

Approximationstheorie

Ergänzungen

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Mathematik!
TU Chemnitz

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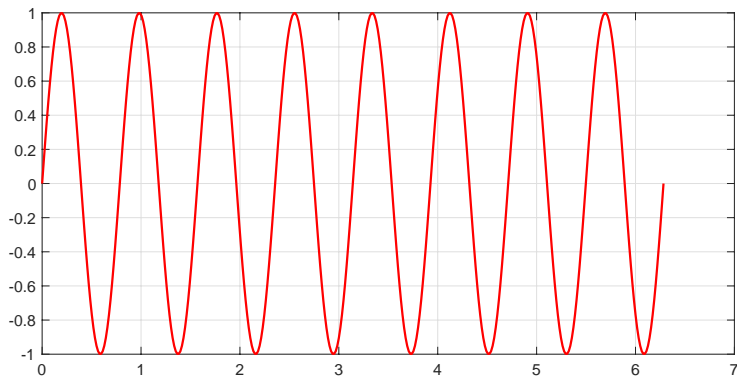
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Aliasing

Most familiar setting

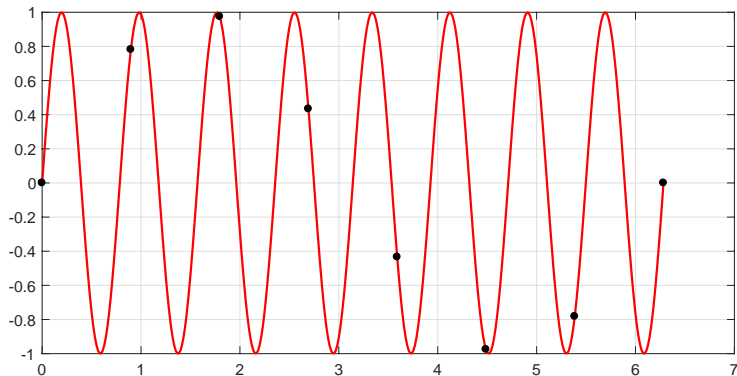
$$f(x) = \sin(8x)$$



Aliasing

Most familiar setting

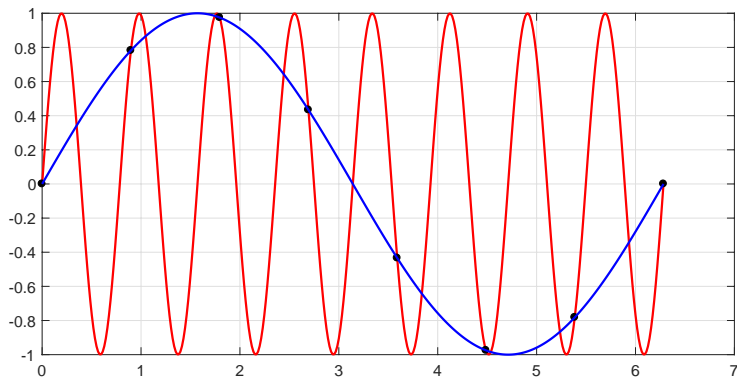
$$f(x) = \sin(8x), \text{ sampled at } x_j = j \cdot 2\pi/7$$



Aliasing

Most familiar setting

$f(x) = \sin(8x)$, sampled at $x_j = j \cdot 2\pi/7$



aliases to $\tilde{f}(x) = \sin x$.

Aliasing

Chebyshev, Laurent and Fourier

Recall that a Lipschitz continuous function f on $[-1, 1]$ has the absolutely and uniformly convergent Chebyshev expansion $f(x) = \sum_{k=0}^{\infty} a_k T_k(x)$.

Given $n \in \mathbb{N}_0$, we also recall the **Chebyshev projection** and **Chebyshev interpolant**

$$p_n(x) = \sum_{k=0}^n c_k T_k(x), \quad f_n(x) = \sum_{k=0}^n a_n T_k(x), \quad x \in [-1, 1].$$

In the variables z and ϑ , where $x = \frac{1}{2}(z + z^{-1})$ and $z = e^{i\vartheta}$, the corresponding interpolations and projections are as follows:

Fourier

Laurent

$$\mathbb{F}(\vartheta) = \mathbb{F}(-\vartheta) = \frac{1}{2} \sum_{k=0}^{\infty} a_k (e^{ik\vartheta} + e^{-ik\vartheta})$$

$$F(z) = F(z^{-1}) = \frac{1}{2} \sum_{k=0}^{\infty} a_k (z^k + z^{-k})$$

$$\mathbb{F}_n(\vartheta) = \frac{1}{2} \sum_{k=0}^n a_k (e^{ik\vartheta} + e^{-ik\vartheta})$$

$$F_n(z) = \frac{1}{2} \sum_{k=0}^n a_k (z^k + z^{-k})$$

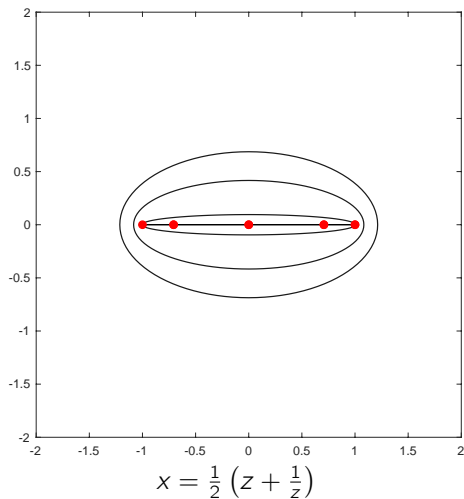
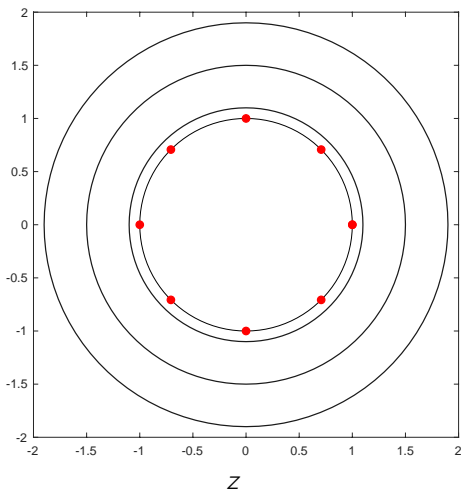
$$\mathbb{P}(\vartheta) = \frac{1}{2} \sum_{k=0}^n c_k (e^{ik\vartheta} + e^{-ik\vartheta})$$

$$P_n(z) = \frac{1}{2} \sum_{k=0}^n c_k (z^k + z^{-k})$$

Aliasing

Joukowski map

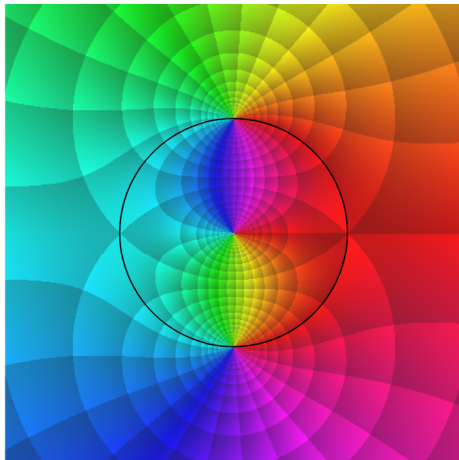
Image of circles around the origin.



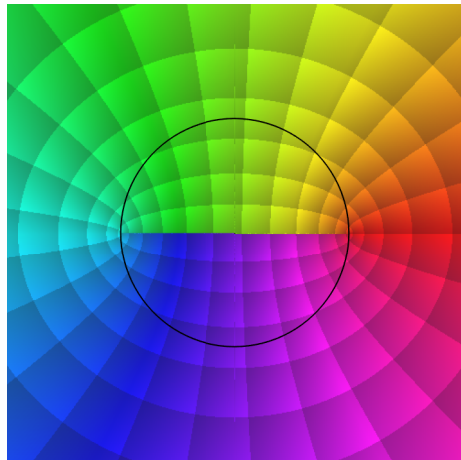
Aliasing

Joukowski map

Phase plots.



z



$$x = \frac{1}{2} \left(z + \frac{1}{z} \right)$$

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Barycentric Interpolation Formula

Review

We recall some basic facts about Lagrange interpolation:

- For a set of $n + 1$ distinct interpolation nodes $\{x_j\}_{j=0}^n$ and $n + 1$ data values $\{f_j\}_{j=0}^n$ there exists a unique polynomial $p \in \mathcal{P}_n$ satisfying the **interpolation conditions**

$$p(x_j) = f_j, \quad j = 0, \dots, n.$$

- The interpolant may be represented in terms of the **Lagrange fundamental polynomials** $\{\ell_j\}_{j=0}^n \subset \mathcal{P}_n$ as

$$p(x) = \sum_{j=0}^n f_j \ell_j(x),$$

where

$$\ell_j(x) = \prod_{\substack{k=0 \\ k \neq j}}^n \frac{x - x_k}{x_j - x_k}, \quad j = 0, \dots, n.$$

Barycentric Interpolation Formula

Review

- The Newton form of the interpolating polynomial is based on the **nodal polynomials**¹

$$\omega_j(x) = \prod_{k=0}^{j-1} (x - x_k) \in \mathcal{P}_j, \quad j = 0, \dots, n,$$

as well as the set of recursively defined **divided differences**

$$f_{i_0, i_1, \dots, i_k} := \frac{f_{i_1, i_2, \dots, i_k} - f_{i_0, i_1, \dots, i_{k-1}}}{x_{i_k} - x_{i_0}} \quad k \geq 1,$$

where $i_0, \dots, i_n \in \{0, 1, \dots, n\}$ are distinct indices, and has the form

$$p(x) = f_0 \omega_0(x) + f_{0,1} \omega_1(x) + \dots + f_{0,1,\dots,n} \omega_n(x).$$

¹(the empty product taken as equal to one)

Barycentric Interpolation Formula

Review

- The divided differences can be generated from left to right in the triangular table:

x_i	$k = 0$	$k = 1$	$k = 2$	$k = 3$	$k = 4$
x_0	f_0				
		$f_{0,1}$			
x_1	f_1		$f_{0,1,2}$		
		$f_{1,2}$		$f_{0,1,2,3}$	
x_2	f_2		$f_{1,2,3}$		$f_{0,1,2,3,4}$
		$f_{2,3}$		$f_{1,2,3,4}$	
x_3	f_3		$f_{2,3,4}$		
		$f_{3,4}$			
x_4	f_4				

Adding a data pair entails adding a 'diagonal' along the bottom of the triangle.

