

The math behind the methods and some madness...

Ananda Dasgupta

PH3105, Autumn Semester 2017

Lagrange interpolation

Given $n + 1$ data points $(x_0, y_0), (x_1, y_1), \dots, (x_n, y_n)$, the Lagrange polynomials are defined by

$$L_i(x) = \frac{(x - x_0) \dots (x - x_{i-1})(x - x_{i+1}) \dots (x - x_n)}{(x_i - x_0) \dots (x_i - x_{i-1})(x_i - x_{i+1}) \dots (x_i - x_n)}$$

Lagrange interpolation

Given $n + 1$ data points $(x_0, y_0), (x_1, y_1), \dots, (x_n, y_n)$, the Lagrange polynomials are defined by

$$L_i(x) = \frac{(x - x_0) \dots (x - x_{i-1})(x - x_{i+1}) \dots (x - x_n)}{(x_i - x_0) \dots (x_i - x_{i-1})(x_i - x_{i+1}) \dots (x_i - x_n)}$$

These satisfy

$$L_i(x_j) = \delta_{ij}$$

Lagrange interpolation

Given $n + 1$ data points $(x_0, y_0), (x_1, y_1), \dots, (x_n, y_n)$, the Lagrange polynomials are defined by

$$L_i(x) = \frac{(x - x_0) \dots (x - x_{i-1})(x - x_{i+1}) \dots (x - x_n)}{(x_i - x_0) \dots (x_i - x_{i-1})(x_i - x_{i+1}) \dots (x_i - x_n)}$$

These satisfy

$$L_i(x_j) = \delta_{ij}$$

Then, the interpolating polynomial between the data points is

$$p_n(x) \equiv \sum_{i=0}^n y_i L_i(x)$$

Lagrange interpolation

Given $n + 1$ data points $(x_0, y_0), (x_1, y_1), \dots, (x_n, y_n)$, the Lagrange polynomials are defined by

$$L_i(x) = \frac{(x - x_0) \dots (x - x_{i-1})(x - x_{i+1}) \dots (x - x_n)}{(x_i - x_0) \dots (x_i - x_{i-1})(x_i - x_{i+1}) \dots (x_i - x_n)}$$

These satisfy

$$L_i(x_j) = \delta_{ij}$$

Then, the interpolating polynomial between the data points is

$$p_n(x) \equiv \sum_{i=0}^n y_i L_i(x)$$

Note that we can write $L_i(x)$ in terms of the function

$\Psi_n(x) \equiv (x - x_0) \dots (x - x_n)$ as

$$L_i(x) = \frac{\Psi_n(x)}{(x - x_i) \Psi'_n(x_i)}$$

Lagrange interpolation

Error

Let $f(x)$ be a function with at least $n + 1$ continuous derivatives.

Lagrange interpolation

Error

Let $f(x)$ be a function with at least $n + 1$ continuous derivatives. Let $p_n(x)$ be the polynomial approximating $f(x)$ by interpolating between the points $(x_i, f(x_i))$ for $i = 0, 1, \dots, n$.

Lagrange interpolation

Error

Let $f(x)$ be a function with at least $n + 1$ continuous derivatives. Let $p_n(x)$ be the polynomial approximating $f(x)$ by interpolating between the points $(x_i, f(x_i))$ for $i = 0, 1, \dots, n$.

How good is this approximation?

Lagrange interpolation

Error

Let $f(x)$ be a function with at least $n + 1$ continuous derivatives. Let $p_n(x)$ be the polynomial approximating $f(x)$ by interpolating between the points $(x_i, f(x_i))$ for $i = 0, 1, \dots, n$.

How good is this approximation?

Let $t \in \mathbb{R}$. Then $\exists \xi \in I_t \equiv \mathcal{H}\{t, x_0, \dots, x_n\}$:

$$f(t) - p_n(t) = \frac{(t - x_0) \dots (t - x_n)}{(n + 1)!} f^{(n+1)}(\xi)$$

Lagrange interpolation

Error - proof

If $t \in \{x_0, \dots, x_n\}$ the result is trivial!

Lagrange interpolation

Error - proof

If $t \in \{x_0, \dots, x_n\}$ the result is trivial!

So, let's assume $t \notin \{x_0, \dots, x_n\}$.

Lagrange interpolation

Error - proof

If $t \in \{x_0, \dots, x_n\}$ the result is trivial!

So, let's assume $t \notin \{x_0, \dots, x_n\}$.

Define

$$\Psi(x) \equiv (x - x_0) \dots (x - x_n)$$

$$E(x) \equiv f(x) - p_n(x)$$

$$G(x) \equiv E(x) - \frac{\Psi(x)}{\Psi(t)} E(t)$$

Lagrange interpolation

Error - proof

If $t \in \{x_0, \dots, x_n\}$ the result is trivial!

So, let's assume $t \notin \{x_0, \dots, x_n\}$.

Define

$$\Psi(x) \equiv (x - x_0) \dots (x - x_n)$$

$$E(x) \equiv f(x) - p_n(x)$$

$$G(x) \equiv E(x) - \frac{\Psi(x)}{\Psi(t)} E(t)$$

Obviously, $\Psi(x_i) = E(x_i) = 0$ for $i = 0, 1, \dots, n$.

Lagrange interpolation

Error - proof

If $t \in \{x_0, \dots, x_n\}$ the result is trivial!

So, let's assume $t \notin \{x_0, \dots, x_n\}$.

Define

$$\Psi(x) \equiv (x - x_0) \dots (x - x_n)$$

$$E(x) \equiv f(x) - p_n(x)$$

$$G(x) \equiv E(x) - \frac{\Psi(x)}{\Psi(t)} E(t)$$

Obviously, $\Psi(x_i) = E(x_i) = 0$ for $i = 0, 1, \dots, n$. Thus

$$G(x_i) = 0, \quad i = 0, 1, \dots, n$$

Lagrange interpolation

Error - proof

If $t \in \{x_0, \dots, x_n\}$ the result is trivial!

