



Orthogonal Polynomials, Quadrature, and Approximation: Computational Methods and Software (in Matlab)

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Orthogonal Polynomials

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- Recurrence coefficients

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- Modified Chebyshev algorithm

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- Discrete Stieltjes and Lanczos algorithm

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- Discretization methods

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- Cauchy integrals of orthogonal polynomials

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- Modification algorithms

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Sobolev Orthogonal Polynomials

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- Moment-based algorithm

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Sobolev Orthogonal Polynomials

- Moment-based algorithm
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- Zeros

Quadrature

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- Gauss-type quadrature formulae

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 - Gauss formula

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- Polynomials orthogonal on several intervals

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- Quadrature estimates of matrix functionals

Approximation

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 - on the positive real line

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- Slowly convergent series

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 - generated by a Laplace transform or derivative thereof

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 - classical
 - constrained
 - in Sobolev spaces
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 - on the positive real line
 - on a compact interval
- Slowly convergent series
 - generated by a Laplace transform or derivative thereof
 - occurring in plate contact problems



References

References

- W. Gautschi, "Orthogonal Polynomials: Computation and Approximation", Oxford University Press, Oxford, 2004
- <http://www.cs.purdue.edu/homes/wxg/papers.html/Madrid.ps>
click on Madrid.ps

References

- W. Gautschi, "Orthogonal Polynomials: Computation and Approximation", Oxford University Press, Oxford, 2004
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- <http://www.cs.purdue.edu/archives/2002/wxg/codes>

Part I

Orthogonal Polynomials

Background

measure (of integration)

absolutely continuous measure

$$d\lambda(t) = w(t)dt \text{ on } [a, b], \quad -\infty \leq a < b \leq \infty$$

discrete measure

$$d\lambda_N(t) = \sum_{k=1}^N w_k \delta(t - x_k) dt, \quad x_1 < x_2 < \cdots < x_N$$

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standing assumption (for absolutely continuous measures)

existence of the moments

$$\mu_r = \int_{\mathbb{R}} t^r d\lambda(t), \quad r = 0, 1, 2, \dots$$

inner product and norm

$$(p, q)_{d\lambda} = \int_{\mathbb{R}} p(t)q(t)d\lambda(t), \quad (p, p)_{d\lambda} = \|p\|_{d\lambda}^2$$

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orthogonal polynomials

$$\pi_k(\cdot) = \pi_k(\cdot; d\lambda) \in \mathbb{P}_k, \quad k = 0, 1, 2, \dots$$

$$(\pi_k, \pi_\ell)_{d\lambda} \begin{cases} = 0, & k \neq \ell \\ > 0, & k = \ell \end{cases}$$

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$$(\pi_k, \pi_\ell)_{\mathbf{d}\lambda} \begin{cases} = 0, & k \neq \ell \\ > 0, & k = \ell \end{cases}$$

orthonormal polynomials

$$\tilde{\pi}_k(\cdot; \mathbf{d}\lambda) = \frac{\pi_k(\cdot; \mathbf{d}\lambda)}{\|\pi_k\|_{\mathbf{d}\lambda}}, \quad k = 0, 1, 2, \dots$$

three-term recurrence relation (for monic orth. pol.'s)

$$\pi_{k+1}(t) = (t - \alpha_k)\pi_k(t) - \beta_k\pi_{k-1}(t), \quad k = 0, 1, \dots, n-1$$

$$\alpha_k = \alpha_k(d\lambda) \in \mathbb{R}, \quad \beta_k = \beta_k(d\lambda) > 0 \quad (\beta_0 = \int_{\mathbb{R}} d\lambda(t))$$

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Proof Expand $\pi_{k+1}(t) - t\pi_k(t) \in \mathbb{P}_k$ in orthogonal polynomials $\pi_0, \pi_1, \dots, \pi_k$ and use orthogonality and the property $(tp, q)_{d\lambda} = (p, tq)_{d\lambda}$ of the inner product. The result is (Darboux)

$$\alpha_k(d\lambda) = \frac{(t\pi_k, \pi_k)_{d\lambda}}{(\pi_k, \pi_k)_{d\lambda}}, \quad k = 0, 1, 2, \dots,$$
$$\beta_k(d\lambda) = \frac{(\pi_k, \pi_k)_{d\lambda}}{(\pi_{k-1}, \pi_{k-1})_{d\lambda}}, \quad k = 1, 2, \dots \quad \square$$

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$$\beta_k(d\lambda) = \frac{(\pi_k, \pi_k)_{d\lambda}}{(\pi_{k-1}, \pi_{k-1})_{d\lambda}}, \quad k = 1, 2, \dots \quad \square$$

normalization constants

$$\|\pi_k\|_{d\lambda}^2 = \beta_0\beta_1 \cdots \beta_k$$

Jacobi matrix of infinite order

$$\mathbf{J}(d\lambda) = \begin{bmatrix} \alpha_0 & \sqrt{\beta_1} & & & 0 \\ \sqrt{\beta_1} & \alpha_1 & \sqrt{\beta_2} & & \\ & \sqrt{\beta_2} & \alpha_2 & \ddots & \\ & & \ddots & \ddots & \\ 0 & & & & \end{bmatrix}$$

of order n

$$\mathbf{J}_n(d\lambda) = \mathbf{J}(d\lambda)_{[1:n,1:n]}$$

Jacobi matrix of infinite order

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of order n

$$\mathbf{J}_n(d\lambda) = \mathbf{J}(d\lambda)_{[1:n,1:n]}$$

three-term recurrence relation (for orthonormal pol's)

in matrix form ($\tilde{\boldsymbol{\pi}}(t) = [\tilde{\pi}_0(t), \tilde{\pi}_1(t), \dots, \tilde{\pi}_{n-1}(t)]^T$)

$$t\tilde{\boldsymbol{\pi}}(t) = \mathbf{J}_n(d\lambda)\tilde{\boldsymbol{\pi}}(t) + \sqrt{\beta_n}\tilde{\pi}_n(t)\mathbf{e}_n$$

Jacobi matrix of infinite order

$$\mathbf{J}(d\lambda) = \begin{bmatrix} \alpha_0 & \sqrt{\beta_1} & & & \mathbf{0} \\ \sqrt{\beta_1} & \alpha_1 & \sqrt{\beta_2} & & \\ & \sqrt{\beta_2} & \alpha_2 & \ddots & \\ & & \ddots & \ddots & \\ \mathbf{0} & & & & \ddots \end{bmatrix}$$

of order n

$$\mathbf{J}_n(d\lambda) = \mathbf{J}(d\lambda)_{[1:n,1:n]}$$

three-term recurrence relation (for orthonormal pol's)

in matrix form ($\tilde{\pi}(t) = [\tilde{\pi}_0(t), \tilde{\pi}_1(t), \dots, \tilde{\pi}_{n-1}(t)]^T$)

$$t\tilde{\pi}(t) = \mathbf{J}_n(d\lambda)\tilde{\pi}(t) + \sqrt{\beta_n}\tilde{\pi}_n(t)\mathbf{e}_n$$

\implies the zeros τ_ν of $\tilde{\pi}_n$ are the **eigenvalues** of $\mathbf{J}_n(d\lambda)$ and $\tilde{\pi}(\tau_\nu)$
corresponding **eigenvectors**

"Classical" weight functions

$$d\lambda(t) = w(t)dt$$

name	$w(t)$	support	comment
Jacobi	$(1-t)^\alpha(1+t)^\beta$	$[-1, 1]$	$\alpha > -1,$ $\beta > -1$
Laguerre	$t^\alpha e^{-t}$	$[0, \infty]$	$\alpha > -1$
Hermite	$ t ^{2\alpha} e^{-t^2}$	$[-\infty, \infty]$	$\alpha > -\frac{1}{2}$
Meixner-Pollaczek	$\frac{1}{2\pi} e^{(2\phi-\pi)t} \Gamma(\lambda + it) ^2$	$[-\infty, \infty]$	$\lambda > 0,$ $0 < \phi < \pi$

"Classical" discrete measures

$$d\lambda(t) = \sum_{k=0}^M w_k \delta(t - k) dt$$

name	M	w_k	comment
discrete Chebyshev	$N - 1$	1	
Krawtchouk	N	$\binom{N}{k} p^k (1 - p)^{N-k}$	$0 < p < 1$
Charlier	∞	$e^{-a} a^k / k!$	$a > 0$
Meixner	∞	$\frac{c^k}{\Gamma(\beta)} \frac{\Gamma(k+\beta)}{k!}$	$0 < c < 1, \beta > 0$
Hahn	N	$\binom{\alpha+k}{k} \binom{\beta+N-k}{N-k}$	$\alpha > -1, \beta > -1$

Matlab

Example `ab=r_jacobi(N,a,b)`

α_0	β_0
α_1	β_1
\vdots	\vdots
α_{N-1}	β_{N-1}

ab

$$N \in \mathbb{N}, a > -1, b > -1$$

Demo #1

```
N=10;
```

```
ab=r_jacobi(N,-.5,1.5);
```

Demo #1

```
N=10;
```

```
ab=r_jacobi(N,-.5,1.5);
```

k	α_k	β_k
0	0.666666666666667	1.71238898038469
1	0.133333333333333	0.138888888888889
2	0.057142857142857	0.210000000000000
3	0.03174603174603	0.22959183673469
4	0.02020202020202	0.23765432098765
5	0.01398601398601	0.24173553719008
6	0.01025641025641	0.24408284023669
7	0.00784313725490	0.245555555555556
8	0.00619195046410	0.24653979238754
9	0.00501253132832	0.24722991689751

Modified Chebyshev algorithm

Modified Chebyshev algorithm

modified and mixed moments

$$m_k = \int_{\mathbb{R}} p_k(t) d\lambda(t), \quad k = 0, 1, 2, \dots$$

$$\sigma_{kl} = \int_{\mathbb{R}} \pi_k(t; d\lambda) p_l(t) d\lambda(t), \quad k, l \geq -1$$