Barycentric Interpolation Formula

Naive construction based on a Vandermonde matrix

The representation of the Lagrange interpolating polynomial with respect to the **monomial basis** $\{x^j\}_{j=0}^n$, i.e.,

$$p(x) = a_0 + a_1x + \cdots + a_nx^n$$

is determined by the $n + 1$ linear equations

$$p(x_j) = f_j, \quad j = 0, \dots, n,$$

or, in matrix form, $\mathbf{V}\mathbf{a} = \mathbf{f}$, where

$$\mathbf{V} = \mathbf{V}(x_0, \dots, x_n) = \begin{bmatrix} 1 & x_0 & x_0^2 & \dots & x_0^n \\ 1 & x_1 & x_1^2 & \dots & x_1^n \\ \vdots & \vdots & \vdots & \dots & \vdots \\ 1 & x_n & x_n^2 & \dots & x_n^n \end{bmatrix}, \quad \mathbf{a} = \begin{bmatrix} a_0 \\ a_1 \\ \vdots \\ a_n \end{bmatrix}, \quad \mathbf{f} = \begin{bmatrix} f_0 \\ f_1 \\ \vdots \\ f_n \end{bmatrix}.$$

In view of $\det \mathbf{V}(x_0, \dots, x_n) = \prod_{i>j} (x_i - x_j)$, this has a unique solution whenever the nodes are distinct.

Barycentric Interpolation Formula

Barycentric weights

In terms of the nodal polynomial associated with $\{x_j\}_{j=0}^n$

$$\omega_{n+1}(x) := (x - x_0)(x - x_1) \cdots (x - x_n) \in \mathcal{P}_{n+1}.$$

we define the **barycentric weights** $\{\lambda_j\}_{j=0}^n$ by

$$\lambda_j := \frac{1}{\prod_{\substack{k=0 \\ k \neq j}}^n (x_j - x_k)} = \frac{1}{\omega'_{n+1}(x_j)}, \quad j = 0, \dots, n, \quad (5.1)$$

in terms of which the Lagrange fundamental polynomials become

$$\ell_j(x) = \omega_{n+1}(x) \frac{\lambda_j}{x - x_j}, \quad j = 0, \dots, n,$$

by means of which we can represent the interpolating polynomial as ...

Barycentric Interpolation Formula

First and second formulas

the **first barycentric formula** (or **modified Lagrange formula**)

$$p(x) = \omega_{n+1}(x) \sum_{j=0}^n f_j \frac{\lambda_j}{x - x_j}.$$

Since the constant function $f \equiv 1$ is always interpolated exactly, we have

$$1 \equiv \omega_{n+1}(x) \sum_{j=0}^n \frac{\lambda_j}{x - x_j},$$

so that, dividing the first barycentric formula by this expression and cancelling common factors yields the **second barycentric formula**

$$p(x) = \frac{\sum_{j=0}^n f_j \frac{\lambda_j}{x - x_j}}{\sum_{j=0}^n \frac{\lambda_j}{x - x_j}}.$$

Barycentric Interpolation Formula

Computational cost

Updating. Addition of new node x_{n+1} :

$$\lambda_j^{\text{new}} := \frac{\lambda_j^{\text{old}}}{x_j - x_{n+1}}, \quad j = 0, \dots, n, \quad (2n + 2 \text{ flops}).$$

λ_{n+1} from old weights, additional $n + 1$ flops, if $x_j - x_{n+1}$ have been stored.

Cost.

- Computation of $\{\lambda_j\}_{j=0}^n$ requires $\sum_{j=1}^n 3j = \frac{3}{2}n(n+1)$ flops.
- For given weights $\{\lambda_j\}_{j=0}^n$ each evaluation of p in additional $5n + 4 = O(n)$ flops.

Further advantages.

- λ_j independent of f_j , i.e., once weights computed arbitrary f can be interpolated in $O(n)$ flops.
- λ_j independent of node numbering (cf. divided differences).

Barycentric Interpolation Formula

Chebyshev nodes

Theorem 5.1

For the $n + 1$ Chebyshev nodes the barycentric weights are

$$\lambda_j = \begin{cases} (-1)^j \frac{2^{n-1}}{n}, & j = 1, \dots, n-1, \\ (-1)^j \frac{2^{n-2}}{n}, & j = 0, n. \end{cases}$$

The associated interpolating polynomial for data $\{f_j\}_{j=0}^n$ in second barycentric form is then

$$p(x) = \frac{\sum_{j=0}^n \prime \frac{(-1)^j f_j}{x - x_j}}{\sum_{j=0}^n \prime \frac{(-1)^j}{x - x_j}},$$

with the primed sums indicating that the first and last term are halved.

Barycentric Interpolation Formula

Remarks

- The exponential growth of the barycentric weights for Chebyshev nodes raises concern about floating point overflow for high interpolation degrees.
- Moreover, the nodal polynomial occurring as a factor in the first barycentric formula has value on the order of 2^{-n} on $[-1, 1]$, which similarly poses a danger of underflow.
- In addition, all these numbers scale with n -th powers when the independent variable is transplanted to a general bounded interval $[a, b] \subset \mathbb{R}$.
- The over- and underflow issues can be addressed by reformulating the expressions in terms of logarithms or mapping the independent variable to an interval of length 4 (logarithmic capacity 1).
- The nodal polynomial factor and the common factors in the barycentric weight, however, cancel out in the second barycentric formula, making it scale invariant and eliminating the risk of over- and underflow.
- Nonetheless, the second barycentric formula has weaker numerical stability properties than the first, as the analysis in [Higham, 2004] makes explicit.

Barycentric Interpolation Formula

Stability analysis of [Higham (2004)]

Definition 5.2

The condition number of $p = p_n$ at $x \in [-1, 1]$ with respect to f is, for $p(x) \neq 0$,

$$\text{cond}(x, n, f) := \limsup_{\epsilon \rightarrow 0} \left\{ \left| \frac{p_f(x) - p_{f+\Delta f}(x)}{\epsilon p_f(x)} \right| : |\Delta f| \leq \epsilon |f| \right\}$$

In $\text{cond}(x, n, f)$, the term 'n' indicates the dependence of cond on the points x_j .

Lemma 5.3

$$\text{cond}(x, n, f) = \frac{\sum_{j=0}^n |\ell_j(x) f_j|}{|p(x)|} \geq 1$$

and for any f with $|\Delta f| \leq \epsilon |f|$ we have

$$\frac{|p_f(x) - p_{f+\Delta f}(x)|}{|p_f(x)|} \leq \text{cond}(x, n, f) \epsilon.$$

Barycentric Interpolation Formula

Stability analysis of [Higham (2004)]

We introduce the **relative error counter** (cf. [Higham, 2002, Section 2.2])

$$\langle k \rangle := \prod_{i=1}^k (1 + \delta_i)^{\rho_i}, \quad \rho_i = \pm 1, \quad |\delta| \leq u \text{ unit roundoff.}$$

Lemma 5.4

The barycentric weights $\{\hat{\lambda}_j\}_{j=0}^n$ computed in floating point arithmetic satisfy

$$\hat{\lambda}_j = \lambda_j \langle 2n \rangle_j, \quad j = 0, \dots, n,$$

while the computed $\hat{\ell}(x)$ satisfies $\hat{\ell}(x) = \ell(x) \langle 2n + 1 \rangle$.

Theorem 5.5

The computed interpolation polynomial $\hat{p}(x)$ using the first barycentric formula satisfies

$$\hat{p}(x) = \ell(x) \sum_{j=0}^n \frac{\lambda_j}{x - x_j} f_j \langle 5n + 5 \rangle.$$

Barycentric Interpolation Formula

Stability analysis of [Higham (2004)]

- The statement of Theorem 5.5 is that the computed value $\hat{p}(x)$ of the interpolating polynomial at a point x is the exact value of a perturbed interpolation problem, where the perturbation is small, i.e., that interpolation via the first barycentric formula is **backward stable**.
- The errors are of the same form, and only $O(n)$ times larger than the errors in rounding the f_j to a floating point number.
- Applying Lemma 5.3 yields a bound for the forward error:

$$\frac{|p(x) - \hat{p}(x)|}{|p(x)|} \leq \gamma_{5n+5} \text{cond}(x, n, f).$$

- If the x_j or x are not floating point numbers then there can be large relative errors in the differences $fl[fl(x_j) - fl(x_k)]$ and $fl[fl(x) - fl(x_k)]$. However, the computed $\hat{p}(x)$ can nevertheless be interpreted as the exact result corresponding to slightly perturbed x and points x_j (namely, the rounded values) and slightly perturbed points f_j ; so if $p(x)$ has a large relative error, then the problem itself must be ill-conditioned with respect to variations in x and the x_j and the f_j .

Barycentric Interpolation Formula

Stability analysis of [Higham (2004)]

Theorem 5.6

The value $\hat{p}(x)$ computed with the second barycentric formula satisfies

$$\begin{aligned}\frac{|p(x) - \hat{p}(x)|}{|p(x)|} &\leq (3n + 4)u \frac{\sum_{j=0}^n \left| \frac{\lambda_j}{x-x_j} f_j \right|}{\left| \sum_{j=0}^n \frac{\lambda_j}{x-x_j} f_j \right|} + (3n + 2)u \frac{\sum_{j=0}^n \left| \frac{\lambda_j}{x-x_j} \right|}{\left| \sum_{j=0}^n \frac{\lambda_j}{x-x_j} \right|} + O(u^2) \\ &= (3n + 4)u \operatorname{cond}(x, n, f) + (3n + 2)u \frac{\sum_{j=0}^n \left| \frac{\lambda_j}{x-x_j} \right|}{\left| \sum_{j=0}^n \frac{\lambda_j}{x-x_j} \right|} + O(u^2) \\ &= (3n + 4)u \operatorname{cond}(x, n, f) + (3n + 2)u \operatorname{cond}(x, n, 1) + O(u^2).\end{aligned}$$

Barycentric Interpolation Formula

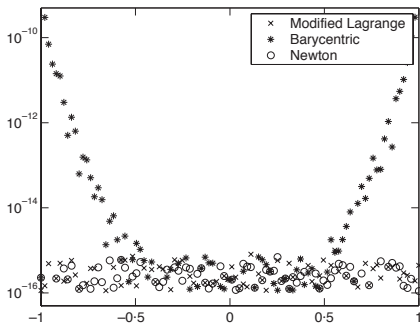
Stability analysis of [Higham (2004)]

- This forward error bound contains a term not present in that for the first formula. This measures the amount of cancellation in the denominator. Since the denominator is independent of f it is clear that the bound can be arbitrarily larger than $\text{cond}(x, n, f)u$ for suitable choices of f and x_j .
- For example: taking $f_1 = 1$ and $f_j = 0$ for $j > 1$ gives $\text{cond}(x, n, f) = 1$, while for suitable choice of the x_j the second term in the bound can become arbitrarily large.
- However, from (4.3) we see that the error bound is significantly larger than that for the first barycentric formula only if $\text{cond}(x, n, 1) \gg \text{cond}(x, n, f)$ a circumstance that intuitively seems unlikely.