So, let's assume $t \notin \{x_0, \dots, x_n\}$.

Define

$$\Psi(x) \equiv (x - x_0) \dots (x - x_n)$$

$$E(x) \equiv f(x) - p_n(x)$$

$$G(x) \equiv E(x) - \frac{\Psi(x)}{\Psi(t)} E(t)$$

Obviously, $\Psi(x_i) = E(x_i) = 0$ for $i = 0, 1, \dots, n$. Thus

$$G(x_i) = 0, \quad i = 0, 1, \dots, n$$

and

$$G(t) = 0$$

Lagrange interpolation

Error - proof

If $t \in \{x_0, \dots, x_n\}$ the result is trivial!

So, let's assume $t \notin \{x_0, \dots, x_n\}$.

Define

$$\Psi(x) \equiv (x - x_0) \dots (x - x_n)$$

$$E(x) \equiv f(x) - p_n(x)$$

$$G(x) \equiv E(x) - \frac{\Psi(x)}{\Psi(t)} E(t)$$

Obviously, $\Psi(x_i) = E(x_i) = 0$ for $i = 0, 1, \dots, n$. Thus

$$G(x_i) = 0, \quad i = 0, 1, \dots, n$$

and

$$G(t) = 0$$

Thus, $G(x)$ has at least $n + 2$ distinct zeros in I_t .

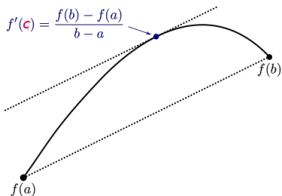
Lagrange interpolation

Error - proof

The Mean Value Theorem

If $f(x)$ is defined and continuous on the interval $[a, b]$ and differentiable on (a, b) , then there is at least one number c in the interval (a, b) (that is $a < c < b$) such that

$$f'(c) = \frac{f(b) - f(a)}{b - a}$$



The tangent to the curve of $f(x)$ is parallel at at least one point to the chord joining the endpoints $(a, f(a))$ and $(b, f(b))$.

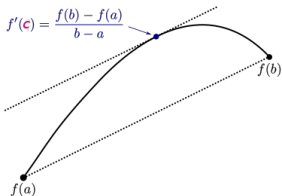
Lagrange interpolation

Error - proof

The Mean Value Theorem

If $f(x)$ is defined and continuous on the interval $[a, b]$ and differentiable on (a, b) , then there is at least one number c in the interval (a, b) (that is $a < c < b$) such that

$$f'(c) = \frac{f(b) - f(a)}{b - a}$$



There is at least one zero of $f'(x)$ between two successive zeros of $f(x)$.

Lagrange interpolation

Error - proof

$$\Psi(x) \equiv (x - x_0) \dots (x - x_n)$$

$$E(x) \equiv f(x) - p_n(x)$$

$$G(x) \equiv E(x) - \frac{\Psi(x)}{\Psi(t)} E(t)$$

$G(x)$ has at least $n + 2$ distinct zeros in I_t .

Lagrange interpolation

Error - proof

$$\Psi(x) \equiv (x - x_0) \dots (x - x_n)$$

$$E(x) \equiv f(x) - p_n(x)$$

$$G(x) \equiv E(x) - \frac{\Psi(x)}{\Psi(t)} E(t)$$

$G(x)$ has at least $n + 2$ distinct zeros in I_t .

$G'(x)$ has at least $n + 1$ distinct zeros in this interval!

Lagrange interpolation

Error - proof

$$\Psi(x) \equiv (x - x_0) \dots (x - x_n)$$

$$E(x) \equiv f(x) - p_n(x)$$

$$G(x) \equiv E(x) - \frac{\Psi(x)}{\Psi(t)} E(t)$$

$G(x)$ has at least $n + 2$ distinct zeros in I_t .

$G'(x)$ has at least $n + 1$ distinct zeros in this interval!

$G^{(j)}(x)$ has at least $n + 2 - j$ distinct zeros in I_t !

Lagrange interpolation

Error - proof

$$\Psi(x) \equiv (x - x_0) \dots (x - x_n)$$

$$E(x) \equiv f(x) - p_n(x)$$

$$G(x) \equiv E(x) - \frac{\Psi(x)}{\Psi(t)} E(t)$$

$G(x)$ has at least $n + 2$ distinct zeros in I_t .

$G'(x)$ has at least $n + 1$ distinct zeros in this interval!

$G^{(j)}(x)$ has at least $n + 2 - j$ distinct zeros in I_t !

$G^{(n+1)}(x)$ has at least one!

Lagrange interpolation

Error - proof

$$\Psi(x) \equiv (x - x_0) \dots (x - x_n)$$

$$E(x) \equiv f(x) - p_n(x)$$

$$G(x) \equiv E(x) - \frac{\Psi(x)}{\Psi(t)} E(t)$$

$G(x)$ has at least $n + 2$ distinct zeros in I_t .

$G'(x)$ has at least $n + 1$ distinct zeros in this interval!

$G^{(j)}(x)$ has at least $n + 2 - j$ distinct zeros in I_t !

$G^{(n+1)}(x)$ has at least one!

Let ξ be a zero of $G^{(n+1)}(x)$ in I_t .

Lagrange interpolation

Error - proof

$$\Psi(x) \equiv (x - x_0) \dots (x - x_n)$$

$$E(x) \equiv f(x) - p_n(x)$$

$$G(x) \equiv E(x) - \frac{\Psi(x)}{\Psi(t)} E(t)$$

$G(x)$ has at least $n + 2$ distinct zeros in I_t .

$G'(x)$ has at least $n + 1$ distinct zeros in this interval!

$G^{(j)}(x)$ has at least $n + 2 - j$ distinct zeros in I_t !

$G^{(n+1)}(x)$ has at least one!

Let ξ be a zero of $G^{(n+1)}(x)$ in I_t .

