

## Conditioning of least squares problems

Conditioning of linear least squares is a more complicated problem than the one for linear systems.

We won't give a full proof:

**Theorem** (Trefethen, Bau, Theorem 18.1)

Consider the linear least squares problem  $\min \|Ax - b\|$ , with  $A \in \mathbb{R}^{m \times n}$  with full column rank. Its relative condition number with respect to the input  $b$  is

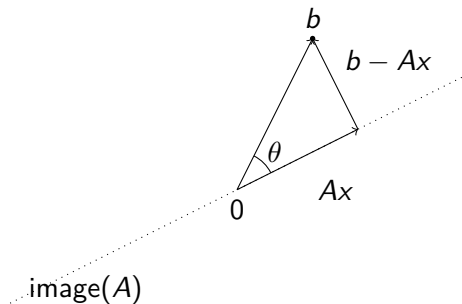
$$\kappa_{rel, b \rightarrow x} \leq \frac{\kappa(A)}{\cos \theta},$$

and with respect to  $A$  it is

$$\kappa_{rel, A \rightarrow x} \leq \kappa(A) + \kappa(A)^2 \tan \theta,$$

where  $\theta$  is the angle such that  $\cos \theta = \frac{\|Ax\|}{\|b\|}$ .

## The geometric picture



$b$  'split' into two orthogonal components:  $Ax$  and  $b - Ax$ .  
QR and SVD reveal their norms: if  $A = QR$ ,  $Q = \begin{bmatrix} Q_1 & Q_2 \end{bmatrix}$  or  
 $A = U\Sigma V^T$ ,  $U = \begin{bmatrix} U_1 & U_2 \end{bmatrix}$  (as in their thing versions) then

$$\begin{aligned}\|Ax\| &= \|Q_1^T b\| = \|U_1^T b\| = \|b\| \cos \theta, \\ \|b - Ax\| &= \|Q_2^T b\| = \|U_2^T b\| = \|b\| \sin \theta.\end{aligned}$$

## Some intuition

A small  $\frac{\|\Delta b\|}{\|b\|}$  may correspond to a large  $\frac{\|Q_1^T \Delta b\|}{\|Q_1^T b\|}$  — the denominator differs by a factor  $\cos \theta$ .

Solving a linear system + this possible error amplification gives

$$\kappa_{rel, b \rightarrow x} \leq \frac{\kappa(A)}{\cos \theta}.$$

This perturbation is more substantial if  $b$  and  $Ax$  are almost orthogonal, i.e.,  $\cos \theta \approx 0$ .

## Some intuition

Perturbing  $\Delta A$  may 'tilt'  $\text{image}(A)$ : this changes both  $Q_1^T b$  and the matrix in the linear system.

This perturbation is less substantial if  $Ax$  and  $b$  are almost aligned, i.e.,  $\sin \theta \approx 0$ .