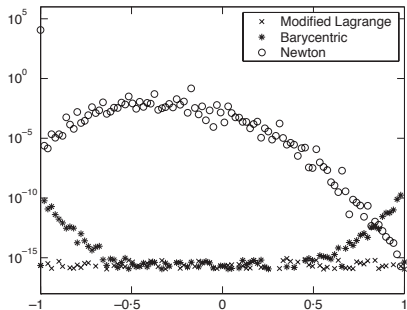
Barycentric Interpolation Formula

Stability analysis of [Higham (2004)]

Numerical experiment: $f_j = 0, j = 0, \dots, n-1, f_n = 1, n = 29$, equispaced points



x_j in increasing order

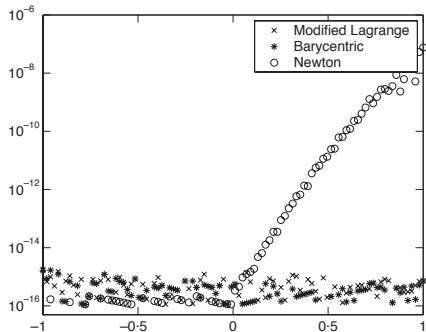


x_j in decreasing order

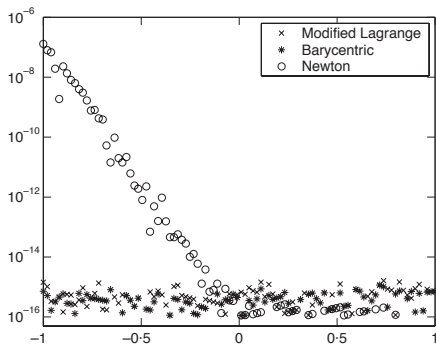
Barycentric Interpolation Formula

Stability analysis of [Higham (2004)]

Numerical experiment: Runge function, $n = 29$, Chebyshev points



x_j in increasing order



x_j in decreasing order

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The Weierstrass Approximation Theorem

Weierstrass 1885 proof

Theorem 6.1

For any continuous function f on $[-1, 1]$ and $\epsilon > 0$ there exists a polynomial p such that $\|f - p\|_{L^\infty(-1,1)} < \epsilon$.

The original 1885 proof by Weierstraß derives the result by first extending f to a continuous function \tilde{f} on \mathbb{R} with compact support and then showing

$$\|\tilde{f} - p\| \leq \|\tilde{f} - \tilde{f}_\epsilon\| + \|\tilde{f}_\epsilon - p\|$$

where

- \tilde{f}_ϵ is obtained from the convolution of \tilde{f} with a Gaussian which is sufficiently narrow that $\|\tilde{f} - \tilde{f}_\epsilon\| < \frac{\epsilon}{2}$ and
- p is a truncated Taylor series (i.e., a polynomial) approximating the entire function \tilde{f}_ϵ sufficiently well that $\|\tilde{f}_\epsilon - p\| < \frac{\epsilon}{2}$.

The Weierstrass Approximation Theorem

Convolutions

Let f and g be two locally integrable² functions on \mathbb{R} . The **convolution** $f * g$ of f and g is a function defined on \mathbb{R} by

$$(f * g)(x) = \int f(x - y)g(y) \, dy = \int f(y)g(x - y) \, dy = (g * f)(x)$$

provided these integrals in question exist.

²i.e., integrable on every compact subset of their domains of definition.

The Weierstrass Approximation Theorem

Convolution

Theorem 6.2 (Generalized Young's inequality)

Let μ be a σ -finite measure on \mathbb{R} as well as $1 \leq p \leq \infty$ and $C > 0$. Suppose K is a measurable function on \mathbb{R}^2 such that

$$\sup_{x \in \mathbb{R}} \int |K(x, y)| d\mu(y) \leq C \quad \text{and} \quad \sup_{y \in \mathbb{R}} \int |K(x, y)| d\mu(x) \leq C.$$

If $f \in L^p(\mathbb{R})$, then the function Tf defined by

$$(Tf)(x) := \int K(x, y)f(y) d\mu(y)$$

is well-defined almost everywhere, lies in $L^p(\mathbb{R})$ and $\|Tf\|_{L^p(\mathbb{R})} \leq C\|f\|_{L^p(\mathbb{R})}$.

As a consequence, if $f \in L^1(\mathbb{R})$ and $g \in L^p(\mathbb{R})$, $1 \leq p \leq \infty$, then $f * g \in L^p(\mathbb{R})$ and $\|f * g\|_{L^p(\mathbb{R})} \leq \|f\|_{L^1(\mathbb{R})}\|g\|_{L^p(\mathbb{R})}$.

Proof. Apply Theorem 6.2 with $K(x, y) = f(x - y)$.

The Weierstrass Approximation Theorem

Convolution

For a function f defined on \mathbb{R} and $a \in \mathbb{R}$ we define $f_a(x) := f(a + x)$.

Lemma 6.3

If $1 \leq p < \infty$ and $f \in L^p(\mathbb{R})$, then $\lim_{a \rightarrow 0} \|f_a - f\|_{L^p(\mathbb{R})} = 0$.

Theorem 6.4

Suppose $\phi \in L^1(\mathbb{R})$ and $\int \phi(x) dx = c$. For each $\epsilon > 0$ define the function ϕ_ϵ by

$$\phi_\epsilon(x) := \frac{1}{\epsilon} \phi\left(\frac{x}{\epsilon}\right).$$

- (a) If $f \in L^p(\mathbb{R})$, $1 \leq p < \infty$, then $f * \phi_\epsilon \rightarrow cf$ in $L^p(\mathbb{R})$ as $\epsilon \rightarrow 0$.
- (b) If $f \in L^\infty(\mathbb{R})$ (and uniformly continuous on a set V), then $f * \phi_\epsilon \rightarrow cf$ uniformly on V as $\epsilon \rightarrow 0$.

The Weierstrass Approximation Theorem

Fourier transform

Definition 6.5

If $f \in L^1(\mathbb{R})$, its Fourier transform \hat{f} is a bounded function on \mathbb{R} defined by

$$\hat{f}(\xi) = \int e^{-2\pi i \xi x} f(x) dx, \quad \xi \in \mathbb{R}.$$

Theorem 6.6 (Convolution and Fourier transform)

If $f, g \in L^1(\mathbb{R})$, then $\widehat{(f * g)} = \hat{f} \cdot \hat{g}$.

Theorem 6.7

The Fourier transform of the function $f(x) = e^{-\pi a x^2}$ with $a > 0$ is given by

$$\hat{f}(\xi) = a^{-1/2} e^{-\pi \xi^2 / a}.$$

The Weierstrass Approximation Theorem

Fourier transform of the Schwartz class

Definition 6.8

The Schwartz class $\mathcal{S} = \mathcal{S}(\mathbb{R})$ is the space of all C^∞ -functions on \mathbb{R} which, together with all their derivatives, decay faster than any power of x as $|x| \rightarrow \infty$:
 $u \in \mathcal{S}$ if $u \in C^\infty(\mathbb{R})$ and

$$\sup_{x \in \mathbb{R}} |x^\alpha \partial^\beta u(x)| < \infty \quad \text{for all } \alpha, \beta \in \mathbb{N}_0.$$

Proposition 6.9

For $f \in \mathcal{S}$ and $\beta \in \mathbb{N}_0$ there holds

- (a) $\hat{f} \in C^\infty$ and $\partial^\beta \hat{f} = [(-2\pi i x)^\beta f]^\wedge$.
- (b) $\widehat{\partial^\beta f} = (2\pi i \xi)^\beta \hat{f}$.

Proposition 6.10

If $f \in \mathcal{S}$, then $\hat{f} \in \mathcal{S}$.

The Weierstrass Approximation Theorem

Heat kernel

The **Cauchy problem** for the **heat equation** in 1D with initial data f

$$\partial_t u - \partial_{xx} u = 0 \text{ on } \mathbb{R} \times (0, \infty), \quad u(x, 0) = f(x),$$

where we assume f a function of rapid decay, can be solved by taking the Fourier transform of the heat equation with respect to x :

$$\partial_t \hat{u}(\xi, t) + 4\pi^2 \xi^2 \hat{u}(\xi, t) = 0, \quad \hat{u}(\xi, 0) = \hat{f}(\xi).$$

This is an ordinary initial value problem which, for each value of the parameter ξ , has the solution

$$\hat{u}(\xi, t) = \hat{f}(\xi) e^{-4\pi^2 \xi^2 t}, \quad t > 0.$$

In other words,

$$u(x, t) = f * K_t, \quad \text{where} \quad \hat{K}_t(\xi) = e^{-4\pi^2 \xi^2 t}.$$

The Weierstrass Approximation Theorem

Heat kernel

By Theorem 6.7, this means

$$K_t(x) =: K(x, t) = (4\pi t)^{-1/2} e^{-x^2/(4t)}, \quad t > 0.$$

The function K defined on $\mathbb{R} \times (0, \infty)$ is called the **Gaussian kernel** or **heat kernel**. Note that

$$K_t(x) = t^{-1/2} K_1(t^{-1/2}x), \quad \int K_t(x) dx = \hat{K}_t(0) = 1.$$

By Theorem 6.4, the family $\{K_t\}_{t>0}$ is an approximation of the identity. (Set $\epsilon = \sqrt{t}$.)

Theorem 6.11

Suppose $f \in L^p(\mathbb{R})$, $1 \leq p \leq \infty$. Then $u(x, t) = f * K_t(x)$ satisfies $\partial_t u - \partial_{xx} u$ on $\mathbb{R} \times (0, \infty)$. If f is bounded and continuous, then u is continuous on $\mathbb{R} \times [0, \infty)$ and $u(x, 0) = f(x)$. If $f \in L^p(\mathbb{R})$ where $p < \infty$, then $u(\cdot, t)$ converges to f in the L^p -norm as $t \rightarrow \infty$.

The Weierstrass Approximation Theorem

Heat kernel, remarks

- Since K_t decays rapidly as $|x| \rightarrow \infty$, $f * K_t$ exists in the interval $(0, T]$ provided only that $|f(x)| \leq Ce^{x^2/(4T)}$. Under this condition, one easily verifies by differentiating under the integral sign that $f * K_t$ satisfies the heat equation and approaches f uniformly on bounded sets as $t \rightarrow 0$ provided f is continuous.
- Moreover, as all derivatives of $K(x, t)$ decay rapidly as $|x| \rightarrow \infty$ we can differentiate under the integral sign to any order, and conclude that $u \in C^\infty$. Thus, the heat kernel immediately smooths out arbitrary data.