Now, $E^{(n+1)}(x) = f^{(n+1)}(x)$

Lagrange interpolation

Error - proof

$$\Psi(x) \equiv (x - x_0) \dots (x - x_n)$$

$$E(x) \equiv f(x) - p_n(x)$$

$$G(x) \equiv E(x) - \frac{\Psi(x)}{\Psi(t)} E(t)$$

$G(x)$ has at least $n + 2$ distinct zeros in I_t .

$G'(x)$ has at least $n + 1$ distinct zeros in this interval!

$G^{(j)}(x)$ has at least $n + 2 - j$ distinct zeros in I_t !

$G^{(n+1)}(x)$ has at least one!

Let ξ be a zero of $G^{(n+1)}(x)$ in I_t .

Now, $E^{(n+1)}(x) = f^{(n+1)}(x)$ and $\Psi^{(n+1)}(x) = (n + 1)!$

Lagrange interpolation

Error - proof

$$\Psi(x) \equiv (x - x_0) \dots (x - x_n)$$

$$E(x) \equiv f(x) - p_n(x)$$

$$G(x) \equiv E(x) - \frac{\Psi(x)}{\Psi(t)} E(t)$$

$G(x)$ has at least $n + 2$ distinct zeros in I_t .

$G'(x)$ has at least $n + 1$ distinct zeros in this interval!

$G^{(j)}(x)$ has at least $n + 2 - j$ distinct zeros in I_t !

$G^{(n+1)}(x)$ has at least one!

Let ξ be a zero of $G^{(n+1)}(x)$ in I_t .

Now, $E^{(n+1)}(x) = f^{(n+1)}(x)$ and $\Psi^{(n+1)}(x) = (n + 1)!$

$$0 = G^{(n+1)}(\xi) = f^{(n+1)}(\xi) - \frac{(n + 1)!}{\Psi(t)} E(t)$$

Lagrange interpolation

Error - estimate

Let us now estimate the error for equally spaced datapoints.

Lagrange interpolation

Error - estimate

Let us now estimate the error for equally spaced datapoints.

Let us use the notation $c_{n+1} = \text{Max}_{t \in I} |f^{(n+1)}(t)|$

- ▶ $n = 1$: Linear interpolation

$$E(t) = \frac{(t-x_0)(t-x_1)}{2!} f''(\xi) \implies |E(t)| \leq \frac{h^2}{8} c_2$$

Lagrange interpolation

Error - estimate

Let us now estimate the error for equally spaced datapoints.

Let us use the notation $c_{n+1} = \text{Max}_{t \in I} |f^{(n+1)}(t)|$

- ▶ $n = 1$: Linear interpolation

$$E(t) = \frac{(t-x_0)(t-x_1)}{2!} f''(\xi) \implies |E(t)| \leq \frac{h^2}{8} c_2$$

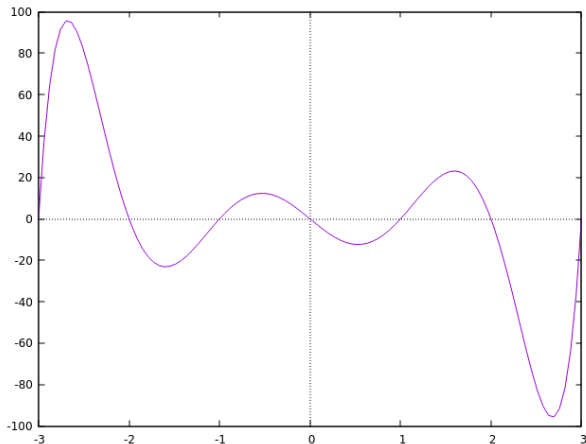
- ▶ $n = 2$:

$$E(t) = \frac{(t-x_0)(t-x_1)(t-x_2)}{2!} f'''(\xi) \implies |E(t)| \leq \frac{\sqrt{3}h^3}{27} c_3$$

Lagrange interpolation

Error - warning!!

Higher order interpolation is bad near the edges!



$\Psi_6(x)$ for equally spaced points $-3, -2, \dots, 2, 3$

Newton interpolation

Another look

Let's say we have a $n - 1$ th order polynomial $p_{n-1}(x)$ interpolating a function $f(x)$ at the n points x_0, x_1, \dots, x_{n-1} .

Newton interpolation

Another look

Let's say we have a $n - 1$ th order polynomial $p_{n-1}(x)$ interpolating a function $f(x)$ at the n points x_0, x_1, \dots, x_{n-1} .
How can we get $p_n(x)$ - the interpolating polynomial if we add one more interpolation point x_n ?

Newton interpolation

Another look

Let's say we have a $n - 1$ th order polynomial $p_{n-1}(x)$ interpolating a function $f(x)$ at the n points x_0, x_1, \dots, x_{n-1} .

How can we get $p_n(x)$ - the interpolating polynomial if we add one more interpolation point x_n ?

We are seeking a n -th order *correction polynomial* $C(x)$

$$p_n(x) = p_{n-1}(x) + C(x)$$

Newton interpolation

Another look

Let's say we have a $n - 1$ th order polynomial $p_{n-1}(x)$ interpolating a function $f(x)$ at the n points x_0, x_1, \dots, x_{n-1} .

How can we get $p_n(x)$ - the interpolating polynomial if we add one more interpolation point x_n ?

We are seeking a n -th order *correction polynomial* $C(x)$

$$p_n(x) = p_{n-1}(x) + C(x)$$

Now $C(x_i) = p_n(x_i) - p_{n-1}(x_i) = 0$ for all $i = 0, 1, \dots, n - 1$.

Newton interpolation

Another look

Let's say we have a $n - 1$ th order polynomial $p_{n-1}(x)$ interpolating a function $f(x)$ at the n points x_0, x_1, \dots, x_{n-1} .

How can we get $p_n(x)$ - the interpolating polynomial if we add one more interpolation point x_n ?

