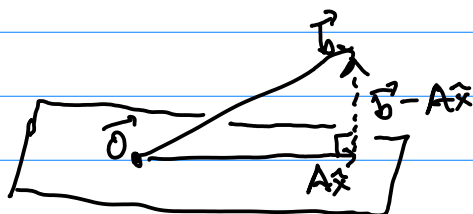


July 20

Least-Squares

To "solve" an inconsistent system $A\vec{x} = \vec{b}$, we may instead minimize $\|A\vec{x} - \vec{b}\|$ (a square root of a sum of squares, hence "least-squares solution". By the Best Approximation Theorem, this occurs when $A\hat{x} = \text{proj}_{\text{Col } A} \vec{b}$, which is to say when $A\hat{x} - \vec{b} \in (\text{Col } A)^\perp$



Since $(\text{Col } A)^\perp = \text{Nul } A^T$, the condition is $A^T(A\hat{x} - \vec{b}) = \vec{0}$, or $A^T A \hat{x} = A^T \vec{b}$.

Thm For $m \times n$ A , the following are equivalent:

1. $A\vec{x} = \vec{b}$ has a unique least-squares solution for each \vec{b} .
2. $\text{rank } A = n$
3. $\text{rank } A^T A = n$ (hence $A^T A$ invertible)

So if any is true, $\hat{x} = (A^T A)^{-1} A^T \vec{b}$ is the unique least-squares solution.

$\|A\hat{x} - \vec{b}\|$ is called the least-squares error or residual.

Alternative methods:

1. If A has orthogonal columns, solve $A\hat{x} = \text{proj}_{\text{Col } A} \vec{b}$ instead.
2. If $A = QR$ is a QR factorization,

$$\text{proj}_{\text{Col } A} \vec{b} = QQ^T \vec{b} \quad (\text{since } \text{Col } A = \text{Col } Q)$$

$$QR\hat{x} = QQ^T \vec{b} \Rightarrow Q^T QR\hat{x} = Q^T QQ^T \vec{b}$$

$$\Rightarrow R\hat{x} = Q^T \vec{b}. \quad \text{Use back-substitution or } \hat{x} = R^{-1} Q^T \vec{b}.$$

Inner Product Spaces

We can speak of orthogonality once we have an inner product (like the dot product).

def An inner product on a vector space V is a function associating a real number to each pair $\langle \vec{u}, \vec{v} \rangle$, with $\vec{u}, \vec{v} \in V$, which satisfies (for all $\vec{u}, \vec{v}, \vec{w} \in V$ and $c \in \mathbb{R}$),

1. $\langle \vec{u}, \vec{v} \rangle = \langle \vec{v}, \vec{u} \rangle$

2. $\langle \vec{u} + \vec{v}, \vec{w} \rangle = \langle \vec{u}, \vec{w} \rangle + \langle \vec{v}, \vec{w} \rangle$

3. $\langle c\vec{u}, \vec{v} \rangle = c\langle \vec{u}, \vec{v} \rangle$

4. $\langle \vec{u}, \vec{u} \rangle \geq 0$

5. if $\langle \vec{u}, \vec{u} \rangle = 0$, $\vec{u} = \vec{0}$.

A vector space with a particular inner product is an inner product space

First, let us examine $\langle \vec{u}, \vec{v} \rangle = \vec{u} \cdot \vec{v}$, the standard inner product on \mathbb{R}^n . If we forgot vectors had entries,

$$\langle \vec{e}_i, \vec{v} \rangle = v_i$$

so the inner product can recover them. A transformation

$T: \mathbb{R}^n \rightarrow \mathbb{R}$ is called a dual vector. Its matrix is a $1 \times n$ matrix, say \vec{w}^T . Then $T(\vec{x}) = \langle \vec{w}, \vec{x} \rangle$.

So every dual vector is an inner product transformation.

In fact, then if $\vec{w} = c_1 \vec{e}_1 + \dots + c_n \vec{e}_n$,

$$\langle \vec{w}, \vec{x} \rangle = c_1 \langle \vec{e}_1, \vec{x} \rangle + \dots + c_n \langle \vec{e}_n, \vec{x} \rangle$$

$$= c_1 x_1 + \dots + c_n x_n$$

But the point is, the dual vector space has dimension n , too.

What about matrices? $\langle \vec{y}, A\vec{x} \rangle = \vec{y}^T A\vec{x} = (A^T \vec{y})^T \vec{x}$

$$= \langle A^T \vec{y}, \vec{x} \rangle$$

This is an adjointness relation. Either apply the dual vector for \vec{y} on $A\vec{x}$ or apply the dual vector for $A^T \vec{y}$ on \vec{x} .

A need not be square! \mathbb{R}^m inner prod. to \mathbb{R}^n inner prod.!

