

Numerical Methods I: Polynomial Interpolation

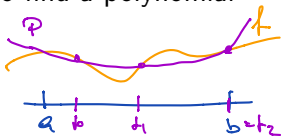
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Classical polynomial interpolation

Given $f_i := f(t_i)$, $i = 0, \dots, n$, we would like to find a polynomial $P \in \mathbf{P}_n$ such that

$$P(t_i) = f_i.$$



Interpolation is thus a map from $\mathbb{R}^{n+1} \rightarrow \mathbf{P}_n$.

Theorem: Given nodes (t_i, f_i) , $0 \leq i \leq n$, with pairwise distinct nodes t_i , then there exists a unique interpolating polynomial

$P \in \mathbf{P}_n$.

Proof: $\dim(\mathbb{R}^{n+1}) = n+1$, $\dim(\mathbf{P}_n) = n+1$,

map $\phi: \begin{pmatrix} f_0 \\ \vdots \\ f_n \end{pmatrix} \rightarrow \mathbf{P}_n$ interpolating polynomial. Sufficient to show

that ϕ is injective: Let $f, g \in \mathbb{R}^{n+1}$: $\phi(f) = \phi(g)$

$\Rightarrow \phi(f-g) = 0$, $\phi(f-g)$ is zero polynomial, $\phi(f)(t_i) = \phi(g)(t_i)$

$\Rightarrow f_i = g_i \quad i=0, \dots, n$
 $\Rightarrow f = g$

To compute that polynomial, we have to choose a basis in \mathbf{P}_n .

$$\phi(f+g) = \phi(f) + \phi(g)$$

$$\phi(\alpha f) = \alpha \phi(f)$$

Classical polynomial interpolation

Monomial basis: $1, t, t^2 \dots$ leads to system with Vandermonde matrix V_n .

$P(t) = a_0 + a_1 t + \dots + a_n t^n$, we want $P(t_i) = f_i$

$$\rightarrow a_0 + a_1 t_i + \dots + a_n t_i^n = f_i \quad i = 0, \dots, n$$

$$\begin{bmatrix} 1 & t_0 & t_0^2 & \dots & t_0^n \\ \vdots & \vdots & \vdots & \dots & \vdots \\ 1 & t_n & t_n^2 & \dots & t_n^n \end{bmatrix} \begin{bmatrix} a_0 \\ \vdots \\ a_n \end{bmatrix} = \begin{bmatrix} f_0 \\ \vdots \\ f_n \end{bmatrix}$$

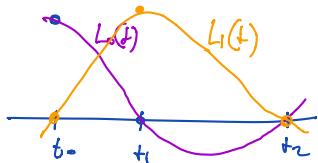
$V_n \dots$ Vandermonde matrix for t_0, \dots, t_n

- ▶ $\det(V_n) = \prod_{i=0}^{n-1} \prod_{j=i+1}^n (t_i - t_j) \neq 0$
- ▶ For larger n , this can be a poorly conditioned system.

Classical polynomial interpolation

Lagrange basis L_i defined by $L_i(t_j) = \delta_{ij}$.

$$L_i(t) = \frac{\prod_{j \neq i} (t - t_j)}{\prod_{j \neq i} (t_i - t_j)}$$



- ▶ Simple interpolant: $P(t) = \sum_{i=0}^n f_i L_i(t)$
- ▶ Not always practical.
- ▶ Lagrange polynomials form an orthogonal basis in P_n w.r. to the inner product

$$(P, Q) := \sum_{i=0}^n P(t_i) Q(t_i) = \int_a^b W(t) P(t) Q(t) dt$$
$$W(t) = \sum_{i=0}^n \delta_{t=t_i} \quad (\text{Dirac delta functions})$$

Classical polynomial interpolation

The **Newton basis** $\omega_0, \dots, \omega_n$ is given by

$$\omega_i(t) := \prod_{j=0}^{i-1} (t - t_j) \in \mathbf{P}_i.$$

These polynomials are linearly independent as their degree increases.

$$\omega_0(t) = 1, \quad \omega_1(t) = (t - t_0), \quad \omega_2(t) = (t - t_0)(t - t_1), \quad \dots$$

polynomial interpolation $a_0 \omega_0(t) + a_1 \omega_1(t) + \dots + a_n \omega_n(t)$
and there's an efficient way to compute a_0, a_1, \dots, a_n .

The coefficients in this basis can be computed efficiently (more later).

Classical polynomial interpolation

Two (slightly) different perspectives

Interpolation can be seen as map between

$$\bar{\Phi} : \mathbb{R}^{n+1} \mapsto \mathbf{P}_n$$

or as map between functions:

$$\Phi : C([a, b]) \mapsto \mathbf{P}_n.$$

Φ is function evaluation at the nodes, followed by $\bar{\Phi}$.

