# MATH578 - Numerical Analysis 1

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## §1 Polynomial Interpolation

In general, the goal of interpolation is, given a function f(x) on [a,b] and a series of distinct ordered points (often called *nodes* or *collocation points*)  $\{x_j\}_{j=1}^n \subseteq [a,b]$ , to find a polynomial P(x) such that  $f(x_j) = P(x_j)$  for each j.

**Theorem 1.1** (Existence and Uniqueness of Lagrange Polynomial): Let  $f \in C[a, b]$  and  $\{x_j\}$  a set of n distinct points. Then, there exists a unique  $P(x) \in \mathbb{P}_{n-1}$ , the space of n-1-degree polynomials, such that  $P(x_j) = f(x_j)$  for each j.

We call such a *P* the *Lagrange polynomial* associated to the points  $\{x_j\}$  for f.

PROOF. We define the following n-1 degree "fundamental polynomials" associated to  $\{x_i\}$ ,

$$\ell_j(x) \equiv \prod_{\substack{1 \le i \le n \\ i \ne j}} \frac{x - x_i}{x_j - x_i}, \quad j = 1, ..., n.$$

Then, one readily verifes  $\ell_j(x_i) = \delta_{ij}$ , and that the distinctness of the nodes guarantees the denominator in each term of the product is nonzero. Define

$$P(x) = \sum_{j=1}^{n} f(x_j) \ell(x),$$

which, being a linear combination of n-1 degree polynomials is also in  $\mathbb{P}_{n-1}$ . Moreover,

$$P(x_i) = \sum f(x_j) \delta_{i,j} = f(x_i),$$

as desired.

For uniqueness, suppose  $\overline{P}$  another n-1 degree polynomial satisfying the conditions of the theorem. Then,  $q(x) \equiv P(x) - \overline{P}(x)$  is also a degree n-1 polynomial with  $q(x_i) = 0$  for each i = 1, ...n. Hence, q a polynomial with more distinct roots than its degree, and thus it must be identically zero, hence  $P = \overline{P}$ , proving uniqueness.

**Theorem 1.2** (Interpolation Error): Suppose  $f \in C^n[a,b]$ , and let P(x) be the Lagrange polynomial for a set of n points  $\{x_j\}$ , with  $x_1 = a, x_n = b$ . Then, for each  $x \in [a,b]$ , there is a  $\xi \in [a,b]$  such that

$$f(x) - P(x) = \frac{f^{(n)}(\xi)}{n!}(x - x_1)\cdots(x - x_n).$$

Moreover, if we put  $h := \max_{i} (x_{i+1} - x_i)$ , then

$$||f - P||_{\infty} \le \frac{h^n}{4n} ||f^{(n)}||_{\infty}.$$

1 Polynomial Interpolation

PROOF. We prove the first identity, and leave the second "Moreover" as a homework problem. Notice that it holds trivially for  $x = x_j$  for any j, so assume  $x \neq x_j$  for any j, and define the function

$$g(t) \coloneqq f(t) - P(t) - \omega(t) \frac{f(x) - P(x)}{\omega(x)}, \qquad \omega(t) \coloneqq (t - x_1) ... (t - x_n) \in \mathbb{P}_n[t].$$

Then, we observe the following:

- $g \in C^n[a,b]$
- g(x) = 0
- $g(t = x_j) = 0$  for each j

Recall that by Rolle's Theorem, if a  $C^1$  function has  $\geq m$  roots, then its derivative has  $\geq m-1$  roots. Thus, applying this principle inductively to g(t), we conclude that  $g^{(n)}(t)$  has at least one root. Take  $\xi$  to be such a root. Then, one readily verifies that  $P^{(n)} \equiv 0$  and  $\omega^{(n)} \equiv n!$  (using polynomial properties), from which we may use the fact that  $g^{(n)}(\xi) = 0$  to simplify to the required identity.

**Remark 1.1**: In general, larger n leads to smaller maximum step size h. However, it is *not* true that  $n \to \infty$  implies  $P \to f$  in  $L^\infty$ . From the previous theorem, one would need to guarantee  $\|f^{(n)}\| \to 0$  (or at least, doesn't grow faster than  $\frac{h^n}{4n}$ ), which certainly won't hold in general; we have no control on the nth-derivative of an arbitrarily given function. However, we can try to optimize our choice of points  $\{x_j\}$  for a given j.

We switch notation for convention's sake to n + 1 points  $x_j$ . Our goal is the optimization problem

$$\min_{x_j} \max_{x \in [a,b]} \left| \prod_j (x - x_j) \right|,$$

the only term in the error bound above that we have control over. Remark that we can expand the product term:

$$\prod_{j} \left( x - x_j \right) = x^{n+1} - r(x),$$

where  $r(x) \in \mathbb{P}_n$ . So, really, we equivalently want to solve the problem

$$\min_{r \in \mathbb{P}_n} \left\| x^{n+1} - r(x) \right\|_{\infty},$$

namely, what n-degree polynomial minimizes the max difference between  $x^{n+1}$ ?

