

# Computing Method

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Yu Xinrui

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# 1. Basic Notes about Arithmetic

- Absolute Error and Relative Error

## Definition

Let  $x$  be a real number and  $x^*$  is its approximation, then the error is  $x - x^*$ . The absolute error is  $|x - x^*|$  The relative error is  $|\frac{x - x^*}{x}|$

- Significant Digits

## Definition

If the absolute error of  $x$  is no more than half of a certain digit, then the total number of digits from this digit to the first non-zero digit is called significance digits.

e.g.

# 1. Basic Notes about Arithmetic

## Principle of value computation:

- ① Avoid subtraction of nearly equal quantities.
- ② Minimize number of calculation.
- ③ Avoid extremely small denominator.

## Frequently used methods:

- ① Taylor expansion
- ② Sum to product formula
- ③ Qin Jiu Shao Algorithm:

$$f(x) = a_n x^n + a_{n-1} x^{n-1} + \cdots + a_1 x + a_0$$

$$= (\cdots (a_n x + a_{n-1}) x + \cdots + a_1) x + a_0$$

## 2.Approximating Functions-Interpolation

### Theorem on Polynomial Intepolation

If  $x_0, \dots, x_n$  are distinct real numbers, then for arbitrary values  $y_0, \dots, y_n$ , there is a unique polynomial  $p_n$  of degree at most  $n$  such that  $p_n(x) = y_i, 0 \leq i \leq n$

- Lagrange intepolation

A table of data pairs  $(x_i, y_i), 0 \leq i \leq n$ , the Lagrange interpolation polynomial of order  $n$  has the form:

$$p(x) = y_0 l_0(x) + y_1 l_1(x) + \dots + y_n l_n(x) = \sum_{i=0}^n y_i l_i(x)$$

where the lagrange bases function :

$$l_i(x) = \prod_{j=0, j \neq i}^n \frac{x - x_j}{x_i - x_j}$$

## 2.Approximating Functions-Interpolation

- Newton interpolation

$$p(x) = \sum_{k=0}^n f[x_0, x_1, \dots, x_k] \prod_{j=0}^{k-1} (x - x_j)$$

- To calculate Newton interpolation polynomial, use Divided Difference Method

### Theorem on Polynomial Interpolation Error

Let  $f$  be a function in  $C^{n+1}[a, b]$ , and let  $p$  be the polynomial of degree at most  $n$  that interpolates the function  $f$  at  $n+1$  distinct points  $x_0, \dots, x_n$  in the interval  $[a, b]$ . To each  $x$  in  $[a, b]$  there corresponds a point  $\xi_x$  in  $(a, b)$  such that

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

## 2. Approximating Functions-Interpolation

- Hermite interpolation

### Theorem on Hermite Interpolation

Let the nodes be  $x_0, x_1, \dots, x_n$ , and suppose that at node  $x_i$  these interpolation conditions are given:

$$p^{(j)}(x_i) = c_{ij}, (0 \leq j \leq k_i - 1, 0 \leq i \leq n)$$

The total number of conditions on  $p$  is denoted by  $m+1$ , and therefore

$$m + 1 = k_0 + k_1 + \dots + k_n$$

Then there exists a unique polynomial  $p$  in  $\Pi_m$  satisfying the Hermite interpolation conditions.

- To calculate Hermite interpolation polynomial, use Divided Difference Method



## 2. Approximating Functions-Interpolation

### ● 3-spline

Suppose there are  $n+1$  nodes on  $[a,b]$ , to derive cubic polynomial on  $n$  intervals, we need  $4n$  conditions. By definition of spline interpolation, we still need  $n+1$  function values and 2 boundary conditions. To calculate  $M_i$  on  $n-1$  inner nodes, there are two common cases:

(1) 给定  $M_0, M_n$  的值, 此时  $n-1$  个方程组有  $n-1$  个未知量  $\{M_i, i = 1, 2, \dots, n-1\}$ . 当  $M_0 = 0, M_n = 0$  时, 称为自然边界条件.

$$\begin{bmatrix} 2 & \lambda_1 & & & \\ \mu_2 & 2 & \lambda_2 & & \\ & \ddots & \ddots & \ddots & \\ & & \lambda_{n-2} & 2 & \lambda_{n-1} \\ & & & \mu_{n-1} & 2 \end{bmatrix} \begin{bmatrix} M_1 \\ M_2 \\ \vdots \\ M_{n-2} \\ M_{n-1} \end{bmatrix} = \begin{bmatrix} d_1 - \mu_1 M_0 \\ d_2 \\ \vdots \\ d_{n-2} \\ d_{n-1} - \lambda_{n-1} M_n \end{bmatrix}$$

