

# CS 357: Numerical Methods

---

## Lecture 12: QR Decomposition Least Squares

Eric Shaffer

# QR review

$$\underline{A} = QR$$

- Reduced QR
- Let A be m by n and  $A=QR$

- What is the shape of Q?  $m \times n$

- What is the shape of R?  $n \times n$

- What are they for Full QR?

$$A = \begin{matrix} \text{Q} \\ m \times m \end{matrix} \begin{pmatrix} R \\ 0 \end{pmatrix} \begin{matrix} \\ m \times n \end{matrix}$$

# QR review

- What is special about Q?

columns

orthonormal  
unitized  
orthogonal to each other

- What space do the  $q_1, \dots, q_n$  columns span?

basis for

range(A)  
= span of  
columns of  
A

# Solving Linear Systems with QR

□  $Ax=b$  for  $A$  an ~~n~~  $n$  by  $n$  matrix

□ If  $A=QR$ , how can we solve for  $x$ ?

$$\begin{aligned} QRx &= b \\ Qy &= b \end{aligned}$$

$$\begin{aligned} Q^T Q y &= Q^T b \\ \boxed{y} &= Q^T b \\ R x &= y = Q^T b \end{aligned}$$

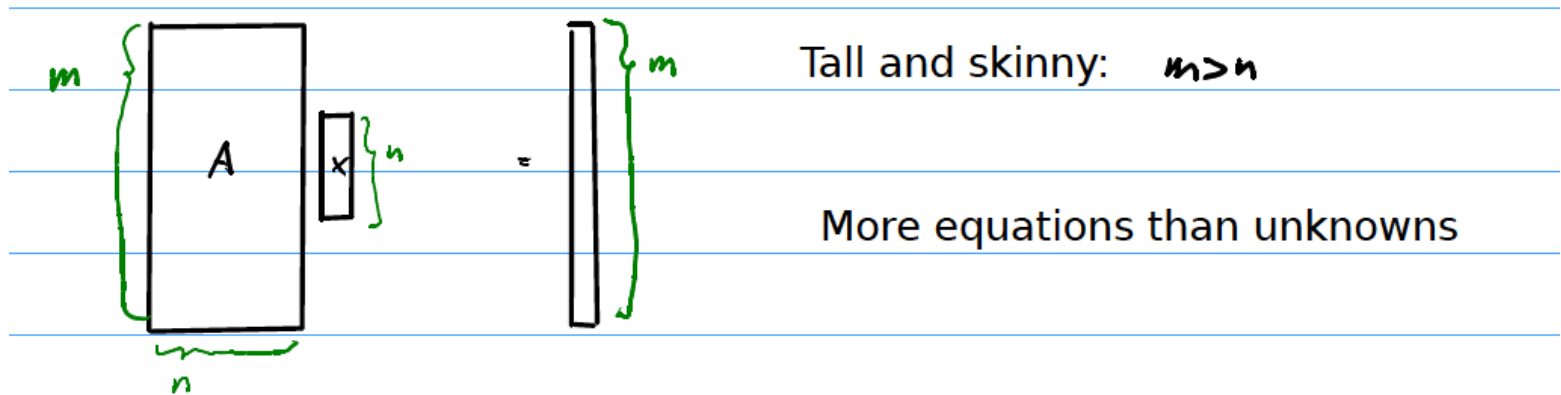
□ What is the computational cost?

$$\begin{aligned} QR &\rightarrow O(n^3) \\ y = Q^T b &\rightarrow O(n^2) \\ \text{solve} &\rightarrow O(n^2) \end{aligned}$$

solve w/  
back  
substitution

# Least Squares with QR

- Tall and skinny systems



- No exact solution....