Modified Chebyshev algorithm

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modified moment map

$$\mathbb{R}^{2n} \mapsto \mathbb{R}^{2n} : \quad [m_k]_{k=0}^{2n-1} \mapsto [\alpha_k, \beta_k]_{k=0}^{n-1}$$

Modified Chebyshev algorithm

modified and mixed moments

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conditioning: G., 1968, 1982, 2004

algorithm: Sack et al., 1971; Wheeler, 1974

assumption

$$p_{k+1}(t) = (t - a_k)p_k(t) - b_k p_{k-1}(t), \quad k = 0, 1, 2, \dots$$

Modified Chebyshev algorithm (cont')

initialization:

$$\begin{aligned}\alpha_0 &= a_0 + m_1/m_0, & \beta_0 &= m_0, \\ \sigma_{-1,\ell} &= 0, & \ell &= 1, 2, \dots, 2n - 2, \\ \sigma_{0,\ell} &= m_\ell, & \ell &= 0, 1, \dots, 2n - 1\end{aligned}$$

Modified Chebyshev algorithm (cont')

initialization:

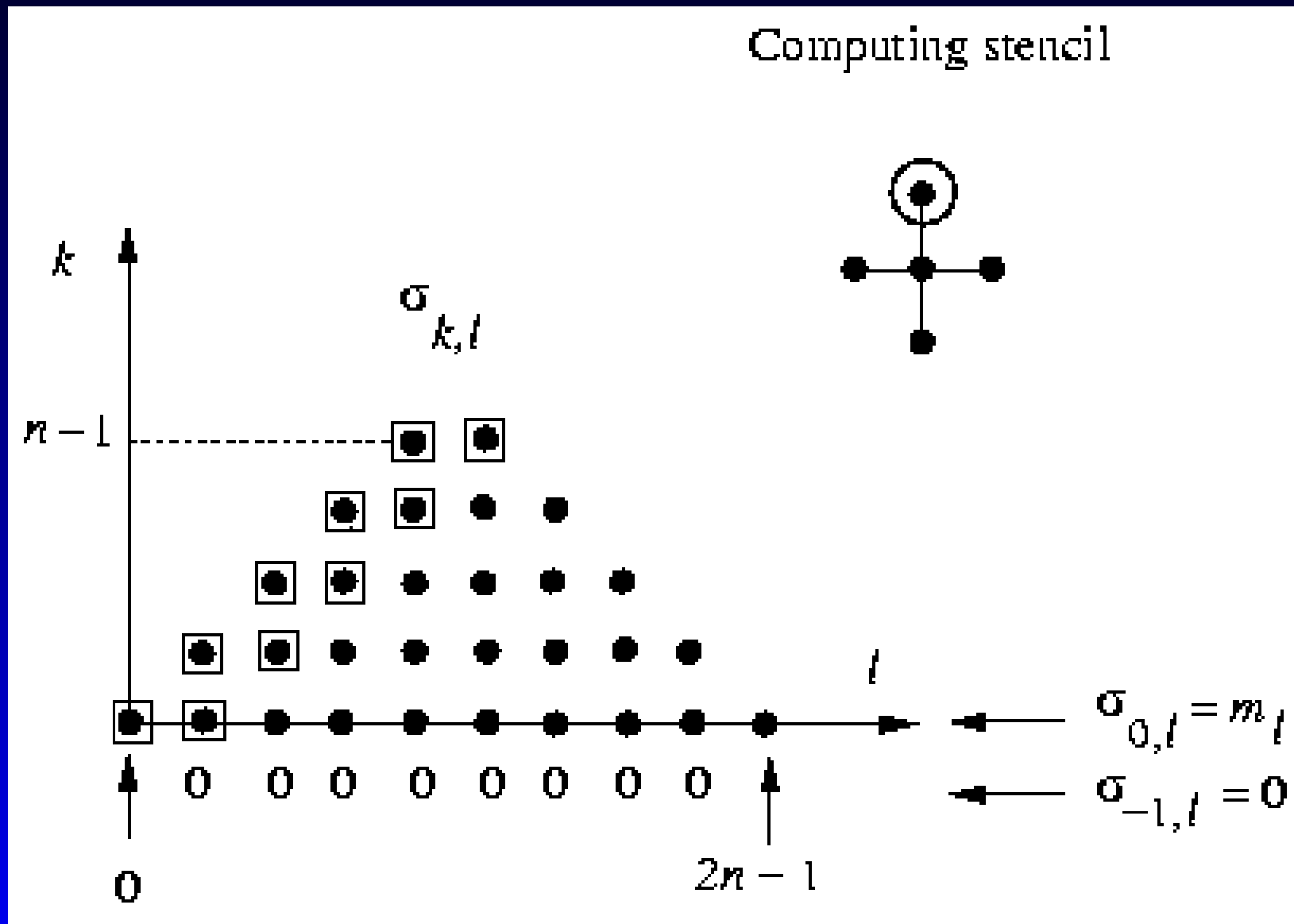
$$\begin{aligned}\alpha_0 &= a_0 + m_1/m_0, & \beta_0 &= m_0, \\ \sigma_{-1,\ell} &= 0, & \ell &= 1, 2, \dots, 2n - 2, \\ \sigma_{0,\ell} &= m_\ell, & \ell &= 0, 1, \dots, 2n - 1\end{aligned}$$

continuation (if $n > 1$): for $k = 1, 2, \dots, n - 1$ do

$$\begin{aligned}\sigma_{k\ell} &= \sigma_{k-1,\ell+1} - (\alpha_{k-1} - a_\ell)\sigma_{k-1,\ell} - \beta_{k-1}\sigma_{k-2,\ell} \\ &\quad + b_\ell\sigma_{k-1,\ell-1}, \quad \ell = k, k + 1, \dots, 2n - k - 1,\end{aligned}$$

$$\alpha_k = a_k + \frac{\sigma_{k,k+1}}{\sigma_{kk}} - \frac{\sigma_{k-1,k}}{\sigma_{k-1,\ell-1}}, \quad \beta_k = \frac{\sigma_{kk}}{\sigma_{k-1,k-1}}$$

Modified Chebyshev algorithm, schematically



Matlab

m_0	m_1	m_2	\cdots	m_{2N-1}
-------	-------	-------	----------	------------

mom

a_0	b_0
a_1	b_1
\vdots	\vdots
a_{2N-2}	b_{2N-2}

abm

`ab=chebyshev(N, mom, abm)`

Demo #2

elliptic orthogonal polynomials

$$d\lambda(t) = [(1 - \omega^2 t^2)(1 - t^2)]^{-1/2} dt \text{ on } [-1, 1],$$
$$0 \leq \omega < 1$$

Demo #2

elliptic orthogonal polynomials

$$d\lambda(t) = [(1 - \omega^2 t^2)(1 - t^2)]^{-1/2} dt \quad \text{on } [-1, 1], \\ 0 \leq \omega < 1$$

Chebyshev moments

$$m_0 = \int_{-1}^1 d\lambda(t), \quad m_k = \frac{1}{2^{k-1}} \int_{-1}^1 T_k(t) d\lambda(t), \quad k \geq 1$$

Demo #2

elliptic orthogonal polynomials

$$d\lambda(t) = [(1 - \omega^2 t^2)(1 - t^2)]^{-1/2} dt \quad \text{on } [-1, 1], \\ 0 \leq \omega < 1$$

Chebyshev moments

$$m_0 = \int_{-1}^1 d\lambda(t), \quad m_k = \frac{1}{2^{k-1}} \int_{-1}^1 T_k(t) d\lambda(t), \quad k \geq 1$$

Matlab

```
function ab=r_elliptic(N,om2)
    abm=r_jacobi(2*N-1,-1/2);
    mom=mm_elliptic(N,om2);
    ab=chebyshev(N,mom,abm);
```

Demo #2 (cont')

$$\omega^2 = .999, \quad N = 40$$

Demo #2 (cont')

$$\omega^2 = .999, \quad N = 40$$

k	β_k	k	β_k	k	β_k	k	β_k
0	9.68226512	10	0.24936494	20	0.24992062	30	0.24998062
1	0.79378214	11	0.24951641	21	0.24993230	31	0.24998288
2	0.11986767	12	0.24962381	22	0.24994197	32	0.24998485
3	0.22704012	13	0.24970218	23	0.24995003	33	0.24998657
4	0.24106088	14	0.24976074	24	0.24995679	34	0.24998806
5	0.24542853	15	0.24980537	25	0.24996249	35	0.24998937
6	0.24730165	16	0.24983998	26	0.24996732	36	0.24999052
7	0.24825871	17	0.24986721	27	0.24997145	37	0.24999154
8	0.24880566	18	0.24988890	28	0.24997497	38	0.24999243
9	0.24914365	19	0.24990639	29	0.24997800	39	0.24999322

Discrete measure

$$d\lambda_N(t) = \sum_{k=1}^N w_k \delta(t - x_k) dt$$

inner product $(p, q)_N = \sum_{k=1}^N w_k p(x_k) q(x_k)$

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Algorithm #1: Stieltjes, 1884; G., 1968

Darboux's formulae

$$(D) \quad \begin{cases} \alpha_k = \frac{(t\pi_k, \pi_k)_N}{(\pi_k, \pi_k)_N}, & k = 0, 1, \dots, n-1, \\ \beta_k = \frac{(\pi_k, \pi_k)_N}{(\pi_{k-1}, \pi_{k-1})_N}, & k = 1, 2, \dots, n-1 \end{cases}$$

Discrete measure

$$d\lambda_N(t) = \sum_{k=1}^N w_k \delta(t - x_k) dt$$

inner product $(p, q)_N = \sum_{k=1}^N w_k p(x_k) q(x_k)$

Algorithm #1: Stieltjes, 1884; G., 1968
Darboux's formulae

$$(D) \quad \begin{cases} \alpha_k = \frac{(t\pi_k, \pi_k)_N}{(\pi_k, \pi_k)_N}, & k = 0, 1, \dots, n-1, \\ \beta_k = \frac{(\pi_k, \pi_k)_N}{(\pi_{k-1}, \pi_{k-1})_N}, & k = 1, 2, \dots, n-1 \end{cases}$$

plus recurrence relation (R)

$$\begin{aligned} \pi_0 = 1 &\xrightarrow{(D)} \alpha_0, \beta_0 \xrightarrow{(R)} \pi_1 \xrightarrow{(D)} \alpha_1, \beta_1 \xrightarrow{(R)} \dots \\ &\xrightarrow{(D)} \alpha_{n-1}, \beta_{n-1} \end{aligned}$$

