

Solving linear least squares problems.

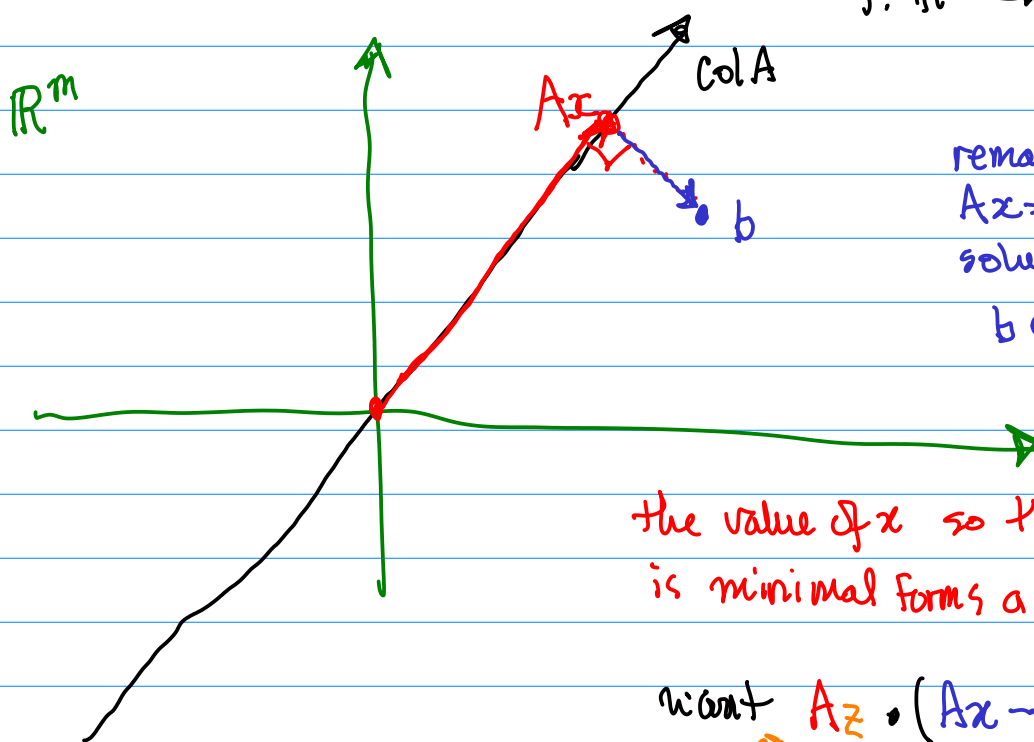
Idea: If $Ax=b$ doesn't have a solution, then instead minimize the residual error $\|Ax-b\|$.

Euclidean norm

Review of linear algebra... $A \in \mathbb{R}^{m \times n}$

$$\text{Col } A = \{ Ax : x \in \mathbb{R}^n \} = \text{range of } f \subseteq \mathbb{R}^m$$

$$\text{where } f(x) = Ax \\ f: \mathbb{R}^n \rightarrow \mathbb{R}^m$$



remark, since $Ax=b$ has no solution, then $b \notin \text{Col } A$.

the value of x so that $\|Ax-b\|$ is minimal forms a right angle.

$$\text{want } Az \cdot (Ax-b) = 0$$

$$(Az)^T (Ax-b) = 0$$

$$z^T A^T (Ax-b) = 0$$

Actually, Az here since the perpendicularity needs to hold for all vectors in $\text{Col } A$

Therefore

$$z^T (A^T A x - A^T b) = 0$$

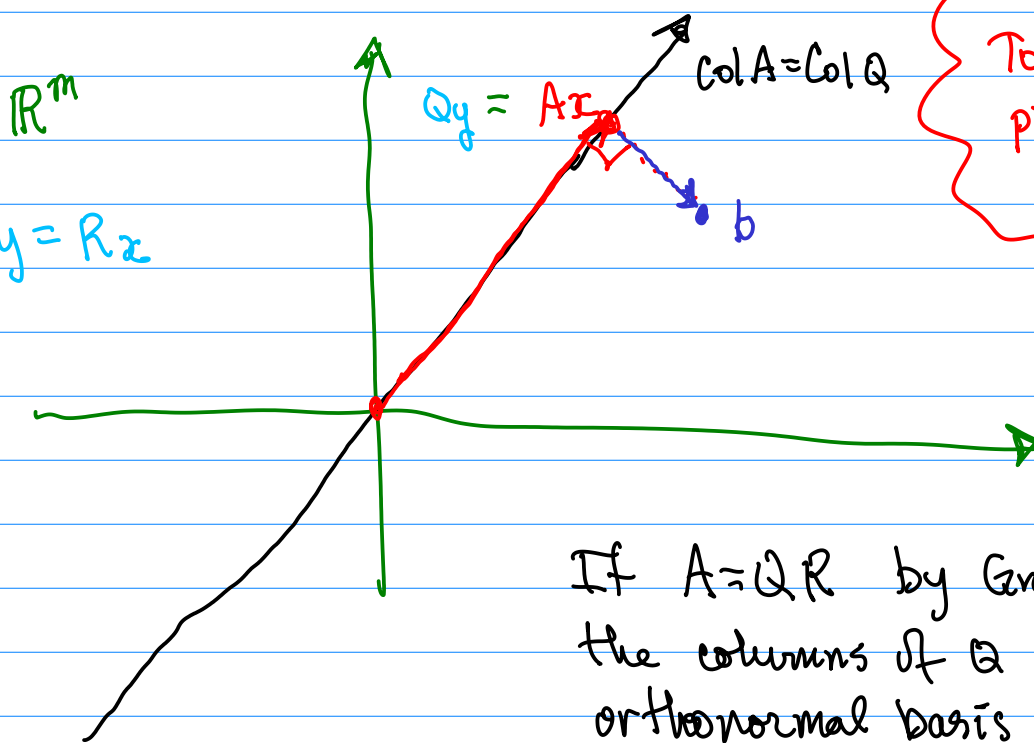
$$z \cdot (A^T A x - A^T b) = 0 \quad \text{for all } z \in \mathbb{R}^n$$

