Newton Polynomials and Divided Differences MATH 375 Numerical Analysis

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Background

Constructing Lagrange polynomials is relatively easy as a pencil and paper technique, but difficult to automate.

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- Neville's iterated interpolation can approximate a function at a single point, but does not construct a polynomial.
- Today we learn an iterated technique for building up the Lagrange interpolating polynomials.

Polynomial Interpolation

Suppose polynomial $P_n(x)$ interpolates the data:

 $\{(x_0, f(x_0)), (x_1, f(x_1)), \dots, (x_n, f(x_n))\}.$

If one more data point is added, say

 $\{(x_0, f(x_0)), (x_1, f(x_1)), \dots, (x_n, f(x_n)), (x_{n+1}, f(x_{n+1}))\},\$

we would like to use $P_n(x)$ to find $P_{n+1}(x)$.

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we would like to use $P_n(x)$ to find $P_{n+1}(x)$.

Imagine that

$$P_{n+1}(x) = P_n(x) + q(x)$$

 $q(x) = P_{n+1}(x) - P_n(x).$

Polynomial q(x) interpolates the data,

$$\{(x_0,0),(x_1,0),\ldots,(x_n,0),(x_{n+1},f(x_{n+1})-P_n(x_{n+1}))\}$$

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Lagrange Form of q(x)

Polynomial q(x) can be expressed as a single Lagrange basis polynomial.

$$q(x) = (f(x_{n+1}) - P_n(x_{n+1})) \prod_{k=0}^n \frac{x - x_k}{x_{n+1} - x_k}$$

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Lagrange Interpolating Polynomial

Suppose f(x) is a function and $P_n(x)$ is the Lagrange interpolating polynomial of degree at most *n* which agrees with f(x) at the distinct points $\{x_0, x_1, \ldots, x_n\}$.

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We can think of $P_n(x)$ as

$$P_n(x) = a_0 + a_1(x - x_0) + a_2(x - x_0)(x - x_1) + \dots + a_n(x - x_0) \dots (x - x_{n-1}) = a_0 + \sum_{i=1}^n a_i \prod_{i=0}^{i-1} (x - x_i)$$

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for an appropriate choice of constants a_0, a_1, \ldots, a_n .

Question: how can we find these constants?

Evaluation of $P_n(x)$

$$P_n(x) = a_0 + a_1(x - x_0) + a_2(x - x_0)(x - x_1) + \cdots + a_n(x - x_0) \cdots (x - x_{n-1})$$

• If $x = x_0$ then $P_n(x_0) = f(x_0) = a_0$.

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▶ If
$$x = x_0$$
 then $P_n(x_0) = f(x_0) = a_0$.
▶ If $x = x_1$ then $P_n(x_1) = f(x_1)$ and

$$P_n(x_1) = a_0 + a_1(x_1 - x_0)$$

$$f(x_1) = f(x_0) + a_1(x_1 - x_0)$$

$$a_1 = \frac{f(x_1) - f(x_0)}{x_1 - x_0}$$

and so on.

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Find a₂

$$P_n(x_2) = a_0 + a_1(x_2 - x_0) + a_2(x_2 - x_0)(x_2 - x_1)$$

$$f(x_2) = f(x_0) + \frac{f(x_1) - f(x_0)}{x_1 - x_0}(x_2 - x_0)$$

$$+ a_2(x_2 - x_0)(x_2 - x_1)$$

$$a_2(x_2 - x_0)(x_2 - x_1) = f(x_2) - f(x_0) - \frac{f(x_1) - f(x_0)}{x_1 - x_0}(x_2 - x_0)$$

$$a_2 = \frac{f(x_2) - f(x_0) - \frac{f(x_1) - f(x_0)}{x_1 - x_0}(x_2 - x_0)}{(x_2 - x_0)(x_2 - x_1)}$$

$$= \frac{\frac{f(x_2) - f(x_1)}{x_2 - x_1} - \frac{f(x_1) - f(x_0)}{x_1 - x_0}}{x_2 - x_0}$$

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Divided Difference Notation (1 of 2)

