

LECTURE 10 HOUSEHOLDER REFLECTORS QR

Previously : GS amounts to the successive application of upper triangular matrices R_i :

$$\underbrace{R_1 R_2 R_3 \dots R_n}_Q = Q$$

R^{-1} (upper triangular)

An alternative QR : Householder. We create Q_i 's so that

$$\underbrace{Q_n Q_{n-1} \dots Q_2 Q_1}_Q A = R, \text{ since } Q^* = Q^{-1}$$

Q_i 's are unitary $\Rightarrow Q$ is unitary.

$$\begin{array}{c} \left[\begin{array}{c|c|c|c} & & & \\ & & & \\ & & & \\ \hline & 1 & 0 & 0 \\ & 0 & 1 & 0 \\ & 0 & 0 & 1 \end{array} \right] \xrightarrow{Q_1} \left[\begin{array}{c|c|c|c} & x & & \\ & 0 & & \\ & 0 & & \\ \hline & \vdots & & \\ & 0 & & 0 \end{array} \right] \xrightarrow{Q_2} \left[\begin{array}{c|c|c|c} x & x & & \\ 0 & x & & \\ 0 & 0 & & \\ \hline & & & \\ & & & \\ & & & \end{array} \right] \xrightarrow{Q_3} \left[\begin{array}{c|c|c|c} x & x & x & \\ x & x & x & \\ 0 & x & x & \\ 0 & 0 & x & \\ 0 & 0 & 0 & \end{array} \right] = R \end{array}$$

Q, A $Q_1 Q_2 Q_3, A$ $Q_3 Q_2 Q_1, A$

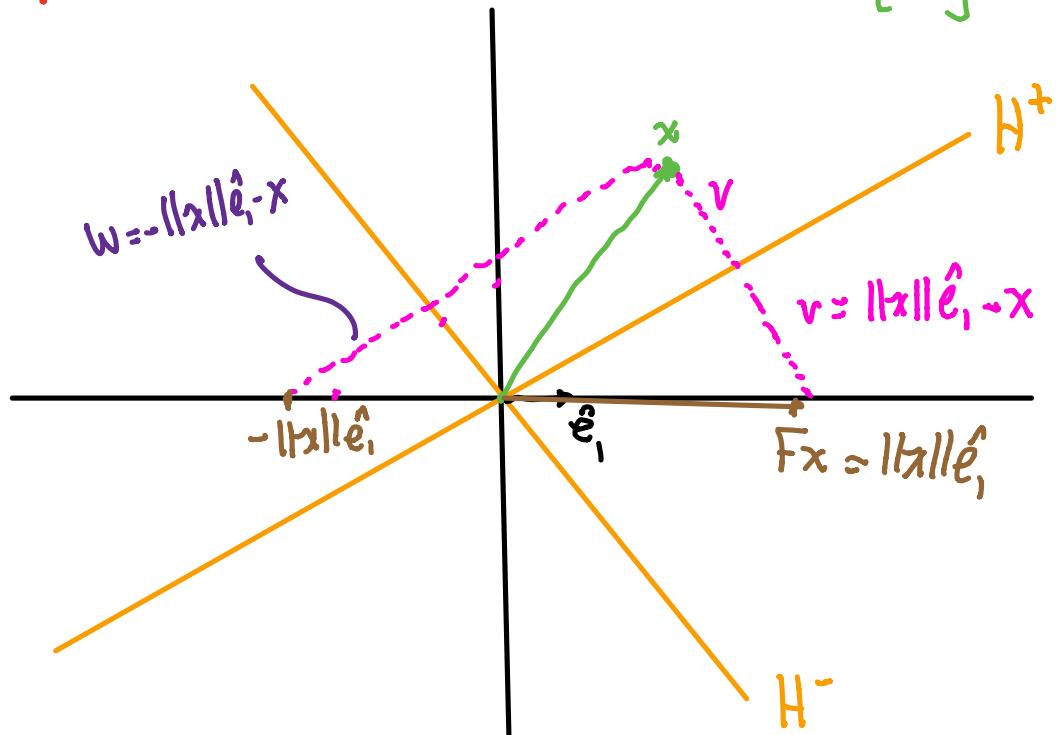
Q_k introduces zeros below the k^{th} row in the k^{th} column w/o destroying the zeros from before