If $A^T A x = A^T b$ then the above holds...
these are called the normal equations...

Solve them?

$$x = (A^T A)^{-1} A^T b \quad \text{is the solution...}$$

where $y = R x$



To draw this picture need col A

If $A = QR$ by Gram-Schmidt, the columns of Q form an orthonormal basis for $\text{col } A$,

$$\text{Col } A = \text{Col } Q$$

Again, perpendicularity must hold for all vectors in $\text{Col } Q$ so z here

$$Qz \cdot (Qy - b) = z^T Q^T (Qy - b)$$

$$= z^T (Q^T Q y - Q^T b) = z \cdot (y - Q^T b)$$

$$y = Rx$$

$$= z \cdot \underbrace{(Rx - Q^T b)}_{=0} = 0 \quad \text{for all } z \in \mathbb{R}^n$$

if $Rx = Q^T b$ then above holds..

Idea is to solve $Rx = Q^T b$ to find the minimizer of $\|Ax - b\|$.

Note: one could define

$$J(x) = \|Ax - b\|^2 = (Ax - b) \cdot (Ax - b)$$

and since $J(x)$ is differentiable one could find the minimum by solving $J'(x) = 0$.

To solve $Rx = Q^T b$ we need to find the factorization $A = QR$ which means Gram-Schmidt in Math 330 and something else next time...

Gram-Schmidt $A = \begin{bmatrix} | & | & \dots & | \\ a_1 & a_2 & \dots & a_n \\ | & | & \dots & | \end{bmatrix}$

$$t_1 = a_1$$

$$q_1 = \frac{t_1}{\|t_1\|}$$

$$t_2 = a_2 - (q_1 \cdot a_2)q_1$$

$$q_2 = \frac{t_2}{\|t_2\|}$$

$$t_3 = a_3 - (q_1 \cdot a_3)q_1 - (q_2 \cdot a_3)q_2$$

$$q_3 = \frac{t_3}{\|t_3\|}$$

$$t_n = a_n - (q_1, a_n)q_1 - \dots - (q_{n-1}, a_n)q_{n-1} \quad q_n = \frac{t_n}{\|t_n\|}$$

Problem: no (or little) flexibility in this algorithm -
But I need flexibility to control propagation of rounding error.

Note solving $Rx = Q^T b$ is a good way to solve $Ax = b$ even when $Ax = b$ has a solution, because minimizing the residual error $\|Ax - b\|$ also minimizes rounding error.

Why is this not ideal? $x = (A^T A)^{-1} A^T b$. Because the matrix $A^T A$ may not be well conditioned...

Note if $A \in \mathbb{R}^{m \times n}$ and $Ax = b$ has no solution, the usual reason is because $m \gg n$. This is overdetermined system of linear equations. But then $A^T A \in \mathbb{R}^{n \times n}$

which is very small in size compared to A . That's another reason the normal equations are not well behaved with rounding error...

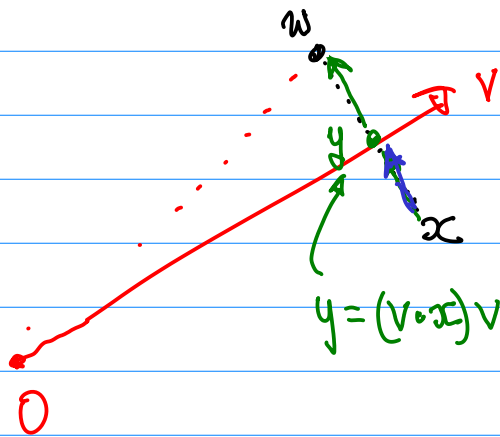
Idea Find $A = QR$ using a different algorithm...

① Method of reflections

② Method of rotations...

Note reflections and rotations are orthogonal transformations, that is they are like the Q matrix.

Let v be a unit vector



reflect x about v
gives w

$$\begin{aligned}
 w &= y + w - y \\
 &= y + y - x \\
 &= 2y - x \\
 &= 2(v \cdot x)v - x \\
 &= 2(v^T x)v - x \\
 &\quad \text{since } v^T x \text{ is a scalar} \\
 &= 2v v^T x - x \\
 &= (2v v^T - I)x
 \end{aligned}$$

Define $H_v x = -w = (I - 2v v^T)x$

$$H_v = I - 2v v^T$$

Next time we use H_v to find QR decomposition of A in a way that behaves well with respect to rounding.