**Theorem 1.3** (De la Vallé-Poussin Oscillation Theorem): Let  $f \in C([a,b])$ , and suppose  $r \in \mathbb{P}_n$  for which there exists n+2 distinct points  $\{x_j\}$  such that  $a \le x_0 < \dots < x_{n+1} \le b$  at which the error f(x) - r(x) "oscillate" sign, i.e.

$$\operatorname{sign}(f(x_i) - r(x_i)) = -\operatorname{sign}(f(x_{i+1}) - r(x_{i+1})).$$

Then,

$$\min_{P \in \mathbb{P}_n} \|f - P\|_{\infty} \ge \min_{0 \le j \le n+1} |f(x_j) - r(x_j)|.$$

 $\hookrightarrow$  **Definition 1.1** (Chebyshev Polynomial): The *degree n Chebyshev polynomial*, defined on [-1,1], is defined by

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

**Remark 1.2**: The fact that  $T_n$  actually is a polynomial follows from the double angle formula for cos, which says

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

In the context of  $T_n$ , this implies that for any  $n \ge 1$ , the recursive formula

$$T_{n+1}(x) = 2xT_n(x) - T_{n-1}(x).$$

This formula with a simple induction argument proves that each  $T_n$  a polynomial, with for instance  $T_0(x) = 1$ ,  $T_1(x) = x$ ,  $T_2(x) = 2x^2 - 1$  and so on.

 $\hookrightarrow$  **Proposition 1.1**:  $\{T_n\}$  are orthogonal with respect to the inner product given by

$$(f,g) \coloneqq \int_{-1}^{1} f(x)g(x)\omega_2(x) \,\mathrm{d}x,$$

where  $\omega_2(x) := (1 - x^2)^{1/2}$ .

**Remark 1.3**: Defining similar *weight* functions by  $\omega_n(x) := (1 - x^n)^{1/n}$ , one can derive a more general class of polynomials called *Geigenbauer polynomials*, which are respectively orthogonal with respect to  $\int \cdots \omega_n$ .

 $\hookrightarrow$  Proposition 1.2 (Some Properties of  $T_n$ ):

- $|T_n(x)| \le 1$  on [-1, 1]
- The roots of  $T_n(x)$  are the n points

$$\xi_j := \cos\left(\frac{(2j-1)\pi}{2n}\right), \qquad j = 1, ..., n.$$

• For  $n \ge 1$ ,  $|T_n(x)|$  is maximal on [-1,1] at the n+1 points

$$\eta_j \coloneqq \cos\left(\frac{j\pi}{n}\right), \quad j = 0, ..., n,$$

with 
$$T_n(\eta_j) = (-1)^j$$
.

Note too that  $T_{n+1}(x)$  has leading coefficient  $2^n$ , which can be seen by the recursive formula above; define the *normalized* Chebyshev polynomials by  $\hat{T}_{n+1}(x) := 2^{-n}T_{n+1}(x)$ . Thus, we may write

$$\hat{T}_{n+1}(x) = x^{n+1} - r_n(x),$$

with  $r_n(x) \in \mathbb{P}_n$ . It follows for one that

$$\max_{x \in [-1,1]} |x^{n+1} - r_n(x)| = 2^{-n}.$$

Moreover, we know that at the n + 2 points  $\eta_i$ , we have

$$\hat{T}_{n+1}(\eta_j) = 2^{-j}(-1)^j = \eta_j^{n+1} - r_n(\eta_j).$$

Namely, because of the inclusion of  $(-1)^j$  term, this means that  $\hat{T}_{n+1}(x)$  oscillates sign between the  $\eta_j$  points, which fulfils the condition stated in the Oscillation Theorem. Thus, these observations readily imply the following result, settling our original question on optimizing locations of interpolation points for Lagrange interpolation:

**Theorem 1.4** (Optimal Approximation of  $x^{n+1}$  in  $\mathbb{P}_n$ ): The optimal approximation of  $x^{n+1}$  in  $\mathbb{P}_n$  on [-1,1] with respect to the  $L^{\infty}$  norm is given by

$$r_n(x) := x^{n+1} - 2^{-n} T_{n+1}(x).$$

Thus, the optimal Lagrange interpolation points are the n+1 roots of  $x^{n+1}-r_n(x)$ , namely  $\xi_j=\cos\left(\frac{(2j+1)\pi}{2n+2}\right)$  for j=0,...,n.

**Remark 1.4**: This, and previous results, were stated over [-1,1]. A linear change of coordinates transforming any closed interval to [-1,1] readily leads to analgous results.