Denote the zeroth divided difference of f with respect to x_i by

 $f[\mathbf{x}_i] = f(\mathbf{x}_i).$

Denote the first divided difference of *f* with respect to x_i and x_{i+1} by

$$f[x_i, x_{i+1}] = \frac{f[x_{i+1}] - f[x_i]}{x_{i+1} - x_i}.$$

Denote the second divided difference of *f* with respect to x_i, x_{i+1}, and x_{i+2} by

$$f[x_i, x_{i+1}, x_{i+2}] = \frac{f[x_{i+1}, x_{i+2}] - f[x_i, x_{i+1}]}{x_{i+2} - x_i}$$

Divided Difference Notation (2 of 2)

Proceeding recursively,

► Denote the *k*th divided difference of *f* with respect to x_i , x_{i+1} , x_{i+2} , ..., x_{i+k} by

$$f[x_i, x_{i+1}, \dots, x_{i+k-1}, x_{i+k}] = \frac{f[x_{i+1}, x_{i+2}, \dots, x_{i+k}] - f[x_i, x_{i+1}, \dots, x_{i+k-1}]}{x_{i+k} - x_i}.$$

Finally, denote the *n*th divided difference of *f* with respect to x₀, x₁, x₂, ..., x_n by

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

Summary and Connections

Recall that

$$P_n(x) = a_0 + \sum_{k=1}^n a_k \prod_{j=0}^{k-1} (x - x_j).$$

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$$P_n(x) = a_0 + \sum_{k=1}^n a_k \prod_{j=0}^{k-1} (x - x_j).$$

Using the divided difference notation we see that

$$a_{0} = f[x_{0}]$$

$$a_{1} = f[x_{0}, x_{1}]$$

$$a_{2} = f[x_{0}, x_{1}, x_{2}]$$

$$\vdots$$

$$a_{n} = f[x_{0}, x_{1}, x_{2}, \dots, x_{n}], \text{ and thus}$$

$$P_{n}(x) = f[x_{0}] + \sum_{k=1}^{n} f[x_{0}, \dots, x_{k}] \prod_{j=0}^{k-1} (x - x_{j}).$$

This is called Newton's interpolatory divided difference formula.

Table Format

Divided Difference Algorithm

INPUT nodes { $(x_0, f(x_0)), \dots, (x_n, f(x_n))$ } STEP 1 For $i = 0, 1, \dots, n$ set $F_{i,0} = f(x_i)$. STEP 2 For $i = 1, 2, \dots, n$ For $j = 1, 2, \dots, i$ set $F_{i,j} = \frac{F_{i,j-1} - F_{i-1,j-1}}{x_i - x_{i-j}}$ STEP 3 OUTPUT $F_{0,0}, F_{1,1}, \dots, F_{n,n}$. STOP.

Remark: the output values are the top entries in the columns of the preceding table.

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Example (1 of 2)

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Complete the divided difference table and construct the interpolating polynomial.

Xi	$f(x_i)$	First	Second	Third	Fourth
3.2	22.0				
		8.4			
2.7	17.8		2.85561		
		2.11765		-0.52748	
1.0	14.2		2.01165		0.255838
		6.34211		0.0865307	
4.8	38.3		2.26259		
		16.75			
5.6	51.7				

Example (2 of 2)

$$\begin{split} P_4(x) &= 22.0 + 8.4(x - 3.2) + 2.85561(x - 3.2)(x - 2.7) \\ &\quad - 0.52748(x - 3.2)(x - 2.7)(x - 1.0) \\ &\quad + 0.255838(x - 3.2)(x - 2.7)(x - 1.0)(x - 4.8) \\ &= 34.96 - 36.1836x + 18.6885x^2 - 3.52078x^3 + 0.255838x^4 \end{split}$$

Graph



Implications of the Mean Value Theorem

$$f[x_i, x_j] = \frac{f(x_j) - f(x_i)}{x_j - x_i} = f'(z)$$

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for some *z* between x_i and x_j according to the MVT.

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This can be generalized.

Theorem

Suppose $f \in C^n[a, b]$ and $x_0, x_1, ..., x_n$ are distinct numbers in [a, b]. There exists $z \in (a, b)$ such that

$$f[x_0, x_1, \ldots, x_n] = \frac{f^{(n)}(z)}{n!}.$$

Proof

• Define
$$g(x) = f(x) - P_n(x)$$
.