Algorithm #2 Lanczos, 1950

$$Q^T \begin{bmatrix} 1 & \sqrt{w_1} & \sqrt{w_2} & \cdots & \sqrt{w_N} \\ \sqrt{w_1} & x_1 & 0 & \cdots & 0 \\ \sqrt{w_2} & 0 & x_2 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \sqrt{w_N} & 0 & 0 & \cdots & x_N \end{bmatrix} Q$$

$$= \begin{bmatrix} 1 & \sqrt{\beta_0} & 0 & \cdots & 0 \\ \sqrt{\beta_0} & \alpha_0 & \sqrt{\beta_1} & \cdots & 0 \\ 0 & \sqrt{\beta_1} & \alpha_1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & \alpha_{N-1} \end{bmatrix}$$

stable version of Lanczos algorithm

Rutishauser, 1963; Gragg and Harrod, 1984

Matlab

$$\left. \begin{array}{l} \text{ab=stieltjes}(n, \text{xw}) \\ \text{ab=lanczos}(n, \text{xw}) \end{array} \right\} n \leq N$$

x_1	w_1
x_2	w_2
\vdots	\vdots
x_N	w_N

XW



Discretization methods G.; 1968, 1982

Discretization methods G.; 1968, 1982

basic idea

$$d\lambda(t) \approx d\lambda_N(t), \quad \begin{cases} \alpha_k(d\lambda) \approx \alpha_k(d\lambda_N) \\ \beta_k(d\lambda) \approx \beta_k(d\lambda_N) \end{cases}$$

Discretization methods G.; 1968, 1982

basic idea

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Example

$$w(t) = (1 - t^2)^{-1/2} + c \text{ on } [-1, 1], \quad c > 0$$

Discretization methods G.; 1968, 1982

basic idea

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$$w(t) = (1 - t^2)^{-1/2} + c \text{ on } [-1, 1], \quad c > 0$$

discretization

$$\begin{aligned} (p, q) &= \\ &\int_{-1}^1 p(t)q(t)(1 - t^2)^{-1/2} dt + c \int_{-1}^1 p(t)q(t) dt \\ &\approx \sum_{k=1}^N w_k^{Ch} p(x_k^{Ch})q(x_k^{Ch}) + c \sum_{k=1}^N w_k^L p(x_k^L)q(x_k^L) \end{aligned}$$

in general

discretize $d\lambda$ on

$$\bigcup_{j=1}^s [a_j, b_j]$$

using

taylor-made quadratures

general-purpose quadratures

} on each $[a_j, b_j]$

Matlab

`ab=mcdis(n, eps0, quad, Nmax)`

global variables to describe details of discretization

mc, mp, iq

$$AB = \begin{array}{|c|c|} \hline a_1 & b_1 \\ \hline a_2 & b_2 \\ \hline \vdots & \vdots \\ \hline a_{mc} & b_{mc} \\ \hline \end{array}, DM = \begin{array}{|c|c|} \hline x_1 & y_1 \\ \hline x_2 & y_2 \\ \hline \vdots & \vdots \\ \hline x_{mp} & y_{mp} \\ \hline \end{array}$$

Example

Jacobi weight function plus a discrete measure

$$d\lambda(t) = (\beta_0^J)^{-1} (1-t)^\alpha (1+t)^\beta dt + \sum_{j=1}^p w_j \delta(t-x_j) dt \text{ on } [-1, 1]$$
$$\beta_0^J = \int_{-1}^1 (1-t)^\alpha (1+t)^\beta dt, \quad \alpha > -1, \beta > -1$$

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discretization (yields $\alpha_k(d\lambda), \beta_k(d\lambda)$ exactly for $k \leq n-1$)

$$\int_{-1}^1 p(t) d\lambda(t) \approx \sum_{\nu=1}^n \lambda_\nu^J p(\tau_\nu^J) + \sum_{j=1}^p w_j p(x_j)$$

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here, $m_c=1$, $m_p=p$, $i_q=1$ (if $x_j \in [-1, 1]$), and

$$AB = \begin{array}{|c|c|} \hline \hline -1 & 1 \\ \hline \hline \end{array} \quad DM = \begin{array}{|c|c|} \hline \hline x_1 & w_1 \\ x_2 & w_2 \\ \vdots & \vdots \\ x_p & w_p \\ \hline \hline \end{array}$$

Demo #3 **logistic density function**

$$d\lambda(t) = \frac{e^{-t}}{(1+e^{-t})^2}, \quad t \in \mathbb{R}$$

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$$\begin{aligned} \int_{\mathbb{R}} p(t) d\lambda(t) &= \int_0^{\infty} \frac{p(-t)}{(1+e^{-t})^2} e^{-t} dt + \int_0^{\infty} \frac{p(t)}{(1+e^{-t})^2} e^{-t} dt \\ &\approx \sum_{\nu=1}^n \lambda_{\nu}^L \frac{p(-\tau_{\nu}^L) + p(\tau_{\nu}^L)}{(1+e^{-\tau_{\nu}^L})^2} \end{aligned}$$

Demo #3 logistic density function

$$d\lambda(t) = \frac{e^{-t}}{(1+e^{-t})^2}, \quad t \in \mathbb{R}$$

discretization

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exact answers

$$\alpha_k(d\lambda) = 0, \quad \beta_0 = 1, \quad \beta_k = k^4 \pi^2 / (4k^2 - 1), \quad k \geq 1$$

numerical results (N=40, eps0=1000 × eps)

n	β_n	err α	err β
0	1.0000000000(0)	7.18(-17)	3.33(-16)
1	3.2898681337(0)	1.29(-16)	2.70(-16)
6	8.9447603523(1)	4.52(-16)	1.43(-15)
15	5.5578278399(2)	2.14(-14)	0.00(+00)
39	3.7535340252(3)	6.24(-14)	4.48(-15)
		6.24(-14)	8.75(-15)

Cauchy integrals of orthogonal polynomials

$$\rho_n(z) = \rho_n(z; d\lambda) = \int_a^b \frac{\pi_n(t; d\lambda)}{z - t} d\lambda(t), \quad z \in \mathbb{C} \setminus [a, b],$$

where $[a, b] = \text{supp}(d\lambda)$. By convention $\rho_{-1}(z; d\lambda) = 1$.

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Let $\alpha_k = \alpha_k(d\lambda)$, $\beta_k = \beta_k(d\lambda)$, $k = 0, 1, 2, \dots$.

Theorem (G., 1981). If $z \in \mathbb{C} \setminus [a, b]$, then $\{\rho_k(z)\}_{k=-1}^{\infty}$ is the **minimal solution** of the three-term recurrence relation

$$y_{k+1} = (z - \alpha_k)y_k - \beta_k y_{k-1}, \quad k = 0, 1, 2, \dots,$$

with initial value $y_{-1} = 1$. \square

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If $z = x \in (a, b)$, the integrals are **Cauchy principal value** integrals. They satisfy the same three-term recurrence relation, but with initial values $\rho_{-1}(x) = 1$, $\rho_0(x) = \int_a^b d\lambda(t)/(x - t)$.

Continued fraction algorithm (G., 1967)

Formally,

$$r_{n-1} := \frac{\rho_n(z)}{\rho_{n-1}(z)} = \frac{\beta_n}{z - \alpha_n -} \frac{\beta_{n+1}}{z - \alpha_{n+1} -} \frac{\beta_{n+2}}{z - \alpha_{n+2} -} \dots$$

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Theorem (Pincherle, 1894). The continued fraction converges if and only if $\{\rho_k(z)\}_{k=-1}^{\infty}$ is a minimal solution of the three-term recurrence relation. \square

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To compute $\rho_n(z)$, $n = -1, 0, \dots, N$, suppose first that r_ν is known for some $\nu \geq N$. Then

$$r_{n-1} = \frac{\beta_n}{z - \alpha_n - r_n}, \quad n = \nu, \nu - 1, \dots, 0,$$

and

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If r_ν is not known, replace it by $r_\nu \approx 0$.

Algorithm

Define

$$r_\nu^{[\nu]} = 0, \quad r_{n-1}^{[\nu]} = \frac{\beta_n}{z - \alpha_n} \frac{\beta_{n+1}}{z - \alpha_{n+1}} \cdots \frac{\beta_\nu}{z - \alpha_\nu}$$

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Convergence is faster the larger $\text{dist}(z, [a, b])$.