(2) 给定  $S'(x_0) = m_0, S'(x_n) = m_n$  的值, 将  $S'(x_0) = m_0, S'(x_n) = m_n$  的值分别代入  $S'(x)$  在  $[x_0, x_1], [x_{n-1}, x_n]$  中的表达式, 得到另外两个方程:

$$2M_0 + M_1 = \frac{6}{h_0}[f[x_0, x_1] - m_0] = d_0$$

$$M_{n-1} + 2M_n = \frac{6}{h_{n-1}}[m_n - f[x_{n-1}, x_n]] = d_n$$

## 2. Approximating Functions-Interpolation

得到  $n + 1$  个未知量,  $n + 1$  个方程组

$$\begin{bmatrix} 2 & 1 & & & \\ u_1 & 2 & \lambda_1 & & \\ & u_2 & 2 & \lambda_2 & \\ & & \ddots & \ddots & \ddots \\ & & & u_{n-2} & 2 & \lambda_{n-1} \\ & & & & 1 & 2 \end{bmatrix} \begin{bmatrix} M_0 \\ M_1 \\ M_2 \\ \vdots \\ M_{n-1} \\ M_n \end{bmatrix} = \begin{bmatrix} d_0 \\ d_1 \\ d_2 \\ \vdots \\ d_{n-1} \\ d_n \end{bmatrix}$$

$$\lambda_i = \frac{h_i}{h_i + h_{i-1}}, \quad \mu_i = 1 - \lambda_i$$

$$d_i = \frac{6}{h_i + h_{i-1}} \left( \frac{y_{i+1} - y_i}{h_i} - \frac{y_i - y_{i-1}}{h_{i-1}} \right) = 6f(x_{i-1}, x_i, x_{i+1})$$

Then, use

$$S_i(x) = \frac{(x_{i+1} - x)^3}{6h_i} M_i + \frac{(x - x_i)^3}{6h_i} M_{i+1} + c(x_{i+1} - x) + d(x - x_i)$$

where  $c = \frac{y_i}{h_i} - \frac{h_i M_i}{6}$ ,  $d = \frac{y_{i+1}}{h_i} - \frac{h_i M_{i+1}}{6}$ ,  $i = 0, 1, \dots, n - 1$  to obtain interpolation polynomials.

## 2. Approximating Functions-Fitting

- Least-Square problem on function fitting

### Definition

Let  $f(x)$  is a function on  $[a,b]$ ,  $x_{i=0}^m$  be  $m+1$  distinct nodes on the  $[a,b]$ ,  $\Phi$  be a given class of functions. Find function  $\phi$  on  $\Phi$  such that  $f(x)$  and  $\phi(x)$  are closest on the  $m+1$  nodes. If the distance is measured by 2-norm, then it is least-square problem. i.e.

$R = \sqrt{\sum_{i=0}^m (\phi(x_i) - f(x_i))^2}$  is minimized.

- If  $\Phi$  is polynomial space, it is the well-known polynomial fitting.

To find fitting polynomial in this way, we form the normal equation:

$$\begin{pmatrix} m & \sum_{i=1}^m x_i & \cdots & \sum_{i=1}^m x_i^n \\ \sum_{i=1}^m x_i & \sum_{i=1}^m x_i^2 & \cdots & \sum_{i=1}^m x_i^{n+1} \\ \vdots & \vdots & & \vdots \\ \sum_{i=1}^m x_i^n & \sum_{i=1}^m x_i^{n+1} & \cdots & \sum_{i=1}^m x_i^{2n} \end{pmatrix} \begin{pmatrix} a_0 \\ a_1 \\ \vdots \\ a_n \end{pmatrix} = \begin{pmatrix} \sum_{i=1}^m y_i \\ \sum_{i=1}^m x_i y_i \\ \vdots \\ \sum_{i=1}^m x_i^n y_i \end{pmatrix}$$

## 2. Approximating Functions-Fitting

- Contradictory Equations and least-square solution

### Explanation

A system of  $m$  equations of  $n$  unknowns is:  $A\alpha = Y$ , if  $m \geq n$ , then it has no solution. The least-square solution of it is the  $x$  that minimizes  $\|Y - A\alpha\|^2$ . Such  $x$  is given by:  $A^*A\alpha = A^*Y$ , which are normal equations.

$$A = \begin{pmatrix} 1 & x_1 & \cdots & x_1^n \\ 1 & x_2 & \cdots & x_2^n \\ \vdots & \vdots & & \vdots \\ 1 & x_m & \cdots & x_m^n \end{pmatrix}, \quad \alpha = \begin{pmatrix} a_0 \\ a_1 \\ \vdots \\ a_n \end{pmatrix}, \quad Y = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{pmatrix}$$

