# Interpolation

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- Data points:  $(x_k, y_k), k = 0,...,n \& x_k < x_{k+1}$
- Find a polynomial of degree n  $P_n(x) = a_n x^n + a_{n-1} x^{n-1} + \dots + a_1 x + a_0$ which satisfies  $P_n(x_k) = y_k$  for  $k = 0, \dots, n$
- $\rightarrow$  Find the coefficients  $a_n, a_{n-1}, \dots, a_1, a_0$

- Application or purpose
  - Function fitting to experimental data
    - A polynomial can be an approximation of some hidden function.
  - To find integrals or derivatives easily
    - Integration or differentiation of polynomials is easy.



Example 2.1 in Wen Shen

$$P_2(x) = a_2 x^2 + a_1 x + a_0.$$

$$x = 0, y = 1: P_2(0) = a_0 = 1,$$

$$x = 1, y = 0 : P_2(1) = a_2 + a_1 + a_0 = 0,$$

$$x = 2/3, y = 0.5$$
:  $P_2(2/3) = (4/9)a_2 + (2/3)a_1 + a_0 = 0.5$ .

$$\begin{pmatrix} 0 & 0 & 1 \\ 1 & 1 & 1 \\ \frac{4}{4} & \frac{2}{2} & 1 \end{pmatrix} \begin{pmatrix} a_2 \\ a_1 \\ a_2 \end{pmatrix} = \begin{pmatrix} 1 \\ 0 \\ 0 & 5 \end{pmatrix} \implies a_2 = -\frac{3}{4}, \quad a_1 = -\frac{1}{4}, \quad a_0 = 1.$$



Van der Monde method

Van der Monde matrix

✓ Solving this by linear algebra

- Van der Monde method
  - The van der Monde matrix  $\mathbf{X}$  is invertible as long as  $x_i$ 's are distinct.
  - But the matrix has usually a large condition number. → nearly singular → often huge numerical errors

Cardinal functions

$$I_i(x_j) = \delta_{ij} = \begin{cases} 1, & i = j \\ 0, & i \neq j \end{cases}$$
  $i = 0, 1, \dots, n$ 

$$I_{i}(x) = \prod_{j=0, j\neq i}^{n} \left(\frac{x-x_{j}}{x_{i}-x_{j}}\right)$$

$$= \frac{x-x_{0}}{x_{i}-x_{0}} \cdot \frac{x-x_{1}}{x_{i}-x_{1}} \cdot \dots \cdot \frac{x-x_{i-1}}{x_{i}-x_{i-1}} \cdot \frac{x-x_{i+1}}{x_{i}-x_{i+1}} \cdot \dots \cdot \frac{x-x_{n}}{x_{i}-x_{n}}$$

Lagrange interpolation polynomials

$$P_n(x) = \sum_{i=0}^n I_i(x) \cdot y_i$$
$$= \sum_{i=0}^n \left[ \prod_{j=0, j \neq i}^n \left( \frac{x - x_j}{x_i - x_j} \right) \right] \cdot y_i$$

- Check 
$$P_n(x_j) = \sum_{i=0}^n I_i(x_j) \cdot y_i = y_j$$
, for every  $j$ .

Example 2.2 in Wen Shen

$$y_{i} \mid 1 \mid 0 \mid 0.5$$

$$l_{0}(x) = \frac{(x - x_{1})(x - x_{2})}{(x_{0} - x_{1})(x_{0} - x_{2})} = \frac{(x - 2/3)}{(0 - 2/3)} \frac{(x - 1)}{(0 - 1)} = \frac{3}{2} \left(x - \frac{2}{3}\right) (x - 1)$$

$$l_{1}(x) = \frac{(x - x_{0})(x - x_{2})}{(x_{1} - x_{0})(x_{1} - x_{2})} = \frac{(x - 0)}{(2/3 - 0)} \frac{(x - 1)}{(2/3 - 1)} = -\frac{9}{2}x(x - 1)$$