Matlab

[rho , r , nu] = cauchy (N , ab , z , eps0 , nu0 , num

$\rho_0(z)$
$\rho_1(z)$
\vdots
$\rho_N(z)$

rho

$r_0(z)$
$r_1(z)$
\vdots
$r_N(z)$

r

α_0	β_0
α_1	β_1
\vdots	\vdots
α_{numax}	β_{numax}

ab

where

$$r_k(z) = \frac{\rho_{k+1}(z)}{\rho_k(z)}, \quad k = 0, 1, \dots, N$$

Modification algorithms

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Problem: given the recurrence coefficients of $d\lambda$, generate those of

$$d\hat{\lambda}(t) = r(t)d\lambda(t), \quad r \geq 0 \text{ on } \text{supp}(d\lambda), \text{ rational}$$

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Example: Galant, 1971

$$r(t) = s(t - c), \quad c \in \mathbb{R} \setminus \text{supp}(d\lambda), \quad s = \pm 1$$

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one step of (symmetric, shifted) LR algorithm:

$$s[\mathbf{J}_{n+1}(d\lambda) - c\mathbf{I}] = \mathbf{L}\mathbf{L}^T$$

$$\mathbf{J}_n(d\hat{\lambda}) = (\mathbf{L}^T\mathbf{L} + c\mathbf{I})_{[1:n,1:n]}$$

nonlinear recurrence algorithm

generalized Christoffel theorem (Uvarov, 1969)

$$d\hat{\lambda}(t) = \frac{u(t)}{v(t)} dt, \quad u(t) = \pm \prod_{\lambda=1}^{\ell} (t - u_{\lambda}), \quad v(t) = \prod_{\mu=1}^m (t - v_{\mu})$$

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Let $m \leq n$. Then

$$u(t)\pi_n(t; d\hat{\lambda}) = \text{const} \times$$

$\pi_{n-m}(t)$	\cdots	$\pi_{n-1}(t)$	$\pi_n(t)$	\cdots	$\pi_{n+l}(t)$
$\pi_{n-m}(u_1)$	\cdots	$\pi_{n-1}(u_1)$	$\pi_n(u_1)$	\cdots	$\pi_{n+l}(u_1)$
\cdots	\cdots	\cdots	\cdots	\cdots	\cdots
$\pi_{n-m}(u_{\ell})$	\cdots	$\pi_{n-1}(u_{\ell})$	$\pi_n(u_{\ell})$	\cdots	$\pi_{n+l}(u_{\ell})$
$\rho_{n-m}(v_1)$	\cdots	$\rho_{n-1}(v_1)$	$\rho_n(v_1)$	\cdots	$\rho_{n+l}(v_1)$
\cdots	\cdots	\cdots	\cdots	\cdots	\cdots
$\rho_{n-m}(v_m)$	\cdots	$\rho_{n-1}(v_m)$	$\rho_n(v_m)$	\cdots	$\rho_{n+l}(v_m)$

where

$$\rho_k(z) = \int_{\mathbb{R}} \frac{\pi_k(t; d\hat{\lambda})}{z-t} d\hat{\lambda}(t), \quad k = 0, 1, 2, \dots \quad \square$$

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\cdots	\cdots	\cdots	\cdots	\cdots	\cdots
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Christoffel's theorem: $m = 0$

Theorem (Uvarov, 1969) Let $m > n$. Then

$$u(t)\pi_n(t; d\hat{\lambda}) = \text{const} \times$$

0	0	...	0	$\pi_0(t)$...	$\pi_{n+l}(t)$
0	0	...	0	$\pi_0(u_1)$...	$\pi_{n+l}(u_1)$
...
0	0	...	0	$\pi_0(u_\ell)$...	$\pi_{n+l}(u_\ell)$
1	v_1	...	v_1^{m-n-1}	$\rho_0(v_1)$...	$\rho_{n+l}(v_1)$
...
1	v_m	...	v_m^{m-n-1}	$\rho_0(v_m)$...	$\rho_{n+l}(v_m)$

where $\rho_k(z)$ is the Cauchy integral defined previously. \square

Theorem (Uvarov, 1969) Let $m > n$. Then

$$u(t)\pi_n(t; d\hat{\lambda}) = \text{const} \times \begin{vmatrix} 0 & 0 & \cdots & 0 & \pi_0(t) & \cdots & \pi_{n+l}(t) \\ 0 & 0 & \cdots & 0 & \pi_0(u_1) & \cdots & \pi_{n+l}(u_1) \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & \cdots & 0 & \pi_0(u_\ell) & \cdots & \pi_{n+l}(u_\ell) \\ 1 & v_1 & \cdots & v_1^{m-n-1} & \rho_0(v_1) & \cdots & \rho_{n+l}(v_1) \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ 1 & v_m & \cdots & v_m^{m-n-1} & \rho_0(v_m) & \cdots & \rho_{n+l}(v_m) \end{vmatrix}$$

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The generalized Christoffel theorems remain valid for complex u_λ, v_μ if orthogonality is understood in the sense of **formal orthogonality**.

linear factor $d\hat{\lambda}(t) = (t - z)d\lambda(t)$, $z \in \mathbb{C} \setminus [a, b]$

Christoffel:

$$(t - z)\hat{\pi}_n(t) = \frac{\begin{vmatrix} \pi_n(t) & \pi_{n+1}(t) \\ \pi_n(z) & \pi_{n+1}(z) \end{vmatrix}}{-\pi_n(z)} = \pi_{n+1}(t) - r_n \pi_n(t), \quad r_n = \frac{\pi_{n+1}(z)}{\pi_n(z)}$$

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write $(t - z)t\hat{\pi}_k(t)$ in two ways (Verlinden, 1999)

$$\begin{aligned} (t - z)t\hat{\pi}_k(t) &= t\pi_{k+1}(t) - r_k \cdot t\pi_k(t) \\ &= \pi_{k+2}(t) + (\alpha_{k+1} - r_k)\pi_{k+1}(t) + (\beta_{k+1} - r_k\alpha_k)\pi_k(t) - r_k\beta_k\pi_{k-1}(t) \end{aligned}$$

$$\begin{aligned} (t - z)t\hat{\pi}_k(t) &= (t - z)[\hat{\pi}_{k+1} + \hat{\alpha}_k\hat{\pi}_k(t) + \hat{\beta}_k\hat{\pi}_{k-1}(t)] \\ &= \pi_{k+2}(t) + (\hat{\alpha}_k - r_{k+1})\pi_{k+1}(t) + (\hat{\beta}_k - r_k\hat{\alpha}_k)\pi_k(t) - r_{k-1}\hat{\beta}_k\pi_{k-1}(t) \end{aligned}$$

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comparison:

$$\hat{\alpha}_k - r_{k+1} = \alpha_{k+1} - r_k, \quad r_{k-1}\hat{\beta}_k = r_k\beta_k$$

Algorithm (Modification by a linear factor $t - z$)

initialization:

$$\begin{aligned} r_0 &= z - \alpha_0, & r_1 &= z - \alpha_1 - \beta_1/r_0, \\ \hat{\alpha}_0 &= \alpha_1 + r_1 - r_0, & \hat{\beta}_0 &= -r_0 \beta_0 \end{aligned}$$

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Matlab

```
ab=chri1(N,ab0,z)
```

Algorithm (quadratic factor $(t-x)^2+y^2 = (t-z)(t-\bar{z})$)

initialization:

$$r_0 = z - \alpha_0, \quad r_1 = z - \alpha_1 - \beta_1/r_0, \quad r_2 = z - \alpha_2 - \beta_2/r_1,$$

$$\hat{\alpha}_0 = \alpha_2 + r'_2 + \frac{r''_2}{r'_1} r'_1 - \left(r'_1 + \frac{r''_1}{r'_0} r'_0 \right),$$

$$\hat{\beta}_0 = \beta_0(\beta_1 + |r_0|^2)$$

Algorithm (quadratic factor $(t-x)^2+y^2 = (t-z)(t-\bar{z})$)

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$$\hat{\beta}_0 = \beta_0(\beta_1 + |r_0|^2)$$

continuation (if $n > 1$): for $k = 1, 2, \dots, n - 1$ do

$$r_{k+2} = z - \alpha_{k+2} - \beta_{k+2}/r_{k+1},$$

$$\hat{\alpha}_k = \alpha_{k+2} + r'_{k+2} + \frac{r''_{k+2}}{r''_{k+1}} r'_{k+1} - \left(r'_{k+1} + \frac{r''_{k+1}}{r''_k} r'_k \right),$$

$$\hat{\beta}_k = \beta_k \frac{r''_{k+1} r''_{k-1}}{[r''_k]^2} \left| \frac{r_k}{r_{k-1}} \right|^2$$

Algorithm (quadratic factor $(t-x)^2+y^2 = (t-z)(t-\bar{z})$)

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Matlab `ab=chri2(N,ab0,x,y)`

linear divisor $d\hat{\lambda}(t) = \frac{d\lambda(t)}{t-z}$, $z \in \mathbb{C} \setminus [a, b]$

generalized Christoffel:

$$\hat{\pi}_n(t) = \frac{\begin{vmatrix} \pi_{n-1}(t) & \pi_n(t) \\ \rho_{n-1}(z) & \rho_n(z) \end{vmatrix}}{-\rho_{n-1}(z)} = \pi_n(t) - r_{n-1}\pi_{n-1}(t), \quad r_n = \frac{\rho_{n+1}(z)}{\rho_n(z)}$$

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Algorithm (Modification by a linear divisor $t - z$)

initialization:

$$\hat{\alpha}_0 = \alpha_0 + r_0, \quad \hat{\beta}_0 = -\rho_0(z)$$

continuation (if $n > 1$): for $k = 1, 2, \dots, n - 1$ do

$$\hat{\alpha}_k = \alpha_k + r_k - r_{k-1},$$

$$\hat{\beta}_k = \beta_{k-1}r_{k-1}/r_{k-2}$$

computation of the r_k : **continued fraction algorithm**

linear divisor $d\hat{\lambda}(t) = \frac{d\lambda(t)}{t-z}$, $z \in \mathbb{C} \setminus [a, b]$

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computation of the r_k : **continued fraction algorithm**

Matlab

`[ab,nu]=chri4(N,ab0,z,eps0,nu0,numax,rho0,iopt)`

quadratic divisor $d\hat{\lambda}(t) = \frac{d\lambda(t)}{(t-x)^2+y^2}$

notations

$$r_n = \frac{\rho_{n+1}(z)}{\rho_n(z)} = r'_n + i r''_n$$

$$s_n = - \left(r'_{n-1} + \frac{r''_{n-1}}{r''_{n-2}} r'_{n-2} \right), \quad n \geq 1; \quad t_n = \frac{r''_{n-1}}{r''_{n-2}} |r_{n-2}|^2, \quad n \geq 2$$

quadratic divisor $d\hat{\lambda}(t) = \frac{d\lambda(t)}{(t-x)^2+y^2}$

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Algorithm

initialization:

$$\hat{\alpha}_0 = x + \rho'_0 y / \rho''_0, \quad \hat{\beta}_0 = -\rho''_0 / y,$$

$$\hat{\alpha}_1 = \alpha_1 - s_2 + s_1, \quad \hat{\beta}_1 = \beta_1 + s_1(\alpha_0 - \hat{\alpha}_1) - t_2,$$

$$\hat{\alpha}_2 = \alpha_2 - s_3 + s_2, \quad \hat{\beta}_2 = \beta_2 + s_2(\alpha_1 - \hat{\alpha}_2) - t_3 + t_2$$