### 3. Solution of non-linear equations

- Bisection
- Newton's Iteration

Derived from Taylor's expansion, the form of Newton's Iteration writes:

$$x_{k+1} = x_k - \frac{f(x_k)}{f'(x_k)}$$

which is of 2-order convergence if  $x$  is simple root, and 1-order if  $x$  is multiple root in most cases. If  $x$  is of multiplicity  $p$ , then the form:

$$x_{k+1} = x_k - p \frac{f(x_k)}{f'(x_k)}$$

is of 2-order.

- Secant Method

To avoid use of  $f'(x)$ , replace newton's method by:

$$x_{k+1} = x_k - \frac{f(x_k)(x_k - x_{k-1})}{f(x_k) - f(x_{k-1})}$$

- Fixed-point iteration

The iteration has the form:

$$x_{k+1} = \varphi(x_k)$$

### Definition of Contractive Mapping

A mapping  $\varphi$  is called contractive if there exists  $\lambda < 1$  such that  $|\varphi(x) - \varphi(y)| \leq \lambda|x - y|$  for all  $x, y$  in the domain of  $\varphi$ .

### Theorem on contractive mapping

Let  $C$  be a closed set on real line. If  $\varphi$  is a contractive mapping of  $C$  into  $C$ , then it has a unique fixed point. And the fixed-point iteration is convergent from any starting point in  $C$ .

Remark: This is another way to describe the theorem 3.1 in the textbook.

## 4. Solution of linear systems of equations

- Gauss Elimination  $-O(n^3)$
- LU Decomposition – Find lower triangular  $L$  and upper triangular  $U$  such that  $A=LU$ . (Not unique)

Doolittle:  $l_{ij} = 1$ . Crout:  $u_{ij} = 1$ . Cholesky:  $U = L^T$

### Theorem 1 (sufficient condition)

If all  $n$  leading principal minors of the  $n \times n$  matrix  $A$  are nonsingular, then  $A$  has an LU-decomposition

### Theorem 2

If  $A$  is a real, symmetric, and positive definite matrix, then it has a unique factorization,  $A = LL^T$ , in which  $L$  is lower triangular with a positive diagonal.

Remark: Gauss elimination is LU decomposition in essence.

## 4. Solution of linear systems of equations

- Diagonally Dominant Matrices:

$$|a_{ii}| > \sum_{j=1, j \neq i}^n |a_{ij}|, (1 \leq i \leq n)$$

### Theorem 3

Gauss elimination without pivoting preserves the diagonal dominance of a matrix.

### Corollary

Every diagonally dominant matrix is nonsingular and has an LU-factorization



## 4. Solution of linear systems of equations

Vector norms:

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

$$\textcircled{2} \|x\|_\infty = \max_{1 \leq i \leq n} |x_i|$$

$$\textcircled{3} \|x\|_1 = \sum_{i=1}^n |x_i|$$

Matrix norms (Defined after vector norm):

$$\textcircled{1} \|A\|_\infty = \max_{1 \leq i \leq n} \sum_{j=1}^n |a_{ij}|$$

$$\textcircled{2} \|A\|_1 = \max_{1 \leq j \leq n} \sum_{i=1}^n |a_{ij}|$$

$$\textcircled{3} \|A\|_2 = \sqrt{\rho(A^T A)}$$

Condition number:  $\kappa(A) = \|A\| \|A^{-1}\|$

### Theorem on bounds involving condition number

In solving systems of equations  $Ax=b$ , the condition number  $\kappa(A)$ , turbulence and solution satisfies:

$$\frac{1}{\kappa(A)} \frac{\|r\|}{\|b\|} \leq \frac{\|e\|}{\|x\|} \leq \kappa(A) \frac{\|r\|}{\|b\|}$$

## 4. Solution of linear systems of equations

- Iteration method

Introduce splitting matrix  $Q$ , and the system of linear equations  $Ax = b$  can be written as:  $Qx = (Q - A)x + b$ . If  $Q$  is nonsingular, then there is iteration formula:  $x^{(k+1)} = (I - Q^{-1}A)x^{(k)} + Q^{-1}b$   
Generally, an iteration method has the form:  $x^{(k+1)} = Gx^{(k)} + c$ ,

### Theorem 4 (Sufficient Condition)

If  $\|I - Q^{-1}A\| < 1$  then the iteration converges from any starting point  $x^{(0)}$ . (Proof)

### Theorem 5 (Sufficient and necessary)

In order that the iteration formula:

$$x^{(k+1)} = Gx^{(k)} + c$$

produce a sequence converging to  $(I - G)^{-1}c$ , for any starting vector  $x^{(0)}$ , it is necessary and sufficient that  $\rho(G) < 1$ .