Each

$$Q_k = \begin{bmatrix} I_{k-1} & 0 \\ 0 & F \end{bmatrix} \quad \text{size } m-k+1 \times m-k+1$$

F is the Householder Reflector

$$x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{bmatrix}$$



$$x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{bmatrix} \xrightarrow{F} \begin{bmatrix} \|\bar{x}\| \\ 0 \\ \vdots \\ 0 \end{bmatrix} = \|\bar{x}\| \hat{e}_i$$

To find the reflector about H^\perp :

$$Py = y - \frac{v v^*}{v^* v} y = y - \left(\frac{v^* y}{v^* v} \right) v$$

for some $y \in \mathbb{C}^m$

is the projection of some vector y onto H^\perp .

To get to the \hat{e}_i axis:

$$Fy = \left(I - \frac{2vv^*}{v^* v} \right) y = y - 2v \left(\frac{v^* y}{v^* v} \right)$$

$$\therefore \text{Matrix } F = I - \frac{2vv^*}{v^* v}$$

Rank: The projector P (rank $m-1$) and the reflector F (full rank & unitary) only differ by the presence of the 2!

The Better of 2 Reflectors:

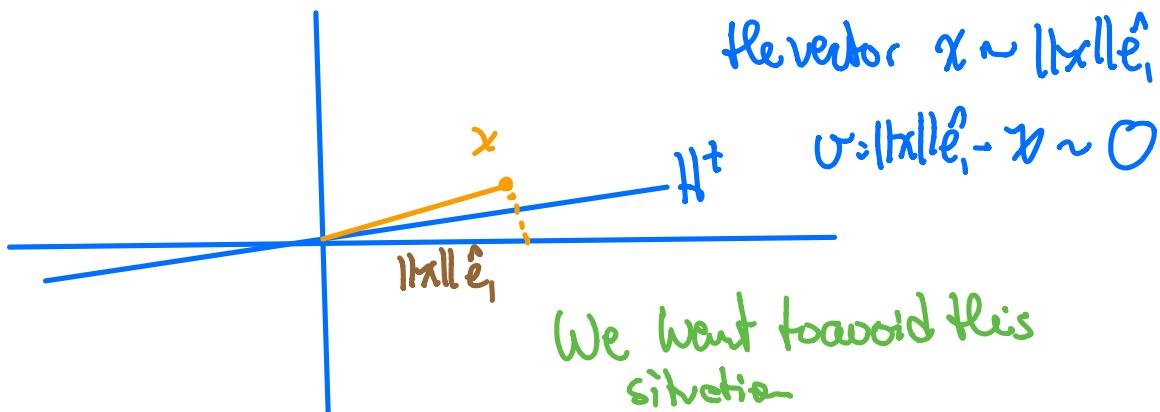
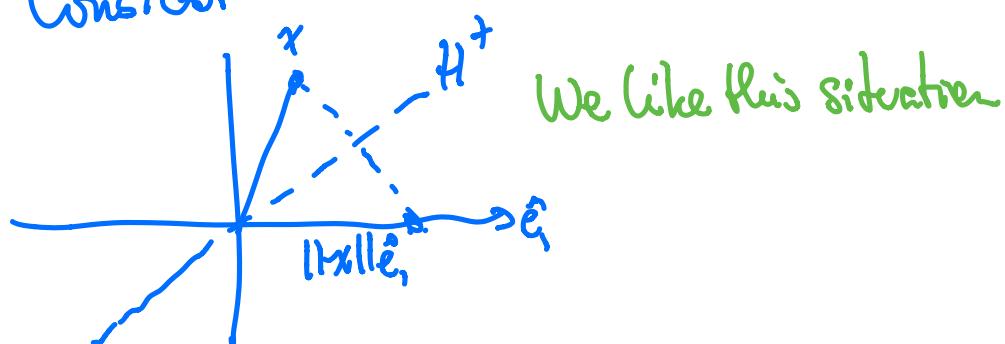
The vector $x \xrightarrow{z} z \|x\| \hat{e}_i$, $z \in \mathbb{C}$ w/ $|z|=1$