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continuation (if $n > 3$): for $k = 3, 4, \dots, n-1$ do

$$\hat{\alpha}_k = \alpha_k - s_{k+1} + s_k, \quad \hat{\beta}_k = \beta_{k-2} t_k / t_{k-1}$$

quadratic divisor $d\hat{\lambda}(t) = \frac{d\lambda(t)}{(t-x)^2+y^2}$

notations

$$r_n = \frac{\rho_{n+1}(z)}{\rho_n(z)} = r'_n + i r''_n$$

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$$\hat{\alpha}_k = \alpha_k - s_{k+1} + s_k, \quad \hat{\beta}_k = \beta_{k-2} t_k / t_{k-1}$$

Matlab

```
[ab,nu]=chri5(N,ab0,z,eps0,nu0,numax,rho0,iopt)
```


Sobolev orthogonal polynomials

Sobolev orthogonal polynomials

Sobolev inner product

$$(p, q)_S = \int_{\mathbb{R}} p(t)q(t)d\lambda_0(t) + \int_{\mathbb{R}} p'(t)q'(t)d\lambda_1(t) \\ + \cdots + \int_{\mathbb{R}} p^{(s)}(t)q^{(s)}(t)d\lambda_s(t)$$

Sobolev orthogonal polynomials

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Sobolev orthogonal polynomials $\{\pi_k(\cdot; S)\}$

$$(\pi_k, \pi_\ell)_S \begin{cases} = 0, & k \neq \ell \\ > 0, & k = \ell \end{cases}$$

Sobolev orthogonal polynomials

Sobolev inner product

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Sobolev orthogonal polynomials $\{\pi_k(\cdot; S)\}$

$$(\pi_k, \pi_\ell)_S \begin{cases} = 0, & k \neq \ell \\ > 0, & k = \ell \end{cases}$$

recurrence relation

$$\pi_{k+1}(t) = t\pi_k(t) - \sum_{j=0}^k \beta_j^k \pi_{k-j}(t), \quad k = 0, 1, 2, \dots$$

Recurrence matrix

recurrence relation

$$\pi_{k+1}(t) = t\pi_k(t) - \sum_{j=0}^k \beta_j^k \pi_{k-j}(t), \quad k = 0, 1, 2, \dots$$

matrix of recurrence coefficients

$$\mathbf{H}_n = \begin{bmatrix} \beta_0^0 & \beta_1^1 & \beta_2^2 & \cdots & \beta_{n-2}^{n-2} & \beta_{n-1}^{n-1} \\ 1 & \beta_0^1 & \beta_1^2 & \cdots & \beta_{n-3}^{n-2} & \beta_{n-2}^{n-1} \\ 0 & 1 & \beta_0^2 & \cdots & \beta_{n-4}^{n-2} & \beta_{n-3}^{n-1} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & 0 & \cdots & \beta_0^{n-2} & \beta_1^{n-1} \\ 0 & 0 & 0 & \cdots & 1 & \beta_0^{n-1} \end{bmatrix}$$

Modified Chebyshev algorithm

Modified Chebyshev algorithm

modified moments

$$m_k^{(\sigma)} = \int_{\mathbb{R}} p_k(t) d\lambda_{\sigma},$$

$$k = 0, 1, 2, \dots, ; \quad \sigma = 0, 1, \dots, s$$

Modified Chebyshev algorithm

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$$m_k^{(\sigma)} = \int_{\mathbb{R}} p_k(t) d\lambda_{\sigma},$$

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modified moment map

$$[m_k^{(\sigma)}]_{k=0}^{2n-1}, \quad \sigma = 0, 1, \dots, s \mapsto \mathbf{H}_n$$

Modified Chebyshev algorithm

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$$[m_k^{(\sigma)}]_{k=0}^{2n-1}, \quad \sigma = 0, 1, \dots, s \mapsto \mathbf{H}_n$$

algorithm G. and Zhang, 1995

conditioning Zhang, 1994

Matlab (for $s = 1$)

`B=chebyshev_sob(N, mom, abm)`

Example $d\lambda_0(t) = dt$, $d\lambda_1(t) = \gamma dt$ on $[-1, 1]$
(Althammer, 1962)

modified moments

$p_k(t)$ = monic Legendre

$$m_0^{(0)} = 2, m_0^{(1)} = 2\gamma; \quad m_k^{(0)} = m_k^{(1)} = 0, k > 0$$

Matlab

```
mom=zeros(2,2*N);  
mom(1,1)=2;    mom(2,1)=2*g;  
abm=r_jacobi(2*N-1);  
B=chebyshev_sob(N,mom,abm);
```

Discretized Stieltjes algorithm

Discretized Stieltjes algorithm

(G. and Zhang, 1995)

$$\beta_j^k = \frac{(t\pi_k, \pi_{k-j})_S}{(\pi_{k-j}, \pi_{k-j})_S}, \quad j = 0, 1, \dots, k$$

Discretized Stieltjes algorithm

(G. and Zhang, 1995)

$$\beta_j^k = \frac{(t\pi_k, \pi_{k-j})_S}{(\pi_{k-j}, \pi_{k-j})_S}, \quad j = 0, 1, \dots, k$$

Gauss quadrature discretization

$$(p, q)_{d\lambda_\sigma} \approx \sum_{k=1}^{n_\sigma} w_k^{(\sigma)} p(x_k^{(\sigma)}) q(x_k^{(\sigma)}), \quad \sigma = 0, 1, \dots, s$$

Matlab

```
B=stieltjes_sob(N,s,nd,xw,a0,same)
a0= $\alpha_0$ ( $d\lambda_0$ )
```

Matlab (cont')

$$XW = \begin{array}{|c|c|c|} \hline x_1^{(0)} & \dots & x_1^{(s)} \\ \hline x_2^{(0)} & \dots & x_2^{(s)} \\ \hline \vdots & & \vdots \\ \hline x_{md}^{(0)} & \dots & x_{md}^{(s)} \\ \hline \end{array} \begin{array}{|c|c|c|} \hline w_1^{(0)} & \dots & w_1^{(s)} \\ \hline w_2^{(0)} & \dots & w_2^{(s)} \\ \hline \vdots & & \vdots \\ \hline w_{md}^{(0)} & \dots & w_{md}^{(s)} \\ \hline \end{array}$$

$$md = \max(nd)$$

Example Althammer's polynomials

Matlab

```
s=1; nd=[N N];  
a0=0; same=1;  
ab=r_jacobi(N);  
zw=gauss(N,ab);  
xw=[zw(:,1) zw(:,1) ...  
      zw(:,2) g*zw(:,2)];  
B=stieltjes_sob(N,s,nd,xw,a0,same);
```

Zeros

if

$$\boldsymbol{\pi}^T(t) = [\pi_0(t), \pi_1(t), \dots, \pi_{n-1}(t)]$$

then

$$t\boldsymbol{\pi}^T(t) = \boldsymbol{\pi}^T(t)\mathbf{H}_n + \pi_n(t)\mathbf{e}_n^T$$

Theorem The zeros τ_ν of π_n are the eigenvalues of \mathbf{H}_n and $\boldsymbol{\pi}^T(\tau_\nu)$ corresponding (left) eigenvectors. \square

Matlab

`z=sobzeros(n,N,B)`

Part II

Quadrature

Gauss quadrature formula

$$\int_{\mathbb{R}} f(t) d\lambda(t) = \sum_{\nu=1}^n \lambda_{\nu}^G f(\tau_{\nu}^G) + R_n^G(f)$$

Gauss quadrature formula

$$\int_{\mathbb{R}} f(t) d\lambda(t) = \sum_{\nu=1}^n \lambda_{\nu}^G f(\tau_{\nu}^G) + R_n^G(f)$$

Theorem (Golub and Welsch, 1969)

The nodes τ_{ν}^G are the eigenvalues of $\mathbf{J}_n(d\lambda)$ and the weights λ_{ν}^G are

$$\lambda_{\nu}^G = \beta_0 \mathbf{v}_{\nu,1}^2$$

where $\beta_0 = \int_{\mathbb{R}} d\lambda(t)$ and $\mathbf{v}_{\nu,1}$ is the first component of the normalized eigenvector \mathbf{v}_{ν} ,

$$\mathbf{J}_n(d\lambda) \mathbf{v}_{\nu} = \lambda_{\nu}^G \mathbf{v}_{\nu}, \quad \mathbf{v}_{\nu}^T \mathbf{v}_{\nu} = 1. \quad \square$$

Gauss quadrature formula

$$\int_{\mathbb{R}} f(t) d\lambda(t) = \sum_{\nu=1}^n \lambda_{\nu}^G f(\tau_{\nu}^G) + R_n^G(f)$$

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$$J_n(d\lambda) \mathbf{v}_{\nu} = \lambda_{\nu}^G \mathbf{v}_{\nu}, \quad \mathbf{v}_{\nu}^T \mathbf{v}_{\nu} = 1. \quad \square$$

Matlab

`xw=gauss(N,ab)`

Corollary If f is sufficiently smooth, then

$$\sum_{\nu=1}^n \lambda_{\nu}^G f(\tau_{\nu}^G) = \beta_0 \mathbf{e}_1^T f(\mathbf{J}_n(\mathbf{d}\lambda)) \mathbf{e}_1, \quad \mathbf{e}_1 = [1, 0, \dots, 0]^T$$

Corollary If f is sufficiently smooth, then

$$\sum_{\nu=1}^n \lambda_{\nu}^G f(\tau_{\nu}^G) = \beta_0 \mathbf{e}_1^T f(\mathbf{J}_n(\mathbf{d}\lambda)) \mathbf{e}_1, \quad \mathbf{e}_1 = [1, 0, \dots, 0]^T$$

