

## Sect 6.3 (Cont...)

Recall: We were interested in problems where there are more equations than unknowns. We called these problems over-determined

$$\begin{array}{c} \left. \begin{array}{c} m, \text{ many} \\ \text{equations} \end{array} \right\} \begin{array}{|c|} \hline A \\ \hline \end{array} \begin{array}{|c|} \hline \underline{x} \\ \hline \end{array} = \begin{array}{|c|} \hline \underline{b} \\ \hline \end{array} \\ \left. \begin{array}{c} n, \text{ few} \\ \text{variables} \end{array} \right\} \end{array}$$

Often, there is no  $\underline{x}$  that exactly satisfies this system, so we try to find an  $\underline{x}$  such that

$$A \underline{x} \approx \underline{b}$$

So, we have a close or approximate solution. We define "close" in terms of the norm,

$$\| \underline{b} - A \underline{x} \|$$

If this norm is small, the  $\underline{x}$  is a better least-squares solution.

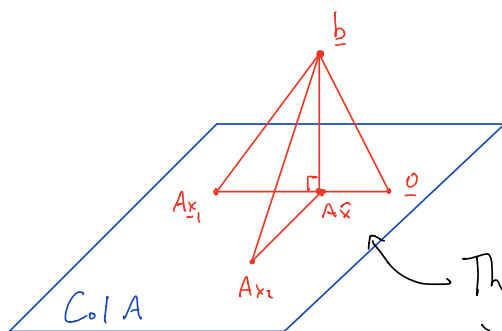
Def

If  $A$  is  $m \times n$ , and  $\underline{b} \in \mathbb{R}^m$ , a least-squares sol. of  $A\underline{x} = \underline{b}$  is  $\hat{\underline{x}} \in \mathbb{R}^n$  such that

$$\|\underline{b} - A\hat{\underline{x}}\| \leq \|\underline{b} - A\underline{x}\|$$

for all  $\underline{x} \in \mathbb{R}^n$ .

Geometrically, this looks like



The least-squares solution  $\hat{\underline{x}}$  is the vector such that  $A\hat{\underline{x}} \in \text{Col}(A)$  is closest to  $\underline{b}$ .

From Sect. 6.3, we know that closest point in  $W = \text{Col } A$  to a vector  $\underline{b}$  is the orth. proj. of  $\underline{b}$  onto  $W$ , given by

$$\hat{\underline{b}} = \text{proj}_{\text{Col } A} \underline{b} = \text{proj}_W \underline{b}$$

Since  $\hat{\underline{b}} \in \text{Col } A$ , the equation  $A\underline{x} = \hat{\underline{b}}$  is consistent and there exists some  $\hat{\underline{x}}$  such that  $A\hat{\underline{x}} = \hat{\underline{b}}$

Note, that  $\underline{b} - \hat{\underline{b}} = \underline{b} - A\hat{\underline{x}}$  is orthogonal to every column of  $A$ , so we have

$$a_i^T (\underline{b} - A\hat{\underline{x}}) = 0$$

Taking this over every column of  $A$ , we get

$$A^T (\underline{b} - A\hat{\underline{x}}) = 0$$

$$A^T \underline{b} - A^T A \hat{\underline{x}} = 0$$

$$A^T A \hat{\underline{x}} = A^T \underline{b} \quad (*)$$

Thus, any least-squares solution to  $A\underline{x} = \underline{b}$  satisfies  $(*)$ , which we call the normal equations

Thm

The set of least-squares solutions to  $A\underline{x} = \underline{b}$  is the non-empty set of solutions to the normal equations:  $A^T A \underline{x} = A^T \underline{b}$

Observations

- $A^T A$  is  $n \times n$  and  $A^T \underline{b} \in \mathbb{R}^n$
- Normal equations are unstable on a computer (learn about this in higher level courses)
- The solution set for the Normal Equations is non-empty, i.e., always consistent!

Ex

Find a least-squares solution to  $Ax = b$  for

$$A = \begin{vmatrix} 4 & 0 \\ 0 & 2 \\ 1 & 1 \end{vmatrix} \quad \underline{b} = \begin{vmatrix} 2 \\ 0 \\ 11 \end{vmatrix}$$

Set up the normal equations

$$A^T A = \begin{vmatrix} 4 & 0 & 1 \\ 0 & 2 & 1 \end{vmatrix} \begin{vmatrix} 4 & 0 \\ 0 & 2 \\ 1 & 1 \end{vmatrix} = \begin{vmatrix} 17 & 1 \\ 1 & 5 \end{vmatrix}$$

$$A^T \underline{b} = \begin{vmatrix} 4 & 0 & 1 \\ 0 & 2 & 1 \end{vmatrix} \begin{vmatrix} 2 \\ 0 \\ 11 \end{vmatrix} = \begin{vmatrix} 19 \\ 11 \end{vmatrix}$$