$$l_{2}(x) = \frac{(x - x_{0})(x - x_{1})}{(x_{2} - x_{0})(x_{2} - x_{1})} = \frac{(x - 0)}{(1 - 0)} \frac{(x - 2/3)}{(1 - 2/3)} = 3x \left(x - \frac{2}{3}\right).$$

$$P_{2}(x) = l_{0}(x)y_{0} + l_{1}(x)y_{1} + l_{2}(x)y_{2}$$

$$= \frac{3}{2} \left(x - \frac{2}{3}\right) (x - 1) - \frac{9}{2}x(x - 1)(0.5) + l_{2}(x) \cdot 0$$

$$= -\frac{3}{4}x^{2} - \frac{1}{4}x + 1.$$



- Lagrange interpolation polynomials
  - Pros
    - Elegant formula
  - Cons
    - Slow computation; Computational time  $\sim O(n^2)$
    - Not flexible; Just one point addition requires recalculation of the whole formula

$$P_n(x) = \sum_{i=0}^n \left[ \prod_{j=0, j\neq i}^n \left( \frac{x - x_j}{x_i - x_j} \right) \right] \cdot y_i$$



- Newton polynomials
  - a.k.a. Newton's divided differences interpolation polynomials
  - Main idea: flexible formula → a recursive form
    - Given  $P_{k-1}(x)$  for k points  $\rightarrow P_k(x)$  for k+1 points
  - How?
    - $P_0(x) = y_0 \text{ for } (x_0, y_0)$
    - $P_1(x) = y_0 + a_1(x x_0)$  for  $(x_0, y_0) & (x_1, y_1)$
    - $P_2(x) = y_0 + a_1(x x_0) + a_2(x x_0)(x x_1)$  for  $(x_0, y_0)$ ,  $(x_1, y_1)$ , &  $(x_2, y_2)$

:

•  $P_k(x) = P_{k-1}(x) + a_k(x - x_0)(x - x_1) \cdots (x - x_{k-1})$ 



- Newton polynomials
  - Computing  $a_k$

• 
$$P_1(x_1) = y_0 + a_1(x_1 - x_0) = y_1 \rightarrow a_1 = (y_1 - y_0)/(x_1 - x_0)$$

• 
$$P_2(x_2) = P_1(x_2) + a_2(x_2 - x_0)(x_2 - x_1) = y_2$$

$$\Rightarrow a_2 = \frac{y_2 - P_1(x_2)}{(x_2 - x_0)(x_2 - x_1)}$$

$$a_k = \frac{y_k - P_{k-1}(x_k)}{(x_k - x_0)(x_k - x_1) \cdots (x_k - x_{k-1})}$$

$$P_k(x) = y_0 + a_1(x - x_0) + a_2(x - x_0)(x - x_1) + \dots + a_k(x - x_0)(x - x_1) \dots (x - x_{k-1})$$



- Newton polynomials
  - Newton's divided differences
    - $f[x_i] \coloneqq y_i$
    - $f[x_i, x_j] := \frac{f[x_i] f[x_j]}{x_i x_j} = \frac{f[x_j] f[x_i]}{x_j x_i}$
    - $f[x_i, x_j, x_k] := \frac{f[x_i, x_j] f[x_j, x_k]}{x_i x_k}$
    - $f[x_0, x_1, ..., x_k] := \frac{f[x_0, x_1, ..., x_{k-1}] f[x_1, ..., x_{k-1}, x_k]}{x_0 x_k}$
  - Computing  $a_k$ 
    - → Tidy if you use Newton's divided differences because  $a_k = f[x_0, x_1, ..., x_k]$



- Newton polynomials
  - Computing  $a_k (= f[x_0, x_1, ..., x_k])$



$$P_3(x) = a_0 + a_1(x - x_0) + a_2(x - x_0)(x - x_1) + a_3(x - x_0)(x - x_1)(x - x_2)$$
  
=  $\boxed{1} + \boxed{-1} x + \boxed{-0.75} x(x - 1) + \boxed{0.441} x(x - 1)(x - 2/3).$ 

- Newton polynomials
  - Nested form

• 
$$P_k(x) = y_0 + a_1(x - x_0) + a_2(x - x_0)(x - x_1) + \dots + a_k(x - x_0)(x - x_1) \dots (x - x_{k-1})$$
  