Proof Let $\mathbf{V} = [\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n]$ and $\mathbf{J} = \mathbf{J}_n(\mathbf{d}\lambda)$.
Then (spectral decomposition of \mathbf{J})

$$\mathbf{J}\mathbf{V} = \mathbf{V}\mathbf{D}_{\tau}, \quad \mathbf{D}_{\tau} = \text{diag}(\tau_1^G, \tau_2^G, \dots, \tau_n^G)$$

and

$$\begin{aligned} \beta_0 \mathbf{e}_1^T f(\mathbf{J}) \mathbf{e}_1 &= \beta_0 \mathbf{e}_1^T \mathbf{V} f(\mathbf{D}_{\tau}) \mathbf{V}^T \mathbf{e}_1 \\ &= \beta_0 \sum_{\nu=1}^n \mathbf{v}_{\nu,1}^2 f(\tau_{\nu}^G) = \sum_{\nu=1}^n \lambda_{\nu}^G f(\tau_{\nu}^G) \end{aligned}$$

since $\beta_0 \mathbf{v}_{\nu,1}^2 = \lambda_{\nu}^G$. \square

Example Zeros of Sobolev orthogonal polynomials of Gegenbauer type (Groenevelt, 2002)

Sobolev inner product

$$(u, v)_S = \int_{-1}^1 u(t)v(t)(1 - t^2)^{\alpha-1} dt + \gamma \int_{-1}^1 u'(t)v'(t) \frac{(1-t^2)^\alpha}{t^2+y^2} dt$$

Example Zeros of Sobolev orthogonal polynomials of Gegenbauer type (Groenevelt, 2002)

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Matlab program

```
s=1; same=0; eps0=1e-14; numax=250; nd=[N N];
ab0=r_jacobi(numax,alpha);
z=complex(0,y);
nu0=nu0jac(N,z,eps0); rho0=0; iopt=1;
ab1=chri6(N,ab0,y,eps0,nu0,numax,rho0,iopt);
zw1=gauss(N,ab1);
ab=r_jacobi(N,alpha-1); zw=gauss(N,ab);
xw=[zw(:,1) zw1(:,1) zw(:,2) gamma*zw1(:,2)];
a0=ab(1,1); B=stieltjes_sob(N,s,nd,xw,a0,same);
z=sobzeros(N,N,B)
```


Demo #4 $N=12, \alpha = \frac{1}{2}, \gamma = 1$

Demo #4 $N=12, \alpha = \frac{1}{2}, \gamma = 1$

y	zeros	y	zeros
.1	.027543282225	.09	.011086169153 i
	.284410786673		.281480077515
	.541878443180		.540697645595
	.756375307278		.755863108617
	.909868274113		.909697039063
	.989848649239		.989830182743

All other zeros are the same with opposite signs

Gauss-Radau formula

$$\int_{\mathbb{R}} f(t) d\lambda(t) = \lambda_0^a f(a) + \sum_{\nu=1}^n \lambda_{\nu}^a f(\tau_{\nu}^a) + R_n^a(f)$$

Gauss-Radau formula

$$\int_{\mathbb{R}} f(t) d\lambda(t) = \lambda_0^a f(a) + \sum_{\nu=1}^n \lambda_{\nu}^a f(\tau_{\nu}^a) + R_n^a(f)$$

Jacobi-Radau matrix

$$\mathbf{J}_{n+1}^{R,a}(\mathbf{d}\lambda) = \begin{bmatrix} \mathbf{J}_n(\mathbf{d}\lambda) & \sqrt{\beta_n} \mathbf{e}_n \\ \sqrt{\beta_n} \mathbf{e}_n^T & \alpha_n^R \end{bmatrix}, \quad \alpha_n^R = a - \beta_n \frac{\pi_{n-1}(a)}{\pi_n(a)}$$

Jacobi resp. Laguerre measure

$$\alpha_n^R = -1 + \frac{2n(n+\alpha)}{(2n+\alpha+\beta)(2n+\alpha+\beta+1)}, \quad \alpha_n^R = n$$

Gauss-Radau formula

$$\int_{\mathbb{R}} f(t) d\lambda(t) = \lambda_0^a f(a) + \sum_{\nu=1}^n \lambda_{\nu}^a f(\tau_{\nu}^a) + R_n^a(f)$$

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Jacobi resp. Laguerre measure

$$\alpha_n^R = -1 + \frac{2n(n+\alpha)}{(2n+\alpha+\beta)(2n+\alpha+\beta+1)}, \quad \alpha_n^R = n$$

Matlab

```
xw=radau(N,ab,end0)
```

```
xw=radau_jacobi(N,iopt,a,b)
```

```
xw=radau_laguerre(N,a)
```

Gauss-Lobatto formula

$$\int_a^b f(t) d\lambda(t) \approx \lambda_0^L f(a) + \sum_{\nu=1}^n \lambda_{\nu}^L f(\tau_{\nu}^L) + \lambda_{n+1}^L f(b)$$

Gauss-Lobatto formula

$$\int_a^b f(t) d\lambda(t) \approx \lambda_0^L f(a) + \sum_{\nu=1}^n \lambda_{\nu}^L f(\tau_{\nu}^L) + \lambda_{n+1}^L f(b)$$

Jacobi-Lobatto matrix

$$\mathbf{J}_{n+2}^L(d\lambda) = \begin{bmatrix} \mathbf{J}_{n+1}(d\lambda) & \sqrt{\beta_{n+1}^L} \mathbf{e}_{n+1} \\ \sqrt{\beta_{n+1}^L} \mathbf{e}_{n+1}^T & \alpha_{n+1}^L \end{bmatrix}$$
$$\begin{bmatrix} \pi_{n+1}(a) & \pi_n(a) \\ \pi_{n+1}(b) & \pi_n(b) \end{bmatrix} \begin{bmatrix} \alpha_{n+1}^L \\ \beta_{n+1}^L \end{bmatrix} = \begin{bmatrix} a\pi_{n+1}(a) \\ b\pi_{n+1}(b) \end{bmatrix}$$

Jacobi measure

$$\alpha_{n+1}^L = \frac{\alpha - \beta}{2n + \alpha + \beta + 2}, \quad \beta_{n+1}^L = 4 \frac{(n + \alpha + 1)(n + \beta + 1)(n + \alpha + \beta + 1)}{(2n + \alpha + \beta + 1)(2n + \alpha + \beta + 2)}$$

Gauss-Lobatto formula

$$\int_a^b f(t) d\lambda(t) \approx \lambda_0^L f(a) + \sum_{\nu=1}^n \lambda_{\nu}^L f(\tau_{\nu}^L) + \lambda_{n+1}^L f(b)$$

Jacobi-Lobatto matrix

$$\mathbf{J}_{n+2}^L(d\lambda) = \begin{bmatrix} \mathbf{J}_{n+1}(d\lambda) & \sqrt{\beta_{n+1}^L} \mathbf{e}_{n+1} \\ \sqrt{\beta_{n+1}^L} \mathbf{e}_{n+1}^T & \alpha_{n+1}^L \end{bmatrix}$$
$$\begin{bmatrix} \pi_{n+1}(a) & \pi_n(a) \\ \pi_{n+1}(b) & \pi_n(b) \end{bmatrix} \begin{bmatrix} \alpha_{n+1}^L \\ \beta_{n+1}^L \end{bmatrix} = \begin{bmatrix} a\pi_{n+1}(a) \\ b\pi_{n+1}(b) \end{bmatrix}$$

Jacobi measure

$$\alpha_{n+1}^L = \frac{\alpha - \beta}{2n + \alpha + \beta + 2}, \quad \beta_{n+1}^L = 4 \frac{(n + \alpha + 1)(n + \beta + 1)(n + \alpha + \beta + 1)}{(2n + \alpha + \beta + 1)(2n + \alpha + \beta + 2)}$$

Matlab

```
xw=lobatto(N,ab,endl,endr)  
xw=lobatto_jacobi(N,a,b)
```


Error bounds

Gauss-Radau formulae

$$\begin{aligned}\int_a^b f(t) d\lambda(t) &= \lambda_0^a f(a) + \sum_{\nu=1}^n \lambda_\nu^a f(\tau_\nu^a) + R_n^a(f) \\ &= \sum_{\nu=1}^n \lambda_\nu^b f(\tau_\nu^b) + \lambda_{n+1}^b f(b) + R_n^b(f)\end{aligned}$$

Theorem If $f \in C^{2n+1}[a, b]$, then

$$R_n^a(f) > 0, \quad R_n^b(f) < 0 \quad \text{if } \operatorname{sgn} f^{(2n+1)} = 1 \text{ on } [a, b],$$

with the inequalities reversed if $\operatorname{sgn} f^{(2n+1)} = -1$.

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Proof (for R_n^a ; for R_n^b the proof is similar)

$$R_n^a(f) = \gamma_n^a \frac{f^{(2n+1)}(\tau^a)}{(2n+1)!}, \quad \gamma_n^a = \int_a^b [\pi_n(t; d\lambda_a)]^2 d\lambda_a(t),$$

where $d\lambda_a(t) = (t-a)d\lambda(t)$. \square

Gauss-Lobatto formula

$$\int_a^b f(t) d\lambda(t) = \lambda_0^L f(a) + \sum_{\nu=1}^n \lambda_{\nu}^L f(\tau_{\nu}^L) + \lambda_{n+1} f(b) + R_n^{a,b}(f)$$

Theorem If $f \in C^{2n+2}[a, b]$, then

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with the inequality reversed if $\operatorname{sgn} f^{(2n+2)} = -1$.

