

POLYNOMIAL

INTERPOLATION - I

Polynomial Interpolation ?

Problem - Given a dataset $(x_0, f_0), \dots, (x_n, f_n)$ consisting of

distinct nodes: $[x_0, x_1, \dots, x_n]$

and values: $[f_0, f_1, \dots, f_n]$

construct a polynomial $p(x)$ of lowest degree such that $p(x_j) = f_j$ for $j = 0:n$.

Vandermonde Interpolating Polynomial.

Thm - consider nodes $[x_0, \dots, x_n]$

values $[f_0, \dots, f_n]$

There exist a polynomial for degree at most n such that $p(x_j) = f_j$ for $j = 0:n$

Proof - Consider the polynomial $p(x) = a_0 x^0 + a_1 x^1 + \dots + a_n x^n$

$p(x_j) = f_j$ for $j = 0:n$

$$\begin{bmatrix} 1 & x_0 & \dots & x_0^n \\ 1 & x_1 & & x_1^n \\ \vdots & \vdots & & \vdots \\ 1 & x_n & & x_n^n \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ \vdots \\ a_n \end{bmatrix} = \begin{bmatrix} f_0 \\ f_1 \\ \vdots \\ f_n \end{bmatrix}$$

Vandermonde Matrix

$$VA = Y$$

~~det~~

$\det(V) \neq 0$ so unique solution.

- The computation is numerically unstable.
- Solution of system require $O(n^3)$ operations.
- Any additional new data (x_{n+1}, f_{n+1}) requires recomputation.
- Evaluation of $p(x)$ at given require $O(n^2)$ operations.

Interpolating polynomial in general basis

Let P_n denote the vector space of polynomials of degree at most n . Let $\phi_0(x), \phi_1(x), \dots, \phi_n(x)$ be a basis of P_n . Let $p(x) = a_0 \phi_0(x) + a_1 \phi_1(x) + \dots + a_n \phi_n(x)$.

$\phi_0(x_0)$	$\phi_1(x_0)$	\dots	$\phi_n(x_0)$	a_0	$=$	f_0
$\phi_0(x_1)$	$\phi_1(x_1)$		\vdots	a_1		f_1
$\phi_0(x_2)$	\vdots		\vdots	\vdots		\vdots
\vdots	\vdots		\vdots	\vdots		\vdots
$\phi_0(x_n)$	$\phi_1(x_n)$		$\phi_n(x_n)$	a_n		f_n

Coefficient matrix is non singular.

The linear system has unique solution.

LAGRANGE INTERPOLATING POLYNOMIAL

Example - Let say for three data points -

$$(x_0, f_0), (x_1, f_1), \dots, (x_2, f_2)$$

define,

$$p(x) = \frac{(x-x_1)(x-x_2)}{(x_0-x_1)(x_0-x_2)} f_0 + \frac{(x-x_0)(x-x_2)}{(x_1-x_0)(x_1-x_2)} f_1 \\ + \frac{(x-x_0)(x-x_1)}{(x_2-x_0)(x_2-x_1)} f_2$$

Then $p(x_0) = f_0$

$$p(x_1) = f_1$$

$$p(x_2) = f_2$$

NOW IN GENERAL -

for data set $(x_0, f_0), (x_1, f_1), \dots, (x_n, f_n)$

define $w(x) = (x-x_0)(x-x_1)\dots(x-x_n) \in P_{n+1}$

$$L_j(x) = \prod_{i \neq j} \left(\frac{x-x_i}{-x_i+x_j} \right) \neq \prod_{i \neq j} \left(\frac{x-x_i}{x_j-x_i} \right)$$

$$w(x) = \prod_{m=0}^n (x-x_m)$$

$$w(x) = (x - x_j) \cdot \prod_{\substack{i=0 \\ i \neq j}}^n (x - x_i) \quad \text{--- (1)}$$

$$w'(x_j) = \frac{d}{dx} \left[(x - x_j) \cdot \prod_{\substack{i=0 \\ i \neq j}}^n (x - x_i) \right]$$

$$= \prod_{\substack{i=0 \\ i \neq j}}^n (x_j - x_i) + \cancel{(x_j - x_j)} \cdot \frac{d}{dx} \left(\prod_{\substack{i=0 \\ i \neq j}}^n (x - x_i) \right)$$

$$w'(x_j) = \prod_{\substack{i=0 \\ i \neq j}}^n (x_j - x_i) \quad \text{--- (2)}$$

from (1) and (2)

$$l_j(x) = \frac{w(x)}{(x - x_j) \cdot w'(x_j)}, \quad \text{for } j = 0, \dots, n$$

