

Numerics Methods and Useful Facts

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1 Linear Algebra

1.1 Classification of Matrices

Matrices are assumed to be complex unless specified otherwise.

1.1.1 Hermetian

Definition: A matrix A is Hermetian if $A^* = A$

Properties:

- \Rightarrow Real eigenvalues
- \Rightarrow Normal
- \Rightarrow Unitarily diagonalizable
- $\Rightarrow \|A\|_2 = \rho(A)$

1.1.2 Skew symmetric

Definition: A real matrix A is skew symmetric if $A^T = -A$

Properties:

- \Rightarrow pure imaginary eigenvalues
- $\Rightarrow I + A$ is invertible

1.1.3 Normal

Definition: A matrix A is normal if $A^*A = AA^*$

Properties:

- \Leftrightarrow Unitarily diagonalizable

1.1.4 Positive definite

Definition: A matrix A is positive definite if all eigenvalues are positive.

Properties:

- $\Leftrightarrow v^*Av > 0$ for all v
- \Leftrightarrow Has Cholesky factorization

1.2 Matrix Decompositions

1.2.1 SVD

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

- U unitary
- Σ diagonal, with real positive entries in non-increasing order
- V unitary

Existence: Always

Uniqueness: *Note: double check* Unique up to complex sign of columns of U and V

Computing:

Why it is useful:

- Rank revealing
- Numerical stability of algorithms using SVD

1.2.2 (P)LU

Existence:

Uniqueness:

Computing: Gaussian Elimination

When is pivoting needed?

1.2.3 Cholesky

Existence: If A is Hermetian positive definite

Uniqueness: Unique up to sign

Why it is useful:

- Save storage space

1.2.4 QR

1.2.5 Eigen

1.3 Matrix and Vector Norms

$$\|A\| = \sup_{u \neq 0} \frac{\|Au\|}{\|u\|} = \sup_{\|u\|=1} \|Au\|$$

$$\|A\| = \sup_{u,v \neq 0} \frac{\langle Au, v \rangle}{\|u\| \|v\|} = \sup_{\|u\|=\|v\|=1} \langle Au, v \rangle$$

If A is self Hermetian, *Note: double check this*

$$\|A\| = \sup_{u \neq 0} \frac{\langle Au, u \rangle}{\|u\|^2} = \sup_{\|u\|=1} \langle Au, u \rangle$$

1.4 Rayleigh Quotients

Note: Anne seems to like these

1.5 Miscellaneous

1.5.1 Gradients of Matrix Vector Forms

$$\nabla x^* Ax = 2Ax$$

1.6 Iterative Methods

1.6.1 Simple Iteration

1.6.2 Conjugate Gradient

1.6.3 GMRES

2 Boundary Value Problems

2.1 Laplacian

3 Initial Value Problems

Note: need better section names

3.1 Runge-Kutta Methods

3.2 LMMs

3.3 Stability

zero stable

region of abs stability

A stable L stable etc

MOL

Von Neumann