The Weierstrass Approximation Theorem

Weierstrass' proof, revisited

- Given $\varepsilon > 0$, by Theorem 6.11 we can find $t > 0$ such that

$$\sup_{x \in \mathbb{R}} |(\tilde{f} * K_t)(x) - \tilde{f}(x)| < \frac{\varepsilon}{2}$$

- But

$$(\tilde{f} * K_t)(x) = (4\pi t)^{-1/2} \int_{\text{supp } \tilde{f}} \tilde{f}(y) e^{(x-y)^2/(4t)} dy$$

- Since the Taylor series for e^x converges uniformly on compact sets, we can replace $e^{(x-y)/(4t)}$ by a partial sum with error less than $(4\pi t)^{1/2} \varepsilon / 2 \|\tilde{f}\|_1$ for $x \in [-1, 1]$ and $y \in \text{supp } \tilde{f}$.
- Thus, $\sup_{x \in [-1, 1]} |(\tilde{f} * K_t)(x) - p(x)| < \frac{\varepsilon}{2}$ where

$$p(x) = (4\pi t)^{-1/2} \int_{\text{supp } \tilde{f}} \tilde{f}(y) \sum_{k=0}^K \frac{(-1)^k}{k!} \left[\frac{(x-y)^2}{4t} \right]^k dy$$

is a polynomial of degree $2K$.

The Weierstrass Approximation Theorem

Bernstein's proof

For a continuous function f defined on $[0, 1]$ the expression

$$B_n(x) = B_{n,f}(x) := \sum_{k=0}^n f\left(\frac{k}{n}\right) \binom{n}{k} x^k (1-x)^{n-k}$$

is called the **Bernstein polynomial** of order n for the function f .

The Weierstrass Approximation Theorem

Bernstein's proof

For a continuous function defined on $[0, 1]$ the expression

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is called the **Bernstein polynomial** of order n for the function f .

- The highlighted expression has the following interpretation from elementary probability theory: It represents the probability of observing exactly k successes in a binomial experiment consisting of n repeated i.i.d. Bernoulli trials with success probability x .
- In this context, the complete expression $B_n(x)$ is the expectation of a random variable whose value (payoff) is $f\left(\frac{k}{n}\right)$ when the number of successes in the above experiment is exactly $k \in \{0, 1, \dots, n\}$.
- Bernstein's proof of the Weierstrass approximation theorem establishes that this expected value, as a function of $x \in [0, 1]$, converges uniformly to f .

The Weierstrass Approximation Theorem

Bernoulli's theorem of large numbers

- Denote by X_i the random outcome of the i -th Bernoulli trial, i.e., equal to 1 with probability x and zero with probability $1 - x$.
- The number of successes in n i.i.d. repeated trials is $k = X_1 + \cdots + X_n$.
- We have

$$\mathbf{E}[X_i] = x, \quad \mathbf{Var} X_i = \mathbf{E}[(X_i - \mathbf{E}[X_i])^2] = x(1 - x),$$
$$\mathbf{E}\left[\frac{k}{n}\right] = x, \quad \mathbf{Var} \frac{k}{n} = \frac{x(1 - x)}{n}.$$

- Intuitively, we expect the relative frequency of success k/n to approach x as n increases. By Chebyshev's inequality, for $\epsilon > 0$,

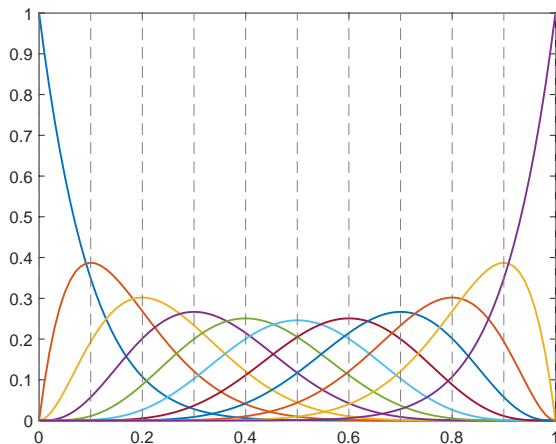
$$\mathbf{P}\left(\left|\frac{k}{n} - x\right| < \epsilon\right) \geq 1 - \frac{x(1 - x)}{n\epsilon^2} \rightarrow 1 \quad (n \rightarrow \infty).$$

- In other words

$$\sum_{\left|\frac{k}{n} - x\right| < \epsilon} \binom{n}{k} x^k (1 - x)^{n-k} \rightarrow 1 \quad (n \rightarrow \infty).$$

The Weierstrass Approximation Theorem

Bernstein basis



$$p_k(x) = \binom{n}{k} x^k (1-x)^{n-k}, \quad k = 0, 1, \dots, n, \quad n = 10.$$

The Weierstrass Approximation Theorem

Bernstein's proof

Theorem 6.12 (Bernstein, 1912)

For a function f bounded on $[0, 1]$, the relation $\lim_{n \rightarrow \infty} B_n(x) = f(x)$ holds at each point of continuity x of f and holds uniformly on $[0, 1]$ for $f \in C[0, 1]$.

Proof:

- With $p_k(x) := \binom{n}{k} x^k (1-x)^{n-k}$, we first compute an expression for the quantity

$$T := \sum_{k=0}^n (k - nx)^2 p_k(x) = \sum_{k=0}^n [k(k-1) - (2nx-1)k + n^2 x^2] p_k(x).$$

Noting that

$$\sum_{k=0}^n p_k(x) = 1, \quad \sum_{k=0}^n k p_k(x) = nx, \quad \sum_{k=0}^n k(k-1) p_k(x) = n(n-1)x^2,$$

we conclude

$$T = n(n-1)x^2 - (2nx-1)nx + n^2 x^2 = nx(1-x).$$

The Weierstrass Approximation Theorem

Bernstein's proof

- Since $|\frac{k}{n} - x| \geq \delta$ implies $\frac{1}{\delta^2} (\frac{k}{n} - x)^2 \geq 1$ and since $x(1-x) \leq \frac{1}{4}$ on $[0, 1]$,

$$\begin{aligned} \sum_{|\frac{k}{n}-x|\geq\delta} p_k(x) &\leq \frac{1}{\delta^2} \sum_{|\frac{k}{n}-x|\geq\delta} \left(\frac{k}{n} - x\right)^2 p_k(x) \leq \frac{1}{n^2\delta^2} \sum_{k=0}^n (k - nx)^2 p_k(x) \\ &= \frac{T}{n^2\delta^2} = \frac{x(1-x)}{n\delta^2} \leq \frac{1}{4n\delta^2}. \end{aligned}$$

- If $|f|$ is bounded on $[0, 1]$ by M and continuous at $x \in [0, 1]$, then for $\epsilon > 0$ there exists $\delta > 0$ such that $|f(x) - f(x')| < \epsilon$ for all x' such that $|x - x'| < \delta$. Hence

$$\begin{aligned} |f(x) - B_n(x)| &= \left| \sum_{k=0}^n [f(x) - f(\frac{k}{n})] p_k(x) \right| \\ &= \underbrace{\sum_{|\frac{k}{n}-x|\geq\delta} |[f(x) - f(\frac{k}{n})]| p_k(x)}_{\leq \frac{2M}{4n\delta^2}} + \underbrace{\sum_{|\frac{k}{n}-x|<\delta} |[f(x) - f(\frac{k}{n})]| p_k(x)}_{\leq \epsilon \sum_{k=0}^n p_k(x) = \epsilon} \end{aligned}$$

The Weierstrass Approximation Theorem

Bernstein's proof

In summary, we have

$$|f(x) - B_n(x)| \leq \epsilon + \frac{M}{2n\delta^2} < 2\epsilon \quad \text{for } n \text{ sufficiently large.} \quad (6.1)$$

If f is continuous on all of $[0, 1]$, then (6.1) holds for all x with δ independent of x , i.e.,

$$B_n(x) \rightarrow f(x) \quad \text{uniformly on } [0, 1].$$



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Convergence for Differentiable functions

Theorem 7.1 (Chebyshev coefficients for differentiable functions)

For an integer $\nu \geq 0$, let f and its derivatives through $f^{(\nu-1)}$ be absolutely continuous on $[-1, 1]$ and suppose the ν -th derivative $f^{(\nu)}$ is of bounded variation V . Then for $k \geq \nu + 1$, the Chebyshev coefficients of f satisfy

$$|a_k| \leq \frac{2V}{\pi k(k-1)\cdots(k-\nu)} \leq \frac{2V}{\pi(k-\nu)^{\nu+1}}. \quad (7.1)$$

Theorem 7.2 (Convergence for differentiable functions)

If f satisfies the conditions of Theorem 7.1, with V again denoting the total variation of $f^{(\nu)}$ for some $\nu \geq 1$, then for any $n > \nu$, its Chebyshev projections satisfy

$$\|f - f_n\| \leq \frac{2V}{\pi\nu(n-\nu)^\nu} \quad (7.2)$$

and its Chebyshev interpolants satisfy

$$\|f - p_n\| \leq \frac{4V}{\pi\nu(n-\nu)^\nu} \quad (7.3)$$

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Best Approximation

Characterization by equioscillation

Definition 10.1

We denote by p_n^* the best approximation of $f \in C[-1, 1]$ by a polynomial $p \in \mathcal{P}_n$ by and set

$$E_n(f) := \inf_{p \in \mathcal{P}_n} \|f - p\|,$$

where $\|\cdot\|$ denotes the maximum norm on $[-1, 1]$.

Theorem 10.2

A function f on $[-1, 1]$ has a unique best approximation $p^* \in \mathcal{P}_n$. If f is real, then p^* is real, too, and in this case a polynomial $p \in \mathcal{P}_n$ is equal to p^* if and only if $f - p$ equioscillates in at least $n + 2$ extreme points.

Best Approximation

Modulus of continuity

Definition 10.3 (Modulus of continuity)

Given a function $f \in C[-1, 1]$, the function $\omega : [0, \infty) \rightarrow [0, \infty]$ defined by

$$\omega(\delta) = \omega(\delta; f) := \sup_{|x-y| < \delta} |f(x) - f(y)|$$

is called the **modulus of continuity** of f .

- Examples: for $f(x) \equiv 1$, $\omega(\delta; f) = 0$; for $f(x) = x$, $\omega(\delta; f) = \delta$; for $f(x) = x^2$, $\omega(\delta; f) = 1 - (1 - \delta)^2$.
- If $0 < \delta_1 \leq \delta_2$, then $\omega(\delta_1) \leq \omega(\delta_2)$.
- A function f is uniformly continuous on $[-1, 1]$ if and only if

$$\lim_{\delta \rightarrow 0} \omega(\delta; f) = 0.$$

Best Approximation

Modulus of continuity

Theorem 10.4 (Jackson)

For $f \in C[-1, 1]$ there holds

$$E_n(f) = 6\omega\left(\frac{1}{n}\right).$$

Definition 10.5 (Total variation)

The **total variation** of a function $f \in C[-1, 1]$ is defined by

$$V = V(f) := \sup \sum_{k=1}^n |f(x_k) - f(x_{k-1})|,$$

where the supremum is taken over all partitions $\{x_0 < x_1 < \dots < x_n\}$ of $[-1, 1]$. A function f is said to be **of bounded variation** if its total variation is finite.

