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- Basic Knowledge 1

舍入误差, Taylor 展开, 均值定理. 以及一些迭代公式与 stable 的问题.

- 1. Mean value theorem
- 2. Taylor expansion
- 3. Roundoff error

\subseteq Solution of Equations

分析收敛与稳定 (Convergence + Stability)

1. Solution of equations with one variable 2

不动点法, 二分法, 牛顿法

1.1 二分法

Theorem \equiv **.** 1 $f \in C[a,b]$ and f(a)f(b) < 0. A sequence $\{p_n\}(n=0,1,2,\cdots)$ approximating a zero p of f with $|p_n-p| \leq \frac{b-a}{2^n}$, where $n \geq 1$.

不能有重根,多根.

1.2 不动点

$$f(x) = 0 \Longleftrightarrow x = g(x)$$

Theorem 二、.2 $g \in [a,b]$, $\exists g'(x)$ and g'(x) = k, $k \in (0,1)$, $p_n = g(p_{n-1})$, 数列收敛于唯一点

有

$$|p_n - p| \le \frac{1}{1 - k} |p_{n+1} - p_n|$$

$$|p_n - p| \le \frac{k^n}{1 - k} |p_1 - p_0|$$

1.3 牛顿迭代

Theorem \equiv **.** 3 $f \in C^2[a,b], p \in [a,b], f(p)=0, f'(p) \neq 0, \exists \delta > 0, \{p_n\}, p_0 \in [p-\delta, p+\delta]$

$$p_n = p_{n-1} - \frac{f(p_{n-1})}{f'(p_{n-1})}, n \ge 1$$

1.4 误差

Theorem 二、.4 $\{p_n\}$ 收于 p, $\exists \alpha, \lambda > 0$,

$$\lim_{n \to \infty} \frac{|p_{n+1} - p|}{|p_n - p|^{\alpha}} = \lambda$$

 $\{p_n\}$ converges to p of order(阶) α , with asymptotic error constant(渐进误差常数) λ .

解决牛顿重根降阶,将根变位:

$$g(x) = x - \frac{f(x)f'(x)}{f'^{2}(x) - f(x)ff''(x)}$$

2. Direct Matrix Solver 6

高斯消元 (会不可用的情况), LU 分解, 其他分解

$$A\vec{x} = b$$

2.1 高斯消元

可解性见线代.

2.2 LU 分解

若 |L|=1, 则分解唯一. 用 $L\vec{y}=\vec{b}$, 再 $U\vec{x}=\vec{y}$ 求解.

3. Iterative Matrix Solver 7

雅可比, 高斯-赛德尔方法, 松弛迭代

3.1 范数

向量范数

(1)
$$\|\vec{x}\|_1 = \sum_{i=1}^n |x_i|$$

(2)
$$\|\vec{x}\|_2 = \sqrt{\sum_{i=1}^n |x_i|^2}$$

(3)
$$\|\vec{x}\|_{n} = \left(\sum_{i=1}^{n} |x_{i}|^{p}\right)^{\frac{1}{p}}$$

(4)
$$\|\vec{x}\|_{\infty} = \max_{1 \le i \le n} |x_i|$$

矩阵范数

- (1) Frobenius Norm: $\left\|A\right\|_F = \sqrt{\sum_{i=1}^n \sum_{j=1}^n \left|a_{ij}\right|^2}$
- (2) Natural Norm(operator norm):

$$\begin{split} \left\|A\right\|_p &= \max_{\vec{x} \neq 0} \frac{\left\|A\vec{x}\right\|_p}{\left\|\vec{x}\right\|_p} \\ &= \max_{\left\|\vec{x}\right\|_p = 1} \left\|A\vec{x}\right\|_p \end{split}$$

a.
$$||A||_{\infty} = \max_{1 \le i \le n} \sum_{j=1}^{n} |a_{ij}|$$

b.
$$||A||_1 = \max_{1 \le j \le n} \sum_{i=1}^n |a_{ij}|$$

c. $\|A\|_2 = \sqrt{\lambda_{max}(A^T A)}$ (spectral norm)(谱范数)

3.2 Jacobi 迭代

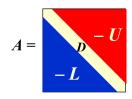


图 1: A=(D-L-U)

$$\vec{x}^{(k)} = D^{-1}(L+U)\vec{x}^{(k-1)} + D^{-1}\vec{b}$$

3.3 Gauss-Seidel 迭代

$$\vec{x}^{(k)} = (D-L)^{-1} U \vec{x}^{(k-1)} + (D-L)^{-1} \vec{b}$$

3.4 松弛迭代

$$\vec{x}^{(k)} = (D - \omega L)^{-1} [(1 - \omega)D + \omega U] \vec{x}^{(k-1)} + (D - \omega L)^{-1} \omega \vec{b}$$

- (1) 若 $a_{ii} \neq 0$, 且 $\rho(T_{\omega}) \geq |\omega 1|$, 迭代要求 $0 < \omega < 2$
- (2) 若 A 正定, 且 $0 < \omega < 2$, 则迭代收
- (3) 若 A 正定且三对角, $\rho(T_g)=[\rho(T_j)]^2<1$, 则 $\omega=\frac{2}{1+\sqrt{1-[\rho(T_j)]^2}}$ 最优, 且有 $\rho(T_\omega)=\omega-1$

3.5 迭代收敛

$$\vec{x}^{(k)}=T\vec{x}^{(k-1)}+\vec{C}$$

$$\vec{e}^{(k)} = T^k \vec{e}^{(0)}$$

当且仅当 $\rho(T) < 1$ 时收. $\rho(T) = max|\lambda|$ (最大特征

值) 误差

$$\left\| \vec{x} - \vec{x}^{(k)} \right\| \leq \frac{\left\| T \right\|^k}{1 - \left\| T \right\|} \left\| \vec{x}^{(1)} - \vec{x}^{(0)} \right\|$$

$$A(\vec{x} + \delta \vec{x}) = \vec{b} + \delta \vec{b},$$

$$\frac{\left\|\delta\vec{x}\right\|}{\left\|\vec{x}\right\|} \leq \left\|A\right\| \left\|A^{-1}\right\| \frac{\left\|\delta\vec{b}\right\|}{\left\|\vec{b}\right\|}$$

 $K(A) = ||A|| ||A^{-1}||$ 被叫做条件数/放大因子.