=  $y_0 + (x - x_0)(a_1 + (x - x_1)(a_2 + (x - 2)(a_3 + \dots + a_k(x - x_{k-1}))) \dots)$ 

Algorithm

$$p = a_n$$
 for  $k = n - 1, n - 2, ..., 0$  
$$p = p(x - x_k) + a_k$$
 end

- Newton polynomials
  - Computational complexity
    - Computing  $a_k$ :  $O(n^2)$
    - Expanding a polynomial
      - Recursion form:  $O(n^2)$
      - Nested form: O(n)

Fundamental theorem of algebra

Every polynomial of degree n, which is not identically zero, has exactly n roots (counting multiplicities. These roots may be real or complex). This means, in particular, if a polynomial of degree n has more than n distinct roots, then it must be identically zero.

 Theorem. (Existence and Uniqueness of Polynomial Interpolation)

Consider data points  $(x_i, y_i)_{i=0}^n$ , with the  $x_i$ 's all distinct. Then there exists one and only polynomial  $P_n(x)$  of degree  $\leq n$  such that

$$P_n(x_i) = y_i, i = 0, 1, \cdots, n.$$

- Proof) Wen Shen p. 29
  - Summary of the proof of the uniqueness
    - Assuming two distinct polynomials
    - Defining a difference function and proving that it is zero, by using the fundamental theorem of algebra



- Errors in polynomial interpolation
  - Meaningful only if a function f(x) (on the interval  $a \le x \le b$ ) is the original function  $\rightarrow$  what to be interpolated:

$$(x_i, f(x_i)), x_i \in [a, b], i = 0, 1, ..., n.$$

- Error function:  $e(x) = f(x) P_n(x)$
- Interpolation error theorem (Wen Shen pp. 30~31)
  - For every  $x \in [a, b]$ , there exists some value  $\xi \in [a, b]$ , such that

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

- Errors in polynomial interpolation
  - Interpolation error theorem
    - Proof

If f is a polynomial of degree n,  $f(x) = P_n(x)$  by the uniqueness theorem of polynomial interpolation. Then e(x) = 0 and the proof is trivial.

Now consider the other case that f is not a polynomial of degree n.

If 
$$x = x_i$$
,  $e(x_i) = f(x_i) - P_n(x_i) = 0$ .

- Errors in polynomial interpolation
  - Interpolation error theorem
    - Proof

If  $x \neq x_i$ , we define

$$W(x) = \prod_{i=0}^{n} (x - x_i)$$
$$\varphi(x) = f(x) - P_n(x) - cW(x)$$

where  $c = \frac{f(y) - P_n(y)}{W(y)}$  for a value y s.t.  $a \le y \le b \ \& \ y \ne x_i$ 

 $\varphi(x)$  has at least (n+2) roots because  $x_i$ 's and y are roots.

- Errors in polynomial interpolation
  - Interpolation error theorem
    - Proof

 $\varphi(x)$  has at least (n+2) roots  $\Rightarrow \varphi'(x)$  has at least (n+1) roots  $\Rightarrow \varphi'''(x)$  has at least n roots  $\Rightarrow \dots \Rightarrow \varphi^{(n+1)}(x)$  has at least 1 root.

So, we can call the root of  $\varphi^{(n+1)}(x)$  as  $\xi$ .

$$\varphi^{(n+1)}(\xi) = f^{(n+1)}(\xi) - 0 - cW^{(n+1)}(\xi) = 0.$$

$$W^{(n+1)}(x) = (n+1)! \rightarrow f^{(n+1)}(\xi) = cW^{(n+1)}(\xi) = \frac{f(y) - P_n(y)}{W(y)} (n+1)!$$

$$\therefore e(x) = f(x) - P_n(x) = \frac{1}{(n+1)!} f^{(n+1)}(\xi) \prod_{i=0}^{n} (x - x_i)$$