\therefore a circle of possible reflections

If $z \in \mathbb{R}$ then $z = \pm 1$ lead to H^+ & H^- cases,
either is OK, but choice is numerically driven.

We want to avoid subtracting nearby quantities.

Consider



We want to avoid this
situation

\therefore for this second case why not reflect
about H^- ? (see figure above)

Choose $v = -\text{sgn}(x_1) \|x\| \hat{e}_1 - x$
(if $x_1 = 0 \Rightarrow \text{sgn} = 0$)

Then $\|v\|$ is never smaller than $\|x\|$

See Algorithm 10.1

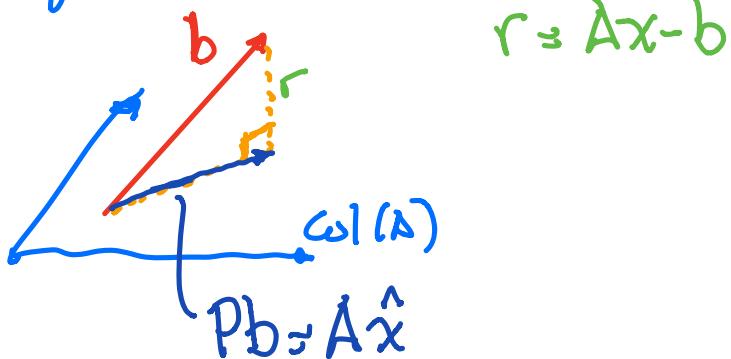
Householder QR

Cost $\sim O(mn^2)$ $\sim O(n^3)$ if square,

but more stable numerically.

Lecture 11 LSQ (least squares)

Solving $Ax = b$



$$r = Ax - b$$

if $r = 0 \Rightarrow Ax = b$

$$\hat{A}\hat{x} = Pb, b = Pb + r$$

Choose r to be "shortest"

$$\|r\|^2 = \|b - Pb\|^2 = \|(I - P)b\|^2$$

The minimizer will be s.t. $r \perp \text{col}(A)$

The orthogonality condition

$$A^* r = 0$$

or $A^*(b - A\hat{x}) = 0$

or $A^* A \hat{x} = A^* b$ The Normal Equations

Solving for $\hat{x} = (A^* A)^{-1} A^* b$

which satisfies $A\hat{x} = Pb = \underbrace{b(A^* A)^{-1} A^*}_P b$

ex) $Ax = b$ $A = \begin{bmatrix} 1 & 2 \\ 1 & 3 \\ 0 & 0 \\ \parallel & \parallel \\ a_1 & a_2 \end{bmatrix}$ $b = \begin{bmatrix} 4 \\ 5 \\ 6 \end{bmatrix}$

so clear that $b \neq x_1 a_1 + x_2 a_2$

but $Pb = \hat{x}_1 a_1 + \hat{x}_2 a_2$ can be found.