# “Best” solution

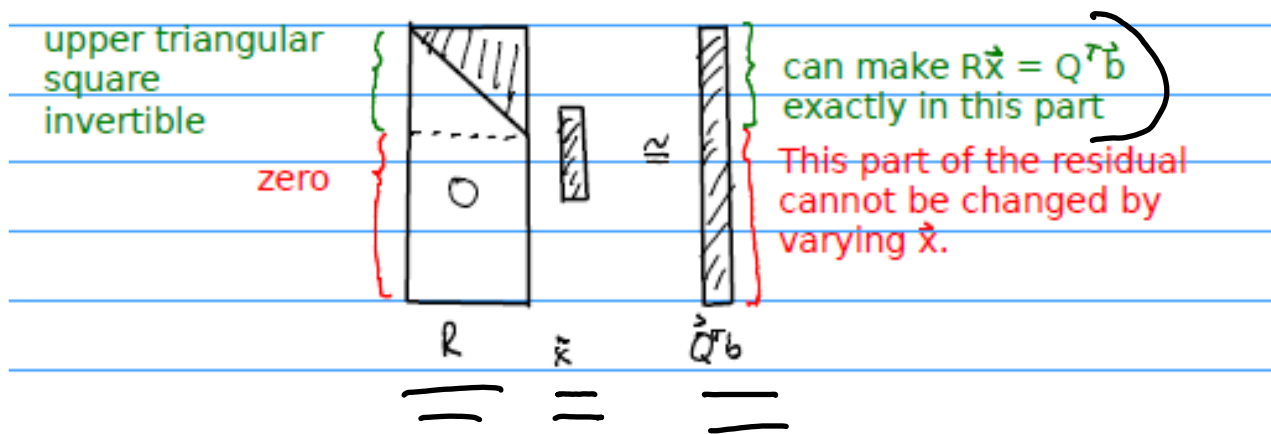
- Find some  $\mathbf{x}$  so that  $\mathbf{Ax}$  is as close to  $\mathbf{b}$  as we can get
- Take the difference...and measure the magnitude using a norm
- We want to minimize  $\|Ax - b\|_2^2$
- The **residual** is  $r = Ax - b$
- We are minimizing the sum of squares of the residual
- This process is called a **least squares problem**

# Notation

- Lots of different notation that means the same thing
  - Find  $x$  so that  $\|Ax - b\|_2^2$  is minimized ✓
  - $x = \underline{\text{argmin}_x \|Ax - b\|_2^2}$
  - $Ax \cong b$

# QR and Least Squares

$$\begin{aligned}
 A &= QR \\
 \underbrace{\|Ax - b\|} &= \|QRx - b\| \\
 &= \|Q^T(QRx - b)\| \\
 &= \|Rx - \underbrace{Q^T b}\|
 \end{aligned}$$

