

Last time: Given $A = [a_1 | a_2 | \dots | a_n]$, can orthogonalize $\{a_i\}$ using Gram-Schmidt.

$$q_1 = a_1 / \|a_1\|$$

$$\hat{q}_2 = a_2 - (q_1^* a_2) q_1$$

$$q_2 = \hat{q}_2 / \|\hat{q}_2\|$$

⋮

$$\hat{q}_k = a_k - \sum_{j=1}^{k-1} (q_j^* a_k) q_j$$

$$q_k = \hat{q}_k / \|\hat{q}_k\|$$



$$\|\hat{q}_k\| q_k + \sum_{j=1}^{k-1} (q_j^* a_k) q_j = a_k$$

$$\Rightarrow \underbrace{\begin{bmatrix} | & | & & | \\ q_1 & q_2 & \dots & q_n \\ | & | & & | \end{bmatrix}}_Q \underbrace{\begin{bmatrix} \|\hat{q}_1\| & q_1^* a_2 & q_1^* a_3 & \dots \\ & \|\hat{q}_2\| & & \dots \\ & & \dots & \dots \\ & & & \dots \end{bmatrix}}_R = \underbrace{\begin{bmatrix} | & | & & | \\ a_1 & a_2 & \dots & a_n \\ | & | & & | \end{bmatrix}}_A$$

This is "classical" Gram-Schmidt.

Main problem: numerical roundoff in

$$\hat{q}_k = a_k - \sum_{j=1}^{k-1} (q_j^* a_k) q_j$$

Example: suppose ϵ is a small number, with $1 + \epsilon^2 \approx 1$ (= | in floating pt. arithmetic)

Consider $A = \begin{bmatrix} 1 & 1 & 1 \\ \epsilon & \epsilon & \epsilon \\ 0 & 0 & 0 \end{bmatrix}$. What happens if we apply classical GS?

$$\hat{q}_1 = a_1 = \begin{bmatrix} 1 \\ \epsilon \\ 0 \\ 0 \end{bmatrix}, \quad q_1 = \frac{\hat{q}_1}{\|\hat{q}_1\|} = \begin{bmatrix} 1 \\ \epsilon \\ 0 \\ 0 \end{bmatrix}$$

$\sqrt{1^2 + \epsilon^2} = 1$

$$\begin{aligned} \hat{q}_2 &= a_2 - (a_2^T q_1) q_1 \\ &= \begin{bmatrix} 1 \\ 0 \\ \epsilon \\ 0 \end{bmatrix} - q_1 \begin{bmatrix} 1 \\ \epsilon \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \\ \epsilon \\ 0 \end{bmatrix} - \begin{bmatrix} 1 \\ \epsilon \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ -\epsilon \\ \epsilon \\ 0 \end{bmatrix} \\ q_1^T \hat{q}_2 &= \begin{bmatrix} 1 \\ \epsilon \\ 0 \\ 0 \end{bmatrix}^T \begin{bmatrix} 0 \\ -\epsilon \\ \epsilon \\ 0 \end{bmatrix} = -\epsilon^2 \\ &= \text{kernel of orthogonal?} \end{aligned}$$

$$q_2 = \hat{q}_2 / \|\hat{q}_2\|, \quad \|\hat{q}_2\| = \sqrt{\epsilon^2 + \epsilon^2} = \sqrt{2} \epsilon$$

$$q_2 = \begin{bmatrix} 0 \\ -1/\sqrt{2} \\ 1/\sqrt{2} \\ 0 \end{bmatrix}$$

$$q_1^T q_2 = \begin{bmatrix} 1 \\ \epsilon \\ 0 \\ 0 \end{bmatrix}^T \begin{bmatrix} 0 \\ -1/\sqrt{2} \\ 1/\sqrt{2} \\ 0 \end{bmatrix} = \frac{-1}{\sqrt{2}} \epsilon$$

$$\begin{aligned} \hat{q}_3 &= a_3 - (a_3^T q_1) q_1 - (a_3^T q_2) q_2 \\ &= \begin{bmatrix} 1 \\ 0 \\ 0 \\ \epsilon \end{bmatrix} - \begin{bmatrix} 1 \\ 0 \\ 0 \\ \epsilon \end{bmatrix} \begin{bmatrix} 1 \\ \epsilon \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \\ 0 \\ \epsilon \end{bmatrix} - \begin{bmatrix} 1 \\ \epsilon \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ -\epsilon \\ 0 \\ \epsilon \end{bmatrix} \end{aligned}$$