So the normal equations are

$$A^T A x = A^T b$$

$$\begin{vmatrix} 17 & 1 \\ 1 & 5 \end{vmatrix} \begin{vmatrix} x_1 \\ x_2 \end{vmatrix} = \begin{vmatrix} 19 \\ 11 \end{vmatrix}$$

The solution is

$$\begin{aligned} \underline{x} &= (A^T A)^{-1} A^T \underline{b} = \frac{1}{84} \begin{vmatrix} 5 & -1 \\ -1 & 17 \end{vmatrix} \begin{vmatrix} 19 \\ 11 \end{vmatrix} \\ &= \frac{1}{84} \begin{vmatrix} 84 \\ 168 \end{vmatrix} = \begin{vmatrix} 1 \\ 2 \end{vmatrix} \end{aligned}$$

Note, here  $A^T A$  is invertible. This may not always be the case. Use row reduction if necessary.

### Thm

Let  $A$  be an  $m \times n$  matrix, then the following are equivalent:

- 1.)  $Ax = b$  has unique least-squares solution for each  $b$  in  $\mathbb{R}^m$
- 2.) The columns of  $A$  are linearly independent
- 3.) The matrix  $A^T A$  is invertible.

When these are true, the least-squares solution is given by

$$\hat{x} = (A^T A)^{-1} A^T b$$

### Note

- The distance of  $A\hat{x}$  to  $b$  is called the least-squares error of the solution

$$\|b - A\hat{x}\|$$

This measures how well the solution  $\hat{x}$  fits the system of equations  $Ax = b$

### Connection to QR-factorization (Sect 6.4)

The normal equations are not the only way to find a least-squares solution. Another common way uses the QR factorization

Thm

Given an  $m \times n$  matrix  $A$  with linearly independent columns, let  $A = QR$  where  $Q$  is an  $m \times n$  orthogonal matrix and  $R$  is an  $n \times n$  upper triangular matrix and invertible, then for each  $\underline{b} \in \mathbb{R}^m$ ,  $A\underline{x} = \underline{b}$  has a unique least-squares solution given by

$$\hat{\underline{x}} = R^{-1} Q^T \underline{b}$$

Pf. Start from  $A\underline{x} = \underline{b}$ . We know a least-squares satisfies the normal equations

$$A^T A \underline{x} = A^T \underline{b}$$

Substitute in  $A = QR$ , we get

$$(QR)^T (QR) \underline{x} = (QR)^T \underline{b}$$

$$R^T \underbrace{Q^T Q}_{=I} R \underline{x} = R^T Q^T \underline{b}$$

$$R^T R \underline{x} = R^T Q^T \underline{b}$$

$$R \underline{x} = \underbrace{(R^T)^{-1} R^T}_{=I} Q^T \underline{b}$$

$$R \underline{x} = Q^T \underline{b}$$

$$\hat{\underline{x}} = R^{-1} Q^T \underline{b}$$

Ex

$$\text{Let } A = \begin{vmatrix} 1 & 3 & 5 \\ 1 & 1 & 0 \\ 1 & 1 & 2 \\ 1 & 3 & 3 \end{vmatrix} \quad \underline{b} = \begin{vmatrix} 3 \\ 5 \\ 7 \\ -3 \end{vmatrix}$$

The QR factorization is

$$A = QR = \begin{vmatrix} 1/2 & 1/2 & 1/2 \\ 1/2 & -1/2 & -1/2 \\ 1/2 & -1/2 & 1/2 \\ 1/2 & 1/2 & -1/2 \end{vmatrix} \begin{vmatrix} 2 & 4 & 5 \\ 0 & 2 & 3 \\ 0 & 0 & 2 \end{vmatrix}$$

$$\text{Then } Q^T \underline{b} = \begin{vmatrix} 1/2 & 1/2 & 1/2 & 1/2 \\ 1/2 & -1/2 & -1/2 & 1/2 \\ 1/2 & -1/2 & 1/2 & -1/2 \end{vmatrix} \begin{vmatrix} 3 \\ 5 \\ 7 \\ -3 \end{vmatrix} = \begin{vmatrix} 6 \\ -6 \\ 4 \end{vmatrix}$$

Lastly back substitute to solve  $R\hat{x} = Q^T \underline{b}$   
and get

$$\begin{vmatrix} 2 & 4 & 5 \\ 0 & 2 & 3 \\ 0 & 0 & 2 \end{vmatrix} \begin{vmatrix} x_1 \\ x_2 \\ x_3 \end{vmatrix} = \begin{vmatrix} 6 \\ -6 \\ 4 \end{vmatrix}$$

$$x_3 = 2$$

$$x_2 = \frac{-6 - 3(2)}{2} = -6 \quad \Rightarrow \quad \hat{\underline{x}} = \begin{vmatrix} 10 \\ -6 \\ 2 \end{vmatrix}$$

$$x_1 = \frac{6 - 5(2) - 4(-6)}{2} = 10$$

Notes:

- QR factorization is usually preferred in computer implementations. It's more stable than the normal equations.