We are seeking a n -th order *correction polynomial* $C(x)$

$$p_n(x) = p_{n-1}(x) + C(x)$$

Now $C(x_i) = p_n(x_i) - p_{n-1}(x_i) = 0$ for all $i = 0, 1, \dots, n - 1$.

$$C(x) = a_n(x - x_0) \dots (x - x_{n-1})$$

Newton interpolation

Another look

Let's say we have a $n - 1$ th order polynomial $p_{n-1}(x)$ interpolating a function $f(x)$ at the n points x_0, x_1, \dots, x_{n-1} . How can we get $p_n(x)$ - the interpolating polynomial if we add one more interpolation point x_n ?

We are seeking a n -th order *correction polynomial* $C(x)$

$$p_n(x) = p_{n-1}(x) + C(x)$$

Now $C(x_i) = p_n(x_i) - p_{n-1}(x_i) = 0$ for all $i = 0, 1, \dots, n - 1$.

$$C(x) = a_n(x - x_0) \dots (x - x_{n-1})$$

Since $p_n(x_n) = f(x_n)$, we have

$$f(x_n) = p_{n-1}(x_n) + a_n(x_n - x_0) \dots (x_n - x_{n-1})$$

Newton interpolation

Another look

Let's say we have a $n - 1$ th order polynomial $p_{n-1}(x)$ interpolating a function $f(x)$ at the n points x_0, x_1, \dots, x_{n-1} .

How can we get $p_n(x)$ - the interpolating polynomial if we add one more interpolation point x_n ?

We are seeking a n -th order *correction polynomial* $C(x)$

$$p_n(x) = p_{n-1}(x) + C(x)$$

Now $C(x_i) = p_n(x_i) - p_{n-1}(x_i) = 0$ for all $i = 0, 1, \dots, n - 1$.

$$C(x) = a_n(x - x_0) \dots (x - x_{n-1})$$

Since $p_n(x_n) = f(x_n)$, we have

$$f(x_n) = p_{n-1}(x_n) + a_n(x_n - x_0) \dots (x_n - x_{n-1})$$

Which gives us $a_n \equiv f[x_0, x_1, \dots, x_n]$

Newton interpolation

Another look

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

Newton interpolation

Another look

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

Alternatively, note that a_n is the coefficient of x^n in $p_n(x)$.

Newton interpolation

Another look

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

Alternatively, note that a_n is the coefficient of x^n in $p_n(x)$.

We already know that

$$p_n(x) = \sum_{i=0}^n \frac{\Psi_n(x)}{(x - x_i) \Psi_n'(x_i)} f(x_i)$$

Newton interpolation

Another look

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

Alternatively, note that a_n is the coefficient of x^n in $p_n(x)$.

We already know that

$$p_n(x) = \sum_{i=0}^n \frac{\Psi_n(x)}{(x - x_i) \Psi_n'(x_i)} f(x_i)$$

Thus

$$f[x_0, x_1, \dots, x_n] = \sum_{i=0}^n \frac{f(x_i)}{\Psi_n'(x_i)}$$

Newton interpolation

Another look

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

Alternatively, note that a_n is the coefficient of x^n in $p_n(x)$.
We already know that

$$p_n(x) = \sum_{i=0}^n \frac{\Psi_n(x)}{(x - x_i) \Psi_n'(x_i)} f(x_i)$$

Thus

$$f[x_0, x_1, \dots, x_n] = \sum_{i=0}^n \frac{f(x_i)}{\Psi_n'(x_i)}$$

Which shows that $f[x_0, x_1, \dots, x_n]$ is invariant under a permutation of the nodes x_0, x_1, \dots, x_n .

Newton interpolation

Another look

We can use this to derive (HW!!!)

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

which is why this is called the **divided difference**!

Newton interpolation

Another look

We can use this to derive (HW!!!)

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

which is why this is called the **divided difference**!

Another form (Hermite-Genocchi) - assuming the function f is n times continuously differentiable

$$f[x_0, x_1, \dots, x_n] = \int \dots \int f^{(n)}(t_0 x_0 + \dots + t_n x_n) dt_1 \dots dt_n$$

where $t_0 + \dots + t_n = 1$ and the integration is over the region $\tau = \{(t_1, \dots, t_n) \mid t_i \geq 0, \sum_{i=1}^n t_i \leq 1\}$

Newton interpolation

Error

Let $t \in \mathbb{R}$ be distinct from the nodes x_0, \dots, x_n used to define an interpolating polynomial $p_n(x)$.

Newton interpolation

Error

Let $t \in \mathbb{R}$ be distinct from the nodes x_0, \dots, x_n used to define an interpolating polynomial $p_n(x)$.

Consider an interpolating polynomial $p_{n+1}(x)$ that has x_0, \dots, x_n, t as nodes.

Newton interpolation

Error

Let $t \in \mathbb{R}$ be distinct from the nodes x_0, \dots, x_n used to define an interpolating polynomial $p_n(x)$.

Consider an interpolating polynomial $p_{n+1}(x)$ that has x_0, \dots, x_n, t as nodes.

$$p_{n+1}(x) = p_n(x) + (x - x_0) \dots (x - x_n) f[x_0, \dots, x_n, t]$$

Newton interpolation

Error

Let $t \in \mathbb{R}$ be distinct from the nodes x_0, \dots, x_n used to define an interpolating polynomial $p_n(x)$.

Consider an interpolating polynomial $p_{n+1}(x)$ that has x_0, \dots, x_n, t as nodes.

$$p_{n+1}(x) = p_n(x) + (x - x_0) \dots (x - x_n) f[x_0, \dots, x_n, t]$$

Since $p_{n+1}(t) = f(t)$, we have

$$f(t) - p_n(t) = (t - x_0) \dots (t - x_n) f[x_0, \dots, x_n, t]$$

Newton interpolation

Error

Let $t \in \mathbb{R}$ be distinct from the nodes x_0, \dots, x_n used to define an interpolating polynomial $p_n(x)$.

