

# 10. Least-norm problems

- definition and examples
- the least-norm solution
- computing the least-norm solution

# Definition

## underdetermined linear equations

$$Ax = b \quad (A \text{ is } m \times n \text{ with } m < n)$$

- $x$  is underspecified; many choices of  $x$  lead to the same  $b$
- if  $Ax = b$  is solvable ( $b \in \mathbf{range}(A)$ ), there are infinitely many solutions

**least-norm solution:** solution of  $Ax = b$  with the smallest norm  $\|x\|$

## least-norm problem

$$\begin{array}{ll} \text{minimize} & \|x\| \\ \text{subject to} & Ax = b \end{array}$$

## Control example

mass-force example of page 1-10

- unit mass, with zero position and velocity at  $t = 0$ , subject to force  $F(t)$
- $F(t) = x_j$  for  $j - 1 \leq t < j$ ,  $j = 1, \dots, 10$  ( $x$  is sequence of forces)
- final position and velocity (at  $t = 10$ ) are given by  $y = Ax$  where

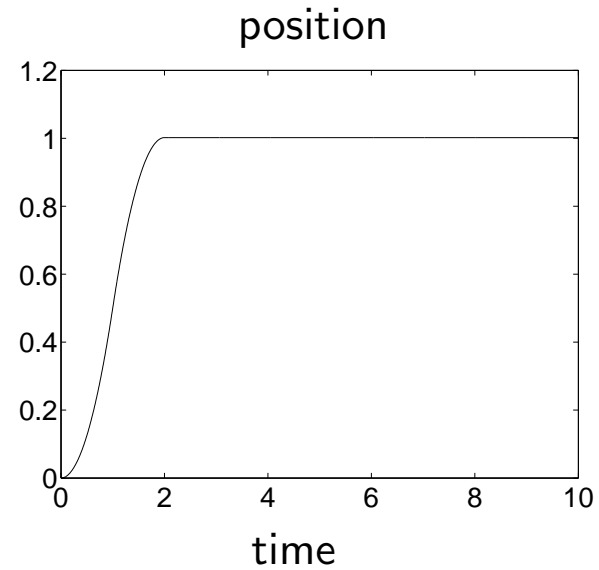
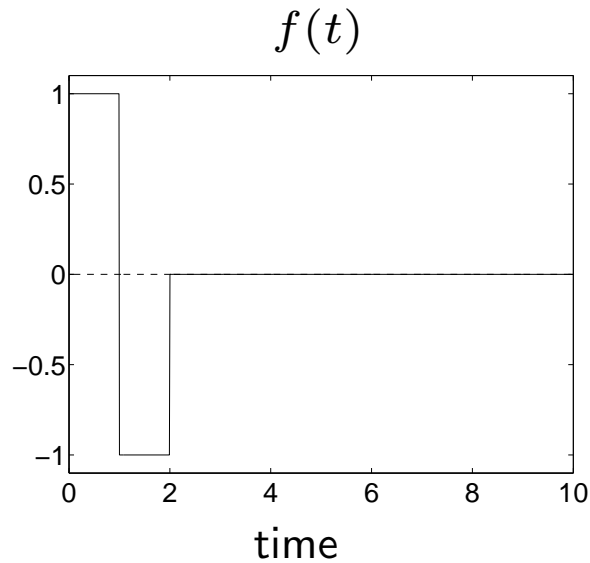
$$A = \begin{bmatrix} 19/2 & 17/2 & 15/2 & \cdots & 1/2 \\ 1 & 1 & 1 & \cdots & 1 \end{bmatrix}$$