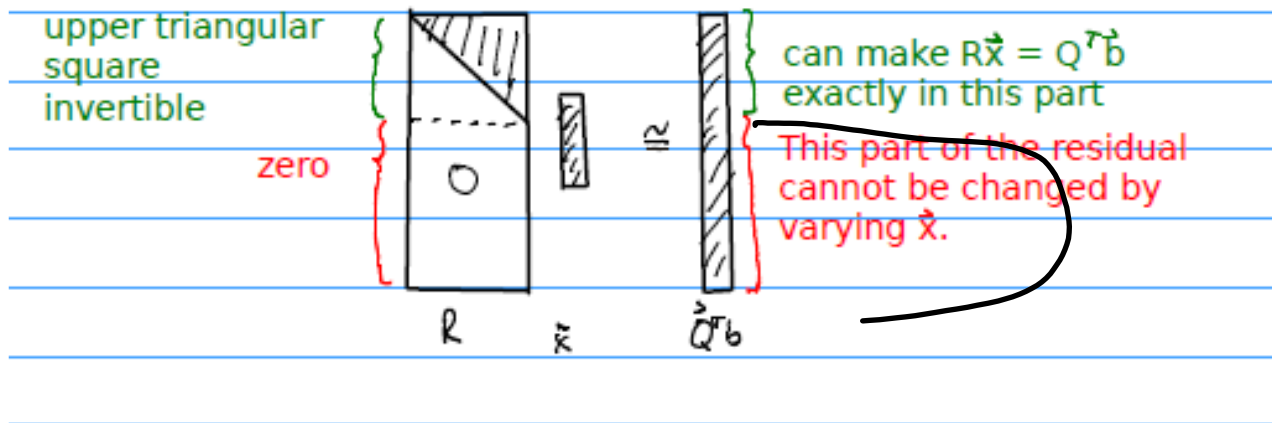




# QR and Least Squares

$R_{\text{top}} x = Q^T b$  solve  
That minimizes  $\|R x - Q^T b\|$

norm of residual  $\|Ax - b\| = \|(Q^T b)_{\text{bottom}}\|$



# The Normal Equations

$$Ax \approx b$$

- Another way of solving Least Squares

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

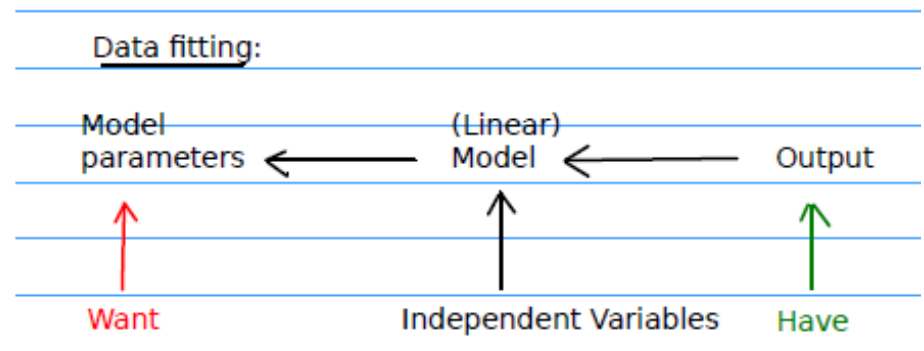
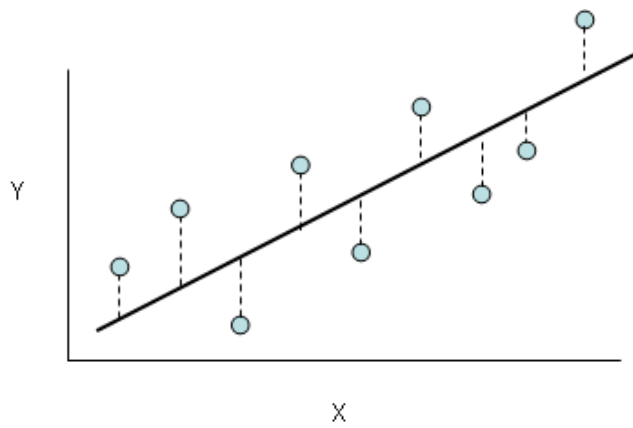
$$\text{condition \# } (A^T A) = (\text{condition \# } (A))^2$$

# Question....

- Why is it called “linear least squares”

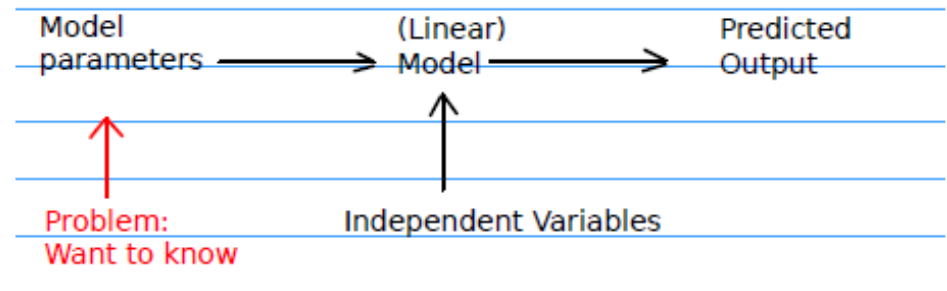
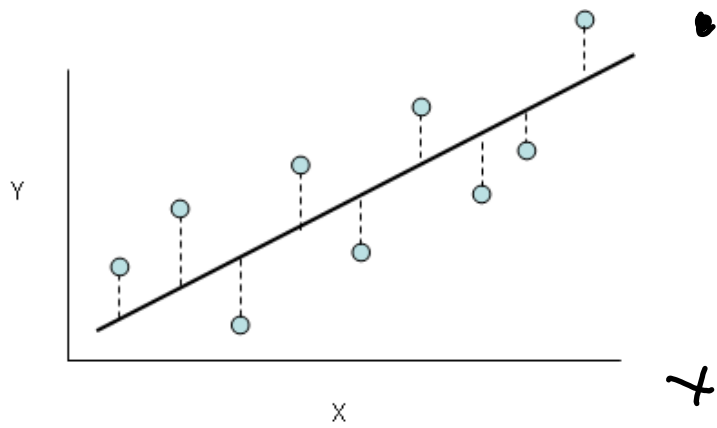
# Data Fitting

- ▣ Lots of interesting problems lack an exact solution....
- ▣ Fit a function to a set of points....



# Data Fitting

- ▣ Lots of interesting problems lack an exact solution....
- ▣ Fit a function to a set of points....



# Fitting a line

$m$  sample points  $p_i = (t_i, y_i)$

$$y_i = x_1 t_i + x_0$$

$$\begin{matrix} & A & & b \\ & & x & \\ m & \begin{bmatrix} 1 & t_1 \\ 1 & t_2 \\ \vdots & \vdots \\ 1 & t_m \end{bmatrix} & \begin{bmatrix} x_0 \\ x_1 \end{bmatrix} & = & \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{bmatrix} \\ & & 2 & & \end{matrix}$$

# Fitting a curve



$$f(t) = \underline{x_2} t^2 + \underline{x_1} t + \underline{x_0}$$

$$\begin{bmatrix} 1 & t_1 & t_1^2 \\ 1 & t_2 & t_2^2 \\ \vdots & \vdots & \vdots \\ 1 & t_m & t_m^2 \end{bmatrix} \begin{bmatrix} x_0 \\ x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} y_1 \\ \vdots \\ y_m \end{bmatrix}$$

"linear" least squares  
→  $x_i$  are linear

# Fitting a curve