Consider an interpolating polynomial $p_{n+1}(x)$ that has x_0, \dots, x_n, t as nodes.

$$p_{n+1}(x) = p_n(x) + (x - x_0) \dots (x - x_n) f[x_0, \dots, x_n, t]$$

Since $p_{n+1}(t) = f(t)$, we have

$$f(t) - p_n(t) = (t - x_0) \dots (t - x_n) f[x_0, \dots, x_n, t]$$

Comparing with $f(t) - p_n(t) = \Psi_n(t) \frac{f^{(n+1)}(\xi)}{(n+1)!}$, we get

$$f[x_0, \dots, x_n, t] = \frac{f^{(n+1)}(\xi)}{(n+1)!}, \quad \text{for some } \xi \in \mathcal{H}\{x_0, \dots, x_n, t\}$$

Newton-Cotes integration

To calculate $\int_a^b f(x) dx$ numerically, we can approximate the function $f(x)$ in (a, b) by an interpolating polynomial $p_n(x)$ and estimate

$$\int_a^b f(x) dx = \int_a^b p_n(x) dx + E \approx \int_a^b p_n(x) dx$$

Newton-Cotes integration

To calculate $\int_a^b f(x) dx$ numerically, we can approximate the function $f(x)$ in (a, b) by an interpolating polynomial $p_n(x)$ and estimate

$$\int_a^b f(x) dx = \int_a^b p_n(x) dx + E \approx \int_a^b p_n(x) dx$$

We usually take the nodes to be an evenly spaced set of $n + 1$ points

$$x_0 = a, x_1 = a + h, \dots, x_j = a + jh, \dots, x_n = b$$

where $h = \frac{b - a}{n}$.

Newton-Cotes integration

$n = 1$ - the Trapezoidal rule

$$f(x) \approx f(a) \frac{x-b}{a-b} + f(b) \frac{x-a}{b-a}$$

Newton-Cotes integration

$n = 1$ - the Trapezoidal rule

$$f(x) \approx f(a) \frac{x-b}{a-b} + f(b) \frac{x-a}{b-a}$$

$$\int_a^b f(x) dx \approx \int_a^b \left[f(a) \frac{x-b}{a-b} + f(b) \frac{x-a}{b-a} \right] dx$$

Newton-Cotes integration

$n = 1$ - the Trapezoidal rule

$$f(x) \approx f(a) \frac{x-b}{a-b} + f(b) \frac{x-a}{b-a}$$

$$\int_a^b f(x) dx \approx \int_a^b \left[f(a) \frac{x-b}{a-b} + f(b) \frac{x-a}{b-a} \right] dx$$

Using $\int_a^b (x-a) dx = \frac{(b-a)^2}{2} = -\int_a^b (x-b) dx$, we get

$$\int_a^b f(x) dx \approx \frac{b-a}{2} [f(a) + f(b)]$$

Newton-Cotes integration

Trapezoidal rule - Error estimate

$$f(x) = f(a) \frac{x-b}{a-b} + f(b) \frac{x-a}{b-a} + (x-a)(x-b) f[a, b, x]$$

Newton-Cotes integration

Trapezoidal rule - Error estimate

$$f(x) = f(a) \frac{x-b}{a-b} + f(b) \frac{x-a}{b-a} + (x-a)(x-b) f[a, b, x]$$

So, the error is

$$E = \int_a^b (x-a)(x-b) f[a, b, x] dx$$

Newton-Cotes integration

Trapezoidal rule - Error estimate

$$f(x) = f(a) \frac{x-b}{a-b} + f(b) \frac{x-a}{b-a} + (x-a)(x-b) f[a, b, x]$$

So, the error is

$$E = \int_a^b (x-a)(x-b) f[a, b, x] dx$$

To evaluate the integral we use the

Integral Mean Value Theorem

Let $w(x)$ be non-negative and integrable on $[a, b]$, and let $f(x)$ be continuous on $[a, b]$. Then $\exists \xi \in (a, b)$:

$$\int_a^b w(x) f(x) dx = f(\xi) \int_a^b w(x) dx$$

Newton-Cotes integration

Trapezoidal rule - Error estimate

$$E = f[a, b, \xi] \int_a^b (x - a)(x - b) dx$$

Newton-Cotes integration

Trapezoidal rule - Error estimate

$$E = f[a, b, \xi] \int_a^b (x - a)(x - b) dx$$

$$E = \left[\frac{1}{2} f''(\eta) \right] \left[-\frac{(b-a)^3}{6} \right]$$

Newton-Cotes integration

Trapezoidal rule - Error estimate

$$E = f[a, b, \xi] \int_a^b (x-a)(x-b) dx$$

$$E = \left[\frac{1}{2} f''(\eta) \right] \left[-\frac{(b-a)^3}{6} \right] = -\frac{(b-a)^3}{12} f''(\eta) \quad \text{for some } \eta \in (a, b)$$

Newton-Cotes integration

Trapezoidal rule - Error estimate

$$E = f[a, b, \xi] \int_a^b (x - a)(x - b) dx$$

$$E = \left[\frac{1}{2} f''(\eta) \right] \left[-\frac{(b-a)^3}{6} \right] = -\frac{(b-a)^3}{12} f''(\eta) \quad \text{for some } \eta \in (a, b)$$

The error is not very small for large intervals

Newton-Cotes integration

Trapezoidal rule - Error estimate

$$E = f[a, b, \xi] \int_a^b (x - a)(x - b) dx$$

$$E = \left[\frac{1}{2} f''(\eta) \right] \left[-\frac{(b-a)^3}{6} \right] = -\frac{(b-a)^3}{12} f''(\eta) \quad \text{for some } \eta \in (a, b)$$

The error is not very small for large intervals - which is why we use the Composite version!