forces  $x$  that transfer mass a unit distance with zero final velocity satisfy

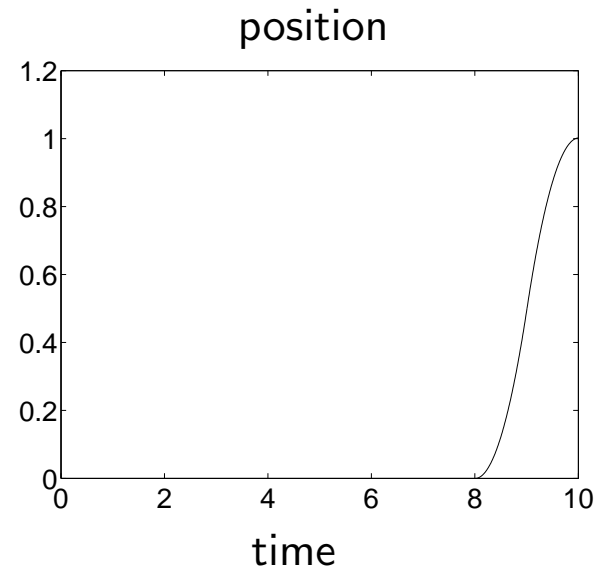
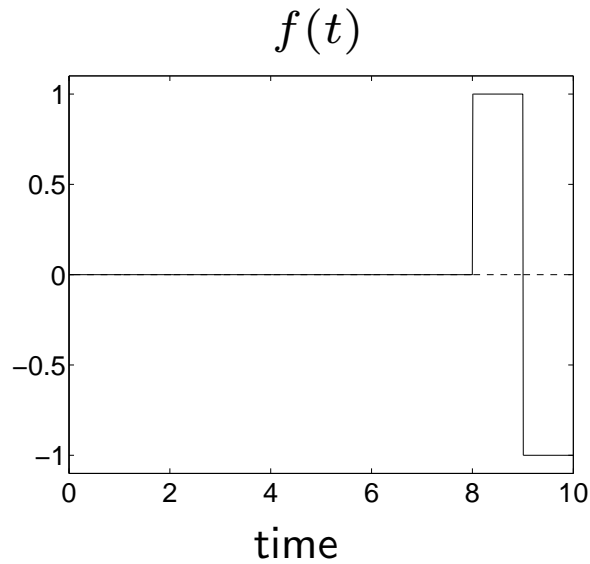
$$\begin{bmatrix} 19/2 & 17/2 & 15/2 & \cdots & 1/2 \\ 1 & 1 & 1 & \cdots & 1 \end{bmatrix} x = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

two equations in ten variables

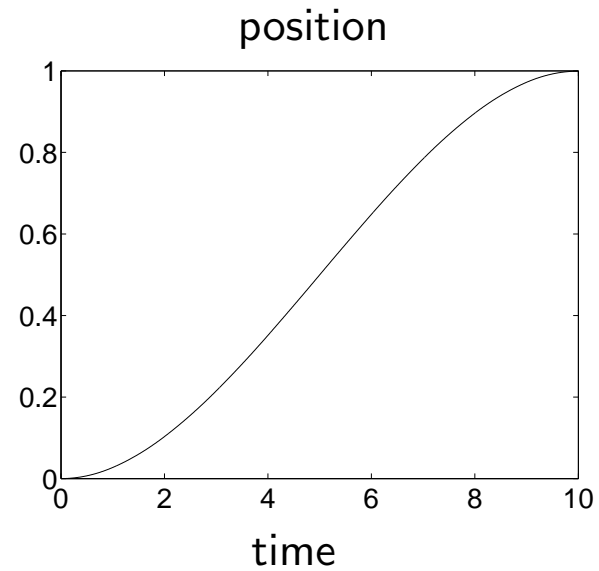
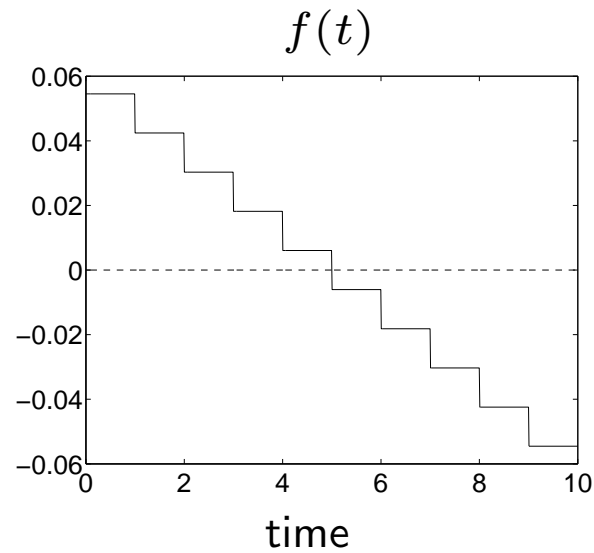
- choose  $x_1 = 1, x_2 = -1, x_3 = \dots = x_{10} = 0$