- If f is differentiable and its derivative is Riemann-integrable, its total variation is given by

$$V(f) = \int_{-1}^1 |f'(x)| dx,$$

(i.e., the vertical component of the arc length of its graph).

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Potential Theory

Counting measures on \mathbb{C} and their limits

- A **Borel measure** on \mathbb{C} is any positive (nonnegative) measure defined on the Borel sets of \mathbb{C} .
- The **support** $\text{supp } \mu$ of a Borel measure μ on \mathbb{C} is the complement of the largest open set with measure zero.
- The **Dirac measure** δ_z , $z \in \mathbb{C}$, is the unit measure defined by

$$\delta_z(B) := \begin{cases} 1 & \text{if } z \in B, \\ 0 & \text{otherwise,} \end{cases} \quad \text{for all Borel sets } B \subset \mathbb{C}.$$

- For a continuous function f on \mathbb{C} there holds

$$\int f(z) d\delta_{z_0}(z) = f(z_0).$$

Potential Theory

Counting measures on \mathbb{C} and their limits

Let $K \subset \mathbb{C}$ be compact in the following.

- We denote by $\mathcal{M}(K)$ the set of all finite positive Borel measures μ with $\text{supp } \mu = K$ and $\mu(K) = 1$.
- The **Riesz representation theorem** states that for any positive³ linear functional ℓ on $C(K)$ there exists a unique **Radon measure** (a Borel measure which is finite for all compact subsets of K) such that

$$\ell(f) = \int f \, d\mu, \quad \text{for all } f \in C(K).$$

- A sequence $(\mu_n)_{n \in \mathbb{N}} \subset \mathcal{M}(K)$ is said to converge to $\mu \in \mathcal{M}(K)$ in the **weak***-sense if

$$\int f \, d\mu_n \rightarrow \int f \, d\mu \quad \forall f \in C(K).$$

- $\mathcal{M}(K)$ is **weak*-compact**, i.e., every sequence $(\mu_n)_{n \in \mathbb{N}}$ has a weak*-convergent subsequence.

³in the sense that $\ell(f) \geq 0$ whenever $f \geq 0$

Potential Theory

Counting measures on \mathbb{C} and their limits

For a set of points $\{z_1, \dots, z_n\} \subset \mathbb{C}$ we denote the associated **normalized counting measure** by

$$\mu_n = \frac{1}{n} \sum_{j=1}^n \delta_{z_j}.$$

Examples:

- (1) The counting measures μ_n associated with uniformly spaced points on $K = [-1, 1]$ converge in weak* sense to $d\mu(t) = \frac{1}{2}dt$.
- (2) The counting measures μ_n associated with the sequence of Chebyshev points on $K = [-1, 1]$ converge in weak* sense to

$$d\mu(t) = \frac{dt}{\pi\sqrt{1-t^2}}.$$

Potential Theory

Logarithmic potential

For $K \subset \mathbb{C}$ compact and $\mu \in \mathcal{M}(K)$, the function $u_\mu : \mathbb{C} \rightarrow (-\infty, \infty]$ defined by

$$u_\mu(z) = \int \log \frac{1}{|z-t|} d\mu(t) = - \int \log |z-t| d\mu(t)$$

is called the **logarithmic potential** of μ .

Examples:

(1) For $d\mu(t) = \frac{1}{2}dt$ we obtain

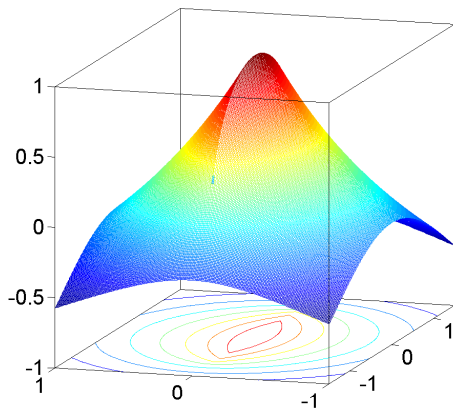
$$u_\mu(z) = 1 + \frac{1}{2} \operatorname{Re} [(z-1) \log(z-1) - (z+1) \log(z+1)], \quad z \in \mathbb{C}.$$

(2) For $d\mu(t) = \frac{d}{\pi\sqrt{1-x^2}}t$ we obtain

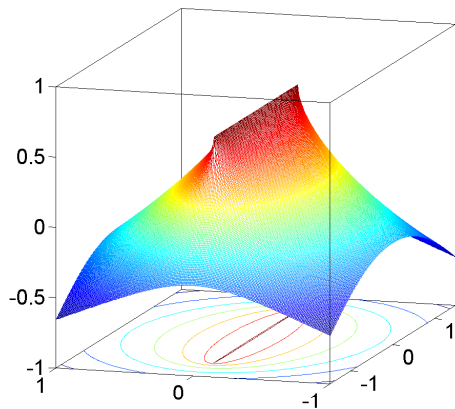
$$u_\mu(z) = \log 2 - \log \left| z + \sqrt{z^2 - 1} \right|, \quad z \in \mathbb{C}.$$

Potential Theory

Limiting measures: equispaced and Chebyshev nodes



equispaced



Chebyshev

Potential Theory

Equilibrium measure and logarithmic capacity

For $K \subset \mathbb{C}$ compact and $\mu \in \mathcal{M}(K)$, the **energy** of the logarithmic potential u_μ is defined as

$$I(\mu) := \int u_\mu \, d\mu = \int \int \frac{1}{\log|z-t|} \, d\mu(t) \, d\mu(z).$$

It satisfies

$$-\infty < I(\mu) \leq \infty.$$

If the number $V(K) := \inf_{\mu \in \mathcal{M}(K)} I(\mu)$, known as the **Robin constant** of K , satisfies $V(K) > -\infty$, then there exists (note that $\mathcal{M}(K)$ is weak*-compact) a measure $\mu = \mu_K \in \mathcal{M}(K)$ such that $I(\mu_K) = V(K)$ known as the **equilibrium distribution** or **equilibrium measure** of K .

The number

$$\text{cap}(K) := \begin{cases} \exp(-V(K)), & \text{if } V(K) > -\infty, \\ 0, & \text{otherwise} \end{cases}$$

is known as the **logarithmic capacity** of K .

Potential Theory

Equilibrium measure and logarithmic capacity

Example: For $K = [-1, 1]$ there holds $\mu_K(t) = \frac{dt}{\pi\sqrt{1-t^2}}$ and $\text{cap}(K) = \frac{1}{2}$.

The following result is known as the **fundamental theorem of potential theory**.

Theorem 12.1 (Frostman)

For $K \subset \mathbb{C}$ compact with $\text{cap}(K) > 0$ the logarithmic potential u_{μ_K} of the equilibrium measure μ_K satisfies

$$u_{\mu_K}(z) \leq V(K) \quad \text{for all } z \in \mathbb{C}$$

$$u_{\mu_K}(z) = V(K) \quad \text{quasi-everywhere in } K.$$

Here **quasi-everywhere** means everywhere except possibly on a set of zero capacity.

Potential Theory

Transfinite diameter, Chebyshev constant

Let $K \subset \mathbb{C}$ be compact.

- For

$$\tau_n(K) := \max_{z_1, \dots, z_n \in K} \left(\prod_{1 \leq j < k \leq n} |z_j - z_k| \right)^{\frac{2}{n(n-1)}},$$

the **transfinite diameter** $\tau(K)$ of K is defined as $\tau(K) := \lim_{n \rightarrow \infty} \tau_n(K)$.

- For $E_n(K) := \min_{p \in \mathcal{P}_{n-1}} \|z^n - p_{n-1}(z)\|_{K, \infty}$, the **Chebyshev constant** $c(K)$ of K is defined as

$$c(K) := \lim_{n \rightarrow \infty} E_n(K)^{1/n}.$$

Theorem 12.2 (Fekete, 1924; Szegő, 1925)

For any compact $K \subset \mathbb{C}$ there holds

$$\text{cap}(K) = c(K) = \tau(K).$$

Potential Theory

Convergence of polynomial interpolation

Theorem 12.3 (V. I. Krylov, 1962)

For a weak*-limiting node distribution μ and associated logarithmic potential u_μ , let f be analytic inside Γ_s , the level curve of u_μ which passes through a singularity s of f . The polynomial interpolant p_n of f associated with the n -th nodal set then converges to f uniformly inside Γ_s , diverges outside Γ_s and

$$\lim_{n \rightarrow \infty} |f(z) - p_n(z)|^{1/n} = \exp(u_\mu(s) - u_\mu(z)).$$

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Equispaced Points, the Runge Phenomenon

- The **Runge phenomenon** refers to the 1901 paper by Carl Runge in which he presented the potential theoretic analysis of the convergence of interpolation of analytic functions. He presented an example of a meromorphic function for which interpolation at equidistant nodes on a fixed interval of analyticity diverges.
- Earlier work by Méray in 1884 and 1886 had made similar observations.
- Faber proved in 1914 that for each node sequence on a compact interval there exists a continuous function f for which the associated sequence of polynomial interpolants fail to converge to f .

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Lebesgue Constants

Definition

Recall the Lagrange representation of the polynomial interpolant $p_n \in \mathcal{P}_n$ at distinct nodes $\{x_j\}_{j=0}^n$ with data $\{f_j\}_{j=0}^n$

$$p_n(x) = \sum_{j=0}^n f_j \ell_j(x)$$

in terms of the Lagrange fundamental polynomials $\{\ell_j\}_{j=0}^n$. For the interpolant $\tilde{p}_n \in \mathcal{P}_n$ on the same grid obtained from perturbed data $\{\tilde{f}_j\}_{j=0}^n$, we have

$$|p_n(x) - \tilde{p}_n(x)| \leq \max_j |f_j - \tilde{f}_j| \sum_{j=0}^n |\ell_j(x)| \leq \epsilon \lambda_n(x)$$

if $|f_j - \tilde{f}_j| \leq \epsilon$ for all j , where we have introduced the **Lebesgue function**

$$\lambda_n(x) := \sum_{j=0}^n |\ell_j(x)|$$

associated with the interpolation nodes $\{x_0, \dots, x_n\}$.

Lebesgue Constants

Definition

We also define the **Lebesgue constant** associated with the same node set as

$$\Lambda_n := \|\lambda_n\|, \quad \|\cdot\| = \|\cdot\|_{\infty,[-1,1]}.$$

Theorem 15.1

For a set $\{x_j\}_{j=0}^n \subset [-1, 1]$ of distinct nodes, the norm of the associated polynomial interpolation operator

$$L_n : C[-1, 1] \rightarrow \mathcal{P}_n, \quad f \mapsto p_n$$

is given by $\|L_n\| = \Lambda_n$.