Newton-Cotes integration

Composite Trapezoidal rule - Error estimate

For the n interval composite trapezoidal rule, the error is

$$E_n = -\frac{h^3}{12} \sum_{i=0}^{n-1} f''(\eta_i) \quad \eta_i \in (a + ih, a + ih + h)$$

Newton-Cotes integration

Composite Trapezoidal rule - Error estimate

For the n interval composite trapezoidal rule, the error is

$$E_n = -\frac{h^3}{12} \sum_{i=0}^{n-1} f''(\eta_i) \quad \eta_i \in (a + ih, a + ih + h)$$

$$E = -\frac{b-a}{12} h^2 \left[\frac{1}{n} \sum_{i=0}^{n-1} f''(\eta_i) \right]$$

Newton-Cotes integration

Composite Trapezoidal rule - Error estimate

For the n interval composite trapezoidal rule, the error is

$$E_n = -\frac{h^3}{12} \sum_{i=0}^{n-1} f''(\eta_i) \quad \eta_i \in (a + ih, a + ih + h)$$

$$E = -\frac{b-a}{12} h^2 \left[\frac{1}{n} \sum_{i=0}^{n-1} f''(\eta_i) \right] = -\frac{b-a}{12} h^2 f''(\eta)$$

Newton-Cotes integration

Composite Trapezoidal rule - Error estimate

For the n interval composite trapezoidal rule, the error is

$$E_n = -\frac{h^3}{12} \sum_{i=0}^{n-1} f''(\eta_i) \quad \eta_i \in (a + ih, a + ih + h)$$

$$E = -\frac{b-a}{12} h^2 \left[\frac{1}{n} \sum_{i=0}^{n-1} f''(\eta_i) \right] = -\frac{b-a}{12} h^2 f''(\eta)$$

Since

$$\lim_{n \rightarrow \infty} \frac{E_n}{h^2} = -\frac{1}{12} \lim_{n \rightarrow \infty} \left[h \sum_{i=0}^{n-1} f''(\eta_i) \right]$$

Newton-Cotes integration

Composite Trapezoidal rule - Error estimate

For the n interval composite trapezoidal rule, the error is

$$E_n = -\frac{h^3}{12} \sum_{i=0}^{n-1} f''(\eta_i) \quad \eta_i \in (a + ih, a + ih + h)$$

$$E = -\frac{b-a}{12} h^2 \left[\frac{1}{n} \sum_{i=0}^{n-1} f''(\eta_i) \right] = -\frac{b-a}{12} h^2 f''(\eta)$$

Since

$$\lim_{n \rightarrow \infty} \frac{E_n}{h^2} = -\frac{1}{12} \lim_{n \rightarrow \infty} \left[h \sum_{i=0}^{n-1} f''(\eta_i) \right] = -\frac{1}{12} [f'(b) - f'(a)]$$

Newton-Cotes integration

Composite Trapezoidal rule - Error estimate

For the n interval composite trapezoidal rule, the error is

$$E_n = -\frac{h^3}{12} \sum_{i=0}^{n-1} f''(\eta_i) \quad \eta_i \in (a + ih, a + ih + h)$$

$$E = -\frac{b-a}{12} h^2 \left[\frac{1}{n} \sum_{i=0}^{n-1} f''(\eta_i) \right] = -\frac{b-a}{12} h^2 f''(\eta)$$

Since

$$\lim_{n \rightarrow \infty} \frac{E_n}{h^2} = -\frac{1}{12} \lim_{n \rightarrow \infty} \left[h \sum_{i=0}^{n-1} f''(\eta_i) \right] = -\frac{1}{12} [f'(b) - f'(a)]$$

For large n , we can estimate

$$E_n \approx -\frac{h^2}{12} [f'(b) - f'(a)]$$

Newton-Cotes integration

Simpson's 1/3rd rule

We can use a quadratic polynomial interpolating $f(x)$ in $[a, b]$.

Newton-Cotes integration

Simpson's 1/3rd rule

We can use a quadratic polynomial interpolating $f(x)$ in $[a, b]$.
The integral works out to be

$$I_2 = \frac{h}{3} \left[f(a) + 4f\left(\frac{a+b}{2}\right) + f(b) \right], \quad h = \frac{b-a}{2}$$

Newton-Cotes integration

Simpson's 1/3rd rule

We can use a quadratic polynomial interpolating $f(x)$ in $[a, b]$.

The integral works out to be

$$I_2 = \frac{h}{3} \left[f(a) + 4f\left(\frac{a+b}{2}\right) + f(b) \right], \quad h = \frac{b-a}{2}$$

The error is given by

$$E_2 = \int_a^b (x-a)(x-b)(x-c) f[a, b, c, x] dx, \quad c = \frac{a+b}{2}$$

Newton-Cotes integration

Simpson's 1/3rd rule

We can use a quadratic polynomial interpolating $f(x)$ in $[a, b]$.
The integral works out to be

$$I_2 = \frac{h}{3} \left[f(a) + 4f\left(\frac{a+b}{2}\right) + f(b) \right], \quad h = \frac{b-a}{2}$$

The error is given by

$$E_2 = \int_a^b (x-a)(x-b)(x-c) f[a, b, c, x] dx, \quad c = \frac{a+b}{2}$$

We can't use the IMVT directly since $(x-a)(x-b)(x-c)$ is not positive definite in $[a, b]$

Newton-Cotes integration

Simpson's 1/3rd rule

We can use a quadratic polynomial interpolating $f(x)$ in $[a, b]$.
The integral works out to be

$$I_2 = \frac{h}{3} \left[f(a) + 4f\left(\frac{a+b}{2}\right) + f(b) \right], \quad h = \frac{b-a}{2}$$

The error is given by

$$E_2 = \int_a^b (x-a)(x-b)(x-c) f[a, b, c, x] dx, \quad c = \frac{a+b}{2}$$

We can't use the IMVT directly since $(x-a)(x-b)(x-c)$ is not positive definite in $[a, b]$

