

Today: $n \times n^2$ $n \times \begin{bmatrix} k \\ j \end{bmatrix} \times Q$
proj-form LRA $A \times Q Q^T A$

two story holes:

- Q from where?

- Computing $Q^T A$ is a killer

"Interpolative Decomposition" $\rightarrow ID$

Giving up optimality

What problem should we actually solve then?

$$\|A - QQ^T A\|_2 = \min_{\text{rank}(X) \leq k} \|A - X\|_2 = \sigma_{k+1}$$

$$\|A - QQ^T A\|_2 = \min_{\text{rank}(X) \leq k} \|A - X\|_2 = \sigma_{k+1} \cdot C$$

column n basis allowed to longer,
keep

Recap: The Power Method

How did the power method work again?

A diagonalizable w/ eigenvalues $\lambda_1, \dots, \lambda_n$ and eigenvectors x_1, \dots, x_n

$$|\lambda_1| > |\lambda_2| > \dots > |\lambda_n| \geq 0$$

$$y = \alpha_1 x_1 + \dots + \alpha_n x_n$$

$$\frac{Ay}{\lambda_1} = \alpha_1 x_1 + \dots + \frac{\lambda_n}{\lambda_1} \alpha_n x_n$$

How do we construct the LRA basis?

Put randomness to work:

1. Draw a $n \times l$ Gaussian (iid) matrix Ω

2. $Y = A\Omega$

3. $Y = QR$

4. Carry on with Q

$\rightsquigarrow \Omega$

Tweaking the Range Finder (I)

Can we accelerate convergence?

$$y = (AA^T)^q A \Omega$$

$$A = U \Sigma V^T$$

$$(\cancel{U \Sigma V^T} \cancel{V \Sigma U^T})^q U \Sigma V^T$$

$$= U \Sigma^q V^T$$

Tweaking the Range Finder (II)

What is ~~one~~ possible issue with the power method?

- overflow / FP problems
- QR after each application of A or A^T can help
- Ω not in the correct space
 - errors will eventually amplify the "biggest" left singular vectors

Even Faster Matvecs for Range Finding

$$A\Omega \rightarrow N^2 \ell$$

Assumptions on Ω are pretty weak—can use more or less anything we want.

→ Make it so that we can apply the matvec $A\Omega$ in $O(n \log \ell)$ time.

How? Pick Ω as a carefully-chosen subsampling of the Fourier transform.

7 x

Errors in Random Approximations

If we use the randomized range finder, how close do we get to the optimal answer?

Theorem

For an $m \times n$ matrix A , a target rank $k \geq 2$ and an oversampling parameter $p \geq 2$ with $k + p \leq \min(m, n)$, with probability $1 - 6 \cdot p^{-p}$,

$$\|A - QQ^T A\|_2 \leq \left(1 + 11\sqrt{k+p}\sqrt{\min(m,n)}\right) \sigma_{k+1}.$$

(given a few more very mild assumptions on p)

[Halko/Tropp/Martinsson '10, 10.3]

Message: We can *probably* (!) get away with oversampling parameters as small as $p = 5$.

A-posteriori and Adaptivity

The result on the previous slide was *a-priori*. Once we're done, can we find out 'how well it turned out'?

estimate $\|A - QQ^T A\|_2$
 $E = (I - QQ^T)A$

We're interested in $\sigma_1(E)$
rand. vecs with $\|w\|_2 = 1$

Use $\|E\|_2 \approx \frac{\|Aw\|_2}{\|w\|_2}$

Adaptive Range Finding: Algorithm

- Compute a small-ish CRA
- Check whether it's OK (by the estimation proc.)
- Too big? Continue with more rand. vec.

Rank-revealing/pivoted QR

Sometimes the SVD is too *good* (aka expensive)—we may need less accuracy/weaker promises, for a significant decrease in cost.

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

$$A \Pi = QR = Q \begin{pmatrix} R_{11} & R_{12} \\ & R_{22} \end{pmatrix}$$

where

$$R_{11} \in \mathbb{R}^{k \times k}$$

$\|R_{22}\|_2$ is "small"

$$Q^T Q = I$$



Using RRQR for LRA

G/vL ch.5

- $\sigma_{k+1} \in \|R_{22}\|_2$ (it won't beat the SVD)
- To precision $\|R_{22}\|_2$, A has num. rank k .

Interpolative Decomposition (ID): Definition

Would be helpful to know *columns of A* that contribute 'the most' to the rank.

(orthogonal transformation like in QR 'muddies the waters')

For a rank- k matrix A

$$A_{m \times n} = A_{[:,j]}_{m \times k} P_{k \times n}$$

- P is well-conditioned (the magnitude of all entries ≤ 2)

ID: Computation

How do we construct this (from RRQR): (short/fat case)

$$A\Pi = Q \begin{pmatrix} R_{11} & R_{12} \end{pmatrix} \quad B = QR_{11} = A_{[:,j]}$$

Q: What is P , in terms of the RRQR?

$$P = \begin{bmatrix} I_d & R_{11}^{-1} R_{12} \end{bmatrix}$$

$$BP = QR_{11} \begin{bmatrix} I_d & R_{11}^{-1} R_{12} \end{bmatrix}$$

$$= Q \begin{bmatrix} R_{11} & R_{12} \end{bmatrix} = A\Pi$$

ID Q vs ID A

What does row selection mean for the LRA?

$$A \approx Q Q^T A$$

$$Q = P Q_{[j,:]}$$

$$A_{[j,:]} = \cancel{P}_{[j,:]} Q_{[j,:]} Q^T A$$

$$P A_{[j,:]} = \underbrace{P}_{\approx Q} Q_{[j,:]} Q^T A$$

[Martinsson, Rokhlin, Tygert '06]

Demo: Interpolative Decomposition

$$A = U \Sigma V^T$$

$$A_{[j,i]} = U_{[j,i]} \Sigma V^T$$

not orth.

What does the ID buy us?

Name a property that the ID has over other factorizations.

All our randomized tools have two stages:

1. Find ONB of approximate range
2. Do actual work only on approximate range

Complexity?

What is the impact of the ID?

ID-based Complexity Reduction

How can we reduce factorization complexity with the ID?