Proof

$$R_n^{a,b}(f) = -\gamma_n \frac{f^{(2n+2)}(\tau)}{(2n+2)!}, \quad \gamma_n = \int_a^b [\pi_n(t; d\lambda_{a,b})]^2 d\lambda_{a,b}(t),$$

where $d\lambda_{a,b}(t) = (t-a)(b-t)d\lambda(t)$. \square

Gauss-Kronrod formula

$$\int_{\mathbb{R}} f(t) d\lambda(t) \approx \sum_{\nu=1}^n \lambda_{\nu}^K f(\tau_{\nu}^G) + \sum_{\mu=1}^{n+1} \lambda_{\mu}^{*K} f(\tau_{\mu}^K)$$

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Jacobi-Kronrod matrix (Laurie, 1997)

$$\mathbf{J}_{2n+1}^K(d\lambda) = \begin{bmatrix} \mathbf{J}_n(d\lambda) & \sqrt{\beta_n} \mathbf{e}_n & \mathbf{0} \\ \sqrt{\beta_n} \mathbf{e}_n^T & \alpha_n & \sqrt{\beta_{n+1}} \mathbf{e}_1^T \\ \mathbf{0} & \sqrt{\beta_{n+1}} \mathbf{e}_1 & \mathbf{J}_n^* \end{bmatrix}$$

The trailing (symmetric, tridiagonal, and partially known) matrix \mathbf{J}_n^* can be computed by **Laurie's Algorithm**

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Matlab

```
ab=r_kronrod(N, ab0)
```

```
xw=kronrod(n, ab)
```

Gauss-Turán formula (Turán, 1950)

$$\int_{\mathbb{R}} f(t) d\lambda(t) \approx \sum_{\nu=1}^n [\lambda_{\nu} f(\tau_{\nu}) + \cdots + \lambda_{\nu}^{(r-1)} f^{(r-1)}(\tau_{\nu})]$$

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power orthogonality ($r = 2s + 1, s \geq 0$)

$$\int_{\mathbb{R}} [\omega_n(t)]^{2s+1} p(t) d\lambda(t) = 0, \quad \text{all } p \in \mathbb{P}_{n-1}$$

where $\omega_n(t) = \prod_{\nu=1}^n (t - \tau_{\nu})$

s-orthogonal polynomial: $\omega_n(t) = \pi_{n,s}(t)$

computation (basic idea): $d\lambda_{n,s}(t) := [\pi_{n,s}(t)]^{2s} d\lambda(t)$

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Matlab

`xw=turan(n,s,eps0,ab0,hom)`

Polynomial/rational quadrature

$$\int_{\mathbb{R}} g(t) d\lambda(t) = \sum_{\nu=1}^n \lambda_{\nu} g(\tau_{\nu}) + R_n(g)$$

Problem: determine $\lambda_{\nu}, \tau_{\nu}$ such that $R_n(g) = 0$ if $g \in \mathcal{S}_{2n}$, where

$$\mathcal{S}_{2n} = \mathcal{Q}_m \oplus \mathcal{P}_{2n-m-1}, \quad 0 \leq m \leq 2n$$

\mathcal{P}_{2n-m-1} = polynomials of degree $\leq 2n - m - 1$

\mathcal{Q}_m = rational functions with prescribed poles

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specifically:

$$\mathbb{Q}_m = \text{span} \left\{ r(t) = \frac{1}{1 + \zeta_{\mu} t}, \quad \mu = 1, 2, \dots, m \right\}$$

$$\zeta_{\mu} \in \mathbb{C}, \quad \zeta_{\mu} \neq 0, \quad 1 + \zeta_{\mu} t \neq 0 \text{ on } \text{supp}(d\lambda)$$

Theorem (G., 2000; Van Assche et al., 2000)

Let $\omega_m(t) = \prod_{\mu=1}^m (1 + \zeta_\mu t)$. Assume the existence of a (polynomial) Gauss formula

$$\int_{\mathbb{R}} g(t) \frac{d\lambda(t)}{\omega_m(t)} = \sum_{\nu=1}^n \lambda_\nu^G g(\tau_\nu^G), \quad g \in \mathbb{P}_{2n-1}.$$

Then

$$\tau_\nu = \tau_\nu^G, \quad \lambda_\nu = \omega_m(\tau_\nu^G) \lambda_\nu^G, \quad \nu = 1, 2, \dots, n,$$

yields the desired formula. \square

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construction (assuming $\omega_m \geq 0$)

- discretization method using Gauss quadrature relative to $d\lambda$
- special techniques for “difficult” poles

Example Fermi-Dirac integral $F_k(\eta, \theta) = \int_0^\infty \frac{t^k \sqrt{1+\theta t/2}}{e^{-\eta+t}+1} dt$
 $\eta \in \mathbb{R}, \theta \geq 0, k \dots$ Boltzmann constant ($= \frac{1}{2}, \frac{3}{2},$ or $\frac{5}{2}$)
equivalently

$$F_k(\eta, \theta) = \int_0^\infty \frac{\sqrt{1+\theta t/2}}{e^{-\eta}+e^{-t}} d\lambda^{[k]}(t), \quad d\lambda^{[k]}(t) = t^k e^{-t} dt$$

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poles at $\eta + \mu i\pi, \mu = \pm 1, \pm 3, \pm 5, \dots$ (all “easy”)

$$\omega_m(t) = \prod_{\nu=1}^{m/2} [(1 + \xi_\nu t)^2 + \eta_\nu t^2], \quad 2 \leq m(\text{even}) \leq 2n$$

where

$$\xi_\nu = \frac{-\eta}{\eta^2 + (2\nu-1)^2 \pi^2}, \quad \eta_\nu = \frac{(2\nu-1)\pi}{\eta^2 + (2\nu-1)^2 \pi^2}$$

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rational Gauss approximation $F_k(\eta, \theta) \approx \sum_{n=1}^N w_n \frac{\sqrt{1+\theta x_n/2}}{e^{-\eta}+e^{-x_n}}$

Matlab

`xw=fermi_dirac(N,m,eta,theta,k,eps0,Nmax)`

Cauchy principal value integral

$$(\mathcal{C}f)(x; d\lambda) = \int_a^b \frac{f(t)}{x-t} d\lambda(t), \quad x \in (a, b)$$

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modified quadrature rule

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can be made "**Gaussian**": $R_n(\mathbb{P}_{2n}) = 0$

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quadrature rule in the strict sense

$$(\mathcal{C}f)(x; d\lambda) = \sum_{\nu=1}^n c_\nu^*(x)f(\tau_\nu^*) + R_n^*(f; x)$$

interpolatory **at best**: $R_n^*(\mathbb{P}_{n-1}) = 0$

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Matlab

`cpvi=cauchyPVI(N,x,f,ddf,iopt,ab,rho0)`

$$\text{ddf}(u,v) = \frac{f(u)-f(v)}{u-v}, \quad \text{rho0} = \int_a^b \frac{d\lambda(t)}{x-t}$$

Polynomials orthogonal on several intervals

$$d\lambda(t) = \sum_j \chi_{[c_j, d_j]}(t) d\lambda_j(t)$$

Problem Given $\mathbf{J}^{(j)} = \mathbf{J}_n(d\lambda_j)$, find $\mathbf{J} = \mathbf{J}_n(d\lambda)$

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Problem Given $\mathbf{J}^{(j)} = \mathbf{J}_n(d\lambda_j)$, find $\mathbf{J} = \mathbf{J}_n(d\lambda)$

Solution by Stieltjes procedure

n -point Gauss quadrature discretization

$$\int_{c_j}^{d_j} p(t) d\lambda_j(t) = \sum_{\nu=1}^n \lambda_{\nu}^{(j)} p(\tau_{\nu}^{(j)}), \quad p \in \mathbb{P}_{2n-1}$$

by the corollary to the Golub-Welsch theorem

$$\int_{c_j}^{d_j} p(t) d\lambda_j(t) = \beta_0^{(j)} \mathbf{e}_1^T p(\mathbf{J}^{(j)}) \mathbf{e}_1, \quad \beta_0^{(j)} = \int_{c_j}^{d_j} d\lambda_j(t)$$

Solution (cont')

computation of the inner products ($k \leq n - 1$)

$$\begin{aligned}(t\pi_k, \pi_k)_{\mathbf{d}\lambda} &= \int_{\mathbb{R}} t\pi_k^2(t) \mathbf{d}\lambda(t) = \sum_j \int_{c_j}^{d_j} t\pi_k^2(t) \mathbf{d}\lambda_j(t) \\ &= \sum_j \beta_0^{(j)} \mathbf{e}_1^T \mathbf{J}^{(j)} [\pi_k(\mathbf{J}^{(j)})]^2 \mathbf{e}_1 \\ &= \sum_j \beta_0^{(j)} \mathbf{e}_1^T [\pi_k(\mathbf{J}^{(j)})]^T \mathbf{J}^{(j)} \pi_k(\mathbf{J}^{(j)}) \mathbf{e}_1\end{aligned}$$

similarly

$$(\pi_k, \pi_k)_{\mathbf{d}\lambda} = \sum_j \beta_0^{(j)} \mathbf{e}_1^T [\pi_k(\mathbf{J}^{(j)})]^T \pi_k(\mathbf{J}^{(j)}) \mathbf{e}_1$$

Algorithm

$$\zeta_k^{(j)} := \pi_k(\mathbf{J}^{(j)})\mathbf{e}_1, \quad \mathbf{e}_1 = [1, 0, \dots, 0]^T$$

initialization:

$$\zeta_0^{(j)} = \mathbf{e}_1, \quad \zeta_{-1}^{(j)} = 0 \quad (\text{all } j),$$

$$\alpha_0 = \frac{\sum_j \beta_0^{(j)} \mathbf{e}_1^T \mathbf{J}^{(j)} \mathbf{e}_1}{\sum_j \beta_0^{(j)}}, \quad \beta_0 = \sum_j \beta_0^{(j)}$$

continuation (if $n > 1$): for $k = 0, 1, \dots, n - 2$ do

$$\zeta_{k+1}^{(j)} = (\mathbf{J}^{(j)} - \alpha_k \mathbf{I})\zeta_k^{(j)} - \beta_k \zeta_{k-1}^{(j)} \quad (\text{all } j),$$

$$\alpha_{k+1} = \frac{\sum_j \beta_0^{(j)} \zeta_{k+1}^{(j)T} \mathbf{J}^{(j)} \zeta_{k+1}^{(j)}}{\sum_j \beta_0^{(j)} \zeta_{k+1}^{(j)T} \zeta_{k+1}^{(j)}}, \quad \beta_{k+1} = \frac{\sum_j \beta_0^{(j)} \zeta_{k+1}^{(j)T} \zeta_{k+1}^{(j)}}{\sum_j \beta_0^{(j)} \zeta_k^{(j)T} \zeta_k^{(j)}}$$