Uniform grid

$$x_i = a + ih, h = \frac{b - a}{n}$$

Lemma

$$\prod_{i=0}^{n} |x - x_i| \le \frac{1}{4} h^{n+1} \cdot n!$$

- Proof) Wen Shen p. 32
  - Summary of the proof
    - »  $x = x_i$ : trivial
    - $x_i < x < x_{i+1}$ : Find  $\max |(x x_i)(x x_{i+1})|$
    - » Consider the other terms in the product



- Uniform grid

$$x_i = a + ih, h = \frac{b - a}{n}$$

Lemma

$$\prod_{i=0}^{n} |x - x_i| \le \frac{1}{4} h^{n+1} \cdot n!$$

From this lemma, we can estimate the error

$$|e(x)| \le \frac{1}{4(n+1)} |f^{(n+1)}(x)| h^{n+1} \le \frac{M_{n+1}}{4(n+1)} h^{n+1}$$

$$M_{n+1} = \max_{x \in [a,b]} |f^{(n+1)}(x)| = ||f^{(n+1)}||_{\infty}$$



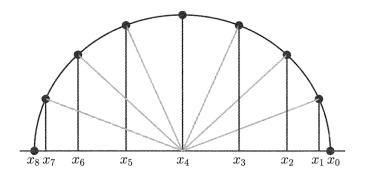


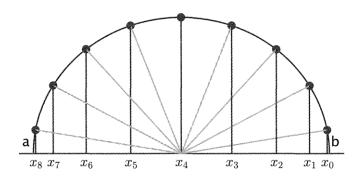
- Errors in polynomial interpolation
  - For an interval [a, b]
  - Chebyshev nodes of type I

$$\bar{x}_i = \frac{1}{2}(a+b) + \frac{1}{2}(b-a)\cos(\frac{i}{n}\pi)$$

Chebyshev nodes of type II

$$\bar{x}_i = \frac{1}{2}(a+b) + \frac{1}{2}(b-a)\cos(\frac{2i+1}{2n+2}\pi)$$





- Errors in polynomial interpolation
  - For an interval [a, b]
  - Chebyshev nodes of type I

$$\bar{x}_i = \frac{1}{2}(a+b) + \frac{1}{2}(b-a)\cos(\frac{i}{n}\pi)$$

- Chebyshev nodes of type II

$$\bar{x}_i = \frac{1}{2}(a+b) + \frac{1}{2}(b-a)\cos(\frac{2i+1}{2n+2}\pi)$$

- Error estimation? → from the property of cos and the interpolation error theorem
- > Chebyshev nodes usually give smaller errors than the uniform grid.

### Do It Yourself

- Consider  $f(x) = \frac{1}{1+16x^2}$  on [-1,1]. Calculate upper bounds for error of polynomials interpolating this function with uniform grids of 4, 8, 16 nodes.
  - You may follow Wen Shen example 2.5 instead.
- [After this class]: Plot f(x), the polynomials and their error functions.

### Do It Yourself

- [After this class]: Consider  $f(x) = \frac{1}{1+16x^2}$  on [-1,1]. Calculate upper bounds for error of polynomials interpolating this function with 4, 8, 16 Chebyshev nodes.
  - You may follow Wen Shen example 2.6 instead.
- [After this class]: Plot f(x), the polynomials and their error functions.



- Convergence
  - Generally, the error function  $e(x) = f(x) P_n(x)$  or  $\int_a^b |e(x)| dx$  does not converge to zero as  $n \to \infty$
  - The convergence depends on  $x_i$ 's.
  - Increasing the order of the polynomial may not increase accuracy.

- Disadvantages of polynomial interpolation
  - $-P_n(x)$  should be n-times differentiable  $\rightarrow$  Too smooth
  - Computational cost  $\sim O(n^2)$
  - Big error in certain regions (especially near the limits)
  - Poor convergence

- Connecting piecewise polynomials
- Properties
  - Correct interpolation
  - Low degree of smoothness (in comparison with polynomial interpolation)
  - Good convergence
- Usage examples
  - Visualization of discrete data
  - Graphic design



