

# NLA 2021-2022

## Special linear systems

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# The least square problem (LSP)

**LSP:** for an  $m \times n$  matrix  $A$  and an  $m$ -vector  $b$ , find the  $n$ -vector  $x_{\min}$  minimizing the quantity

$$\|Ax - b\|_2$$

$\rightsquigarrow$  gives the linear combination of the columns

$$Ax = \sum_{j=1}^n x_j \operatorname{col}_j(A) \in \mathbb{R}^m$$

that best approaches (in the 2-norm) the  $m$ -vector  $b$

- If  $m = n$  and  $A$  is nonsingular then  $Ax_{\min} = b$
- If  $m > n$  then typically  $Ax = b$  has no solution, and the minimum is positive

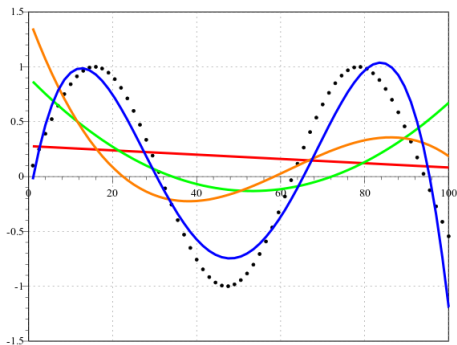
**Central case:**  $m \geq n$  and  $\operatorname{rank}(A) = n$

# Example

Suppose we have pairs

$$(y_i, b_i) \in \mathbb{R}^2, \quad i = 1, \dots, m,$$

and we want to find the polynomial of degree  $d$  that best fits the  $b_i$ 's as a function of the  $y_i$ 's



## Example (cont.)

Boils down to computing the polynomial

$$p(y) = \sum_{j=0}^d x_j y^j$$

minimizing the 2-norm of the *residual*  $p(y_i) - b_i$ ,  $i = 1, \dots, m$ :

$$\sum_{i=1}^m (p(y_i) - b_i)^2$$

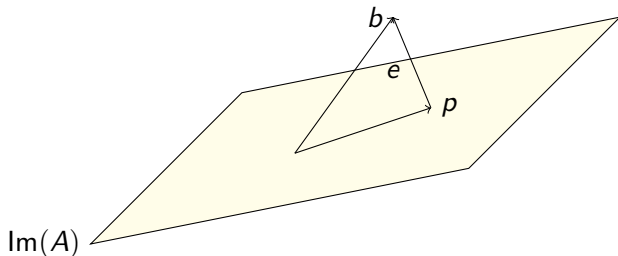
LSP for the data

$$A = \begin{bmatrix} 1 & y_1 & \cdots & y_1^d \\ \vdots & \vdots & & \vdots \\ 1 & y_m & \cdots & y_m^d \end{bmatrix} \in \mathbb{R}^{m \times (d+1)} \quad \text{and} \quad b = \begin{bmatrix} b_1 \\ \vdots \\ b_m \end{bmatrix} \in \mathbb{R}^m$$

# Three ways

- normal equations
- QR factorization
- SVD

# LSP and its solution



- $p = Ax_{\min}$  the orthogonal projection of  $b$  into  $\text{Im}(A)$
- $e = b - p$  the error vector

# Normal equations

The  $m$ -vector  $e$  is perpendicular to  $\text{Im}(A)$ : for all  $x \in \mathbb{R}^n$

$$0 = \langle Ax, e \rangle = (Ax)^T(b - Ax_{\min}) = x^T A^T(b - Ax_{\min})$$

Hence

$$\boxed{A^T A x_{\min} = A^T b} \quad (1)$$

The  $n \times n$  matrix  $A^T A$  is symmetric and positive definite

$\Rightarrow$  it is nonsingular and  $x_{\min}$  is the only solution of (1)

By Pythagoras theorem, the 2-norm of the error is

$$\|e\|_2 = (\|b\|_2^2 - \|Ax\|_2^2)^{1/2}$$

# Normal equations algorithm

We can solve the normal equations with Cholesky factorization:

Compute the lower triangular part of  $C \leftarrow A^T A$

Compute  $d \leftarrow A^T b$

Compute the Cholesky factorization  $C = G G^T$

Solve  $G y = d$  and  $G^T x_{\min} = y$

Its *complexity* is

$$\left(m + \frac{n}{3}\right) n^2 + O(n^2) \text{ flops}$$

For  $m \gg n$  the complexity  $m n^2$  of computing the product  $A^T A$  dominates

- uses standard algorithms
- reliable when  $A$  is far from rank deficient (but unstable otherwise)