- Since $f(x_i) = P_n(x_i)$ for i = 0, 1, ..., n, then function g has n + 1 distinct roots in [a, b].
- According to the Generalized Rolle's Theorem, g⁽ⁿ⁾(z) = 0 for some z ∈ (a, b).

$$0 = g^{(n)}(z)$$

= $f^{(n)}(z) - P_n^{(n)}(z)$
 $P_n^{(n)}(z) = f^{(n)}(z)$
 $n! f[x_0, x_1, \dots, x_n] = f^{(n)}(z)$
 $f[x_0, x_1, \dots, x_n] = \frac{f^{(n)}(z)}{n!}$

Remarks

- The coordinates of the nodes x₀, x₁, ..., x_n need not be in ascending order.
- The spacing between the nodes $\Delta x_i = x_{i+1} x_i$ need not be uniform.

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Remarks

- The coordinates of the nodes x₀, x₁, ..., x_n need not be in ascending order.
- ► The spacing between the nodes ∆x_i = x_{i+1} − x_i need not be uniform.

However, if the nodes are in ascending order and the spacing between nodes is uniform, we can modify Newton's divided difference formula.

Forward Differences (1 of 4)

Suppose $x_{i+1} - x_i = h > 0$ for i = 0, 1, ..., n - 1, then

- For any *x* there exists *s* such that $x = x_0 + sh$.
- ln particular $x_i = x_0 + ih$ for $i = 0, 1, \dots, n$.
- For $i = 0, 1, \ldots, n$ the difference

$$x - x_i = (x_0 + sh) - x_i = (x_0 + sh) - (x_0 + ih) = (s - i)h.$$

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$$x - x_i = (x_0 + sh) - x_i = (x_0 + sh) - (x_0 + ih) = (s - i)h.$$

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

$$P_n(x_0 + sh) = f[x_0] + \sum_{k=1}^n f[x_0, \dots, x_k] \prod_{j=0}^{k-1} (x_0 + sh - x_0 - jh)$$

$$= f[x_0] + \sum_{k=1}^n f[x_0, \dots, x_k] \prod_{j=0}^{k-1} ((s - j)h)$$

$$= f[x_0] + \sum_{k=1}^n h^k f[x_0, \dots, x_k] \prod_{j=0}^{k-1} (s - j)$$

Forward Differences (2 of 4)

Using the binomial coefficient notation

$$\binom{s}{k} = \frac{s!}{(s-k)! \, k!}$$
$$= \frac{s(s-1)\cdots(s-k+1)}{k!}$$
$$= \frac{\prod_{j=0}^{k-1}(s-j)}{k!}$$
$$s(s-1)\cdots(s-k+1) = k! \binom{s}{k},$$

we can write

$$P_n(x) = f[x_0] + \sum_{k=1}^n h^k f[x_0, \dots, x_k] \prod_{j=0}^{k-1} (s-j)$$

= $f[x_0] + \sum_{k=1}^n h^k k! {\binom{s}{k}} f[x_0, \dots, x_k].$

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Forward Differences (3 of 4)

Recalling Aitken's Δ^2 notation we may write

$$f[x_0, x_1] = \frac{f(x_1) - f(x_0)}{x_1 - x_0} = \frac{\Delta f(x_0)}{h}$$

$$f[x_0, x_1, x_2] = \frac{f[x_1, x_2] - f[x_0, x_1]}{x_2 - x_0} = \frac{1}{2h} \left(\frac{\Delta f(x_1)}{h} - \frac{\Delta f(x_0)}{h}\right) = \frac{\Delta^2 f(x_0)}{2h^2}$$

$$\vdots$$

$$f[x_0, x_1, \dots, x_k] = \frac{f[x_1, x_2, \dots, x_k] - f[x_0, x_1, \dots, x_{k-1}]}{x_k - x_0}$$

$$= \frac{1}{kh} \left(\frac{\Delta^{k-1} f(x_1)}{(k-1)!h^{k-1}} - \frac{\Delta^{k-1} f(x_0)}{(k-1)!h^{k-1}}\right) = \frac{\Delta^k f(x_0)}{k!h^k}.$$

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Forward Differences (4 of 4)

Finally, we may write the Newton Forward-Difference Formula:

$$P_{n}(x) = f[x_{0}] + \sum_{k=1}^{n} h^{k} k! {\binom{s}{k}} f[x_{0}, \dots, x_{k}]$$

= $f[x_{0}] + \sum_{k=1}^{n} h^{k} k! {\binom{s}{k}} \frac{1}{k! h^{k}} \Delta^{k} f(x_{0})$
= $f[x_{0}] + \sum_{k=1}^{n} {\binom{s}{k}} \Delta^{k} f(x_{0})$

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Comments

Forward-differences on the nodes

$$x_0 < x_1 < \cdots < x_{n-1} < x_n$$

are useful when x is nearer to x_0 than to x_n since generally $f(x_0)$ will be closer to f(x) than will $f(x_n)$.