so let $r = b - Pb = (I - P)b$

Find \hat{x} s.t. $A^T r = 0$

$A^T A \hat{x} = A^T b$ the Normal Eqs

$$A^T A = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 3 & 0 \\ 2 & 0 & 0 \end{bmatrix} \begin{bmatrix} 1 & 2 \\ 1 & 3 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} 2 & 5 \\ 5 & 13 \end{bmatrix}$$

$$\hat{x} = (A^T A)^{-1} A^T b = \begin{bmatrix} 13 & 5 \\ -5 & 2 \end{bmatrix}^{-1} \begin{bmatrix} 1 & 1 & 0 \\ 2 & 3 & 0 \end{bmatrix} \begin{bmatrix} 4 \\ 5 \\ 6 \end{bmatrix} = \begin{bmatrix} 2 \\ 1 \end{bmatrix}$$

$$Pb = A\hat{x} = \begin{bmatrix} 1 & 2 \\ 1 & 3 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 2 \\ 1 \end{bmatrix} = \begin{bmatrix} 4 \\ 5 \\ 0 \end{bmatrix}$$

$$b - Pb = r = \begin{bmatrix} 0 \\ 0 \\ 6 \end{bmatrix} = (I - P)b \quad \therefore \|r\|_2 = 6 //$$

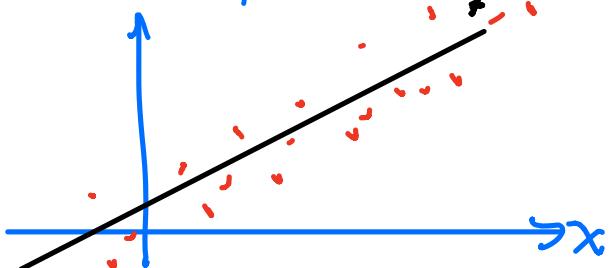
FITTING DATA TO MODELS

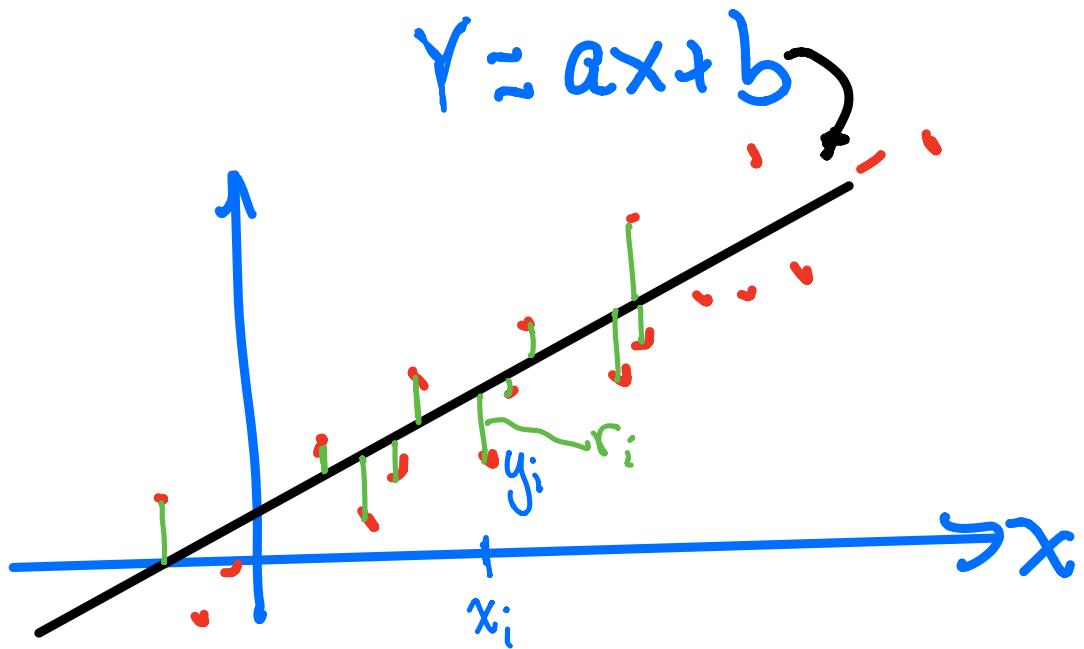
Data:

x_1	y_1
x_2	y_2
\vdots	\vdots
x_m	y_m

"Model" look like a straight line

$$Y = ax + b$$





$$r_i = Y(x_i) - y_i$$

Variance
energy = $\sum |r_i|^2$

Find a, b s.t. energy is minimized.

