

The QR-factorization ← the foundation of NLA, in
some sense. (Minimum least squares solution.)

Three scenarios

$$\textcircled{I} \quad \begin{matrix} n \\ m \end{matrix} \begin{matrix} A \end{matrix} = \begin{matrix} n \\ m \end{matrix} \begin{matrix} Q \end{matrix} \begin{matrix} R \end{matrix}$$

$$\textcircled{II} \quad \begin{matrix} n \\ m \end{matrix} \begin{matrix} A \end{matrix} = \begin{matrix} m \\ m \end{matrix} \begin{matrix} Q \end{matrix} \begin{matrix} R \end{matrix}$$

"full QR"

$$\textcircled{III} \quad \begin{matrix} n \\ m \end{matrix} \begin{matrix} A \end{matrix} = \begin{matrix} m \\ m \end{matrix} \begin{matrix} Q \end{matrix} \begin{matrix} R \end{matrix}$$

Assuming rank $A = \min(m, n)$,
reduced-rank next

There are two basic approaches for computing QR :

(1) Gram-Schmidt \downarrow orthogonalization

(2) Householder reflection \uparrow triangularization
 \uparrow orthogonal

Consider type I first.

$$\boxed{A} = \boxed{Q} \begin{matrix} \text{R} \\ \diagdown \end{matrix}$$

\Rightarrow

$$\boxed{A} \boxed{R^{-1}} = \boxed{Q}$$

orthogonal

This says to compute entries of R^{-1}

such that they orthogonalize the
columns of $A \Rightarrow$ Gram-Schmidt

I.e. if $A = (\vec{a}_1, \vec{a}_2, \dots, \vec{a}_n)$

$$Q = (\vec{q}_1, \vec{q}_2, \dots, \vec{q}_n)$$

then $\vec{a}_1 = r_{11} \vec{q}_1$
 $\vec{a}_2 = r_{12} \vec{q}_1 + r_{22} \vec{q}_2$
 \vdots
 $\vec{a}_n = r_{1n} \vec{q}_1 + \dots + r_{nn} \vec{q}_n$

{ (*)

G-S: Turn $\vec{a}_1, \dots, \vec{a}_n$ into $\vec{q}_1, \dots, \vec{q}_n$

On step j , set $\vec{v}_j = \vec{a}_j - (q_1, \vec{a}_j) \vec{q}_1 - \dots - (q_{j-1}, \vec{a}_j) \vec{q}_{j-1}$

and then $\vec{q}_j = \frac{\vec{v}_j}{\|\vec{v}_j\|}$

Comparing with (*) we see that

~~they're the same~~

Comparing with (*) this

implies that $r_{ij} = (q_i, \vec{a}_j)$

and $|r_{jj}| = \|\vec{v}_j - \sum_{i=1}^{j-1} r_{ij} \vec{q}_i\|$

$$\text{since } \vec{r}_{jj} \vec{q}_j = \vec{a}_j - r_{1j} \vec{q}_1 - \dots - r_{j-1,j} \vec{q}_{j-1}$$

(and take norms)

Code

do for $j=1, n$

$$\vec{v}_j = \vec{a}_j$$

do $i=1, j-1$

$$r_{ij} = (\vec{q}_i, \vec{a}_j)$$

$$\vec{v}_j = \vec{v}_j - r_{ij} \hat{q}_i$$

end

$$r_{jj} = \|\vec{v}_j\|$$

$$\hat{q}_j = \vec{v}_j / r_{jj}$$

end

$$\left(\vec{q}_1 = \frac{\vec{a}_1}{\|\vec{a}_1\|} \right)$$

This G-S algorithm

is unstable!

round-off error can
accumulate

An alternative way to think
about this algorithm:

Define \hat{Q}_{j-1} as $\hat{Q}_{j-1} = (\hat{q}_1, \hat{q}_2, \dots, \hat{q}_{j-1})$

and P_j as the projector onto the subspace orthogonal
to $\text{col}(\hat{Q}_{j-1})$: $P_j = I - \hat{Q}_{j-1} \hat{Q}_{j-1}^*$

The "classical" G-S algorithm is then

$$\hat{q}_1 = \frac{\vec{a}_1}{\|\vec{a}_1\|} = \frac{P_1 \vec{a}_1}{\|P_1 \vec{a}_1\|}$$

:

$$\hat{q}_j = \frac{P_j \vec{a}_j}{\|P_j \vec{a}_j\|}$$

"Modified" G-S is stable, and writes this projection
in a different form:

$$\begin{aligned} P_j &= I - \hat{Q}_{j-1} \hat{Q}_{j-1}^* \\ &= \underbrace{(I - \hat{q}_{j-1} \hat{q}_{j-1}^*)}_{P_{\perp \hat{q}_{j-1}}} \underbrace{(I - \hat{q}_{j-2} \hat{q}_{j-2}^*)}_{P_{\perp \hat{q}_{j-2}}} \dots (I - \hat{q}_1 \hat{q}_1^*) \end{aligned}$$

These are mathematically equivalent, but numerically
different.