- choose  $x_1 = \dots = x_8 = 0, x_9 = 1, x_{10} = -1$



- $x$  with smallest  $\|x\|^2 = x_1^2 + x_2^2 + \dots + x_{10}^2$  ('least-norm' solution)



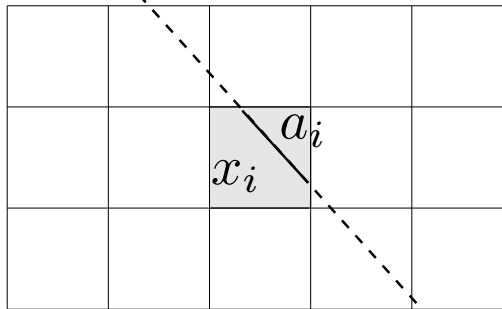
least-norm solution has  $\|x\| = 0.110$

# Image reconstruction from projections

**problem:** estimate density of a 3-dimensional object

partition object in  $n$  small elements ('pixels' or 'voxels') and assume density is constant on each element

X-ray beam with intensity  $I_0$



measured intensity  $I = I_0 e^{-\sum_{i=1}^n a_i x_i}$

$x_i$ : (unknown) density in element  $i$ ;

$a_i$ : (known) length of path through element  $i$  (up to a physical constant)

after taking logs:

$$\sum_{i=1}^n a_i x_i = \log(I_0/I)$$

one linear equation in the variables  $x_i$

repeat with  $m$  different source locations and beam directions:

$$Ax = b$$

- $m$  linear equations in  $n$  variables
- usually  $m \ll n$ ; many solutions  $x$

a popular method: pick a solution  $x$ , consistent with the measurements, and close to a prior guess

$$\begin{array}{ll} \text{minimize} & \|x - \hat{x}\| \\ \text{subject to} & Ax = b \end{array}$$

where  $\hat{x}$  is a prior guess of the density (*e.g.*, uniform density)

# The least-norm solution

if  $A$  is right-invertible, then

$$x_{\text{ln}} = A^T (AA^T)^{-1} b$$

is the unique solution of the least-norm problem

$$\begin{array}{ll} \text{minimize} & \|x\| \\ \text{subject to} & Ax = b \end{array}$$

- in other words if  $Ax = b$ ,  $x \neq x_{\text{ln}}$ , then  $\|x\| > \|x_{\text{ln}}\|$
- recall from page 4-27 that  $AA^T$  is positive definite and that

$$A^T (AA^T)^{-1}$$

is a right inverse of  $A$

## proof

1.  $x_{\text{ln}}$  satisfies the equation

$$Ax_{\text{ln}} = AA^T(AA^T)^{-1}b = b$$

2. suppose  $Ax = b$ ,  $x \neq x_{\text{ln}}$

$$\begin{aligned}(x - x_{\text{ln}})^T x_{\text{ln}} &= (x - x_{\text{ln}})^T A^T(AA^T)^{-1}b \\ &= (Ax - Ax_{\text{ln}})^T(AA^T)^{-1}b \\ &= 0\end{aligned}$$

therefore

$$\begin{aligned}\|x\|^2 &= \|x - x_{\text{ln}} + x_{\text{ln}}\|^2 \\ &= \|x - x_{\text{ln}}\|^2 + 2(x - x_{\text{ln}})^T x_{\text{ln}} + \|x_{\text{ln}}\|^2 \\ &= \|x - x_{\text{ln}}\|^2 + \|x_{\text{ln}}\|^2 \\ &> \|x_{\text{ln}}\|^2\end{aligned}$$