Classical polynomial interpolation

Conditioning

Theorem: Let $a \leq t_0 < \dots < t_n \leq b$ be pairwise distinct and L_i be the corresponding Lagrange polynomials. Then the absolute condition number of the polynomial interpolation:

$$\Phi : C([a, b]) \rightarrow \mathbf{P}_n$$

Supremum norm of f
is: $\|f\|_\infty = \sup_{x \in [a, b]} |f(x)|$

w.r. to the supremum norm is the **Lebesgue** constant

$$\kappa_{\text{abs}} = \Lambda_n = \max_{t \in [a, b]} \sum_{i=1}^n |L_i(t)|.$$

Note that the Lebesgue constant depends on n and the location of the t_i .

Classical polynomial interpolation

Conditioning

$$f \in C([a,b])$$

Proof: $t \in [a,b]$: $|\phi(f)(t)| = \left| \sum_{i=0}^n f(t_i) L_i(t) \right|$

$$\leq \sum_{i=0}^n |f(t_i)| |L_i(t)| \leq \|f\|_{\infty} \sum_{i=0}^n |L_i(t)|$$

$$\leq \max_{t \in [a,b]} \underbrace{\sum_{i=0}^n |L_i(t)|}_{= \Lambda_n}$$

$$\Rightarrow \|\phi(f)\|_{\infty} \leq \|f\|_{\infty} \Lambda_n$$

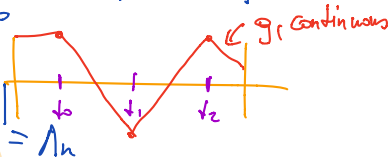
$$\Rightarrow K_{abs} \leq \Lambda_n$$

Show that this estimate is sharp: $g \in C([a,b])$, target is to find τ with $\phi(g)(\tau) = \|g\|_{\infty} \Lambda_n$; choose τ where the maximum in the Lebesgue constant is obtained, i.e. $\sum_{i=0}^n |L_i(\tau)| = \Lambda_n$, choose

$$g \text{ with } \|g\|_{\infty} = 1, g(t_i) = \text{sgn } L_i(\tau)$$

$$\Rightarrow |\phi(g)(\tau)| = \left| \sum_{i=0}^n g(t_i) L_i(\tau) \right| = \sum_{i=0}^n |L_i(\tau)| = \Lambda_n$$

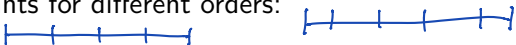
$$\Rightarrow K_{abs} \geq \Lambda_n \Rightarrow K_{abs} = \Lambda_n$$



Classical polynomial interpolation

Conditioning

Lebesgue constants for different orders:



n	Λ_n for equidistant nodes	Λ_n for Chebyshev nodes
5	3.106292	2.104398
10	29.890695	2.489430
15	512.052451	2.727778
20	10986.533993	2.900825

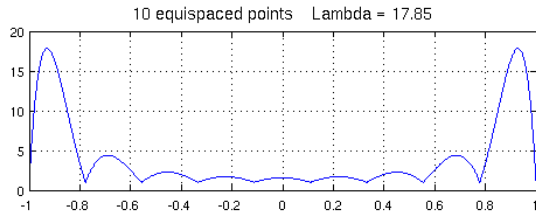
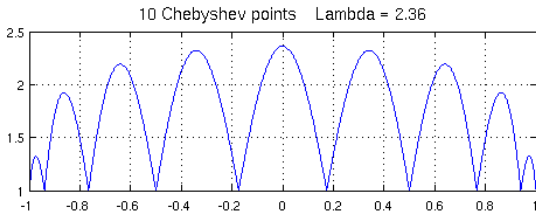
Chebyshev nodes are the roots of the Chebyshev polynomials:

$$t_i = \cos\left(\frac{2i+1}{2n+2}\pi\right), \text{ for } i = 0, \dots, n$$

Classical polynomial interpolation

Conditioning

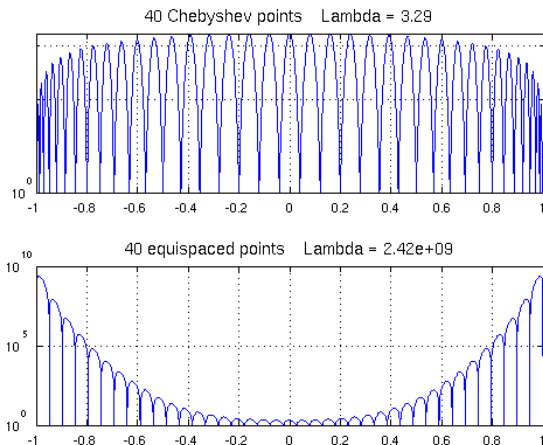
Lebesgue constant for $n = 10$, uniform vs. Chebyshev nodes:



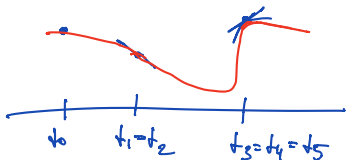
Classical polynomial interpolation

Conditioning

Lebesgue constant for $n = 40$, uniform vs. Chebyshev nodes:



Hermite interpolation



Assume

$$a = t_0 \leq t_1 \leq \dots \leq t_n = b$$

with possibly **duplicate**d nodes. If the node t_i occurs k times, the corresponding node values correspond to $f(t_i), f'(t_i), \dots, f^{k-1}(t_i)$.

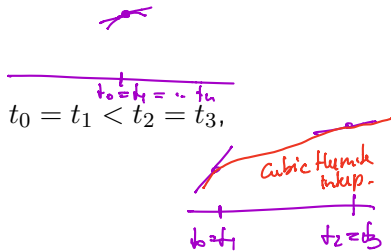
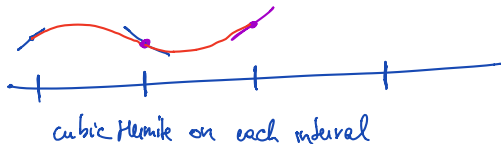
The **Hermite interpolation** polynomial $p(x)$ is a polynomial of order n , which coincides with the nodal values (and, for duplicated nodes, derivatives at nodal values) at the nodes.

Hermite interpolation

Theorem: (somewhat loosely formulated version) Given $n + 1$ nodes and nodal values (possibly of derivatives), then there exists a unique interpolating Hermite polynomial $p \in \mathbf{P}_n$.

Examples:

- ▶ All $t_0 = \dots = t_n$.
- ▶ Cubic Hermite interpolation: Nodes: $t_0 = t_1 < t_2 = t_3$,
Values: $f(t_0), f'(t_0), f(t_1), f'(t_1)$.
- ▶ locally cubic Hermite interpolation.



Classical polynomial interpolation

Newton polynomial basis

The **Newton basis** $\omega_0, \dots, \omega_n$ is given by

$$\omega_i(t) := \prod_{j=0}^{i-1} (t - t_j) \in \mathbf{P}_i.$$

The leading coefficient a_n of the interpolation polynomial of f

$$P(f|t_0, \dots, t_n) = a_n x^n + \dots$$

is called the *n-th divided difference*, $[t_0, \dots, t_n]f := a_n$.

Classical polynomial interpolation

Newton polynomial basis

Theorem: For $f \in C^n$, the interpolation polynomial $P(f|t_0, \dots, t_n)$ is given by

$$P(t) = \sum_{i=0}^n [t_0, \dots, t_i] f \omega_i(t).$$

If $f \in C^{n+1}$, then

$$f(t) = P(t) + [t_0, \dots, t_n, t] f \omega_{n+1}(t).$$

This property allows to estimate the interpolation error.

Classical polynomial interpolation

Newton polynomial basis

Proof: $n=0$ ✓ Let $n > 0$, true for $n-1$ i.e.

$$P_{n-1} = P(f|t_0, \dots, t_{n-1}) = \sum_{i=0}^{n-1} \underbrace{[t_0, \dots, t_i]}_{\in \mathbb{R}, i\text{-th divided difference}} f w_i(t)$$

$$P_n = P(f|t_0, \dots, t_n) = [t_0, \dots, t_n] f t^n + \dots$$

$$= [t_0, \dots, t_n] f w_n(t) + Q_{n-1}(t)$$

$$Q_{n-1}(t) = P_n - [t_0, \dots, t_n] f w_n(t)$$

interpolates f at t_0, \dots, t_{n-1} because $P(t_i) = f_i$
 $w_n(t_i) = 0$

↖ $\in P_{n-1}$

use result
for $n-1$

$$\implies Q_{n-1} = P_{n-1, n-1}$$

$$\implies P_n = [t_0, \dots, t_n] f w_n(t) + \sum_{i=0}^{n-1} [t_0, \dots, t_i] f w_i(t) \implies \checkmark$$

remaining claim: use that

$P_n(t) + [t_0, \dots, t_n, t] f w_{n+1}$ interpolates at t_0, \dots, t_n, t

Classical polynomial interpolation

Divided differences

The divided differences $[t_0, \dots, t_n]f$ satisfy the following properties:

- ▶ $[t_0, \dots, t_n]P = 0$ for all $P \in \mathbf{P}_{n-1}$.