Newton-Cotes integration

Simpson's 1/3rd rule

We can use $w(x) = \int_a^x (t - a)(t - b)(t - c) dt$

Newton-Cotes integration

Simpson's 1/3rd rule

We can use $w(x) = \int_a^x (t-a)(t-b)(t-c) dt$, which obeys

$$w(a) = w(b) = 0, \quad w(x) > 0 \text{ for } x \in (a, b)$$

Newton-Cotes integration

Simpson's 1/3rd rule

We can use $w(x) = \int_a^x (t-a)(t-b)(t-c) dt$, which obeys

$$w(a) = w(b) = 0, \quad w(x) > 0 \text{ for } x \in (a, b)$$

Integrating by parts

$$E_2 = \int_a^b w'(x) f[a, b, c, x] dx$$

Newton-Cotes integration

Simpson's 1/3rd rule

We can use $w(x) = \int_a^x (t-a)(t-b)(t-c) dt$, which obeys

$$w(a) = w(b) = 0, \quad w(x) > 0 \text{ for } x \in (a, b)$$

Integrating by parts

$$E_2 = \int_a^b w'(x) f[a, b, c, x] dx = - \int_a^b w(x) f''[a, b, c, x] dx$$

Newton-Cotes integration

Simpson's 1/3rd rule

We can use $w(x) = \int_a^x (t-a)(t-b)(t-c) dt$, which obeys

$$w(a) = w(b) = 0, \quad w(x) > 0 \text{ for } x \in (a, b)$$

Integrating by parts

$$E_2 = \int_a^b w'(x) f[a, b, c, x] dx = - \int_a^b w(x) f[a, b, c, x, x] dx$$

Now we can use IMVT to determine

$$E_2 = -f[a, b, c, \xi, \xi] \int_a^b w(x) dx \quad \text{for some } \xi \in (a, b)$$

Newton-Cotes integration

Simpson's 1/3rd rule

We can use $w(x) = \int_a^x (t-a)(t-b)(t-c) dt$, which obeys

$$w(a) = w(b) = 0, \quad w(x) > 0 \text{ for } x \in (a, b)$$

Integrating by parts

$$E_2 = \int_a^b w'(x) f[a, b, c, x] dx = - \int_a^b w(x) f[a, b, c, x, x] dx$$

Now we can use IMVT to determine

$$E_2 = -f[a, b, c, \xi, \xi] \int_a^b w(x) dx \quad \text{for some } \xi \in (a, b)$$

leading to

$$E_2 = -\frac{h^5}{90} f^{(4)}(\eta) \quad \text{for some } \eta \in (a, b)$$

Hermite interpolation

Sometimes, we need to interpolate both values and derivatives!

Hermite interpolation

Sometimes, we need to interpolate both values and derivatives!

We are seeking a $2n - 1$ degree polynomial satisfying

$$p(x_i) = y_i, \quad p'(x_i) = y'_i, \quad i = 1, 2, \dots, n$$

Hermite interpolation

Sometimes, we need to interpolate both values and derivatives!

We are seeking a $2n - 1$ degree polynomial satisfying

$$p(x_i) = y_i, \quad p'(x_i) = y'_i, \quad i = 1, 2, \dots, n$$

We need to find $2n$ polynomials $h_1, \dots, h_n, \tilde{h}_1, \dots, \tilde{h}_n$, each of degree $2n - 1$ satisfying

$$h_i(x_j) = \delta_{ij}, \quad h'_i(x_j) = 0$$

and

$$\tilde{h}_i(x_j) = 0, \quad \tilde{h}'_i(x_j) = \delta_{ij}$$

Hermite interpolation

Sometimes, we need to interpolate both values and derivatives!

We are seeking a $2n - 1$ degree polynomial satisfying

$$p(x_i) = y_i, \quad p'(x_i) = y'_i, \quad i = 1, 2, \dots, n$$

We need to find $2n$ polynomials $h_1, \dots, h_n, \tilde{h}_1, \dots, \tilde{h}_n$, each of degree $2n - 1$ satisfying

$$h_i(x_j) = \delta_{ij}, \quad h'_i(x_j) = 0$$

and

$$\tilde{h}_i(x_j) = 0, \quad \tilde{h}'_i(x_j) = \delta_{ij}$$

Then

$$H_n(x) = \sum_{i=1}^n \left[y_i h_i(x) + y'_i \tilde{h}_i(x) \right]$$

is the Hermite interpolating polynomial.

Hermite interpolation

We already have a set of $n - 1$ degree polynomials $L_i(x)$ that satisfy $L_i(x_j) = \delta_{ij}$.

Hermite interpolation

We already have a set of $n - 1$ degree polynomials $L_i(x)$ that satisfy $L_i(x_j) = \delta_{ij}$. Let us try the $2n - 1$ degree polynomial

$$\tilde{h}_i(x) = (ax + b) [L_i(x)]^2$$

Hermite interpolation

We already have a set of $n - 1$ degree polynomials $L_i(x)$ that satisfy $L_i(x_j) = \delta_{ij}$. Let us try the $2n - 1$ degree polynomial

$$\tilde{h}_i(x) = (ax + b) [L_i(x)]^2$$

Then

$$\tilde{h}'_i(x) = a [L_i(x)]^2 + 2(ax + b) L'_i(x) L_i(x)$$

Hermite interpolation

We already have a set of $n - 1$ degree polynomials $L_i(x)$ that satisfy $L_i(x_j) = \delta_{ij}$. Let us try the $2n - 1$ degree polynomial

$$\tilde{h}_i(x) = (ax + b) [L_i(x)]^2$$

Then

$$\tilde{h}'_i(x) = a [L_i(x)]^2 + 2(ax + b) L'_i(x) L_i(x)$$

Demanding $\tilde{h}_i(x_j) = 0$ leads to

$$ax_j + b = 0$$

Hermite interpolation

We already have a set of $n - 1$ degree polynomials $L_i(x)$ that satisfy $L_i(x_j) = \delta_{ij}$. Let us try the $2n - 1$ degree polynomial

