mathbf{x}$ is an arbitrary vector in R(A), the column space of A. Hence the length of $r(\mathbf{x}) = \mathbf{b} - A\mathbf{x}$ is minimal if $A\mathbf{x}$ is the orthogonal projection of \mathbf{b} onto R(A). That is, if $r(\mathbf{x})$ is orthogonal to R(A).

We know that $R(A)^{\perp} = N(A^{T})$, the nullspace of the transpose matrix. Thus $\hat{\mathbf{x}}$ is a least squares solution if and only if

$$A^T r(\hat{\mathbf{x}}) = \mathbf{0} \iff A^T (\mathbf{b} - A\hat{\mathbf{x}}) = \mathbf{0} \iff A^T A\hat{\mathbf{x}} = A^T \mathbf{b}.$$

Find the least squares solution to

$$\begin{cases} x + 2y = 3\\ 3x + 2y = 5\\ x + y = 2.09 \end{cases}$$

$$y = 2y = 2$$

$$\begin{pmatrix} x + y = 2.0 \\ 2 \\ 2 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix}$$

$$\frac{2}{1}$$

$$\begin{pmatrix} 2 \\ 2 \\ 1 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix}$$

$$\begin{pmatrix} 2 \\ 2 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} =$$

$$\begin{pmatrix} 1 & 2 \\ 3 & 2 \\ 1 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} 3 \\ 5 \\ 2.09 \end{pmatrix}$$

$$1/\sqrt{y}$$

$$\begin{pmatrix} 1 & 3 & 1 \\ 2 & 2 & 1 \end{pmatrix} \begin{pmatrix} 1 & 2 \\ 3 & 2 \\ 1 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} 1 & 3 & 1 \\ 2 & 2 & 1 \end{pmatrix} \begin{pmatrix} 3 \\ 5 \\ 2.09 \end{pmatrix}$$

$$\binom{2}{2}$$

$$2$$
) (x)

 $\begin{pmatrix} 11 & 9 \\ 9 & 9 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} 20.09 \\ 18.09 \end{pmatrix} \iff \begin{cases} x = 1 \\ y = 1.01 \end{cases}$