If p_n^* denotes the best uniform approximation of f from \mathcal{P}_n , then

$$\|f - p_n\| \leq (1 + \Lambda_n)\|f - p_n^*\|.$$

Lebesgue Constants

Some Lebesgue Constants

Theorem 15.2

The Lebesgue constants Λ_n for degree $n \geq 0$ polynomial interpolation in any set of $n + 1$ distinct nodes in $[-1, 1]$ satisfy

$$\Lambda_n \geq \frac{2}{\pi} \log(n + 1) + c, \quad (15.1)$$

where $c = (2/\pi)(\gamma + \log(4/\pi)) \approx 0.52125$ with Euler's constant $\gamma \approx 0.577$.

For Chebyshev points they satisfy

$$\Lambda_n \leq \frac{2}{\pi} \log(n + 1) + 1 \quad \text{and} \quad \Lambda_n \sim \frac{2}{\pi} \log n \quad (n \rightarrow \infty).$$

For equispaced points they satisfy

$$\Lambda_n > \frac{2^{n-2}}{n^2} \quad (n \in \mathbb{N}) \quad \text{and} \quad \Lambda_n \sim \frac{2^{n+1}}{e n \log n} \quad (n \rightarrow \infty).$$

Lebesgue Constants

Lebesgue constants for projection

Theorem 15.3

The Lebesgue constants Λ_n for degree $n \geq 1$ Chebyshev projection in $[-1, 1]$ are given by

$$\Lambda_n = \frac{1}{2\pi} \int_{-\pi}^{\pi} \left| \frac{\sin((n+1/2)t)}{\sin(t/2)} \right| dt$$

and satisfy

$$\Lambda_n \leq \frac{4}{\pi^2} \log(n+1) + 3 \quad \text{and} \quad \Lambda_n \sim \frac{4}{\pi^2} \log n \quad (n \rightarrow \infty).$$

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Best and Near-Best

Chebyshev interpolation and truncation vs. best approximation

Theorem 16.1

Let $f \in C[-1, 1]$ have degree n Chebyshev projection f_n , Chebyshev interpolant p_n , and best approximant p_n^* , $n \geq 1$. Then

$$\|f - f_n\| \leq \left(4 + \frac{4}{\pi^2} \log(n+1)\right) \|f - p_n^*\| \quad (16.1)$$

and

$$\|f - p_n\| \leq \left(2 + \frac{2}{\pi} \log(n+1)\right) \|f - p_n^*\|. \quad (16.2)$$

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Orthogonal Polynomials

Measures

- Let $\alpha : \mathbb{R} \rightarrow \mathbb{R}$ denote a **distribution function**, i.e., a non-decreasing function with infinitely many points of increase which is not constant and possesses finite limits for $x \rightarrow \pm\infty$.
- Assume that all monomial **moments**, i.e., the Lebesgue-Stieltjes integrals

$$\mu_n := \int x^n d\alpha(x), \quad n \in \mathbb{N}_0,$$

are finite.

- Then a symmetric bilinear form is defined on the vector space of all (real) polynomials \mathcal{P} by

$$(p, q) := \int p(x)q(x) d\alpha(x), \quad p, q \in \mathcal{P}. \quad (17.1)$$

- If $d\alpha$ is absolutely continuous with respect to Lebesgue measure on \mathbb{R} , then there exists a **weight function** $w : \mathbb{R} \rightarrow \mathbb{R}_0^+$ such that $d\alpha(x) = w(x)dx$ and hence

$$(p, q) = \int p(x)q(x)w(x) dx.$$

Orthogonal Polynomials

Common weight functions

The classical weight functions associated with orthogonal polynomials are

supp w	$w(x)$	Name
$[-1, 1]$	1	Legendre
$[-1, 1]$	$(1 - x^2)^{-1/2}$	Chebyshev
$[-1, 1]$	$(1 - x)^\alpha(1 + x)^\beta, \alpha, \beta > -1$	Jacobi
$[0, \infty)$	$\exp(-x)$	Laguerre
$(-\infty, \infty)$	$\exp(-x^2)$	Hermite

Orthogonal Polynomials

Moments

The n -th **moment matrix** associated with the bilinear form (17.1) is given by the Hankel matrix

$$\mathbf{M}_n = \begin{bmatrix} \mu_0 & \mu_1 & \dots & \mu_{n-1} \\ \mu_1 & \mu_2 & \dots & \mu_n \\ \vdots & & & \vdots \\ \mu_{n-1} & \mu_n & \dots & \mu_{2n-2} \end{bmatrix} \in \mathbb{R}^{n \times n}, \quad n \in \mathbb{N}.$$

Proposition 17.1

The bilinear form (17.1) is an inner product on \mathcal{P} if and only if $\det \mathbf{M}_n > 0$ for all $n \in \mathbb{N}$.

Orthogonal Polynomials

Definition, normalizations

Definition 17.2

A sequence of polynomials $(p_k)_{k \in \mathbb{N}_0} \subset \mathcal{P}$ is called a **system of orthogonal polynomials** with respect to an inner product (\cdot, \cdot) on \mathcal{P} if

- (a) $\deg p_k = k$ for all $k \in \mathbb{N}_0$ and
- (b) $(p_j, p_k) = 0$ for all $j \neq k, j, k \in \mathbb{N}_0$.

A system of orthogonal polynomials is unique up to normalization. Common normalizations are

- **monic** orthogonal polynomials characterized by a leading coefficient of one,
- **orthonormal polynomials** characterized by $(p_n, p_n) = 1$ for all $n \in \mathbb{N}_0$,
- polynomials taking the value one at a specific point in the support of the measure, typically the right endpoint of a bounded interval.

Orthogonal Polynomials

Monic coefficients

Lemma 17.3

The coefficient vector $\mathbf{a}^{(n)} = [a_0^{(n)}, \dots, a_{n-1}^{(n)}]^\top$ of the n -th monic orthogonal polynomial

$$p_n(x) = x^n + a_{n-1}^{(n)}x^{n-1} + \dots + a_1^{(n)}x + a_0^{(n)}$$

with respect to an inner product (\cdot, \cdot) is given by the unique solution of the linear system of equations

$$\mathbf{M}_n \mathbf{a}^{(n)} = -\mathbf{m}_n$$

with the moment matrix \mathbf{M}_n and right hand side

$$\mathbf{m}_n = \begin{bmatrix} \mu_n \\ \mu_{n+1} \\ \vdots \\ \mu_{2n-1} \end{bmatrix}.$$

Orthogonal Polynomials

Three-term recurrence

Theorem 17.4

A system of orthogonal polynomials satisfies a **three-term recurrence** relation

$$\gamma_n p_n(x) = (x - \alpha_n) p_{n-1}(x) - \beta_n p_{n-2}(x), \quad n = 1, 2, \dots, \quad (17.2a)$$

$$\text{with } p_{-1} := 0, \quad p_0(x) \equiv \text{const.} \quad (17.2b)$$

The coefficients are given by

$$\alpha_n = \frac{(x p_{n-1}, p_{n-1})}{(p_{n-1}, p_{n-1})}, \quad n = 1, 2, \dots$$

$$\gamma_n = \frac{(x p_{n-1}, p_n)}{(p_n, p_n)}, \quad n = 1, 2, \dots$$

$$\beta_n = \frac{(x p_{n-2}, p_{n-1})}{(p_{n-2}, p_{n-2})} = \gamma_{n-1} \frac{(p_{n-1}, p_{n-1})}{(p_{n-2}, p_{n-2})}, \quad n = 2, 3, \dots, \quad \beta_1 \text{ arbitrary.}$$

Orthogonal Polynomials

Three-term recurrence

Remark 17.5

- (a) Rescaling a system of orthogonal polynomials $\{p_k\}_{k \geq 0}$ to $\hat{p}_k = \delta_k p_k$, $\delta_k \neq 0$, yields a system of orthogonal polynomials with associated recurrence coefficients

$$\hat{\alpha}_k = \alpha_k, \quad \hat{\gamma}_k = \frac{\delta_{k-1}}{\delta_k} \gamma_k, \quad k = 1, 2, \dots,$$

$$\hat{\beta}_k = \frac{\delta_{k-1}}{\delta_{k-2}} \beta_k, \quad k = 2, 3, \dots$$

- (b) For monic orthogonal polynomials there holds $\gamma_k = 1 \forall k$, i.e.

$$p_{-1} = 0, \quad p_0(x) = 1, \quad p_k(x) = (x - \alpha_k)p_{k-1}(x) - \beta_k p_{k-2}(x).$$

Moreover

$$\beta_k = \frac{(p_{k-1}, p_{k-1})}{(p_{k-2}, p_{k-2})} > 0, \quad k \geq 2.$$

- (c) For orthonormal polynomials there holds $\beta_k = \gamma_{k-1}$, $k \geq 2$.

Orthogonal Polynomials

Three-term recurrence

We can obtain a matrix expression of the three-term recurrence (17.2a) by collecting its first n equations in a vector of polynomials

$$\mathbf{p}_n(x) := [p_0(x), p_1(x), \dots, p_{n-1}(x)]^\top,$$

resulting in the relation

$$x\mathbf{p}_n(x) = \mathbf{J}_n\mathbf{p}_n(x) + \gamma_n p_n(x)\mathbf{e}_n, \quad \mathbf{J}_n = \begin{bmatrix} \alpha_1 & \gamma_1 & & & \\ \beta_2 & \alpha_2 & \gamma_2 & & \\ & \ddots & \ddots & \ddots & \\ & & & \gamma_{n-1} & \\ & & & \beta_n & \alpha_n \end{bmatrix}, \quad \mathbf{e}_n = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ 1 \end{bmatrix}.$$

Rescaling the orthogonal polynomial system is reflected in the matrix relation as a diagonal scaling $\hat{\mathbf{p}}_n(x) = \mathbf{D}_n\mathbf{p}_n(x)$, $\mathbf{D}_n = \text{diag}(\delta_0, \dots, \delta_{n-1})$, of the polynomial vector, resulting in a diagonal similarity transformation of the tridiagonal matrix as

$$\hat{\mathbf{J}}_n = \mathbf{D}_n\mathbf{J}_n\mathbf{D}_n^{-1}.$$

Orthogonal Polynomials

Zeros

Theorem 17.6

The zeros of the orthogonal polynomials associated with the inner product (17.1) are real, simple and lie in the support interval (a, b) of $d\alpha(x) = w(x)dx$.

- For each zero of p_n , the matrix form of the three-term recurrence becomes an eigenvector-eigenvalue relation for the tridiagonal matrix \mathbf{J}_n , hence each zero of p_n is an eigenvalue of \mathbf{J}_n .
- The simplicity of the eigenvalues are also a consequence of the (unreduced) tridiagonal structure of \mathbf{J}_n .
- The diagonal scaling to obtain orthonormal polynomials results in a **symmetric** matrix \mathbf{J}_n , known as the **Jacobi matrix**.