$l_j(x) = \delta_{ij}$ where δ_{ij} is Dirac Delta Function.

Hence - $p(x) = f_0 l_0(x) + \dots + f_n l_n(x)$

interpolates the dataset $(x_0, f_0) \dots (x_n, f_n)$.

The basis $l_0(x), l_1(x), \dots, l_n(x)$
is called Lagrange basis of P_n and $p(x)$
is called Lagrange interpolating polynomial.

IMP

$$\sum_{j=0}^n l_j(x) = 1$$

at given x
→ Computation of $p(x)$ require $O(n^2)$ operation

Why?

Calculating single $l_j(x)$ takes
multiplyin n terms so
takes $O(n)$.

$$\text{Total time} = O(n^2)$$

→ Cannot accomodate new $(x_{n+1}, m+1)$. Any
additional data requires recomputation.

A

DOUBT-

Computation of $p(x)$ requires $O(n^2)$ operations?

BARYCENTRIC LAGRANGE INTERPOLATION

$$l_j = \frac{w(x)}{(x-x_j) \cdot w'(x_j)} = \frac{w(x) \cdot w_j}{(x-x_j)}$$

where $w_j = \frac{1}{w'(x_j)}$

$$p(x) = \sum_{j=0}^n f_j(x) l_j(x)$$

$$= w(x) \sum_{j=0}^n \frac{f_j(x) \cdot w_j}{x-x_j} \quad \text{--- (1)}$$

Barycentric Form 1

Also,

$$1 = \sum_{j=0}^n l_j(x)$$

$$1 = w(x) \sum_{j=0}^n \frac{w_j}{x-x_j} \quad \text{--- (2)}$$

$$\text{(1)} \div \text{(2)}$$

$$\frac{p(x)}{1} = \frac{\sum_{j=0}^n w_j f_j(x)}{\sum_{j=0}^n \frac{w_j \cdot w(x)}{x-x_j}} = \frac{\sum_{j=0}^n \frac{w_j \cdot w(x) \cdot f_j(x)}{x-x_j}}{\sum_{j=0}^n \frac{w_j \cdot w(x)}{x-x_j}}$$

$$P(x) = \sum_{j=0}^n \frac{w_j f_j}{x - x_j} \quad \left\{ \begin{array}{l} \text{Barycentric} \\ \text{Form} \\ 2 \end{array} \right\}$$

Advantages -

- ① Once I know w_j . Evaluating $P(x)$ at $x = x_k$ takes $O(n)$ time.

However calculating every w_j takes $O(n^2)$

→ $O(n)$ for one j .

→ $O(n^2)$ for all j .

- ② To incorporate a new data point (x_{n+1}, f_{n+1})

- (a) updating or existing weights takes $O(2n+1)$ operations.

$$w_j^{\text{old}} = \frac{1}{\prod_{\substack{k=0 \\ k \neq j}}^n (x_j - x_k)}$$

$$w_j^{\text{new}} = \frac{1}{\prod_{\substack{k=0 \\ k \neq j}}^{n+1} (x_j - x_k)} = \frac{w_j^{\text{old}}}{(x_j - x_{n+1})}$$

② Computing the new weight w_{n+1} takes $O(2n+3)$

$$w_{n+1} = \frac{1}{\prod_{k=0}^n (x_{n+1} - x_k)}$$

③ Barycentric formulas has beautiful symmetry.

The weights w_j appear in denominator exactly as in numerators, except with factor f_j . This means any common factor in all the weights w_j may be cancelled without affecting the value of $p(x)$.

