

Welcome back to Ma221! Lecture 21, Oct 11

Solving Low rank LS using QR
with column pivoting

Ex: $A = \begin{bmatrix} e & 1 \\ 0 & 0 \end{bmatrix}$ e tiny $\arg\min_x \|Ax - b\|_2$

$\Rightarrow x = \begin{bmatrix} (b_1 - x_2)e \\ x_2 \end{bmatrix}$ e tiny \Rightarrow
very sensitive to
 b_1 or x_2

$AP = \begin{bmatrix} 1 & e \\ 0 & 0 \end{bmatrix} \Rightarrow x = \begin{bmatrix} b_1 - e \cdot x_2 \\ x_2 \end{bmatrix}$
insensitive to changes in b, x_2

What does a good R look like in general?

Compare $\begin{matrix} k & n-k \\ \begin{bmatrix} R_{11} & R_{12} \\ 0 & R_{22} \end{bmatrix} \end{matrix}$ with $\begin{matrix} k & n-k \\ \begin{bmatrix} \Sigma_1 & 0 \\ 0 & \Sigma_2 \end{bmatrix} \end{matrix}$

Def Rank Revealing QR (RRQR)
is $A \cdot P = QR$ $P = \text{permutation}$ s.t.

① R_{22} is "small", ideally $\|R_{22}\|_2 = \sigma_{k+1}(A)$
 R_{22} "contains" smallest $n-k$ singular
values

② R_{11} is "large", ideally
 $\sigma_{\min}(R_{11}) = \sigma_k(A)$,
not too much smaller

If in addition

③ $\|R_{11}^{-1} R_{12}\|_2$ not "too large"

then $AP = QR$ called "strong RQR"

Thm: if ①, ②, ③ hold then

$$\sigma_i(A) \geq \sigma_i(R_{11}) \geq \frac{\sigma_i(A)}{\sqrt{1 + \|R_{11}^{-1} R_{12}\|_2^2}} \quad \text{for } i=1 \dots k$$

$$\sigma_i(A) \leq \sigma_{\max}(R_{22}) \cdot \sqrt{1 + \|R_{11}^{-1} R_{12}\|_2^2} \quad i = k+1 \dots n$$

Leading k columns of AP contain most information about $\text{range}(A)$

$$AP = \begin{bmatrix} A_1 & A_2 \end{bmatrix} = QR = \begin{bmatrix} Q_1 & Q_2 \end{bmatrix} \begin{bmatrix} R_{11} & R_{12} \\ \mathbf{0} & R_{22} \end{bmatrix}$$

$$\approx \begin{bmatrix} Q_1 & Q_2 \end{bmatrix} \cdot \begin{bmatrix} R_{11} & R_{12} \\ \mathbf{0} & \mathbf{0} \end{bmatrix} \quad \text{where } \sigma_{k+1}(A) \text{ small}$$

$$\begin{aligned} &= \begin{bmatrix} Q_1 \end{bmatrix} \begin{bmatrix} R_{11} & R_{12} \end{bmatrix} = Q_1 R_1 \begin{bmatrix} I & R_{11}^{-1} R_{12} \end{bmatrix} \\ &= A_1 \begin{bmatrix} I & \underbrace{R_{11}^{-1} R_{12}}_{\text{not large}} \end{bmatrix} \end{aligned}$$

How to compute P

Algorithm: QR with column pivoting

QRCP for short

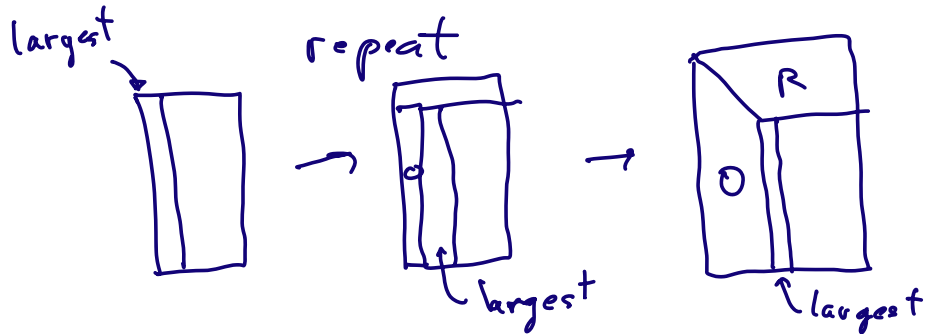
analogous to partial pivoting:

simple greedy algorithm

often works; like GEPP, can fail in

rare cases by factor 2^n

First step: pick largest (in norm) column of A
 move it to front
 take one step of QR
 among remaining columns, pick one
 with largest orthogonal component
 to first column
 repeat



for $i=1$ to $\min(m-1, n)$ or
 when R_{22} small enough
 ("truncated QR")

choose largest column in norm
 in trailing matrix

$$\operatorname{argmin}_{j \geq i} \|A(i:m, j)\|_2$$

if $i \neq j$, swap columns i & j
 multiply $A(i:m, i:n)$ by Householder
 matrix to zero out $A(i+1:m, i)$

Suppose we stop after k steps
 because $\|R_{22}\| < \text{user threshold}$
 $\Rightarrow \text{cost} = 4 \cdot m \cdot n \cdot k$ vs. $O(mn^2)$ for
 full QR

Naive way to compute column norms
costs $O(mn^2)$, too much

cheaper: $O(mn)$ by subtracting out
one row at each step

oops: get roundoff if norm small
at later step \Rightarrow if norm
small enough, recompute, continue

Drawbacks: can fail in rare cases
maximizes communication

Lapack: `geqpf` (truncated QR
in next release)

Matlab: $[Q, R, P] = qr(A)$

Matlab demo: (code in typed notes)

How to fix failure, communication (i.e. all
BLAS 2 so far)

Strong RRQR alg: Gu, Eisenstat

- avoids failures by pivoting correctly
- more complicated pivoting rule
exchange a column in R_{ii} and one
not in R_{ii} to maximize $\det(R_{ii})$
- guarantees strong RRQR i.e. $\|R_{ii}^{-1} R_{i+1,i}\|$
bounded by $\text{poly}(n)$
- more expensive, still $O(m \cdot n \cdot k)$ if
stop after k steps

Avoiding communication:

All BLAS2 so far \Rightarrow

touch whole trailing submatrix
at each step via Householder

\Rightarrow data movement = $O(mn^2)$

vs. $O\left(\frac{mn^2}{\sqrt{\text{cache size}}}\right)$

Use BLAS3 as in QR \Rightarrow can only do
half flops in BLAS3

Hit lower bound:

Tournament Pivoting: pick b columns
at a time, not 1

Randomization (Duersch, Gu, 2017)

Low Rank Factorization without
Orthogonal Factors

Why avoid orthogonality:

- ① maintain sparsity
- ② explainability in data science

Ex: A : rows represent people
cols " characteristics
age, weight, etc

Suppose a column of Q is

$$= .2 \cdot \text{age} - .3 \cdot \text{height} + .1 \cdot \text{income}$$

hard to interpret as a prediction of another column, say "been treated for some disease"

Instead: approximate each column by linear combinations of as few other columns as possible:

Def: CUR decomposition of A

C = subset of k columns of A

R = " " k rows of A

U = $k \times k$ matrix

where $\|A - C \cdot U \cdot R\|$ is small, close to

lots of algorithms (see web page ^{σ_{\min}})

(1) Choose C : perform QR with column pivoting: " k most linearly independent columns"

$J = \{j_1, j_2, \dots, j_k\}$ = indices of cols

$$C = A(:, J)$$

(2) Perform: GEPP on C to pick " k most linearly independent rows" of C

$$I = \{i_1, i_2, \dots, i_k\} \quad R = A(I, :)$$

(3) pick U : (HWQ 3.12)
choose U to minimize $\|A - CUR\|_F$
answer: $U = C^+ A R^+$

(c) cheaper: choose U so $CUR = A$
in rows I and columns J
 $U = (A(I, J))^{-1}$