

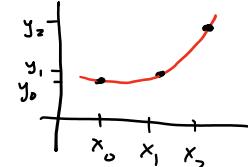
Newton's Divided Difference Method

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Alternative algorithm to basic Lagrange interpolation or Barycentric version

A **classic** but it was especially important for doing calculations by hand, less important these days.

Same setup: nodes $\{x_0, x_1, \dots, x_n\}$ w/ values $\{y_0, y_1, \dots, y_n\}$



From last time: we can write the n degree interpolating polynomial as

$$P_n(x) = \sum_{k=0}^n y_k L_{n,k}(x), \quad L_{n,k}(x) = \prod_{\substack{i=0 \\ i \neq k}}^n \frac{(x-x_i)}{(x_k-x_i)}$$

All we're going to do is write P_n differently,

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

"Newton's form"

It's not immediately obvious this is possible. The idea is that a_0 is determined by y_0 since $P_n(x_0) = a_0 + 0 + 0 + 0 + \dots + 0 = y_0$

Then, note $P_n(x_1) = a_0 + a_1(x_1-x_0) + 0 + 0 + \dots + 0 = y_1$,

we already determined a_0

$$\text{so } a_1 = \frac{y_1 - a_0}{x_1 - x_0} = \frac{y_1 - y_0}{x_1 - x_0}$$

... and so on. We're going to formalize this now.

computation order matters!
Do a_0 first,
then a_1

We'll need notation:

$\overrightarrow{n+1 \text{ of these, } i=0, 1, \dots, n}$ • the 0^{th} divided difference is $f[x_i] := y_i$ (and $y_i = f(x_i)$ often)

$\overrightarrow{n \text{ of these, } i=0, 1, \dots, n-1}$ • the 1^{st} divided difference is $f[x_i, x_{i+1}] = \frac{f[x_{i+1}] - f[x_i]}{x_{i+1} - x_i}$

$\overrightarrow{n-1 \text{ of these } i=0, \dots, n-2}$ • the 2^{nd} divided difference is $f[x_i, x_{i+1}, x_{i+2}] = \frac{f[x_{i+2}] - f[x_{i+1}, x_{i+2}]}{x_{i+2} - x_i}$

$\overrightarrow{n-k \text{ of these } i=0, \dots, n-k}$ • the k^{th} divided difference is $f[x_i, x_{i+1}, \dots, x_{i+k}] = \frac{f[x_{i+k}, \dots, x_{i+k}] - f[x_i, \dots, x_{i+k-1}]}{x_{i+k} - x_i}$

Square brackets tell us it's a divided difference

$\stackrel{\curvearrowleft}{\text{1 of these}}$ Stop at the n^{th} divided difference

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

Back to our polynomial

$$P_n(x) = a_0 + a_1(x-x_0) + a_2(x-x_0)(x-x_1) + \dots + a_n(x-x_0)(x-x_1)\dots(x-x_n)$$

$\underbrace{= f[x_0]}_{\text{we proved above}} \quad \underbrace{= f[x_0, x_1]}_{\text{can prove but it's messy}} \quad \underbrace{= f[x_0, x_1, x_2]}_{\text{can prove but it's messy}} \quad \vdots \quad \underbrace{= f[x_0, x_1, \dots, x_n]}$

So

$$P_n(x) = f[x_0] + \sum_{k=1}^n f[x_0, x_1, \dots, x_k] \cdot (x-x_0)(x-x_1)\dots(x-x_{k-1})$$

* note: we didn't need to assume $x_0 < x_1 < x_2 < \dots$
so you are free to **reorder** the points

