MA 322: Scientific Computing Lecture - 9



Convergence of Lagrange's Interpolating polynomial

Result

• Suppose x_0, x_1, \ldots, x_n are distinct real numbers, and let f be a given real valued function with n+1 continuous derivatives on the interval $I_t = \mathcal{H}\{t, x_0, x_1, \ldots, x_n\}$, with t some given real number. Then there exits a number $\xi_t \in I_t$ such that

$$f(t) - p_n(t) = \frac{f^{(n+1)}(\xi_t)}{(n+1)!}(t-x_0)(t-x_1)\dots(t-x_n), \qquad (1)$$

where $p_n(t) = \sum_{j=0}^n f(x_j) \ell_j(t)$ is the Lagrange interpolating polynomial of f with degree n.

Proof. We define the error function *E* by

$$E(t) = f(t) - p_n(t), \quad p_n(t) = \sum_{j=0}^{n} f(x_j) \ell_j(t)$$
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and a user defined function G by

$$G(x) = E(x) - \frac{\Psi(x)}{\Psi(t)}E(t)$$
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$$\Psi(x) = (x - x_0)(x - x_1) \dots (x - x_n)$$
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Then for the user defined function

$$G(x) = E(x) - \frac{\Psi(x)}{\Psi(t)}E(t), \quad \Psi(x) = (x - x_0)(x - x_1)\dots(x - x_n), \quad (4)$$

observe that

$$G(x_i) = E(x_i) - \frac{\Psi(x_i)}{\Psi(t)}E(t) = 0, \quad i = 0, 1, 2, ..., n$$
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Therefore, we have

$$G^{(n+1)}(x) = f^{(n+1)}(x) - \frac{(n+1)!}{\Psi(t)} E(t)$$
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Hence, for any real number x, we have following error representations

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Remark:

• Now, we wish to calculate the distance between f and p_n , which is done by introducing norm over function spaces.

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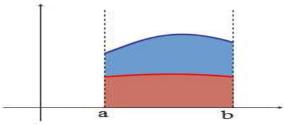
$$d(x,y) = ||x - y|| \ \forall x, y \in X.$$



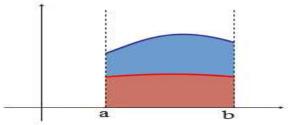
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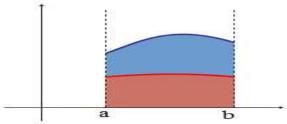
• Therefore, in order to define the distance between two functions in C[a, b], we first try to associate vector space C[a, b] a norm.



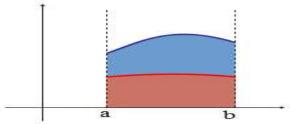
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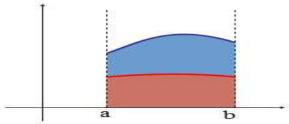
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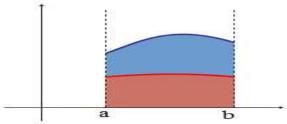
• For $f,g \in C[a,b]$, the distance between f and g at a particular x is given by |f(x)-g(x)|. To measure the distance, which takes care all x, we may try to evaluate $\max_{x \in [a,b]} |f(x)-g(x)|$.



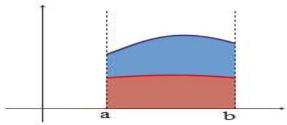
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- For f, g ∈ C[a, b], the distance between f and g at a particular x is given by |f(x) g(x)|. To measure the distance, which takes care all x, we may try to evaluate max_{x∈[a,b]} |f(x) g(x)|. Does it represents the distance between f and g? It will measure the distance between f and g provided this distance is generated from a norm.
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- It is an easy exercise to verify that $||f||_{\infty} = \max_{x \in [a,b]} |f(x)|$ defines a norm on C[a,b], known as infinity norm. The distance associated with this norm is given by

$$d_{\infty}(f,g) = \max_{x \in [a,b]} |(f-g)(x)| = \max_{x \in [a,b]} |f(x) - g(x)|.$$

- lacksquare In $(C[a,b],d_{\infty})$
 - A sequence $\langle f_n \rangle$ in C[a,b] is said to be convergent w.r.t d_{∞} , if there exists a $f \in C[a,b]$ s. t.

$$d_{\infty}(f_n, f) \to 0$$
 or equivalently $||f_n - f||_{\infty} \to 0$ as $n \to \infty$. (12)

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Remark:

- Convergence with respect to the $\|\cdot\|_{\infty}$ norm leads to uniform convergence. Again uniform convergence has following consequences
 - Uniform limit of a sequence of continuous functions is also continuous.
 - If $f_n \to f$ converges in $(C[a, b], d_\infty)$, then

$$\lim_{n\to\infty}\int_a^b f_n(x)dx = \int_a^b \lim_{n\to\infty} f_n(x)dx = \int_a^b f(x)dx. \tag{13}$$



About Uniform Convergence of Interpolating Polynomials

Consider again the error formula

$$f(x) - p_n(x) = \frac{(x - x_0)(x - x_1)\dots(x - x_n)}{(n+1)!} f^{(n+1)}(\xi_x), \tag{14}$$

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where $\xi_x \in \mathcal{H}\{x, x_0, x_1, \dots, x_n\}$. Then for any interval I that contains $\mathcal{H}\{x, x_0, x_1, \dots, x_n\}$ and for $f \in C^{(n+1)}(I)$, we obtain

$$\max_{x \in I} |f(x) - p_n(x)| \le \frac{1}{(n+1)!} \max_{x \in I} |f^{(n+1)}(\xi_x)| \max_{x \in I} |\Psi_n(x)|, \tag{15}$$

where $\Psi_n(x) = (x - x_0)(x - x_1) \dots (x - x_n)$

Remark:

• Now, $p_n \to f$ uniformly provided quantities

$$M_{n+1} = \max_{x \in I} |f^{(n+1)}(\xi_x)|$$
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are uniformly bounded in I. More precisely, we may expect $\|f-p_n\|_{\infty}\to 0$ as $n\to\infty$ for C^{∞} (infinitely many times differentiable functions) functions when

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Unfortunately, this is not so, since the sequence

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Example: Consider the function $f(x) = \frac{1}{1+x^2}$, $x \in [-5, 5]$ and let us try to calculate $||f - p_n||$ for different values of n.

Unfortunately, this is not so, since the sequence

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Example: Consider the function $f(x) = \frac{1}{1+x^2}$, $x \in [-5, 5]$ and let us try to calculate $||f - p_n||$ for different values of n.

Degree n	Max error
2	0.65
4	0.44
6	0.61
8	1.04
10	1.92
12	3.66
14	7.15
16	14.25
18	28.74
20	58.59
22	121.02
24	252.78