

Numerics Methods and Useful Facts

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1 Calculus

1.1 Gradient and Jacobian

For $f : \mathbb{R}^n \rightarrow \mathbb{R}$ we define the gradient as,

$$\nabla f = \left[\frac{\partial f}{\partial x_1}, \frac{\partial f}{\partial x_2}, \dots, \frac{\partial f}{\partial x_n} \right]$$

For $f : \mathbb{R}^n \rightarrow \mathbb{R}^m$ we define the Jacobian as,

$$J_f = \begin{bmatrix} \nabla f_1 \\ \nabla f_2 \\ \vdots \\ \nabla f_m \end{bmatrix} = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} & \dots & \frac{\partial f_1}{\partial x_n} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} & \dots & \frac{\partial f_2}{\partial x_n} \\ \vdots & \vdots & & \vdots \\ \frac{\partial f_m}{\partial x_1} & \frac{\partial f_m}{\partial x_2} & \dots & \frac{\partial f_m}{\partial x_n} \end{bmatrix}$$

Note that a linear approximation to f at x_0 is given by,

$$f(x_0) + J_f x$$

1.2 Gradients of Matrix Vector Forms

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

$$\nabla x^T A x = (A + A^T)x$$

1.3 Taylor Expansions

2d case.

1.3.1 Computing Expansions in Mathematica

2 Matrices

2.1 Classification of Matrices

Matrices are assumed to be complex unless specified otherwise.

2.1.1 Hermetian

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

Properties:

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

2.1.2 Skew symmetric

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

Properties:

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

2.1.3 Normal

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

Properties:

- \Leftrightarrow Unitarily diagonalizable

2.1.4 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

2.2 ???

Where should I put things like similarity transform, unitarily diagonalizable, etc.

Also things like

2.3 Matrix Decompositions

2.3.1 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

2.3.2 (P)LU

Existence:

Uniqueness:

Computing: Gaussian Elimination

When is pivoting needed?

2.3.3 Cholesky

Existence: If A is Hermetian positive definite

Uniqueness: Unique up to sign

Why it is useful:

- Save storage space

2.3.4 QR

2.3.5 Eigen

2.3.6 Shur

2.3.7 Jordan Normal

2.4 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*

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

2.5 Rayleigh Quotients

Note: Anne seems to like these

3 Linear Systems

3.1 Direct Methods

3.1.1 QR

3.1.2 Gaussian Elimination

3.1.3 SVD

3.2 Iterative Methods

3.2.1 Simple Iteration

3.2.2 Conjugate Gradient

3.2.3 GMRES

3.3 Solving Least Squares

The linear least squares problem is,

$$\min_x \|b - Ax\|_2$$

This is solved when x solve the linear system (called the normal equations),

$$A^T Ax = A^T b$$

3.3.1 Derivations of Normal Equations

Using Projectors:

Using Calculus:

Note that

$$\|b - Ax\| = (b - Ax)^T(b - Ax) = b^T b + -2b^T Ax + x^T(A^T A)x$$

Therefore, taking the gradient of $\|b - Ax\|$, we know it is minimized when $2A^T Ax - 2A^T b = 0$.

Note: How do we do derivative of things like x^*Ax

3.3.2 Solving Least Squares Numerically

4 Boundary Value Problems

4.1 Laplacian

5 Initial Value Problems

Note: need better section names

5.1 Runge-Kutta Methods

5.2 LMMs

5.3 Stability

zero stable

region of abs stability

A stable L stable etc

MOL

Von Neumann