# Computing the least-norm solution

$$x_{\text{ln}} = A^T (AA^T)^{-1} b$$

## method 1 (Cholesky factorization)

1. form  $C = AA^T$  ( $m^2 n$  flops)
2. Cholesky factorization  $C = LL^T$  ( $(1/3)m^3$  flops)
3. forward substitution: solve  $Lw = b$  ( $m^2$  flops)
4. back substitution: solve  $L^T z = w$  ( $m^2$  flops)
5. multiply with  $A^T$ :  $x = A^T z$  ( $2mn$  flops)

total cost for large  $m, n$

$$m^2 n + (1/3)m^3 \text{ flops}$$

## method 2 (QR factorization)

QR factorization of  $A^T$ :  $A^T = QR$  ( $R$  upper triangular,  $Q^T Q = I$ )

$$\begin{aligned}x_{\text{ln}} &= A^T (AA^T)^{-1} b \\ &= QR (R^T Q^T QR)^{-1} b \\ &= QR (R^T R)^{-1} b \\ &= QR^{-T} b\end{aligned}$$

1. QR factorization of  $A^T = QR$  ( $2m^2n$  flops)
2. forward substitution to solve  $R^T z = b$  ( $m^2$  flops)
3. form  $x = Qz$  ( $2mn$  flops)

total cost for large  $m, n$ :

$$2m^2n \text{ flops}$$

more accurate than method 1; up to twice as expensive if  $n \gg m$

## Example

$$A = \begin{bmatrix} 1 & -1 & 1 & 1 \\ 1 & 0 & 1/2 & 1/2 \end{bmatrix}, \quad b = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

**Cholesky factorization method:** solve  $AA^T z = b$  and evaluate  $x = A^T z$

- Cholesky factorization  $AA^T = LL^T$

$$\begin{bmatrix} 4 & 2 \\ 2 & 3/2 \end{bmatrix} = \begin{bmatrix} 2 & 0 \\ 1 & 1/\sqrt{2} \end{bmatrix} \begin{bmatrix} 2 & 1 \\ 0 & 1/\sqrt{2} \end{bmatrix}$$

- solve  $Lw = b$

$$\begin{bmatrix} 2 & 0 \\ 1 & 1/\sqrt{2} \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$w_1 = 0, w_2 = \sqrt{2}$$

- solve  $L^T z = w$

$$\begin{bmatrix} 2 & 1 \\ 0 & 1/\sqrt{2} \end{bmatrix} \begin{bmatrix} z_1 \\ z_2 \end{bmatrix} = \begin{bmatrix} 0 \\ \sqrt{2} \end{bmatrix}$$

$$z_1 = -1, z_2 = 2$$

- evaluate  $x = A^T z$

$$x = \begin{bmatrix} 1 & 1 \\ -1 & 0 \\ 1 & 1/2 \\ 1 & 1/2 \end{bmatrix} \begin{bmatrix} -1 \\ 2 \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \\ 0 \\ 0 \end{bmatrix}$$

## QR factorization method

- QR factorization  $A^T = QR$

$$\begin{bmatrix} 1 & 1 \\ -1 & 0 \\ 1 & 1/2 \\ 1 & 1/2 \end{bmatrix} = \begin{bmatrix} 1/2 & 1/\sqrt{2} \\ -1/2 & 1/\sqrt{2} \\ 1/2 & 0 \\ 1/2 & 0 \end{bmatrix} \begin{bmatrix} 2 & 1 \\ 0 & 1/\sqrt{2} \end{bmatrix}$$

- solve  $R^T z = b$

$$\begin{bmatrix} 2 & 0 \\ 1 & 1/\sqrt{2} \end{bmatrix} \begin{bmatrix} z_1 \\ z_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$z_1 = 0, z_2 = \sqrt{2}$$

- evaluate  $x = Qz = (1, 1, 0, 0)$