(def. of divided differences)

- ▶ If $t_0 = \dots = t_n$: (Taylor expansion)

$$[t_0, \dots, t_n]f = \frac{f^{(n)}(t_0)}{n!}$$

nodes.

Classical polynomial interpolation

Divided differences

- ▶ The following recurrence relation holds for $t_i \neq t_j$ (nodes with a hat are removed):

$$[t_0, \dots, t_n]f = \frac{([t_0, \dots, \hat{t}_i, \dots, t_n]f - [t_0, \dots, \hat{t}_j, \dots, t_n]f)}{t_j - t_i}$$

- ▶ If $f \in C^n$ $[t_0, \dots, t_n]f = \frac{1}{n!} f^{(n)}(\tau)$ with an $a \leq \tau \leq b$, and the divided differences depend continuously on the nodes.

Classical polynomial interpolation

Divided differences

Let us use divided differences to compute the coefficients for the Newton basis for the cubic interpolation polynomial p that satisfies $p(0) = 1$, $p(0.5) = 2$, $p(1) = 0$, $p(2) = 3$.

t_i				-----		
0	$[t_0]f = 1$					
0.5	$[t_1]f = 2$	$[t_0t_1]f = \frac{[t_1]f - [t_0]f}{t_1 - t_0} = 2$	$= \frac{2-1}{0.5-0} = 2$			
1	$[t_2]f = 0$	$[t_1t_2]f = \frac{[t_2]f - [t_1]f}{t_2 - t_1} = -4$		$[t_0t_1t_2]f = -6$	$= \frac{-4-2}{1-0} = -6$	
2	$[t_3]f = 3$	$[t_2t_3]f = \frac{[t_3]f - [t_2]f}{t_3 - t_2} = 3$		$[t_1t_2t_3]f = \frac{14}{3}$	$\frac{16}{3}$	

Thus, the interpolating polynomial is

$$p(t) = 1 + 2t + (-6)t(t - 0.5) + \frac{16}{3}t(t - 0.5)(t - 1).$$

Classical polynomial interpolation

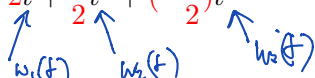
Divided differences

Let us now use divided differences to compute the coefficients for the Newton basis for the cubic interpolation polynomial p that satisfies $p(0) = 1$, $p'(0) = 2$, $p''(0) = 1$, $p(1) = 3$.

t_i				
0	$[t_0]f = 1$			
0	$[t_0]f = 1$	$[t_0t_1]f = p'(0) = 2$		
0	$[t_0]f = 1$	$[t_1t_2]f = p'(0) = 2$	$[t_0t_1t_2]f = \frac{p''(0)}{2!} = \frac{1}{2}$	
1	$[t_3]f = 3$	$[t_2t_3]f = \frac{[t_3]f - [t_0]f}{t_3 - t_0} = 2$	0	$-\frac{1}{2}$

Thus, the interpolating polynomial is

$$p(t) = 1 + 2t + \frac{1}{2}t^2 + \left(-\frac{1}{2}\right)t^3$$



Classical polynomial interpolation

Approximation error

If $f \in C^{(n+1)}$, then

$$f(t) - P(f|t_0, \dots, t_n)(t) = \frac{f^{(n+1)}(\tau)}{(n+1)!} \omega_{n+1}(t)$$

for an appropriate $\tau = \tau(t)$, $a < \tau < b$.

In particular, the error depends on the choice of the nodes.

For Taylor interpolation, i.e., $t_0 = \dots = t_n$, this results in:

$$f(t) - P(f|t_0, \dots, t_n)(t) = \frac{f^{(n+1)}(\tau)}{(n+1)!} (t - t_0)^{n+1}$$

Classical polynomial interpolation

Approximation error

Consider functions

$$\{f \in C^{n+1}([a, b]) : \sup_{\tau \in [a, b]} |f^{(n+1)}(\tau)| \leq M(n+1)!\}$$

for some $M > 0$, then the approximation error depends on $\omega_n(t)$, and thus on t_0, \dots, t_n .

Thus, one can try to minimize

$$\max_{a \leq t \leq b} |\omega_{n+1}(t)|,$$

which is achieved by choosing the nodes as the roots of the Chebyshev polynomial of order $(n+1)$.

Classical polynomial interpolation

Approximation error

Summary on **pointwise convergence**:

- ▶ If an interpolating polynomial is close/converges to the original function depends on the regularity of the function and the choice of interpolation nodes
- ▶ For a good choice of interpolation nodes, fast convergence can be obtained for almost all functions

Classical polynomial interpolation

Interpolation/Least square approximation/Splines

- ▶ Polynomial interpolation
- ▶ Least squares with polynomials
- ▶ Splines (i.e., piecewise polynomial interpolation):