$$q_3 = \begin{bmatrix} 0 \\ -1/\sqrt{2} \\ 0 \\ 1/\sqrt{2} \end{bmatrix}$$

$$q_1 = \begin{bmatrix} 1 \\ \epsilon \\ 0 \\ 0 \end{bmatrix}, \quad q_2 = \begin{bmatrix} 0 \\ -1/\sqrt{2} \\ 1/\sqrt{2} \\ 0 \end{bmatrix}, \quad q_3 = \begin{bmatrix} 0 \\ -1/\sqrt{2} \\ 0 \\ 1/\sqrt{2} \end{bmatrix}$$

$$q_1^* q_2 = O(\epsilon)$$

$$q_1^* q_3 = O(\epsilon)$$

$$q_2^* q_3 = -\frac{1}{2}$$

"Modified" Gram-Schmidt: main fix

$$\hat{q}_k = a_k - \underbrace{(q_1^* a_k)}_{r_{1k}} q_1 - \underbrace{(q_2^* a_k)}_{r_{2k}} q_2 - \dots - \underbrace{(q_{k-1}^* a_k)}_{r_{k-1,k}} q_{k-1}$$

$$r_{jk} = q_j^* a_k = q_j^* (a_k - r_{1k} q_1 - r_{2k} q_2 - \dots - r_{j-1,k} q_{j-1})$$

$$\text{Since } q_j \perp q_1, q_2, \dots, q_{j-1} \quad \rightarrow \quad = q_j^* (a_k - q_{j-1})$$

$$\text{b/c } q_j^* q_{j-1} = 0$$

Classical GS: given $\{a_j\}$,

for $k=1:n$

$$\hat{q}_k = a_k$$

for $j=1:k-1$

$$|\hat{q}_k = \hat{q}_k - (q_j^* a_k) q_j$$

$$q_k = \hat{q}_k / \|\hat{q}_k\|$$

Modified GS: $\hat{a}_k = a_k$

for $j=1:n$

$k=j+1:n$

$$r_{jj} = \|\hat{q}_j\|$$

$$q_j = \hat{q}_j / r_{jj}$$

for $k=j+1, \dots, n$

$$r_{jk} = q_j^* \hat{q}_k$$

$$\hat{q}_k = \hat{q}_k - r_{jk} q_j$$

r_{jk} "absorb" numerical losses of orthogonality,

$$\hat{q}_k = \underbrace{a_k - q_1(q_1^* a_k)}_{q_k^{(1)}} - \underbrace{q_2(q_2^* a_k)}_{q_k^{(2)}} - \underbrace{q_3(q_3^* a_k)}_{q_k^{(3)}} - \dots$$

$$\begin{aligned} q_k^{(1)} &= a_k - q_1(q_1^* a_k) \\ q_k^{(2)} &= q_k^{(1)} - q_2(q_2^* q_k^{(1)}) \rightarrow \text{vs } (q_2^* a_k) \\ q_k^{(3)} &= q_k^{(2)} - q_3(q_3^* q_k^{(2)}) \rightarrow \text{vs } (q_3^* a_k) \end{aligned}$$

Orthogonalizes against roundoff errors is $q_k^{(j)}$ ($j \geq k$)

Example: $A = \begin{bmatrix} 1 & 1 & 1 \\ \epsilon & & \\ & \epsilon & \\ & & \epsilon \end{bmatrix}$ $q_1 = \begin{bmatrix} 1 \\ \epsilon \\ 0 \\ 0 \end{bmatrix}$ $q_2 = \begin{bmatrix} 0 \\ -1/\sqrt{2} \\ 1/\sqrt{2} \\ 0 \end{bmatrix}$

$$\begin{aligned} \hat{q}_3^{(1)} &= a_3 - (q_1^* a_3) q_1 \rightarrow \begin{bmatrix} 1 \\ 0 \\ 0 \\ \epsilon \end{bmatrix} - \begin{bmatrix} 1 \\ 3\epsilon \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ -\epsilon \\ 0 \\ \epsilon \end{bmatrix} \\ \hat{q}_3^{(2)} &= \hat{q}_3^{(1)} - (q_2^* \hat{q}_3^{(1)}) q_2 \end{aligned}$$

$$\begin{bmatrix} 0 \\ -1/\sqrt{2} \\ 1/\sqrt{2} \\ 0 \end{bmatrix}^* \begin{bmatrix} 0 \\ -\epsilon \\ 0 \\ \epsilon \end{bmatrix} = \epsilon/\sqrt{2}$$

