

Linear Least Squares Supplement

FP Ch22

Consider a system of p linear equations in q unknowns

$$a_{11}x_1 + a_{12}x_2 + \dots + a_{1q}x_q = y_1$$

$$a_{21}x_1 + a_{22}x_2 + \dots + a_{2q}x_q = y_2$$

$$\vdots$$

$$a_{p1}x_1 + a_{p2}x_2 + \dots + a_{pq}x_q = y_p$$

or $Ax = b$

$$\begin{bmatrix} a_{11} & a_{12} & \dots & a_{1q} \\ \vdots & & \ddots & \vdots \\ a_{p1} & \dots & a_{pq} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_q \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_p \end{bmatrix}$$

or $[c_1 \dots c_q] \rightarrow$ columns

$p < q$ set of solutions forms a $(q-p)$ -dimensional vector subspace of \mathbb{R}^q

Gaussian Elimination $\left. \begin{array}{l} p = q \end{array} \right\}$ unique solution

$p > q$ no solution

All true in the case that $\text{rank}(A) = \min(p, q)$

Consider the overconstrained case $p > q$
and assume $\text{rank}(A) = q$.

No exact solution, so we seek one that minimizes the error measure

$$E(x) \doteq \sum_{i=1}^p (a_{i1}x_1 + \dots + a_{iq}x_q - y_i)^2$$

$$= \|Ax - y\|^2, \quad \|\cdot\| \text{ Euclidean norm}$$

This is a linear least-squares problem.

→ E is proportional to the mean-squared error with the equations, and each term is linear before squaring.

Solve ~~m~~ $e \doteq Ax - y$, $E = ee^T$ $2e \frac{\partial e}{\partial x_i}$

$$\frac{\partial E}{\partial x_i} = 2 \frac{\partial e}{\partial x_i} \cdot e = 0, \quad \text{for } i = 1, \dots, q$$

$$\frac{\partial e}{\partial x_i} = \frac{\partial}{\partial x_i} (x_1 c_1 + \dots + x_q c_q - y) = \underline{c_i}$$

column i of A

$$\text{So, } \frac{\partial E}{\partial x_i} = 0 \Rightarrow \underline{c_i}^T (Ax - y) = 0$$

Stacking these constraints for each q coordinates of x

$$0 = \begin{pmatrix} c_1^T \\ \vdots \\ c_q^T \end{pmatrix} (Ax - y) = \left. \begin{aligned} &= A^T (Ax - y) \\ &\Leftrightarrow A^T A x = A^T y \end{aligned} \right\} \begin{array}{l} \text{the "normal equations"} \\ \text{for our problem} \end{array}$$

When A has maximal rank q , $A^T A$ is invertible

$$x = \underbrace{(A^T A)^{-1} A^T}_{A^+} y$$

A^+ \rightarrow the "pseudoinverse"

$$A^+ = (A^T A)^{-1} A^T$$