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Gauss and Clenshaw-Curtis Quadrature

Interpolatory quadrature rules

The goal of **numerical quadrature** is to approximate integrals

$$I(f) = \int f(x) d\alpha(x).$$

Here $d\alpha(x)$ is a measure associated with distribution function α with support on a subset of the real axis as described in the chapter on orthogonal polynomials. The most common approach for constructing **quadrature formulas** proceeds by approximating the integrand f by a polynomial $p_n \in \mathcal{P}_n$ and then integrating the p_n exactly:

$$p_n \approx f, \quad I(f) \approx Q(f) := \int p_n(x) d\alpha(x).$$

In terms of the Lagrange representation $p_n(x) = \sum_{j=0}^n f(x_j) \ell_j(x)$ we obtain

$$Q(f) = \sum_{j=0}^n w_j f(x_j) \quad \text{with } \mathbf{quadrature weights} \quad w_j := \int \ell_j(x) d\alpha(x). \quad (19.1)$$

Gauss and Clenshaw-Curtis Quadrature

Interpolatory quadrature rules

By construction, interpolatory quadrature formulas with $n + 1$ nodes are **exact** for all $p \in \mathcal{P}_n$, i.e.,

$$Q_n(p) = I(p) \quad \forall p \in \mathcal{P}_n.$$

Conversely, every $(n + 1)$ -point quadrature formula with exactness degree n is interpolatory.

Well-known families of interpolatory quadrature formulas are the

- **Newton-Cotes** formulas, characterized by equispaced nodes. These include the midpoint rule ($n = 0$), the trapezoidal rule ($n = 1$), Simpson's rule ($n = 2$), the 3/8-rule ($n = 3$), Milne's rule ($n = 4$) and Weddle's rule ($n = 6$). The degree of exactness of is actually $n + 1$ for n even⁴. For $n \geq 7$ these rules have negative weights (which also grow exponentially with n), leading to numerical instability (cancellation) and, as shown in [Polya, 1933], a non-convergent sequence of rules even for analytic functions.
- The **Clenshaw-Curtis** formulas result from choosing Chebyshev nodes.

⁴i.e., for an *odd* number of nodes

Gauss and Clenshaw-Curtis Quadrature

Interpolatory quadrature rules

For a given node set $\{x_j\}_{j=0}^n$, interpolatory quadrature formulas determine the *weights* to achieve a degree of exactness n . **Gauss quadrature rules** additionally choose the *nodes* in a clever way to achieve a higher degree of exactness.

Theorem 19.1 (Jacobi, 1826)

The quadrature rule (19.1) possesses degree of exactness $d = n + m$ for $m \in \mathbb{N}_0$ if and only if

- (a) (19.1) is interpolatory and
- (b) the nodal polynomial $\omega_{n+1}(x) = \prod_{j=0}^n (x - x_j)$ is orthogonal to \mathcal{P}_{m-1} with respect to the inner product

$$(p, q) = \int p(x)q(x) d\alpha(x), \quad p, q \in \mathcal{P}. \quad (19.2)$$

Remark 19.2

Maximal achievable exactness degree is $d = 2n + 1$ corresponding to $m = n + 1$.

Gauss and Clenshaw-Curtis Quadrature

Gauss quadrature rules

- From Theorem 19.1 we immediately conclude that an optimal choice of quadrature (interpolation) nodes results when the associated nodal polynomial ω_{n+1} is orthogonal to \mathcal{P}_n .
- With the zeros of the Legendre polynomial P_{n+1} as nodes we obtain

$$Q_n(p) = \int_{-1}^1 p(x) \frac{1}{2} dx \quad \forall p \in \mathcal{P}_{2n+1}. \quad (\text{Gauss-Legendre quadrature})$$

Similarly, with the zeros of the Jacobi polynomials $P_{n+1}^{(\alpha,\beta)}$,

$$Q_n(p) = \int_{-1}^1 p(x) (1-x)^\alpha (1+x)^\beta dx \quad \forall p \in \mathcal{P}_{2n+1}. \quad (\text{Gauss-Jacobi quadrature})$$

- In the same way, **Gauss-Laguerre** and **Gauss-Hermite** quadrature formulas are obtained for the intervals $(0, \infty)$ and $(-\infty, \infty)$, respectively.

Gauss and Clenshaw-Curtis Quadrature

The Golub-Welch algorithm

Theorem 19.3

For the recurrence coefficients $\alpha_k, \beta_k, k \geq 1$ of the monic orthogonal polynomials with respect to (19.2), define the sequence of **Jacobi-matrices**

$$J_n = \begin{bmatrix} \alpha_1 & \sqrt{\beta_2} & & & \\ \sqrt{\beta_2} & \alpha_2 & \ddots & & \\ & \ddots & \ddots & \ddots & \\ & & & \sqrt{\beta_n} & \\ & & & & \alpha_n \end{bmatrix} \in \mathbb{R}^{n \times n}, \quad (n \in \mathbb{N}), \text{ then}$$

- (a) the nodes of the Gauss quadrature rule of order $n - 1$ associated with (19.2) are the n (distinct) eigenvalues of J_n and
- (b) if \mathbf{u}_j denote normalized eigenvectors of J_n associated with eigenvalues λ_j , i.e. $J_n \mathbf{u}_j = \lambda_j \mathbf{u}_j$, $\|\mathbf{u}_j\|_2 = 1$ ($j = 1, \dots, n$) then the associated weights w_j are given by

$$w_j = \beta_0 [\mathbf{u}_j]_1^2 \quad (j = 1, \dots, n), \quad \beta_0 := \int d\alpha(x).$$

Gauss and Clenshaw-Curtis Quadrature

The Golub-Welch algorithm and successors

- This observation leads to an elegant algorithm proposed by [Golub & Welsch, 1969] for generating the nodes and weights of classical Gauss quadrature rules as well as those for any measure $d\alpha$ for which one can generate the recurrence coefficients.
- Simple modifications of Jacobi measures lead to quadrature rules with one or both endpoints as nodes known as **Gauss-Radau** or **Gauss-Lobatto** rules, respectively, which can also be constructed this way by a low-rank modification of the Jacobi matrix.
- Since it involves computing the eigenvalues of a symmetric tridiagonal $n \times n$ matrix, this algorithm has complexity $O(n^2)$.
- More recently, [Glaser, Liu & Rokhlin, 2007] introduced an algorithm with superior complexity $O(n)$, which was subsequently improved in [Hale & Townsend, 2012]. This allows the stable and fast computation of Gauss quadrature rules of essentially any order.

Gauss and Clenshaw-Curtis Quadrature

Clenshaw-Curtis and Gauss quadrature

Proposition 19.4

The Gauss-Chebyshev quadrature nodes and weights for weight function $w(x) = (1 - x^2)^{-1/2}$ are given by

$$x_j = \cos \frac{(2j+1)\pi}{2(n+1)}, \quad w_j = \frac{\pi}{n}, \quad j = 0, 1, \dots, n.$$

The integral over $[-1, 1]$ of a Chebyshev polynomial of odd degree is zero, and for even degree it is

$$\int_{-1}^1 T_k(x) dx = \frac{2}{1 - k^2}. \quad (19.3)$$

Proposition 19.5

The integral of a polynomial $p_n \in \mathcal{P}_n$ in Chebyshev representation is given by

$$\int_{-1}^1 p_n(x) dx = \sum_{\substack{k=0 \\ k \text{ even}}}^n \frac{2a_k}{1 - k^2}, \quad p_n(x) = \sum_{k=0}^n a_k T_k(x).$$

Gauss and Clenshaw-Curtis Quadrature

Clenshaw-Curtis and Gauss quadrature

Theorem 19.6 (Quadrature for analytic integrands)

Let a function f be analytic in $[-1, 1]$ and analytically continuable to the open Bernstein ellipse E_ρ ($\rho > 1$) where it satisfies $|f(z)| \leq M$ for some M . Then $(n + 1)$ -point Clenshaw-Curtis quadrature with $n \geq 2$ applied to f satisfies

$$|I(f) - Q_n(f)| \leq \frac{64 M \rho^{1-n}}{15 \rho^2 - 1} \quad (19.4)$$

and $(n + 1)$ -point Gauss quadrature with $n \geq 1$ satisfies

$$|I(f) - Q_n(f)| \leq \frac{64 M \rho^{-2n}}{15 \rho^2 - 1}. \quad (19.5)$$

The factor ρ^{1-n} in (19.4) can be improved to ρ^{-n} if n is even, and the factor $64/15$ can be improved to $144/35$ if $n \geq 4$ in (19.4) or $n \geq 2$ in (19.5).

Gauss and Clenshaw-Curtis Quadrature

Clenshaw-Curtis and Gauss quadrature

Theorem 19.7 (Quadrature for differentiable integrands)

- (a) For any $f \in C[-1, 1]$, both Clenshaw-Curtis and Gauss quadratures $Q_n(f)$ converge to the integral $I(f)$ as $n \rightarrow \infty$.
- (b) For an integer $\nu \geq 1$, let f and its derivatives through $f^{(\nu-1)}$ be absolutely continuous on $[-1, 1]$ and suppose the ν -th derivative $f^{(\nu)}$ is of bounded variation V . Then $(n+1)$ -point Clenshaw-Curtis quadrature applied to f satisfies

$$|I(f) - Q_n(f)| \leq \frac{32}{15} \frac{V}{\pi \nu (n - \nu)^\nu} \quad \text{for } n > \nu \quad (19.6)$$

and $(n+1)$ -point Gauss quadrature satisfies

$$|I(f) - Q_n(f)| \leq \frac{32}{15} \frac{V}{\pi \nu (n - 2\nu - 1)^{2\nu+1}} \quad \text{for } n > 2\nu + 1. \quad (19.7)$$

Gauss and Clenshaw-Curtis Quadrature

Refined Clenshaw-Curtis bound

Theorem 19.8

Under the hypotheses of Theorem 19.7, the same conclusion (19.7) also holds for $(n + 1)$ -point Clenshaw-Curtis quadrature:

$$|I(f) - Q_n(f)| \leq \frac{32}{15} \frac{V}{\pi \nu (n - 2\nu - 1)^{2\nu+1}}. \quad (19.8)$$

The only difference is that this bound applies for all sufficiently large n (depending on ν but not f) rather than for $n > 2\nu + 1$.

Gauss and Clenshaw-Curtis Quadrature

Barycentric weights for Legendre nodes

Proposition 19.9

The barycentric weights λ_j for polynomial interpolation at Legendre points can be written as

$$\lambda_j = (-1)^j \sqrt{(1 - x_j^2)} w_j,$$

where $\{x_j\}$ and $\{w_j\}$ are the nodes and weights for $(n+1)$ -point Gauss-Legendre quadrature.

Gauss and Clenshaw-Curtis Quadrature

ATAP Exercise 19.8

- Approximating $I(f) = \int_0^1 f(x) dx$ by $Q_n(f) = \int_0^1 B_{n,f}(x) dx$, where $B_{n,f}$ denotes the Bernstein polynomial of degree n associated with f , results in the equal-weight quadrature formula

$$Q_n(f) = \frac{1}{n+1} \sum_{j=0}^n f\left(\frac{j}{n}\right),$$

as can be verified by a simple induction.

