

Lecture 20

To solve an arbitrary system, are there any common cases where using a rank-k update on a triangular matrix is slower than directly applying LU decomposition?

If k is big enough - $k > 1/2, 1/10$?

Trading rank k

You can solve more slowly how!

From lecture: We discussed the problem $(d x) / (d t) = A x(t)$. There we used $(d x) / (d t) \approx (x(t+h) - x(t)) / h = A x(t+h)$. My question is: Is the first approximation really saying the following?

$$(d x) / (d t) \approx (x(t+h) - x(t)) / h \approx x(t+h) - x(t) / h = A x(t+h)$$

$$\frac{dx}{dt} \approx \frac{x(t+h) - x(t)}{h}$$

$$= A x(t+h) \text{ (using } t+h, t \text{ to approx)}$$

$$\text{OR } = A x(t) \text{ (using } t, t+h \text{ to approx)}$$

$$\downarrow$$

$$x(t+h)$$

For SMW and a problem in HW1, I think about the problem of "change in A^{-1} with infinitesimal perturbation δB " and I get $A^{-1} \delta B A^{-1}$ (handwavy) is that generally useful?

$$A^{-1} \delta B A^{-1} \text{ or } (A + \delta B)^{-1}$$

$$\frac{d}{dt} \approx \frac{x(t+h) - x(t)}{h}$$

$$= A x(t+h) \text{ (using } t+h, t \text{ to approx)}$$

$$\text{OR } = A x(t) \text{ (using } t, t+h \text{ to approx)}$$

$$\downarrow$$

$$x(t+h)$$

$$A^{-1} \delta B A^{-1}$$

$$x_i(A) = A^{-1} e_i \Rightarrow A x_i(A) = e_i$$

For matrix functions, what if the matrix isn't symmetric/diagonalizable, how would we define $f(A)$?

Can we generalize the notion of matrix functions to non-symmetric matrices using the SVD? By defining functions over singular values instead of eigenvalues?

What is $f(A)$?

1. If $f(x)$ has a convergent power series $f(x) = \sum \alpha_k x^k$

$$\text{Then } f(A) = \sum \alpha_k A^k$$

$$2. A = X J X^{-1} \text{ is Jordan form.}$$

$$f(A) = X f(J) X^{-1}$$

Applications where generalized eigenvalue decomposition show up?

When perturbing A with a rank-1 update $(A+uv^T)y=c$, how do we know what c is?

Why the rank-1 update drastically reduces computation compared to re-factoring the entire matrix? Is there a scenario where applying a rank-1 update is especially beneficial?

In general, can every solver that solves $Ax = b$ efficiently be adapted to also solve $AX = B$ efficiently?

Why is factorization (LU, QR, or Cholesky) still the best approach even when right-hand sides depend on previous solutions?

Apps of gen. λ -vols:

• Speeches Cluster

• Find Eigen

• $Ax = \lambda Bx$

• $Ax = \lambda Mx$

• M - mass matrix

• State - See Eigen + state learning.

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