$$\hat{q}_3^{(2)} = \begin{bmatrix} 0 \\ -\epsilon \\ 0 \\ \epsilon \end{bmatrix} - \epsilon/\sqrt{2} \begin{bmatrix} 0 \\ -1/\sqrt{2} \\ 1/\sqrt{2} \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ -\epsilon \\ 0 \\ \epsilon \end{bmatrix} + \begin{bmatrix} 0 \\ \epsilon/2 \\ -\epsilon/2 \\ 0 \end{bmatrix}$$

$$\hat{Q}_3^{(2)} = \begin{bmatrix} 0 \\ \frac{1}{\sqrt{2}} \\ -\frac{1}{\sqrt{2}} \\ \varepsilon \end{bmatrix}, \quad Q_3 = \begin{bmatrix} 0 \\ -\frac{1}{\sqrt{6}} \\ -\frac{1}{\sqrt{6}} \\ \sqrt{2/3} \end{bmatrix}$$

$$Q_2^* Q_3 = \begin{bmatrix} 0 \\ -\frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \\ 0 \end{bmatrix} \begin{bmatrix} 0 \\ -\frac{1}{\sqrt{6}} \\ -\frac{1}{\sqrt{6}} \\ \sqrt{2/3} \end{bmatrix} = 0$$

Same cost $O(n^3)$

Note: need modifications if $A \in \mathbb{R}^{m \times n}$ but $\text{rank}(A) < n$
 \Rightarrow rank deficient matrix

$$\begin{pmatrix} | & & | & & | \\ a_1 & \dots & a_k & \dots & a_n \\ | & & | & & | \end{pmatrix} \quad \begin{matrix} \hat{Q}_k = 0 \\ \hat{Q}_k = \frac{0}{0} \end{matrix}$$

$a_k = \text{linearly dep. on } a_1, \dots, a_{k-1}$

\Rightarrow can avoid by permuting / ignoring \hat{Q}_k
 (pivoting)

QR: solving linear systems. $A \in \mathbb{R}^{n \times n}$
 $Q \in \mathbb{R}^{n \times n}, R \in \mathbb{R}^{n \times n} \quad QR = A$

$$Ax = b \Rightarrow QRx = b \quad \text{since } Q^*Q = I$$

$$\Rightarrow Rx = Q^*b = y$$

Solve via backsubstitution

$$\begin{bmatrix} r_{11} & r_{12} & \dots & \dots \\ & r_{22} & r_{23} & \dots \\ & & r_{33} & \dots \\ & & & \ddots \\ & & & & r_{nn} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix}$$

$$\left. \begin{array}{l} \textcircled{1} \quad r_{nn} x_n = y_n \Rightarrow x_n = \frac{y_n}{r_{nn}} \\ \textcircled{2} \quad r_{n-1,n-1} x_{n-1} + r_{n-1,n} x_n = y_{n-1} \\ \Rightarrow x_{n-1} = \frac{y_{n-1} - x_n r_{n-1,n}}{r_{n-1,n-1}} \\ \textcircled{j} \quad x_j = \frac{1}{r_{jj}} \left(y_j - \sum_{k=j+1}^n r_{jk} x_k \right) \end{array} \right\} \begin{array}{l} O(n^2) \\ \text{operations} \end{array}$$

$$\left. \begin{array}{l} A = QR = O(n^3) \\ \text{Mult. by } Q^* = O(n^2) \\ \text{Backsub} = O(n^2) \end{array} \right\} \begin{array}{l} \text{If you need} \\ Ax_i = b_i \quad i=1, \dots, 100 \\ \Rightarrow \text{compute QR once} \\ \& \text{ use } Q^* \& \text{ backsubs} \end{array}$$

QR very suitable for matrix least square problems!

$$A \in \mathbb{R}^{m \times n} \quad m \geq n$$

Cannot solve $Ax=b$ exactly

$$\Rightarrow \text{min } \|Ax - b\|^2$$

$$\Rightarrow A^T A x = A^T b \quad \left(\begin{array}{l} \text{sub } q_n \\ A = QR \end{array} \right)$$

$$(QR)^T(QR)x = (Q^T Q^T) b$$

$$R^T \underbrace{Q^T Q}_I R x = R^T Q^T b$$

$$R^T(Rx) = R^T(Q^T b)$$

$$\Rightarrow Rx = Q^T b$$