- Data points:  $(x_i, y_i), i = 0, ..., n \& x_i < x_{i+1}$
- Spline function
  - Concatenation of piecewise polynomials

$$S(x) \doteq \begin{cases} S_0(x), & x_0 \le x \le x_1 \\ S_1(x), & x_1 \le x \le x_2 \\ \vdots & \vdots \\ S_{n-1}(x), & x_{n-1} \le x \le x_n \end{cases}$$

– Continuous or smooth at  $x = x_1, x_2, ..., x_{n-1}$ 

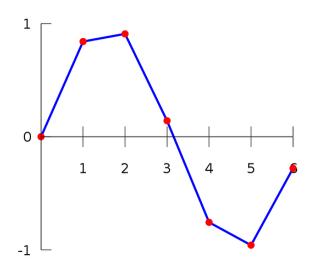
- Data points:  $(x_i, y_i), i = 0, ..., n \& x_i < x_{i+1}$
- A spline of degree k
  - $-S_i(x)$  is a polynomial of degree  $\leq k$
  - -S(x) is (k-1) times differentiable at x=

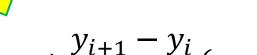
$$x_1, x_2, ..., x_{n-1}$$
  $(i = 1, ..., n - 1)$   
 $S_{i-1}(x_i) = S_i(x_i),$   
 $S'_{i-1}(x_i) = S'_i(x_i),$   
 $\vdots$   
 $S_{i-1}^{(k-1)}(x_i) = S_i^{(k-1)}(x_i).$ 



- Splines of degree 1

$$S_0(x_0) = y_0$$
  
 $S_{i-1}(x_i) = S_i(x_i) = y_i$   
 $(i = 1, ..., n - 1)$   
 $S_{n-1}(x_n) = y_n$ 





$$S_i(x) = y_i + \frac{y_{i+1} - y_i}{x_{i+1} - x_i}(x - x_i)$$



- Linear splines
  - Error theorem (Wen Shen pp. 50~51)
    - Let a function f(x) (on the interval  $a \le x \le b$ ) be the original function:  $S(x_i) = f(x_i)$
    - If f' is continuous,

$$|f(x) - S(x)| \le \max_{i} \left\{ \frac{1}{2} h_{i} \max_{t_{i} \le x \le t_{i+1}} |f'(x)| \right\} \le \frac{1}{2} h \max_{x} |f'(x)|$$

If f'' is continuous,

$$|f(x) - S(x)| \le \max_{i} \left\{ \frac{1}{8} h_i^2 \max_{t_i \le x \le t_{i+1}} |f''(x)| \right\} \le \frac{1}{8} h^2 \max_{x} |f''(x)|$$

- where  $h = \max_i h_i$  and  $h_i = x_{i+1} - x_i$ 



Splines of degree 3 with end point conditions

$$S_{i}(x_{i}) = y_{i} (i = 0, 1, ..., n - 1)$$

$$S_{i}(x_{i+1}) = y_{i+1} (i = 0, 1, ..., n - 1)$$

$$S'_{i-1}(x_{i}) = S'_{i}(x_{i}) (i = 1, 2, ..., n - 1)$$

$$S''_{i-1}(x_{i}) = S''_{i}(x_{i}) (i = 1, 2, ..., n - 1)$$

$$S''_{0}(x_{0}) = S''_{n-1}(x_{n}) = 0$$

- How to find  $S_i(x)$ ?
  - $S_i''(x)$  is a polynomial of degree 1 and  $S_{i-1}''(x_i) = S_i''(x_i)$  $\rightarrow$  You can use the technique of linear splines



- Assume  $S_i^{\prime\prime}(x_i)=z_i$  (of course,  $z_0=z_n=0$ )
- Then  $S_i''(x) = z_i + \frac{z_{i+1} z_i}{h_i}(x x_i)$ 
  - where  $h_i = x_{i+1} x_i$
- But this form is not convenient. So, change its form  $S_i''(x) = \frac{z_{i+1}}{h_i}(x x_i) \frac{z_i}{h_i}(x x_{i+1})$