How to compute divided differences

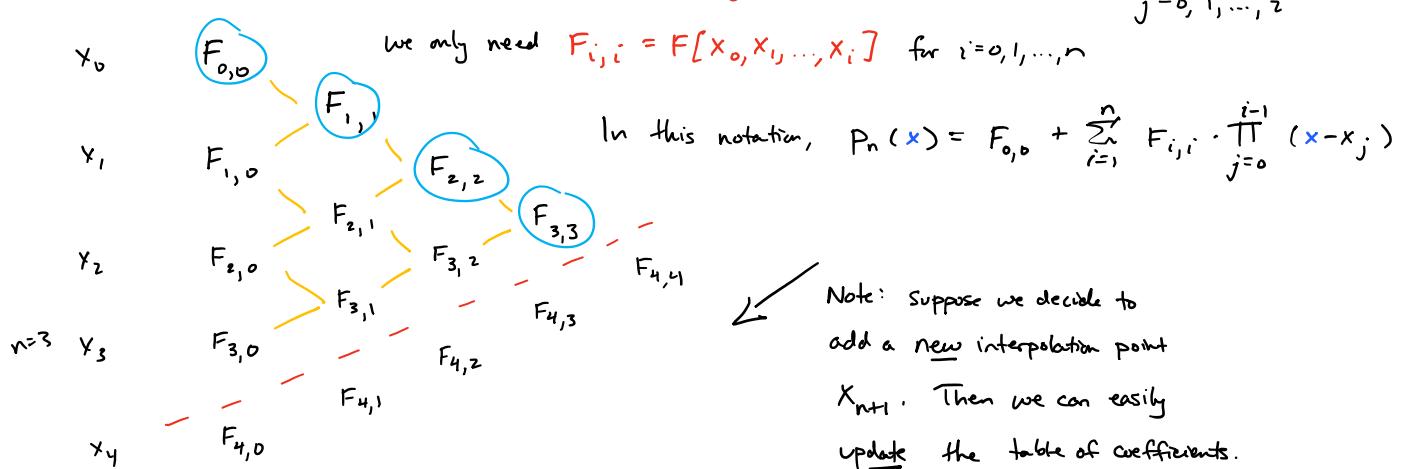
Ex. w/ $n=3$

$$\begin{aligned} f[x_0] &= y_0 \\ f[x_0, x_1] &= \frac{f[x_1] - f[x_0]}{x_1 - x_0} \\ f[x_1] &= y_1 \\ f[x_1, x_2] &= \frac{f[x_2] - f[x_1]}{x_2 - x_1} \\ f[x_2] &= y_2 \\ f[x_2, x_3] &= \frac{f[x_3] - f[x_2]}{x_3 - x_2} \\ f[x_3] &= y_3 \end{aligned}$$

$$\begin{aligned} f[x_0, x_1, x_2] &= \frac{f[x_1, x_2] - f[x_0, x_1]}{x_2 - x_0} \\ f[x_0, x_1, x_2, x_3] &= \frac{f[x_0, x_1, x_2] - f[x_1, x_2, x_3]}{x_3 - x_0} \end{aligned}$$

We only need the terms circled, but to compute these, we have to generate all the previous terms

Using the shorthand notation $F_{i,j} = F[x_{i-j}, \dots, x_i]$ for $i=0, 1, \dots, n$ $j=0, 1, \dots, i$



i.e., "Algo 3.2"

① For $i = 1, 2, \dots, n$

NEWTON DIVIDED DIFFERENCES

For $j = 1, 2, \dots, i$

$$F_{i,j} = \frac{F_{i,j-1} - F_{i-1,j-1}}{x_i - x_{i-j}}$$

Computational Complexity

① two "for" loops,

$O(1)$ computation at the innermost level,
repeat i times,
for $j=1, 2, \dots, n$

so flop count is $\sum_{i=1}^n i$ }
(\hookrightarrow floating point operation)

$$so = n \left(\frac{n+1}{2} \right) = O(n^2)$$

② then to evaluate $p_n(x)$,

$$\text{use } p_n(x) = F_{0,0} + \sum_{i=1}^n F_{i,i} \cdot \prod_{j=0}^{i-1} (x - x_j)$$

you may recall from Calc. I.

