

Dec 16, 2020

$Ax = b$

$PA = LU$
 $A = LL^T$

$k_2(A) = \sigma_{max} / \sigma_{min}$

$\min \|Ax - b\|_2$

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

$k_2(A)$ b , $\text{range}(A)$
orthog. matrices

$Ax = \lambda x$

$A = V \Lambda V^T$
 $A = Q T Q^H$
 $A = U H U^T$
 $A = U \Sigma W^T$



orthog matrices

condition number \Rightarrow sensitivity to perturbations

$AQ_k = Q_{k+1} \bar{T}_k$

$AQ_k = Q_{k+1} \bar{H}_k$

$AV_k = U_{k+1} \bar{R}_k$

$A^T U_k = V_{k+1} \bar{R}_{k+1}^T$

condition number \Rightarrow convergence

structure matters!!!

- sparse
- symm
- blocked
- fast operators
- diag dominant

orthog

symm
orthog

Other tools

- optimization / analysis: CG (Krylov), Gauss-Seidel \Leftrightarrow coord desc.

$$2x^T A^T A x = 2A^T b$$

$$\Rightarrow A^T A x = A^T b$$

$$r(x) = \frac{x^T A x}{x^T x}$$

- graph theory: sparse direct
- hardware: blocking / BLAS 3, layouts, floating point
- statistics: trunc. SVD \Leftrightarrow reg LS
- approx theory: convergence of iterative methods

Where to go from here

CS 6220: Data-sparse matrix computations
structure \Rightarrow super fast

- rank-structured mats $Ax=b$ in $O(n)$ time
- Rand NLA
- FMM, FFT

CS 6241: Matrix comps in data science

- NMF, other facts
- GPs / kernel methods
- Graph data

Thank you!