CODE

```
DO j=1,n
     $\vec{v}_j = \vec{a}_j$ 
END
```

} initialize the \vec{v}_j 's } cost: $\theta(mn)$, no-ops

(4)

DO $i=1, n$

$$r_{ii} = \|\vec{v}_i\| \quad \dots \dots \quad \Theta(m)$$

$$\hat{q}_i = \vec{v}_i / r_{ii} \quad \dots \dots \quad \Theta(m)$$

DO $j=1+i, n$

$$r_{ij} = (\hat{q}_i, \vec{v}_j) \quad \dots \dots \quad \Theta(m)$$

$$\vec{v}_j = \vec{v}_j - r_{ij} \hat{q}_i \quad \left. \right\} P_{\perp \hat{q}_i} \quad \dots \dots \quad \Theta(m)$$

END

END

¶ This is the GS algorithm used in practice.

How expensive is it? (See flop counts above)

$$\sum_{i=1}^n \left(3m + \sum_{j=1+i}^n (2m+2m) \right) \sim \sum_{i=1}^n \sum_{j=1+i}^n 4m \sim \boxed{\Theta(2mn^2)}.$$

- This is a cubic algorithm (like Gaussian elim, basically).

- Suited to Type I factorizations:

$$_m^n A = _m^n Q \begin{matrix} n \\ \diagdown \end{matrix} _n R$$

Aside: "big-oh" notation
 $f(n) \sim \Theta(g(n))$ if
 $f(n) \leq Cg(n)$ for
all $n > n_0 > 0$.

Next, consider Type II:

$$\begin{matrix} n \\ m \end{matrix} \boxed{A} = \begin{matrix} m \\ m \end{matrix} \boxed{\hat{Q}} = \begin{matrix} n \\ m \end{matrix} \boxed{R}$$

G-S will not produce an orthonormal basis for \mathbb{R}^m when $m > n$ — we need an alternative.

Consider the following: If $A = \hat{Q}R$ (as above)

then $\hat{Q}^* A = R$. Can we construct a \hat{Q}^* that transforms A into an upper triangular matrix? Yes! Using "Householder Reflections".

Step 1 Consider the first column of R :

$$\begin{matrix} n \\ m \end{matrix} \boxed{R}$$

→ Every element is zero except for the first one.

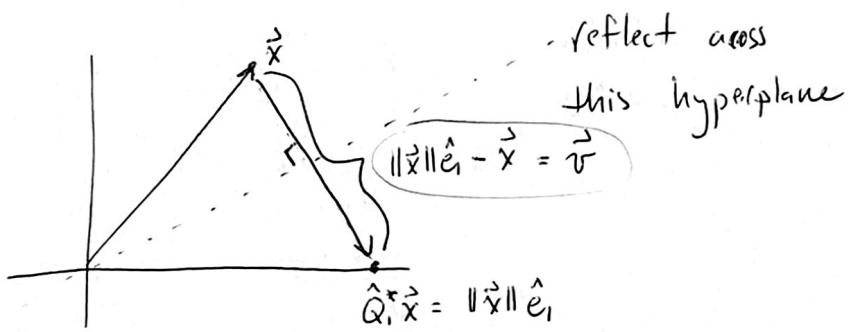
Q: Can we find \hat{Q}_1^* such that $\hat{Q}_1^* \cancel{\hat{Q}_1} \vec{a}_1 = \begin{matrix} ? \\ 0 \end{matrix}$?

It must be that $\|\vec{r}_1\| = \|\vec{a}_1\|$ since \hat{Q}_1^* is orthogonal.

This can be achieved using a Householder reflection.

(numerically as, or more, stable than Gram-Schmidt).

Geometrically:

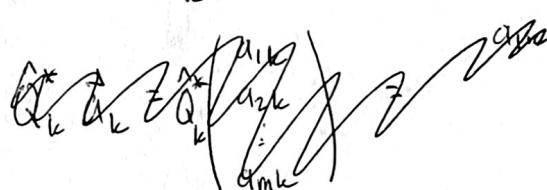


$$\hat{Q}_1^* \begin{pmatrix} x_1 \\ \vdots \\ x_m \end{pmatrix} = \begin{pmatrix} \|x\| \\ 0 \\ \vdots \\ 0 \end{pmatrix} = \|x\| \hat{e}_1$$

Easy to show that this \hat{Q}_1^* is given by $\hat{Q}_1^* = I - 2 \frac{\hat{v} \hat{v}^*}{\hat{v}^* \hat{v}}$
 (One could also reflect the "other" way to $- \|x\| \hat{e}_1$, should choose the direction furthest from \hat{x} for stability reasons.)

What about \hat{Q}_k^* ?

Need



$$\hat{Q}_k^* \hat{x} = \hat{Q}_k^* \begin{pmatrix} x_1 \\ \vdots \\ x_k \\ x_{k+1} \\ \vdots \\ x_m \end{pmatrix} = \begin{pmatrix} x_1 \\ \vdots \\ x_{k-1} \\ \|x_k - x_m\| \\ 0 \\ \vdots \\ 0 \end{pmatrix} = \begin{pmatrix} I_{k \times k} & 0 \\ 0 & F_{(m-k) \times (m-k)} \end{pmatrix}$$

Reflector of size $(m-k) \times (m-k)$.