NEWTON INTERPOLATING POLYNOMIAL

Example - For data set (x_0, f_0) , (x_1, f_1) , (x_2, f_2)

$$p(x) = a_0 + a_1(x-x_0) + a_2(x-x_0)(x-x_1)$$

$$p(x_0) = f_0$$

$$p(x_1) = f_1$$

$$p(x_2) = f_2$$

$$\begin{bmatrix} 1 & 0 & 0 \\ 1 & (x_1-x_0) & 0 \\ 1 & (x_2-x_0) & (x_2-x_0)(x_2-x_1) \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} f_0 \\ f_1 \\ f_2 \end{bmatrix}$$

General -

$$N_0(x) = 1$$

$$N_j(x) = (x-x_0)(x-x_1)\dots(x-x_{j-1})$$

for $j=1$ to N

$$N_j(x_i) = 0 \quad \text{for } i=0:j-1 \text{ and } j=1:N$$

$$N_{j+1}(x) = N_j(x) \cdot (x-x_j)$$

$$N_0(x), N_1(x), \dots, N_n(x) \rightarrow \text{Newton's Basis}$$

$$p(x) = a_0 N_0(x) + a_1 N_1(x) + \dots + a_n N_n(x)$$

$P(x_j) = f_j$ for $j=0:n$ yields -

$$\begin{bmatrix} N_0(x_0) & 0 & 0 & \dots & 0 \\ N_0(x_1) & N_1(x_1) & 0 & \dots & 0 \\ N_0(x_2) & N_1(x_2) & N_2(x_2) & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ N_0(x_n) & N_1(x_n) & N_2(x_n) & \dots & N_n(x_n) \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix} = \begin{bmatrix} f_0 \\ f_1 \\ f_2 \\ \vdots \\ f_n \end{bmatrix}$$

Remark -

- Solution of lower Δ system requires $O(n^2)$ flops.
- Can accomodate new data (x_{n+1}, f_{n+1}) with addition $O(n)$ operations
- Evaluation of $p(x)$ at a given x require $O(n^2)$ operations.
- Computation of $p(x)$ requires $O(n^2)$ operations.

Computation of $N_j(x_j)$ may be prone OVERFLOW / UNDERFLOW.

Ask Ask remark 2

DIVIDED DIFFERENCE-

For example - consider (x_0, f_0) , (x_1, f_1) , (x_2, f_2)

or Newton's Polynomial is -

$$p(x) = a_0 + a_1(x-x_0) + a_2(x-x_1)(x-x_0)$$

$$f[x_j] := f_j \quad \text{for } j=0, 1, 2$$

$$p(x_0) = f_0, \quad p(x_1) = f_1, \quad p(x_2) = f_2$$

$$\checkmark a_0 = f[x_0] = f_0$$

$$a_1 = f[x_1]$$

$$a_2 = f[x_2]$$

$$\checkmark a_1 = \frac{f[x_1] - f[x_0]}{x_1 - x_0} = f[x_0, x_1]$$

$$\checkmark a_2 = \left(\frac{f[x_2] - f[x_0]}{x_2 - x_0} - f[x_0, x_1] \right) / (x_2 - x_1)$$

$$= \left(\frac{f[x_2] - f[x_1]}{x_2 - x_0} + \frac{f[x_1] - f[x_0]}{x_2 - x_0} - f[x_0, x_1] \right)$$

$$(x_2 - x_1)$$

$$= \frac{f[x_1, x_2] - f[x_0, x_1]}{x_2 - x_0} = f[x_0, x_1, x_2]$$

General case-

Divided difference can be generated
Using table of divided difference.

x	f				
x_0	f_0				
x_1	f_1	$f[x_0, x_1]$			
x_2	f_2	$f[x_1, x_2]$	$f[x_0, x_1, x_2]$		
x_3	f_3	$f[x_2, x_3]$	$f[x_1, x_2, x_3]$	$f[x_0, x_1, x_2, x_3]$	
\vdots					

$f[x_0, x_1, x_2] = \frac{f[x_1, x_2] - f[x_0, x_1]}{x_2 - x_0}$
 diagonal - left
 go to diagonal extreme - left of x

$n+1$ diagonals \rightarrow coefficients of Newton Interpolating polynomial

Adding new data $(x_{n+1}, f_{n+1}) \rightarrow$ Adding a new row at the bottom of the table. Additional $O(n)$ operations.