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If we need to approximate f at x near x_n then we should reorder the nodes as

$$x_n>x_{n-1}>\cdots>x_1>x_0.$$

The interpolating polynomial becomes

$$P_n(x) = f[x_n] + \sum_{i=1}^n f[x_n, \dots, x_{n-i}](x - x_n) \cdots (x - x_{n-i+1}).$$

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Backward Differences (1 of 4)

Definition

Given the sequence $\{p_n\}_{n=0}^{\infty}$ we define the **backward difference** ∇p_n as

$$\nabla p_n = p_n - p_{n-1}$$
, for $n \ge 1$.

For $k \ge 2$ we define the *k*th order backward difference as

$$\nabla^k p_n = \nabla (\nabla^{k-1} p_n).$$

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Backward Differences (2 of 4)

Using the backward difference notation we may write

$$f[x_n, x_{n-1}] = \frac{f(x_{n-1}) - f(x_n)}{x_{n-1} - x_n} = \frac{f(x_n) - f(x_{n-1})}{x_n - x_{n-1}} = \frac{1}{h} \nabla f(x_n)$$
$$f[x_n, x_{n-1}, x_{n-2}] = \frac{1}{2h^2} \nabla^2 f(x_n)$$
$$\vdots$$
$$f[x_n, x_{n-1}, \dots, x_{n-k}] = \frac{1}{k! h^k} \nabla^k f(x_n).$$

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Backward Differences (3 of 4)

Writing $x = x_n + sh$ where s < 0 and $x - x_i = (s + n - i)h$ then the interpolating polynomial can be written as

$$P_n(x) = f[x_n] + \sum_{i=1}^n f[x_n, \dots, x_{n-i}](x - x_n) \cdots (x - x_{n-i+1})$$

= $f[x_n] + \sum_{i=1}^n h^i s(s+1) \cdots (s+n-i) f[x_n, \dots, x_{n-i}]$
= $f[x_n] + \sum_{i=1}^n \frac{s(s+1) \cdots (s+n-i)}{i!} \nabla^i f[x_n].$

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Backward Differences (4 of 4)

Since s < 0 we must modify the binomial coefficient notation.

$$\binom{-s}{k} = \frac{-s(-s-1)\cdots(-s-k+1)}{k!} = (-1)^k \frac{s(s+1)\cdots(s+k-1)}{k!}$$

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Backward Differences (4 of 4)

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$$\binom{-s}{k} = \frac{-s(-s-1)\cdots(-s-k+1)}{k!} = (-1)^k \frac{s(s+1)\cdots(s+k-1)}{k!}$$

Then we may write the interpolating polynomial as

$$P_n(x) = f[x_n] + \sum_{i=1}^n \frac{s(s+1)\cdots(s+n-i)}{i!} \nabla^i f[x_n]$$
$$= f[x_n] + \sum_{i=1}^n (-1)^i \binom{-s}{i} \nabla^i f[x_n]$$

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This is known as the Newton backward-difference formula.

Example (1 of 4)

Suppose we create forward and backward difference interpolating polynomials for $f(x) = \cos x$ using nodes $x_i = 0.2(i + 1)$ for i = 0, 1, 2, 3.

X	cos X	First	Second	Third
0.2	0.980067			
		-0.295028		
0.4	0.921061		-0.458997	
		-0.478627		0.0795056
0.6	0.825336		-0.411294	
		-0.643145		
0.8	0.696707			

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Forward divided difference:

 $P_3(x) = 0.998536 + 0.015353x - 0.554404x^2 + 0.0795056x^3$

Backward divided difference:

 $P_3(x) = 0.998537 + 0.0153524x - 0.554404x^2 + 0.0795056x^3$

Example (3 of 4)



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Example (4 of 4)

Difference between the forward and backward interpolation functions.

Error of the forward and backward interpolation functions.

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Homework

Read Section 3.3.

Exercises: 1a, 3a, 5a, 13, 17