Least squares problem:

let $A = \begin{bmatrix} 1 & x_1 \\ 1 & x_2 \\ 1 & x_3 \\ \vdots & \vdots \\ 1 & x_m \end{bmatrix}$ $\mathbf{z} = \begin{bmatrix} a \\ b \end{bmatrix}$ $\mathbf{y} = \begin{bmatrix} y_{11} \\ y_{22} \\ \vdots \\ y_{mm} \end{bmatrix}$
 $\mathbf{r} = \begin{bmatrix} r_1 \\ r_2 \\ \vdots \\ r_m \end{bmatrix}$

$$Az = \mathbf{y} + \mathbf{r}$$

Solve for $\hat{\mathbf{z}}$ s.t. $\|\mathbf{r}\|_2^2$ is smallest.

POLYNOMIAL DATA FITTING

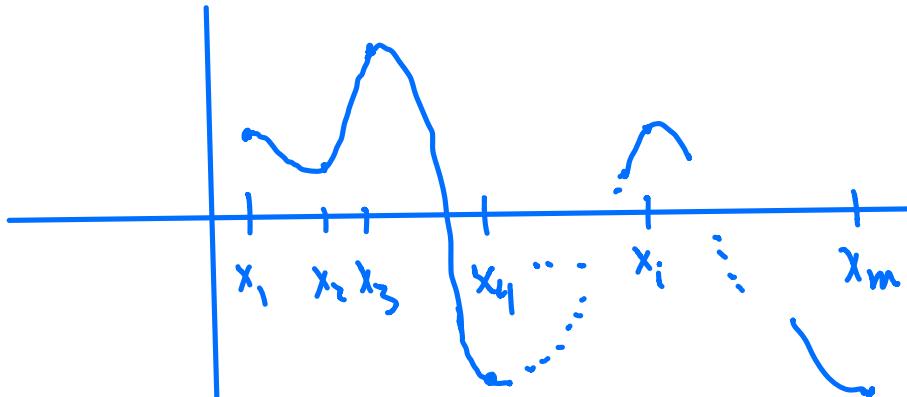
$$\{x_i\}_{i=1}^m \quad \{y_i\}_{i=1}^m \quad x \in \mathbb{C}^m \\ y \in \mathbb{C}^m$$

$\exists !$ polynomial interpolant

$$P(x) = c_0 + c_1 x + c_2 x^2 + \dots + c_{m-1} x^{m-1}$$

$$\text{s.t. at } x_i \quad P(x_i) = y_i$$

m eqs & m unknowns, the powers of x are linearly independent.



The condition $p(x_i) = y_i \quad i=1, 2, \dots, m$
generates

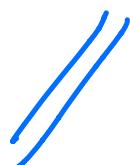
Rule: in interpolation we insist that $p(x_i) = y_i, i=1 \dots m$
 \therefore we need m equations for m unknowns.

$$\begin{bmatrix} 1 & x_1 & x_1^2 & \dots & x_1^{m-1} \\ 1 & x_2 & x_2^2 & \dots & x_2^{m-1} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_m & x_m^2 & \dots & x_m^{m-1} \end{bmatrix} \begin{bmatrix} G_0 \\ G_1 \\ \vdots \\ G_{m-1} \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{bmatrix}$$

↑
Vandermonde Matrix

So imagine fitting 10^6 points... using
a polynomial of deg $10^6 - 1$??

... Highly unstable process on a finite
precision machine.



Rule: In approximation we don't insist that $p(x_i) = y_i$
for $i=1,..,m$. Instead we propose an approximating
polynomial that has some optimizing
characteristic. For example, we can insist
that we find an approximating polynomial
that minimizes a residual $p(x_i) - y_i$.