If we want entry i of $A\vec{x}$, $\langle \vec{e}_i, A\vec{x} \rangle = \langle A^T \vec{e}_i, \vec{x} \rangle$

$$= \langle \vec{r}_i, \vec{x} \rangle$$

where \vec{r}_i is row i of A . This is how we compute it already!

Note: we are very close to the idea of "tensor" here, but let's save that for multilinear algebra.

A symmetric matrix A has $A = A^T$. It is self-adjoint:

$$\langle \vec{y}, A\vec{x} \rangle = \vec{y}^T A\vec{x} = \vec{y}^T A^T \vec{x} = \langle A\vec{y}, \vec{x} \rangle.$$

This is important for eigenvectors. Say $A\vec{x} = \lambda\vec{x}$ and $A\vec{y} = \mu\vec{y}$.

$$\langle \vec{y}, A\vec{x} \rangle = \langle \vec{y}, \lambda\vec{x} \rangle = \lambda \langle \vec{y}, \vec{x} \rangle$$

$$\langle A\vec{y}, \vec{x} \rangle = \langle \mu\vec{y}, \vec{x} \rangle = \mu \langle \vec{y}, \vec{x} \rangle$$

so $(\lambda - \mu) \langle \vec{y}, \vec{x} \rangle = 0$. Either $\lambda = \mu$ or \vec{x}, \vec{y} orthogonal.
(this is part of the upcoming spectral theorem).

A common nonstandard inner product on \mathbb{R}^n is

$\langle \vec{x}, \vec{y} \rangle = \vec{x}^T A \vec{y}$ where A is an $n \times n$ positive definite matrix. That is, A must be a matrix where this is an inner product! Checking $\vec{x}^T A \vec{x} > 0$ for $\vec{x} \neq \vec{0}$ is

sufficient. This means every vector \vec{x} has $A\vec{x}$ within 90° of it. So, $A = \begin{pmatrix} 0 & -1 \\ 1 & 0 \end{pmatrix}$ is not positive definite:

$$\vec{x}^T A \vec{x} = [x_1 \ x_2] A \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = [x_1 \ x_2] \begin{bmatrix} -x_2 \\ x_1 \end{bmatrix} = 0$$

If A is diagonal with positive diagonal entries, it is pos. def.
6.7 Ex 1 is $A = \begin{pmatrix} 4 & 0 \\ 0 & 5 \end{pmatrix}$.

Length/norm, distance, projection, orthogonal/orthonormal sets, Gram-Schmidt: these all carry over since they relied only on inner product properties, not dot product properties.

ex $V = \mathbb{P}_2$, $\langle p(x), q(x) \rangle = \left\langle \begin{bmatrix} p(-1) \\ p(0) \\ p(1) \end{bmatrix}, \begin{bmatrix} q(-1) \\ q(0) \\ q(1) \end{bmatrix} \right\rangle$ is pullback of std. inner prod on \mathbb{R}^3 to \mathbb{P}_2 using evaluation transformation.

Orthogonal basis of V ?

$1, x, x^2$ basis

$$\langle 1, x \rangle = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \cdot \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix} = 0 \quad \text{so already orthogonal}$$

$$\langle 1, x^2 \rangle = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \cdot \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix} = 2 \quad \langle 1, 1 \rangle = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \cdot \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} = 3$$

$$\langle x, x^2 \rangle = \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix} \cdot \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix} = 0$$

$x^2 - \frac{2}{3}$ is third vector.

$1, x, x^2 - \frac{2}{3}$ is orthogonal basis.

ex On $C([0,1])$ $\langle f, g \rangle = \int_0^1 f(t)g(t)dt$ is an inner product.

For instance,

$$\begin{aligned}\langle \sin(n\pi x), \sin(m\pi x) \rangle &= \int_0^1 \sin(n\pi x) \sin(m\pi x) dx \\ &= \int_0^1 \frac{1}{2} (\cos((n-m)\pi x) - \cos((n+m)\pi x)) dx\end{aligned}$$

$$\begin{aligned}\text{if } n=m, &= \frac{1}{2} \int_0^1 (1 - \cos((n+m)\pi x)) dx \\ &= \frac{1}{2} \left[x - \frac{1}{\pi(n+m)} \sin((n+m)\pi x) \right]_0^1\end{aligned}$$

$$\begin{aligned}&= \frac{1}{2} \\ \text{if } n \neq m &= \frac{1}{2} \left[\frac{1}{\pi(n-m)} \sin((n-m)\pi x) - \frac{1}{\pi(n+m)} \sin((n+m)\pi x) \right]_0^1 \\ &= 0.\end{aligned}$$

So orthogonal.

Can also check $\cos(n\pi x)$ are ortho to these, and to each other.