- The degree of exactness is 1 for $n \geq 1$, hence Q_n is not interpolatory.
- For integrands of bounded variation, it follows from Koksma's inequality that the error of this quadrature formula is $O(n^{-1})$.

Gauss and Clenshaw-Curtis Quadrature

Koksma's inequality

Theorem 19.10 (Koksma's inequality)

Given a function of bounded variation $V(f)$ on $[0, 1]$ and a point set $\{x_j\}_{j=1}^n \subset [0, 1]$ with star discrepancy D_n^* , then

$$\left| \frac{1}{n} \sum_{j=1}^n f(x_j) - \int_0^1 f(x) dx \right| \leq V(f) D_n^*.$$

The star-discrepancy of a point set $\{x_j\}_{j=1}^n \subset [0, 1]$ is defined at

$$D_n^*(x_1, \dots, x_n) := \sup_{\alpha \in (0,1]} \left| \frac{A((0, \alpha]; \{x_j\})}{n} - \alpha \right|.$$

Here $A((0, \alpha])$ denotes the number of points of the set $\{x_j\}_{j=1}^n$ contained in $(0, \alpha]$.

Gauss and Clenshaw-Curtis Quadrature

A discrepancy bound

The following result of Niederreiter allows us to calculate the star-discrepancy of an equispaced point set:

Theorem 19.11 (Niederreiter)

Let $x_1, \leq x_2 \leq \dots \leq x_n$ be n numbers in $[0, 1]$. Then their star-discrepancy D_n^* is given by

$$D_n^* = \max_{j=1, \dots, n} \max \left\{ \left| x_j - \frac{j}{n} \right|, \left| x_j - \frac{j-1}{n} \right| \right\} = \frac{1}{2n} + \max_{j=1, \dots, n} \left| x_j - \frac{2j-1}{2n} \right|.$$

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Carathéodory-Fejér Approximation

Setting

- To approximate a real-valued function f on $[-1, 1]$ by a polynomial of degree $n \geq 0$, suppose f has an absolutely convergent Chebyshev expansion

$$f(x) = \sum_{k=0}^{\infty} a_k T_k(x).$$

- For now, suppose a_{n+1} is the first nonzero coefficient and that the expansion is finite, terminating at $k = N \geq n + 1$:

$$f(x) = \sum_{k=n+1}^N a_k T_k(x).$$

- Now make the familiar substitution $x = \frac{1}{2}(z + z^{-1}) = \operatorname{Re} z$, $|z| = 1$, and define F on $|z| = 1$ by $F(z) = F(z^{-1}) = f(x)$, leading to a Laurent expansion of F as

$$F(z) = \frac{1}{2} \sum_{k=n+1}^N a_k (z^k + z^{-k}).$$

Carathéodory-Fejér Approximation

Setting

- Separating $F(z) = G(z) + G(z^{-1})$ into its **analytic part**

$$G(z) = \frac{1}{2} \sum_{k=n+1}^N a_k z^k$$

and **co-analytic part** $G(z^{-1})$, we note that the former can be analytically continued to $|z| \leq 1$ and the latter to $|z| \geq 1$.

- Consider the problem of approximating G on $|z| = 1$ by a function defined by a series

$$\tilde{P}(z) = \frac{1}{2} \sum_{k=-\infty}^n b_k z^k$$

converging in $|z| \geq 1$.

Carathéodory-Fejér Approximation

Result of Carathéodory, Fejér and Schur

Theorem 20.1 (Carathéodory & Fejér (1911); Schur (1918))

The approximation problem described on the previous slide has a unique solution \tilde{P} given by the error formula

$$(G - \tilde{P})(z) = \lambda z^{n+1} \frac{u(z)}{u(z)}, \quad (20.1)$$

where λ is the eigenvalue of largest magnitude of the Hankel matrix

$$H = \begin{bmatrix} a_{n+1} & a_{n+2} & a_{n+3} & \dots & a_N \\ a_{n+2} & a_{n+3} & & & \\ a_{n+3} & & \ddots & & \\ \vdots & & & & \\ a_N & & & & \end{bmatrix} \quad \text{with associated real eigenvector} \quad \begin{bmatrix} u_0 \\ u_1 \\ \vdots \\ u_{N-n-1} \end{bmatrix}$$

and $u(z) = u_0 + u_1 z + \dots + u_{N-n-1} z^{N-n-1}$. The function $G - \tilde{P}$ maps the unit circle to a circle of radius $|\lambda|$ and winding number $\geq n + 1$ with equality holding if $|\lambda| > |\mu|$ for all other $\mu \in \Lambda(H)$.

Carathéodory-Fejér Approximation

The CF approximation

- To construct a *polynomial* approximant from \tilde{P} , note that, since $G - \tilde{P}$ maps $|z| = 1$ to a circle of winding number $\geq n + 1$, its real part (times 2)

$$(G - \tilde{P})(z) + (G - \tilde{P})(z^{-1})$$

maps $[-1, 1]$ to an error curve which equioscillates $\geq n + 2$ times.

- This suggests $\tilde{p}(x) := \tilde{P}(z) + \tilde{P}(z^{-1})$ as an approximation with the correct error equioscillation behavior. However, \tilde{p} is not a polynomial of degree n .
- By truncating the Laurent expansion of \tilde{P} to $P_{\text{CF}}(z) := \frac{1}{2} \sum_{k=-n}^n b_k z^k$ with real part

$$p_{\text{CF}}(x) := P_{\text{CF}}(z) + P_{\text{CF}}(z^{-1}) = \frac{1}{2} \sum_{k=-n}^n (b_k + b_{-k}) z^k,$$

we obtain a polynomial approximation $p_{\text{CF}} \in \mathcal{P}_n$ whose error curve $f - p_{\text{CF}}$ will nearly match the equioscillation behavior of $f - \tilde{p}$ on $[-1, 1]$ if the truncated terms are small.

Carathéodory-Fejér Approximation

The CF approximation

- To understand why this approximation can be expected to be good, suppose f is analytic on $[-1, 1]$ with geometrically decaying Chebyshev coefficients $a_k = O(\rho^k)$.
- Then the dominant degree $n + 1$ term of f is of order ρ^{-n-1} and the terms $b_n, b_{n-1}, \dots, b_{-n}$ are of orders $\rho^{-n-2}, \rho^{-n-3}, \dots, \rho^{-3n-2}$, which suggests an error of order ρ^{-3n-3} is committed by the truncation from \tilde{p} to p_{CF} .
- This is generally small compared to, e.g., the error of best approximation $\|f - p^*\|$, which is of order ρ^{-n-1} .

Carathéodory-Fejér Approximation

The CF and best approximation

Theorem 20.2 (Gutknecht & Trefethen (1982))

For any fixed $m \geq 0$, let f have a Lipschitz continuous derivative of order $3m+3$ on $[-1, 1]$ with a nonzero $(m+1)$ st derivative at $x = 0$, and for each $s \in (0, 1]$, let p^* and p_{CF} be the best and CF approximations of degree m to $f(sx)$ in $[-1, 1]$, respectively. Then as $s \rightarrow 0$,

$$\|f - p^*\| = O(s^{m+1}), \quad (20.2)$$

$$\|f - p^*\| \neq O(s^{m+2}), \quad (20.3)$$

$$\|p_{\text{CF}} - p^*\| = O(s^{3m+4}). \quad (20.4)$$

Carathéodory-Fejér Approximation

Remarks

- Theorem 20.1 still applies if f is not a polynomial of degree N but has an absolutely convergent Chebyshev series. In this case H is the matrix representation of a compact operator on ℓ^2 or ℓ^1 and $u(z)$ is defined by an infinite series of eigenvector entries.
[Hayashi, Trefethen & Gutknecht, 1990].
- The theory of CF approximation also extends to *rational* in place of polynomial approximation. Seminal work here is attributed to the Ukrainian mathematicians [Adamyan, Arov & Krein, 1971].

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Spectral Methods

- **Spectral methods** refers to a class of methods for approximating the solution of differential equations.
- Like finite element methods, they construct solution approximations in finite dimensional function spaces. Approximations are selected by applying sufficiently many constraints, either by imposing a variational equality or requiring the equation to hold *exactly* at a finite number of **collocation points**.
- Unlike finite element methods, based on piecewise polynomials as trial functions, spectral methods use global algebraic or trigonometric polynomials.
- Spectral methods converge exponentially when the solutions are analytic, and approximate derivatives of the solution to the same order.
- They are difficult to apply to non-separable geometries and are therefore commonly used in turbulence simulation and atmospheric simulations, where domains are simple and the solutions smooth.
- Fundamental techniques for solving random differential equations as arise in **uncertainty quantification**, sometimes known as **polynomial chaos expansions** going back to Norbert Wiener in the 1930s, are spectral methods based originally on Hermite expansions.

Spectral Methods

Convergence of derivatives

Theorem 21.1

Let a function f be analytic in $[-1, 1]$ and analytically continuable to the closed Bernstein ellipse \overline{E}_ρ for some $\rho > 1$. Then for each integer $\nu \geq 0$, the ν th derivatives of the Chebyshev projections f_n and interpolants p_n satisfy as $n \rightarrow \infty$

$$\|f^{(\nu)} - f_n^{(\nu)}\| = O(\rho^{-n}), \quad \|f^{(\nu)} - p_n^{(\nu)}\| = O(\rho^{-n}) \quad (21.1)$$

cf. [Tadmor, 1986].

Spectral Methods

Differentiation matrices

- In spectral collocation methods, the approximate solution of a differential equation (DE) is sought in a finite-dimensional space of trial functions and determined uniquely by requiring the approximation to solve the DE **exactly** at an appropriate number of **collocation points**.
- If the approximate solution is represented as the interpolant

$$u_n(x) = \sum_{j=1}^n \alpha_j \ell_j(x)$$

of its function values $u_n(x_j) = \alpha_j$ at the collocation points $\{x_j\}_{j=1}^n$, then applying the differential operator d/dx to u_n and evaluating at a collocation point x_k yields

$$\frac{d}{dx} u_n(x_k) = \sum_{j=1}^n \alpha_j \ell'_j(x_k).$$

- Thus, the linear mapping that takes the vector of function values $u_n(x_k)$ to the derivatives $u'_n(x_k)$ is represented by the **differentiation matrix** $D = [\ell'_j(x_k)]_{k,j=1}^n$.

- Closed form representation of differentiation matrices can be derived. E.g. for the first derivative we have

$$\ell_j'(x_k) = \begin{cases} \frac{\lambda_j}{\lambda_k(x_k - x_j)} & j \neq k, \\ \frac{x_j}{1 - x_j^2} & j = k, \end{cases}$$

where the λ_j denote the barycentric weights associated with the collocation points.