$$\tilde{h}_i(x) = (ax + b) [L_i(x)]^2$$

Then

$$\tilde{h}'_i(x) = a [L_i(x)]^2 + 2(ax + b) L'_i(x) L_i(x)$$

Demanding $\tilde{h}_i(x_j) = 0$ leads to

$$ax_j + b = 0$$

Demanding $\tilde{h}'_i(x_j) = \delta_{ij}$ leads to

$$a + 2(ax + b) L'_i(x_j) = 1$$

Hermite interpolation

We already have a set of $n - 1$ degree polynomials $L_i(x)$ that satisfy $L_i(x_j) = \delta_{ij}$. Let us try the $2n - 1$ degree polynomial

$$\tilde{h}_i(x) = (ax + b) [L_i(x)]^2$$

Then

$$\tilde{h}'_i(x) = a [L_i(x)]^2 + 2(ax + b) L'_i(x) L_i(x)$$

Demanding $\tilde{h}_i(x_j) = 0$ leads to

$$ax_j + b = 0$$

Demanding $\tilde{h}'_i(x_j) = \delta_{ij}$ leads to

$$a + 2(ax + b) L'_i(x_j) = 1$$

This leads to

$$\tilde{h}_i(x) = (x - x_j) [L_i(x)]^2$$

Hermite interpolation

We already have a set on $n - 1$ degree polynomials $L_i(x)$ that satisfy $L_i(x_j) = \delta_{ij}$. Let us try the $2n - 1$ degree polynomial

$$\tilde{h}_i(x) = (ax + b) [L_i(x)]^2$$

Then

$$\tilde{h}'_i(x) = a [L_i(x)]^2 + 2(ax + b) L'_i(x) L_i(x)$$

Demanding $\tilde{h}_i(x_j) = 0$ leads to

$$ax_j + b = 0$$

Demanding $\tilde{h}'_i(x_j) = \delta_{ij}$ leads to

$$a + 2(ax + b) L'_i(x_i) = 1$$

This leads to

$$\tilde{h}_i(x) = (x - x_i) [L_i(x)]^2$$

Similarly

$$h_i(x) = (1 - 2L'_i(x_i)(x - x_i)) [L_i(x)]^2$$

Hermite interpolation

Uniqueness

Let $G_n(x)$ be another polynomial of degree $2n - 1$ that interpolates the same values and derivatives.

Hermite interpolation

Uniqueness

Let $G_n(x)$ be another polynomial of degree $2n - 1$ that interpolates the same values and derivatives.

Consider $R(x) = G_n(x) - H_n(x)$

Hermite interpolation

Uniqueness

Let $G_n(x)$ be another polynomial of degree $2n - 1$ that interpolates the same values and derivatives.

Consider $R(x) = G_n(x) - H_n(x)$

Then $R(x)$ is at most of degree $2n - 1$

Hermite interpolation

Uniqueness

Let $G_n(x)$ be another polynomial of degree $2n - 1$ that interpolates the same values and derivatives.

Consider $R(x) = G_n(x) - H_n(x)$

Then $R(x)$ is at most of degree $2n - 1$

But it must have double roots at x_1, \dots, x_n (Since $R(x_i) = R'(x_i) = 0$)

Hermite interpolation

Uniqueness

Let $G_n(x)$ be another polynomial of degree $2n - 1$ that interpolates the same values and derivatives.

Consider $R(x) = G_n(x) - H_n(x)$

Then $R(x)$ is at most of degree $2n - 1$

But it must have double roots at x_1, \dots, x_n (Since $R(x_i) = R'(x_i) = 0$)

Thus $R(x)$ must be identically zero!

Hermite interpolation

Uniqueness

Let $G_n(x)$ be another polynomial of degree $2n - 1$ that interpolates the same values and derivatives.

Consider $R(x) = G_n(x) - H_n(x)$

Then $R(x)$ is at most of degree $2n - 1$

But it must have double roots at x_1, \dots, x_n (Since $R(x_i) = R'(x_i) = 0$)

Thus $R(x)$ must be identically zero!

The error can be shown to be

$$f(x) - H_n(x) = [\Psi_n(x)]^2 \frac{f^{(2n)}(x)}{(2n)!}$$

Gauss quadrature

Recall that the Gauss quadrature formula is

$$\int_{-1}^1 f(x) dx \approx \sum_{i=1}^n w_i f(x_i)$$

where the freedom of choice of the n weights w_i and the n nodes x_i is exploited to get an expression that is correct for all polynomials up to degree $2n - 1$.

Gauss quadrature

Recall that the Gauss quadrature formula is

$$\int_{-1}^1 f(x) dx \approx \sum_{i=1}^n w_i f(x_i)$$

where the freedom of choice of the n weights w_i and the n nodes x_i is exploited to get an expression that is correct for all polynomials up to degree $2n - 1$.

As we have already seen, in principle we can find the w_i and x_i from the $2n$ equations

$$\sum_{i=1}^n w_i x_i^j = \begin{cases} 0 & \text{for } j = 1, 3, \dots, 2n - 1 \\ \frac{2}{j+1} & \text{for } j = 2, 4, \dots, 2n - 2 \end{cases}$$

Gauss quadrature

Recall that the Gauss quadrature formula is

$$\int_{-1}^1 f(x) dx \approx \sum_{i=1}^n w_i f(x_i)$$

where the freedom of choice of the n weights w_i and the n nodes x_i is exploited to get an expression that is correct for all polynomials up to degree $2n - 1$.

As we have already seen, in principle we can find the w_i and x_i from the $2n$ equations

$$\sum_{i=1}^n w_i x_i^j = \begin{cases} 0 & \text{for } j = 1, 3, \dots, 2n - 1 \\ \frac{2}{j+1} & \text{for } j = 2, 4, \dots, 2n - 2 \end{cases}$$

This is a set of non-linear equations - not only are they difficult to solve, the existence of solutions for general n is not even clear *a priori*.

Gauss quadrature