# §2 Fourier Transform

Recall that the Fourier transform of a (Lebesgue) measurable function u(x) on  $\mathbb{R}$  is defined

$$(\mathcal{F}u)(\xi) = \hat{u}(\xi) = \int_{\mathbb{R}} e^{-i\xi x} u(x) dx.$$

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**→Theorem 2.1**: Let  $u \in L^2(\mathbb{R})$ . Then,

- 1.  $\hat{u} \in L^2$
- 2. the *inversion* formula holds, ie  $u(x) = \int_{\mathbb{R}} \hat{u}(\xi) e^{i\xi x} dx = (\mathcal{F}^{\{-1\}}u)(x)$
- 3.  $\|\hat{u}\|_2 = \sqrt{2\pi} \|u\|_2$
- 4. for  $u \in L^2$ ,  $v \in L^1$ ,  $u * v \in L^2$ , and  $\widehat{u * v} = \widehat{u}\widehat{v}$ .

**→Theorem 2.2** (Further Properties of Fourier Transform): Let  $u, v \in L^2$ . Then,

- 1.  $\mathcal{F}$  is linear over  $\mathbb{R}$
- 2.  $\mathcal{F}(u(\cdot + x_0))(\xi) = e^{i\xi x_0} \hat{u}(x_0)$
- 3.  $\mathcal{F}\left(e^{i\xi_0x}u(x)\right)(\xi) = \hat{u}(\xi x_0)$ 4. If  $c \neq 0$ ,  $\mathcal{F}(u(c \cdot))(\xi) = \frac{\hat{u}\left(\frac{\xi}{c}\right)}{c}$
- 5.  $\mathcal{F}(\overline{u})(\xi) = \overline{\hat{u}(-\xi)}$
- 6. if  $u_x$  exists and is in  $L^2$ , then

$$\mathcal{F}(u_x)(\xi) = i\xi \hat{u}(\xi).$$

By extension, if  $\partial_{\alpha} u \in L^2$ , then  $\widehat{\partial_{\alpha} u}(\xi) = (i\xi)^{\alpha} \widehat{u}(\xi)$ 

7. 
$$(\mathcal{F}^{-1}u)(\xi) = \frac{1}{2\pi}\hat{u}(-\xi)$$
.

In a sense, 6. implies a duality between the smoothness of u(x) and rapid decay (as  $|\xi| \to \infty$ ) of  $\hat{u}(x)$ ; 7. indicates that the same analogy holds switching the roles of u and  $\hat{u}$ . We make this more precise.

 $\hookrightarrow$  **Definition 2.1** (Bounded Variation): We say a function u on  $\mathbb{R}$  is of bounded variation or write  $\in$  BV if there exists a constant M such that for any finite integer m and collection of points  $x_0 < x_1 < ... < x_m$ ,

$$\sum_{j=1}^{m} |u(x_j) - u(x_{j-1})| \le M.$$

In a sense, this notion of BV captures a notion of "limited oscillation".

 $\hookrightarrow$  Theorem 2.3: Let  $u \in L^2$ . Then:

1. If u has p-1 continuous derivatives in  $L^2$  and its pth derivative is in BV, then

$$\hat{u}(\xi) = \mathcal{O}(|\xi|^{-p-1}).$$

2. If u has infinitely many derivatives all in  $L^2$ , then

$$\hat{u}(\xi) = \mathcal{O}\big(|\xi|^{-M}\big), \qquad \forall M \geq 1.$$

### §2.1 Discrete Fourier Transform

Let h > 0 be a *step size*. Let  $x_j = jh$  for  $j \in \mathbb{Z}$ . We write  $v = \{v_j\}_{j \in \mathbb{Z}}$  for discrete approximations of a function u on the grid  $\{x_j\}_{j\in\mathbb{Z}}$ , i.e.  $v_j \approx u(x_j)$ .

The  $\ell_h^2$  norm is defined for such v by

$$||v||_2 := \left[ h \sum_{j \in \mathbb{Z}} |v_j|^2 \right]^{1/2}.$$

Then,  $\ell_h^2$  is defined as the space of such sequences v such that this norm is finite. analogous definitions hold for other  $\ell_h^p$  spaces and norms.

**Proposition 2.1** (Nesting):  $\ell_h^p \subset \ell_h^q$  for each  $q \ge p$ .

**Remark 2.1**: Note that the analogous result to this does *not* hold for  $L^p$  spaces (unless restricted to a compact domain).

We define the convolution of two sequences v, w by the new sequence v \* w with entries

$$(v*w)_m = h \sum_{j \in \mathbb{Z}} v_j w_{m-j} = h \sum_{j \in \mathbb{Z}} v_{m-j} w_j.$$

For any  $v \in \ell_h^2$ , we define too the *semi-discrete Fourier transform* of v by

$$\hat{v}(\xi) = (\mathcal{F}_h v)(\xi) = h \sum_{j \in \mathbb{Z}} e^{-i\xi x_j} v_j, \qquad \xi \in \left[ -\frac{\pi}{h}, \frac{\pi}{h} \right],$$

where we remark that  $\hat{v}(\xi)$   $\frac{2\pi}{h}$ -periodic (hence the domain restriction) and continuous.

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