- (1) 若 A 对称, $K(A)_2 = \frac{\max |\lambda|}{\min |\lambda|}$
- (2) $K(A)_p \ge 1$

示

- (3) 若 A 正交矩 $(A^{-1}=A^T)$, $K(A)_2=1$
- (4) $K(\alpha A) = K(A)$
- (5) $K(RA)_2 = K(AR)_2 = K(A)_2$

4. Initial value problem 5

(微分方程)Euler, Runge-kutta, multi-step, 隐式与显

Ξ_{λ} Interpolation and approximation

插值与逼近,分析 Error

1. interpolation 3

Lagrange polynomial, Piecewise polynomial, 其他多项式

1.1 Lagrange 多项式

$$\begin{split} P(x) &= \sum_{k=0}^{n} f(x_k) L_{n,k}(x) \\ L_{n,k}(x) &= \prod_{i=0, i \neq k}^{n} \frac{x - x_i}{x_k - x_i} \\ &= \begin{cases} 0, & x = x_i, & i \neq k \\ 1, & x = x_k \end{cases} \end{split}$$

$$\begin{array}{l} R_n(x) = \frac{f^{(n+1)(\xi_x)}}{(n+1)!} \prod_{i=0}^n (x-x_i) \\ \text{Lagrange} \ {\bf 3} 项式是唯一的. \end{array}$$

1.2 Neville's Method

定义
$$P_{m_1,\cdots,m_k}(x)$$
 为 x_{m_1},\cdots,x_{m_k} 插值

$$P(x) = \frac{(x - x_j) P_{0, \cdots, j-1, j+1, \cdots, k}(x) - (x - x_i) P_{0, \cdots, i-1, i+1, \cdots, k}(x)}{x_i - x_j}$$

1.3 Newton's Divided Differences

$$f[x_0,\cdots,x_{k+1}] = \frac{f[x_0,\cdots,x_k] - f[x_0,\cdots,x_{k-1},x_{k+1}]}{x_k - x_{k+1}}$$

$$f(x) = N_n(x) + R_n(x),$$

$$\begin{split} N_n(x) = & f\left(x_0\right) + f\left[x_0, x_1\right](x - x_0) + f\left[x_0, x_1, x_2\right](x - x_0)\left(x - x_{\{\!\!\!\ p\ \!\!\!\}}\right) \ \,$$
 截断误差 (插值与逼近)
$$& + \ldots + f\left[x_0, \ldots, x_n\right](x - x_0) \ldots (x - x_{n-1}) \end{split} \qquad \text{Lagrange polynomial}$$

$$R_n(x) = & f\left[x, x_0, \ldots, x_n\right](x - x_0) \ldots (x - x_{n-1})\left(x - x_n\right)$$

$$R_n(x) = f\left[x, x_0, \dots, x_n\right] \left(x - x_0\right) \dots \left(x - x_{n-1}\right) \left(x - x_n\right)$$

1.4 Hermite 插值

$$\begin{split} H_{2n+1}(x) &= \sum_{i=0}^n f(x_i) h_i(x) + \sum_{i=0}^n f'(x_i) \hat{h}_i(x) \\ h_i(x) &= \delta_{ij}, h'_i(x) = 0 \\ \hat{h}_i(x) &= 0, \hat{h}'_i(x) = \delta_{ij} \\ R_n(x) &= \frac{f^{(2n+2)}(\xi_x)}{(2n+2!) \prod_{i=0}^n (x-x_i)^2} \end{split}$$

1.5 Cubic Spline

S(x)

$$(1)$$
 $S_i(x)$ 为 $[x_i,x_{i+1}]$ 区间

(2)
$$S(x_i) = f(x_i), (n+1)$$

(3)
$$S_{i+1}(x_{i+1}) = S_i(x_{i+1}), \text{ (n-1) } \uparrow$$

(4)
$$S'_{i+1}(x_{i+1}) = S'_i(x_{i+1}), \text{ (n-1) } \uparrow$$

(5)
$$S_{i+1}''(x_{i+1}) = S_i''(x_{i+1}), \text{ (n-1) } \uparrow$$

(具体见笔记)

更多条件:

(1)
$$S'(a) = f'(x_0), S'(b) = f'(x_n)$$
 导数边界

(2)
$$S''(a) = f''(x_0), S''(b) = f''(x_n)$$
 为 0 时叫 Natural Spline

(3)
$$S'(a^+) = S'(b^-)$$

2. Numerical differentiation and Numerical integration 4

数值微分与数值积分, 很多法则

3. approximation 8

Least squares, Orthogonal polynomials, Chebyshev polynomial

误差 四、

- (1) 舍入误差 (计算机带来的)
- (2) 真值误差 (解方程)

Lagrange polynomial

$$R_n(x) = \frac{f^{(n+1)}(\xi_x)}{(n+1)!} \prod_{i=0}^n (x - x_i)$$

Taylor expansion

$$R_n(x) = \frac{f^{(n+1)}(\xi_x)}{(n+1)!} (x - x_0)^{n+1}$$