Linear Least Squares

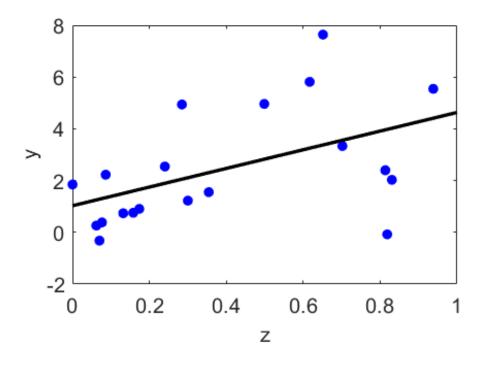
CPSC 406 – Computational Optimization

Overview

- Least-quares for data fitting
- Solution properties
- Solution methods

Fitting a line to data

- Given data points (z_i,y_i) , $i=1,\ldots,m$
- Find a line y = c + sz that best fits the data



 $\min_{c,s} \; \sum_{i=1}^m (y_i - ar y_i)^2 \; \; ext{ st } \; \; ar y_i = c + s z_i$

Matrix formulation

Generic form

$$\min_x \|Ax-b\|_2^2 = \sum_{i=1}^m (a_i^Tx-b_i)^2 \quad ext{where} \quad A = egin{bmatrix} a_1^T \ dots \ a_m^T \end{bmatrix}$$

Example

$$\min_{c,s} ~~ \sum_{i=1}^m (y_i - ar y_i)^2 ~~~ ext{st} ~~~ ar y_i = c + s z_i$$

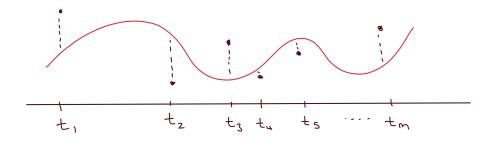
where

$$A = egin{bmatrix} 1 & z_1 \ dots & dots \ 1 & z_m \end{bmatrix}, \quad b = egin{bmatrix} y_1 \ dots \ y_m \end{bmatrix}, \quad x = egin{bmatrix} c \ s \end{bmatrix}$$

Example: Polynomial data fitting

Given m measurements y_i taken at times t_i :

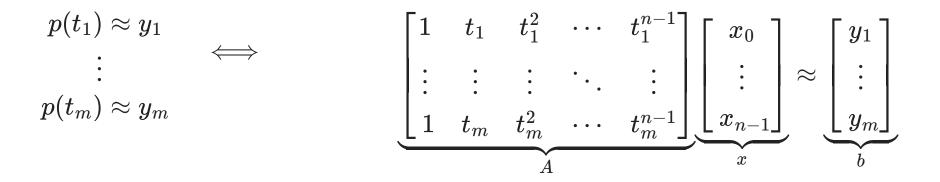
 $(t_1,y_1),\ldots,(t_m,y_m)$



Polynomial model p(t) of degree (n-1):

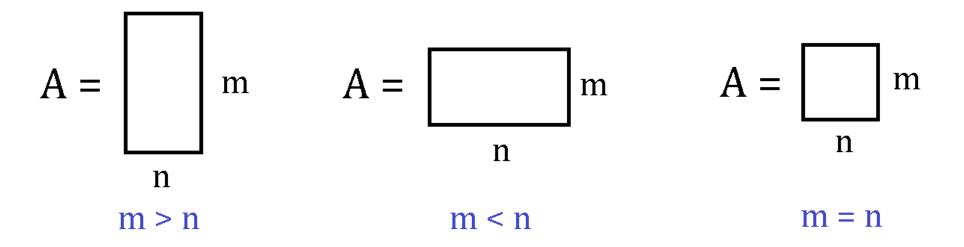
$$p(t) = x_0 + x_1 t + x_2 t^2 + \dots + x_{n-1} t^{n-1}$$
 $(x_i = ext{coeff's})$

Find coefficients $x_0, x_1, \ldots, x_{n-1}$ such that



Solving linear systems

Find x where Ax pprox b



- m>n (overdetermined): possibly no exact solution
- m < n (underdetermined): possibly infinitely many solutions
- m=n (square): possibly unique solution

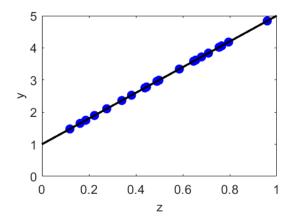
Question

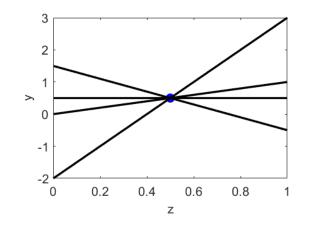
Suppose that A is an m imes n full-rank matrix with m > n. Then