\hookrightarrow Underflow / Overflow problem is solved.

Thm - let $p(x) = a_0 N_0(x) + \dots + a_n N_n(x)$

such that $p(x_j) = f_j$ for $j = 0:n$.
then,

$$a_j = f[x_0, x_1, \dots, x_j] \quad \text{for } j = 0:n$$

Proof - Proof using induction.

The result is true for $n=0$.

Assume that the result is true for Newton interpolating polynomials of degree $\leq n-1$.

$$\text{let } q(x) = \sum_{j=0}^{n-1} b_j N_j(x)$$

↳ for data set $(x_1, f_1) \dots (x_n, f_n)$

$$\text{let } s(x) = \sum_{j=0}^{n-1} c_j N_j(x)$$

↳ for dataset $(x_0, f_0) \dots (x_{n-1}, f_{n-1})$

By induction hypothesis $b_n = f[x_1, x_2, \dots, x_n]$
 $c_{n-1} = f[x_0, x_1, \dots, x_{n-1}]$

$r(x) =$

For the dataset $(x_0, f_0) \dots (x_n, f_n)$
 $r(x)$ be interpolating polynomial.

$$r(x) = q(x) + \frac{x - x_n}{x_n - x_0} (q(x) - s(x))$$

→ $r(x)$ satisfies for data - $(x_1, f_0) \dots (x_{n+1}, f_{n+1})$

$$\text{because } q(x) - s(x) = 0$$

$$r(x) = q(x).$$

→ For (x_0, f_0)

$$\begin{aligned} r(x) &= q(x_0) + (q(x_0) - s(x_0)) \\ &= s(x_0) = f_0 \end{aligned}$$

→ For (x_n, f_n)

$$\begin{aligned} r(x_n) &= q(x_n) + 0 \\ &= f_n \end{aligned}$$

Hence $r(x)$ interpolates $(x_0, f_0) \dots (x_n, f_n)$

Now the coefficient of x^n in $r(x)$

$$a_n = \frac{f[x_1, x_2, \dots, x_n] - f[x_0, x_1, \dots, x_{n-1}]}{x_n - x_0}$$

$$a_n = f[x_0, x_1, \dots, x_n]$$

RUNGE PHENOMENON

Consider the Runge function

$f: [-1, 1] \rightarrow \mathbb{R}$ given by

$$f(x) = \frac{1}{1+25x^2}$$

Then for equally spaced nodes (x_0, \dots, x_n)
and values $f_j = f(x_j)$ for $j=0:n$

The interpolant $p_n(x)$ doesn't converge to $f(x)$. In fact $\max_{|x| \leq 1} |f(x) - p_n(x)| \rightarrow \infty$
as $n \rightarrow \infty$

But for Chebyshev Nodes $x_j = \cos\left(\frac{(2j+1)\pi}{2n+2}\right)$

for $j=0:n$ ~~at~~ $\max_{|x| \leq 1} |f(x) - p_n(x)| \rightarrow 0$

as $n \rightarrow \infty$.

The Runge phenomenon is eliminated by
choosing Chebyshev nodes in interpolation points
in $[-1, 1]$

Chebyshev Polynomial

$$\text{Let } \theta \in [0, \pi]$$

$$x \in [-1, 1]$$

$$\text{Define } T_n(x) = \cos(n \cos^{-1} x).$$

$$T_0(x) = 1$$

$$T_1(x) = x$$

$$T_2(x) = 2x^2 - 1$$

$T_n(x)$ is n -degree polynomial and is called Chebyshev Polynomial.