- Integrating twice,

$$S_i'(x) = \frac{z_{i+1}}{2h_i}(x - x_i)^2 - \frac{z_i}{2h_i}(x - x_{i+1})^2 + C_i$$

$$S_i(x) = \frac{z_{i+1}}{6h_i}(x - x_i)^3 - \frac{z_i}{6h_i}(x - x_{i+1})^3 + C_ix + D_i$$



- Natural cubic splines
  - Continuity condition  $(S_i(x_i) = y_i \& S_i(x_{i+1}) = y_{i+1})$  determines  $C_i \& D_i$

$$C_i = \frac{y_{i+1} - y_i}{h_i} - \frac{h_i}{6} (z_{i+1} - z_i)$$

– The conditions for  $S'_i(x)$  determines  $z_i$ 's.

$$S'_{i-1}(x_i) = S'_i(x_i)$$

- where  $b_i = \frac{y_{i+1} y_i}{h_i}$
- Remember  $z_0 = z_n = 0$

- Natural cubic splines
  - $\rightarrow$  Hz = b matrix-vector form

$$\mathbf{Z} = \begin{pmatrix} z_1 \\ z_2 \\ z_3 \\ \vdots \\ z_{n-2} \\ z_{n-1} \end{pmatrix} \qquad \mathbf{b} = \begin{pmatrix} 6(b_1 - b_0) \\ 6(b_2 - b_1) \\ 6(b_3 - b_2) \\ \vdots \\ 6(b_{n-2} - b_{n-3}) \\ 6(b_{n-1} - b_{n-2}) \end{pmatrix}$$

$$\mathbf{H} = \begin{pmatrix} 2(h_0 + h_1) & h_1 \\ h_1 & 2(h_1 + h_2) & h_2 \\ h_2 & 2(h_2 + h_3) & h_3 \\ \vdots \\ h_{n-3} & 2(h_{n-3} + h_{n-2}) & h_{n-2} \\ h_{n-2} & 2(h_{n-2} + h_{n-1}) \end{pmatrix}$$

- Natural cubic splines
  - Algorithm
    - ① Set up the (tridiagonal) matrix-vector equation
    - ② Solve for  $z_i$ 's
    - $\odot$  Complete  $S_i(x)$
  - Computational cost: O(n)



- Theorem on natural cubic splines
  - Let S be the natural cubic spline function that interpolates a twice-continuously differentiable function f at knots

$$a = x_0 < x_1 < \dots < x_n = b$$

then

$$\int_{a}^{b} [S''(x)]^{2} dx \le \int_{a}^{b} [f''(x)]^{2} dx$$

- ➤ The natural cubic spline gives the least curvature among all interpolating functions.
- > Most natural



Proof

Let 
$$g(x) = f(x) - S(x) \Rightarrow g(x_i) = 0 \ (i = 0, 1, ..., n)$$
  
 $f'' = S'' + g'' \Rightarrow (f'')^2 = (S'')^2 + (g'')^2 + 2S''g''$   
 $\Rightarrow \int_a^b (f'')^2 dx = \int_a^b (S'')^2 dx + \int_a^b (g'')^2 dx + 2 \int_a^b S''g'' dx$   
 $\int_a^b S''g'' dx = -\int_a^b S'''g' dx = \sum_{i=0}^{n-1} C_i \int_{x_i}^{x_{i+1}} g' dx = \sum_{i=0}^{n-1} C_i [g(x_{i+1}) - g(x_i)]$   
 $= 0$   
where  $C_i = \frac{z_{i+1} - z_i}{h_i} [S_i''(x_i) = z_i \& h_i = x_{i+1} - x_i]$ 

- Theorem on natural cubic splines
  - Proof

$$\int_{a}^{b} (f'')^{2} dx = \int_{a}^{b} (S'')^{2} dx + \int_{a}^{b} (g'')^{2} dx$$
$$\therefore \int_{a}^{b} (f'')^{2} dx \ge \int_{a}^{b} (S'')^{2} dx$$

### References

Wen Shen,
 An Introduction to Numerical Computation

- C. Moler,
   Numerical Computing with MATLAB
- Wikipedia

# **Further Study**

Lebesgue constants

 Piecewise constant interpolation and quadratic Splines