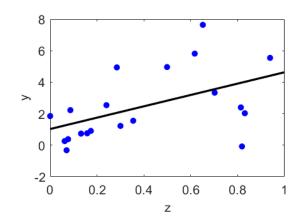
a. Ax = b has a unique solution for every $b \in \mathbb{R}^m$ b. Ax = b has a solution only if $b \in \mathbf{range}(A)$ c. Ax = b has a solution only if $b \in \mathbf{range}(A^T)$ d. A is invertible

Over and underdetermined systems

Find x where Ax = b







- 1 solution
- overdetermined
- feasible
- $b \in \mathbf{range}(A)$

- infinitely many solutions
- underdetermined
- feasible
- $b \in \mathbf{range}(A)$

- no solution
- overdetermined
- infeasible
- $b \notin \mathbf{range}(A)$

Least-squares optimality

$$x^* = \operatorname*{argmin}_x f(x) := rac{1}{2} \|Ax - b\|_2^2 = rac{1}{2} \sum_{i=1}^m (a_i^T x - b_i)^2$$

• quadratic objective

$$\|r\|_2^2 = r^T r \quad \Longrightarrow \quad f(x) = rac{1}{2}(Ax-b)^T(Ax-b) = rac{1}{2}x^T A^T Ax - b^T Ax + rac{1}{2}b^T b$$

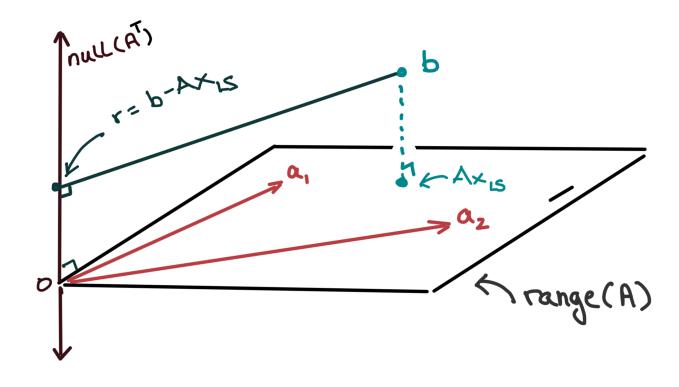
- gradient: $abla f(x) = A^T A x A^T b$
- the solution of LS must be a stationary point of *f*:

$$abla f(x^*) = 0 \quad \Longleftrightarrow \quad A^TAx^* - A^Tb = 0 \quad \Longleftrightarrow \quad \underbrace{A^TAx^* = A^Tb}_{ ext{normal equations}}$$

• If A has full column rank $\implies x^* = (A^T A)^{-1} A^T b$ (unique)

Geometric view

 $A = [a_1 \ a_2 \ \cdots \ a_n] \quad ext{where} \quad a_i \in \mathbb{R}^m$



 $egin{aligned} \mathbf{range}(A) &= \{y \mid y = Ax ext{ for some } \quad x \in \mathbb{R}^n\} \ \mathbf{null}(A^T) &= \{z \mid A^T z = 0\} \ \mathbf{range}(A)^\perp &= \mathbf{null}(A^T) \end{aligned}$

Orthogonal projection

- orthogonality of residual r = b - Ax and columns of A

$$egin{aligned} a_1^T r &= 0 \ a_2^T r &= 0 \ dots & a_2^T r &= 0 \ dots & a_n^T r &= 0 \end{aligned} \quad & \iff \quad egin{aligned} a_1^T \ a_2^T \ dots & d$$

- the following conditions are equivalent
 - 1. $A^T r = 0$ 2. $r \in \mathbf{null}(A^T)$ 3. $A^T A x = A^T b$
- projection is unique:

$$y^* = Ax^* = \mathbf{proj}_{\mathbf{range}(A)}(b)$$

Question

Consider the single-variable least-squares problem with data

$$A = \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix} \quad \text{and} \quad b = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_m \end{bmatrix} \quad (n = 1)$$

If m=3 and b=(1,3,5), what is the least-squares solution x^st ?

a. $x^*=1$ b. $x^*=3$ c. $x^*=5$ d. $x^*=9$

In-class exercise

Run the greenhouse gas example in the least-squares notebook:



• Compute the sum-of-squares residual in the trendline.