$$T_n(x) \text{ satisfies } T_{n+1}(x) = 2xT_n(x) - T_{n-1}(x)$$

Why? If $x = \cos \theta$

$$\cos((n+1)\theta) + \cos((n-1)\theta) = 2\cos\theta \cos n\theta$$

$$\begin{bmatrix} T_1(x) \\ T_2(x) \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -1 & 2x \end{bmatrix} \begin{bmatrix} 1 \\ x \end{bmatrix}$$

$$\begin{bmatrix} T_n(x) \\ T_{n+1}(x) \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -1 & 2x \end{bmatrix} \begin{bmatrix} T_{n-1}(x) \\ T_n(x) \end{bmatrix}$$

$$\hookrightarrow \begin{bmatrix} T_n(x) \\ T_{n+1}(x) \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -1 & 2x \end{bmatrix}^n \begin{bmatrix} 1 \\ x \end{bmatrix}$$

$$T_n(x) = \sum_{j=0}^{\lfloor n/2 \rfloor} \binom{n}{2j} x^{n-2j} (x^2-1)^j$$

Chebyshev NODES

$$T_n(x) = \cos(n \cos^{-1} x)$$

we have $|T_n(x)| \leq 1$ for $x \in [-1, 1]$

Chebyshev
NODES

$$\Rightarrow T_n(x_j) = 0 \quad \text{for } x_j = \cos\left(\frac{(2j+1)\pi}{2n}\right)$$

$$j=0, 1, \dots, n-1$$

GAUSS

$$\text{LOBATTO} \Rightarrow T_n(x_j) = (-1)^j \quad \text{for } x_j = \cos\left(\frac{j\pi}{n}\right)$$

NODES

$$j=0, 1, \dots, n$$

Chebyshev Nodes

Connection of Chebyshev nodes -

We want build $p(x)$ of degree $\leq n$ through $n+1$ Chebyshev nodes.

The zeros of $T_{n+1}(x)$ will give exactly $n+1$ points in $[-1, 1]$ i.e. - Chebyshev nodes will be zeros of $T_{n+1}(x)$.

Barycentric Lagrange Interpolation with Chebyshev Nodes

$$p(x) = \frac{\sum_{j=0}^n w_j f_j / (x - x_j)}{\sum_{j=0}^n w_j / (x - x_j)}$$

where $w_j = \frac{1}{\prod_{i \neq j} (x_j - x_i)}$ for $j = 0:n$

For Chebyshev nodes: $\cos \left(\frac{j\pi}{n} \right)$ -

$$x_j = \cos \left(\frac{j\pi}{n} \right) \quad j = 0, 1, \dots, n$$

$$w_j = \begin{cases} \frac{1}{2} (-1)^j & j=0 \text{ or } j=n \\ (-1)^j & \text{otherwise} \end{cases}$$

$$p(x) = \frac{\sum_{j=0}^n (-1)^j f_j / (x - x_j)}{\sum_{j=0}^n w_j (-1)^j / (x - x_j)}$$

\sum' means that terms $j=0$ and $j=n$ are multiplied by $1/2$.

NOTE - Barycentric interpolation formula remains valid for Chebyshev nodes $[a, b]$

Approximation

Let $C[a, b] := \{f : [a, b] \rightarrow \mathbb{R} \mid f \text{ is continuous}\}$

For $f \in C[a, b]$, define

$$\|f\|_{\infty} = \max \{ |f(x)| \mid x \in [a, b] \}$$

- ① $\|f\|_{\infty} = 0 \iff f = 0$
- ② $\|\alpha f\|_{\infty} = |\alpha| \|f\|_{\infty}$
- ③ $\|f + g\|_{\infty} \leq \|f\|_{\infty} + \|g\|_{\infty}$

Weierstrass approx theorem:

Let $f \in C[a, b]$ and $\epsilon > 0$. Then there is a polynomial $p(x)$ such that $\|f - p\|_{\infty} < \epsilon$.

(or)

$$\max \{ |f(x) - p(x)| : x \in [a, b] \} < \epsilon$$

Question - Does $p_n(x)$ approx $f(x)$ for large enough n ? In other words, does $\|p_n - f\|_{\infty} \rightarrow 0$ as $n \rightarrow \infty$?