The trick:

$$\begin{aligned} 1 + 2 + 3 + 4 + 5 &= \underbrace{3}_{\text{(odd)}} + \underbrace{6}_{\text{(even)}} + \underbrace{6}_{\text{(even)}} + \underbrace{10}_{\text{(odd)}} + \underbrace{10}_{\text{(odd)}} \\ &= \frac{(n+1)}{2} + \frac{(n-1)}{2} \cdot (n+1) \\ &= \boxed{\frac{n \cdot (n+1)}{2}} \end{aligned}$$

② Evaluating at a point x

It looks like $\sum_{i=1}^n i$ again

but in fact it is $\sum_{i=1}^n 1 = O(n)$

because we can save values

$$\begin{aligned} \prod_{j=0}^{i-1} (x - x_j) &= (x - x_{i-1}) \cdot \underbrace{\prod_{j=0}^{i-2} (x - x_j)}_{\text{already computed.}} \\ &= \underbrace{7 \cdot 7 \cdot 7 \cdot 7}_{n-2} = \boxed{\frac{n(n+1)}{2}} \end{aligned}$$

$$\prod_{j=0}^{i-1} (x - x_j) = (x - x_{i-1}) \cdot \prod_{j=0}^{i-2} (x - x_j)$$

Minor details (see book ch. 3.3)

① since $f[x_0, x_1] = \frac{f(x_1) - f(x_0)}{x_1 - x_0}$, then if f is differentiable, the Mean Value Thm
 $\Rightarrow \exists \xi \in (x_0, x_1) \text{ s.t. } f[x_0, x_1] = f'(\xi)$

and in fact a more general statement is true:

Thm 3.6 If $f \in C^n([a, b])$ and $\{x_0, \dots, x_n\} \subseteq [a, b]$ are distinct, then $\exists \xi \in (a, b)$

$$\text{s.t. } f[x_0, x_1, \dots, x_n] = \frac{f^{(n)}(\xi)}{n!}$$

② As for Lagrange and Barycentric formulas, if $\{x_0, x_1, \dots, x_n\}$ are uniformly spaced, i.e.,

$$x_1 = x_0 + h$$

$$x_2 = x_0 + 2 \cdot h \quad \dots \quad x_n = x_0 + n \cdot h$$

then things simplify.

To write $x - x_i$, let $x = x_0 + s \cdot h$ (s is probably not an integer)

then $x - x_i = (s-i) \cdot h$ and we can simplify w/ binomial coefficients

Combined with our forward difference operator Δ

$$\text{where } \Delta y_0 = y_1 - y_0, \quad \Delta^2 y_0 = \Delta y_1 - \Delta y_0$$

then we get a particularly compact formula

$$P_n(x) = y_0 + \sum_{i=1}^n \binom{s}{i} \Delta^i y_0 \quad \text{where } s = \frac{x - x_0}{h} \quad [\text{For uniform spacing}]$$

(3) There's a backward differences formula

Not too important for this class, but let's define the notation
in case we see it again

Recall, if (x_n) is a sequence, the

$$\text{forward difference} \quad \Delta x_n := x_{n+1} - x_n$$

Now define the

$$\text{backward difference} \quad \nabla x_n := x_n - x_{n-1}$$

$$\text{and } \Delta^2 x_n = \Delta(\Delta x_n), \quad \nabla^2 x_n = \nabla(\nabla x_n)$$

(4) How to use in practice

We might have a big, precalculated table of $F_{i,j}$

To evaluate at x , if x is close to x_0 or x_1 , then even
low degree interpolants will be accurate, and we can
compute $P_k(x)$ for $k < n$ and save time.

If x is close to x_{n-1} or x_n , we can do the backwards version
and again evaluate $P_k(x)$ in $O(k)$ time

If x is close to $x_{n/2}$, the above schemes to
compute $P_k(x)$ are not efficient... some other schemes are
sometimes useful

ex: Stirling's method