## 4.Solution of linear systems of equations

	Splitting mtx	Iteration mtx
Jacobi	$D$	$I - D^{-1}A = -D^{-1}(L + U)$
Gauss-Seidel	$D+L$	$-(D + L)^{-1}U$
SOR	$\frac{1}{\omega}D + L$	$(D + \omega L)^{-1}((1 - \omega)D - \omega U)$

- SOR Iteration

If we view Gauss-Seidel iteration as:  $x^{(k+1)} = x^{(k)} - D^{-1}r^{(k)}$ , then we want to modify the item  $-D^{-1}r^{(k)}$ , so that the formula can converge faster. Introduce  $\omega$ , SOR iteration has the form:

$$x^{(k+1)} = x^{(k)} - \omega D^{-1}r^{(k)}$$

# 4. Solution of linear systems of equations

Jacobi:

$$\begin{cases} x_1^{(k+1)} = -\frac{1}{a_{11}}(a_{12}x_2^{(k)} + \dots + a_{1n}x_n^{(k)} - b_1) \\ x_2^{(k+1)} = -\frac{1}{a_{22}}(a_{21}x_1^{(k)} + a_{23}x_3^{(k)} + \dots + a_{2n}x_n^{(k)} - b_2) \\ x_3^{(k+1)} = -\frac{1}{a_{33}}(a_{31}x_1^{(k)} + a_{32}x_2^{(k)} + a_{34}x_4^{(k)} + \dots + a_{3n}x_n^{(k)} - b_3) \\ \vdots \\ x_n^{(k+1)} = -\frac{1}{a_{nn}}(a_{n1}x_1^{(k)} + a_{n2}x_2^{(k)} + \dots + a_{n,n-1}x_{n-1}^{(k)} - b_n) \end{cases}$$

Gauss-Seidel:

$$\begin{cases} x_1^{(k+1)} = -\frac{1}{a_{11}}(a_{12}x_2^{(k)} + \dots + a_{1n}x_n^{(k)} - b_1) \\ x_2^{(k+1)} = -\frac{1}{a_{22}}(a_{21}x_1^{(k+1)} + a_{23}x_3^{(k)} + \dots + a_{2n}x_n^{(k)} - b_2) \\ x_3^{(k+1)} = -\frac{1}{a_{33}}(a_{31}x_1^{(k+1)} + a_{32}x_2^{(k+1)} + a_{34}x_4^{(k)} + \dots + a_{3n}x_n^{(k)} - b_3) \\ \vdots \\ x_n^{(k+1)} = -\frac{1}{a_{nn}}(a_{n1}x_1^{(k+1)} + a_{n2}x_2^{(k+1)} + \dots + a_{n,n-1}x_{n-1}^{(k+1)} - b_n) \end{cases}$$

SOR:

$$\begin{cases} x_1^{(k+1)} = x_1^{(k)} - \frac{\omega}{a_{11}}(a_{11}x_1^{(k)} + a_{12}x_2^{(k)} + \dots + a_{1n}x_n^{(k)} - b_1) \\ x_2^{(k+1)} = x_2^{(k)} - \frac{\omega}{a_{22}}(a_{21}x_1^{(k+1)} + a_{22}x_2^{(k)} + a_{23}x_3^{(k)} + \dots + a_{2n}x_n^{(k)} - b_2) \\ x_3^{(k+1)} = x_3^{(k)} - \frac{\omega}{a_{33}}(a_{31}x_1^{(k+1)} + a_{32}x_2^{(k+1)} + a_{33}x_3^{(k)} + \dots + a_{3n}x_n^{(k)} - b_3) \\ \vdots \\ x_n^{(k+1)} = x_n^{(k)} - \frac{\omega}{a_{nn}}(a_{n1}x_1^{(k+1)} + a_{n2}x_2^{(k+1)} + \dots + a_{n,n-1}x_{n-1}^{(k+1)} + a_{nn}x_n^{(k)} - b_n) \end{cases}$$

## 4.Solution of linear systems of equations

### Theorem on Convergence 1

If  $A$  is diagonally dominant, then Jacobi and Gauss-Seidel converges from any starting point.

### Theorem on Convergence 2

If  $A$  is real, symmetric and positive definite, then SOR converges from any starting point for any  $0 < \omega < 2$ . (Including Gauss-Seidel)