ANS - NO, for equispaced we saw $n \rightarrow \infty$ the error was ∞

Interpolation error -

Let $f \in C[a, b]$ and $[x_0, \dots, x_n]$
be distinct nodes in $[a, b]$, $f_j = f(x_j)$
for $j = 0:n$.

Lagrange polynomial -

$$p(x) = f_0 l_0(x) + f_1 l_1(x) + \dots + f_n l_n(x)$$

Define :

$$\{\text{LEBESGUE FUNC}\} \quad \lambda_n(x) = |l_0(x)| + \dots + |l_n(x)|$$

$$\{\text{LEBESGUE CONST}\} \quad \Lambda_n = \|\lambda_n\|_\infty$$

Set :

$$E_n(f) = \min \{ \|f - p\|_\infty : p \in P_n \}$$

Proof 1 - $|p_n(x)| \leq \Lambda_n \|f\|_\infty$

Proof - $|p_n(x)| = \left| \sum_{j=0}^n f_j l_j(x) \right|$

$$\leq \sum_{j=0}^n |f_j| |l_j(x)|$$

$$\leq \|f\|_\infty \sum_{j=0}^n |l_j(x)|$$

$$\leq \|f\|_\infty \lambda_n(x)$$

$$\begin{aligned} \|p_n(x)\| &\leq \|f\|_\infty \|\lambda_n\|_\infty \\ &= \|f\|_\infty \Lambda_n \end{aligned}$$

$$|p_n(x)| \leq \|f\|_\infty \Lambda_n \quad \left\{ \begin{array}{l} \text{Point wise also} \\ \text{holds true} \end{array} \right\}$$

Proof 2 - $\|f - P_n\|_\infty \leq (1 + \Lambda_n) E_n(f)$

Proof -

- Interpolation error is at most the best possible polynomial error multiplied by $1 + \Lambda_n$. If Λ_n is large → worse. Small Λ_n → better.
- Λ_n depends only on nodes not on f . So node choice matters.

FACT - for equispaced nodes, the Runge function $f(x) = \frac{1}{1+x^2}$
 $\Lambda_n \sim \frac{2^n}{n \log n}$ and for Chebyshev $\Lambda_n \leq \frac{2 \log n}{n}$

ERROR TERM FOR SMOOTH FUNCTION -

Let $C^n[a, b]$ denote the set of n times continuously differentiable functions in $[a, b]$.

Theorem -

If $f \in C^n[a, b]$ and $p_n(x)$ be unique polynomial of degree at most n passing through $(x_0, f(x_0)), \dots, (x_n, f(x_n))$

$$f(x) - p_n(x) = \frac{f^{(n+1)}(\theta x)}{(n+1)!} \cdot w(x)$$

for some $\theta x \in [x_{\min}, x_{\max}]$ where x_{\min} and x_{\max} are the largest and the smallest nodes in $[x_0, x_1, \dots, x_n, x]$ and $w(x) = \prod_{i=0}^n (x - x_i)$

Proof -

$$\text{so, } |f(x) - p_n(x)| < \frac{\|f^{(n+1)}\|_{\infty}}{(n+1)!} |w(x)|$$

ERROR

Error is dependent on $w(x)$, so we want to minimize $|w(x)|$

Chebyshev's Thm -

Goal - Choose nodes x_0, \dots, x_n in $[a, b]$ that minimizes $\max_{x \in [a, b]} \prod_{j=0}^n |x - x_j|$

$$\min_{x_0, \dots, x_n} \max_{x \in [a, b]} \prod_{j=0}^n |x - x_j|$$

ASK - If proof is there or not.

classmate

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Thm- In $x \in [-1, 1]$

$$\min_{x_0, x_1, \dots, x_n} \max_{x \in [-1, 1]} \prod_{j=0}^n |x - x_j| = 2^{-n}$$

and the minimum is attained when

$$w(x) = \prod_{j=0}^n (x - x_j) = 2^{-n} T_{n+1}(x)$$

Minimum is attained when x_0, \dots, x_n are Chebyshev nodes in $[-1, 1]$.

Hence,

$$|f(x) - p_n(x)| \leq \frac{\|f^{(n+1)}\|_{\infty}}{(n+1)! 2^n}$$