Matlab

```
ab=r_multidomain_sti(N,abmd)
```

Solution by modified Chebyshev algorithm

modified moments (by n -point Gauss quadrature, $k \leq 2n - 1$)

$$m_k = \sum_j \int_{c_j}^{d_j} p_k(t) d\lambda_j(t) = \sum_j \beta_0^{(j)} \mathbf{e}_1^T p_k(\mathbf{J}^{(j)}) \mathbf{e}_1$$

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Algorithm

$$\mathbf{z}_k^{(j)} := p_k(\mathbf{J}^{(j)}) \mathbf{e}_1, \quad \mathbf{e}_1 = [1, 0, \dots, 0]^T$$

initialization:

$$\mathbf{z}_0^{(j)} = \mathbf{e}_1, \quad \mathbf{z}_{-1}^{(j)} = 0 \text{ (all } j), \quad m_0 = \sum_j \beta_0^{(j)}$$

continuation: for $k = 0, 1, \dots, 2n - 2$ do

$$\begin{aligned} \mathbf{z}_{k+1}^{(j)} &= (\mathbf{J}^{(j)} - a_k \mathbf{I}) \mathbf{z}_k^{(j)} - b_k \mathbf{z}_{k-1}^{(j)} \quad (\text{all } j), \\ m_{k+1} &= \sum_j \beta_0^{(j)} \mathbf{z}_{k+1}^{(j)T} \mathbf{e}_1 \end{aligned}$$

\implies modified Chebyshev algorithm

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\implies modified Chebyshev algorithm

Matlab `ab=r_multidomain_cheb(N,abmd,abmm)`

Quadrature estimates of matrix functionals

Problem Given $A \in \mathbb{R}^{N \times N}$ positive definite, and f sufficiently smooth, find lower and upper bounds for the quadratic form

$$\mathbf{u}^T f(A) \mathbf{u}, \quad \mathbf{u} \in \mathbb{R}^N, \quad \|\mathbf{u}\| = 1$$

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connection with **quadrature** (spectral resolution of A)

$$A\mathbf{V} = \mathbf{V}\Lambda, \quad \Lambda = \text{diag}(\lambda_1, \lambda_2, \dots, \lambda_N), \quad \mathbf{V} = [\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_N]$$

$$\mathbf{u} = \sum_{k=1}^N \rho_k \mathbf{v}_k = \mathbf{V}\boldsymbol{\rho}, \quad \boldsymbol{\rho} = [\rho_1, \rho_2, \dots, \rho_N]^T$$

$$\implies \mathbf{u}^T f(A) \mathbf{u} = \boldsymbol{\rho}^T \mathbf{V}^T \mathbf{V} f(\Lambda) \mathbf{V}^T \mathbf{V} \boldsymbol{\rho} = \boldsymbol{\rho}^T f(\Lambda) \boldsymbol{\rho},$$

$$= \sum_{k=1}^N \rho_k^2 f(\lambda_k) =: \int_{\mathbb{R}_+} f(t) d\rho_N(t)$$

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$$= \sum_{k=1}^N \rho_k^2 f(\lambda_k) =: \int_{\mathbb{R}_+} f(t) d\rho_N(t)$$

Solution (for f with derivatives of constant sign)

- generate $\mathbf{J}_N(d\rho_N)$: Lanczos algorithm
- apply Gauss-type quadrature to

$$\mathbf{u}^T f(\mathbf{A}) \mathbf{u} = \int_{\mathbb{R}_+} f(t) d\rho_N(t)$$

Lanczos algorithm

$$\mathbf{h}_0 = \sum_{k=1}^N \rho_k \mathbf{v}_k, \quad \|\mathbf{h}_0\| = 1 \quad (\mathbf{h}_0 = \mathbf{u})$$

initialization:

$$\mathbf{h}_0 \text{ prescribed with } \|\mathbf{h}_0\| = 1, \quad \mathbf{h}_{-1} = \mathbf{0}$$

continuation: for $j = 0, 1, \dots, N - 1$ do

$$\alpha_j = \mathbf{h}_j^T \mathbf{A} \mathbf{h}_j,$$

$$\tilde{\mathbf{h}}_{j+1} = (\mathbf{A} - \alpha_j \mathbf{I}) \mathbf{h}_j - \gamma_j \mathbf{h}_{j-1},$$

$$\gamma_{j+1} = \|\tilde{\mathbf{h}}_{j+1}\|,$$

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Theorem

$$\mathbf{J}_N(\mathbf{d}\rho_N) = \begin{bmatrix} \alpha_0 & \gamma_1 & & & \mathbf{0} \\ \gamma_1 & \alpha_1 & \gamma_2 & & \\ & \ddots & \ddots & \ddots & \\ & & \gamma_{N-2} & \alpha_{N-2} & \gamma_{N-1} \\ \mathbf{0} & & & \gamma_{N-1} & \alpha_{N-1} \end{bmatrix}$$

Example

error bounds for linear algebraic systems

$$\mathbf{Ax} = \mathbf{b}, \quad \mathbf{A} \text{ symmetric, positive definite}$$

if $\mathbf{x}^* \approx \mathbf{x} := \mathbf{A}^{-1}\mathbf{b}$ and $\mathbf{r} = \mathbf{b} - \mathbf{Ax}^*$ then

$$\|\mathbf{x} - \mathbf{x}^*\|^2 = \mathbf{r}^T \mathbf{A}^{-2} \mathbf{r}$$

hence

$$\|\mathbf{x} - \mathbf{x}^*\|^2 = \|\mathbf{r}\|^2 \cdot \mathbf{u}^T f(\mathbf{A}) \mathbf{u}$$

where $\mathbf{u} = \mathbf{r}/\|\mathbf{r}\|$, $f(t) = t^{-2}$

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derivatives of f

$$f^{(2n)}(t) > 0, \quad f^{(2n+1)}(t) < 0 \quad \text{for } t \in \mathbb{R}_+$$

Example (cont')

$$\|\mathbf{x} - \mathbf{x}^*\| = \|\mathbf{r}\|^2 \int_{\mathbb{R}_+} t^{-2} d\rho_N(t)$$

assume $\text{supp } d\rho_N \subseteq [a, b]$, $0 < a < b$

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- n -point Gauss applied to $\int_{\mathbb{R}_+} t^{-2} d\rho_N(t)$
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upper bounds for $\|\mathbf{x} - \mathbf{x}^*\|^2$

- left-handed $(n + 1)$ -point Gauss-Radau
- $(n + 2)$ -point Gauss-Lobatto

Part II

Approximation

Least squares approximation

classical least squares problem: given N data points (t_k, f_k) , $k = 1, 2, \dots, N$, and the discrete measure $d\lambda_N(t) = \sum_{k=1}^N w_k \delta(t - t_k)$, find $\hat{p}_n \in \mathbb{P}_n$, $n < N$, such that

$$\|\hat{p}_n - f\|_{d\lambda_N}^2 \leq \|p - f\|_{d\lambda_N}^2, \quad \text{all } p \in \mathbb{P}_n$$

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solution

$$\hat{p}_n(t) = \sum_{i=0}^n \hat{c}_i(f) \pi_i(t; d\lambda_N), \quad \hat{c}_i(f) = \frac{(f, \pi_i)_{d\lambda_N}}{\|\pi_i\|_{d\lambda_N}^2}$$

π_i not necessarily monic: $\pi_i(t) = d_i t^i + \dots$

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Matlab

```
[phat, c]=least_squares(n, f, xw, ab, d)
```

Demo #5

L_2 error vs L_∞ error for **equally weighted** least squares approximation on **equally spaced** points on $[-1, 1]$

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```
N=10; k=(1:N)'; d=ones(1,N);  
xw(k,1)=-1+2*(k-1)/(N-1); xw(:,2)=2/N;  
ab=r_hahn(N-1); ab(:,1)=-1+2*ab(:,1)/(N-1);  
ab(:,2)=(2/(N-1))^2*ab(:,2); ab(1,2)=2;  
[phat,c]=least_squares(N-1,f,xw,ab,d);
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[phat,c]=least_squares(N-1,f,xw,ab,d);
```

Example $f(t) = \ln(2 - t), -1 \leq t \leq 1; N=10$

n	\tilde{E}_n	E_n^∞
0	4.88(-01)	6.37(-01)
3	2.96(-03)	3.49(-03)
6	2.07(-05)	7.06(-05)
9	1.74(-16)	3.44(-06)

Constrained least squares approximation constraints

$$p(\mathbf{s}_j) = f_j, \quad j = 1, 2, \dots, m; \quad m \leq n$$

interpolation and constraint polynomials

$$p_m(t) = p_m(f; \mathbf{s}_1, \dots, \mathbf{s}_m; t), \quad \sigma_m(t) = \prod_{j=1}^m (t - \mathbf{s}_j)$$

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reduction to **unconstrained** least squares

$$\hat{p}_n(t) = p_m(f; \mathbf{s}_1, \dots, \mathbf{s}_m; t) + \sigma_m(t) \hat{q}_{n-m}(t)$$

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where

$$\|f^* - \hat{q}_{n-m}\|_{d\lambda_N^*}^2 \leq \|f^* - q\|_{d\lambda_N^*}, \quad \text{all } q \in \mathbb{P}_{n-m}$$
$$f^*(t) = [\mathbf{s}_1, \dots, \mathbf{s}_m, t]f, \quad d\lambda_N^*(t) = \sigma_m^2(t) d\lambda_N(t)$$

modification algorithm

Demo #6

Example Bessel function $J_0(t)$ for $0 \leq t \leq j_{0,3}$
constraints ($m=3$)

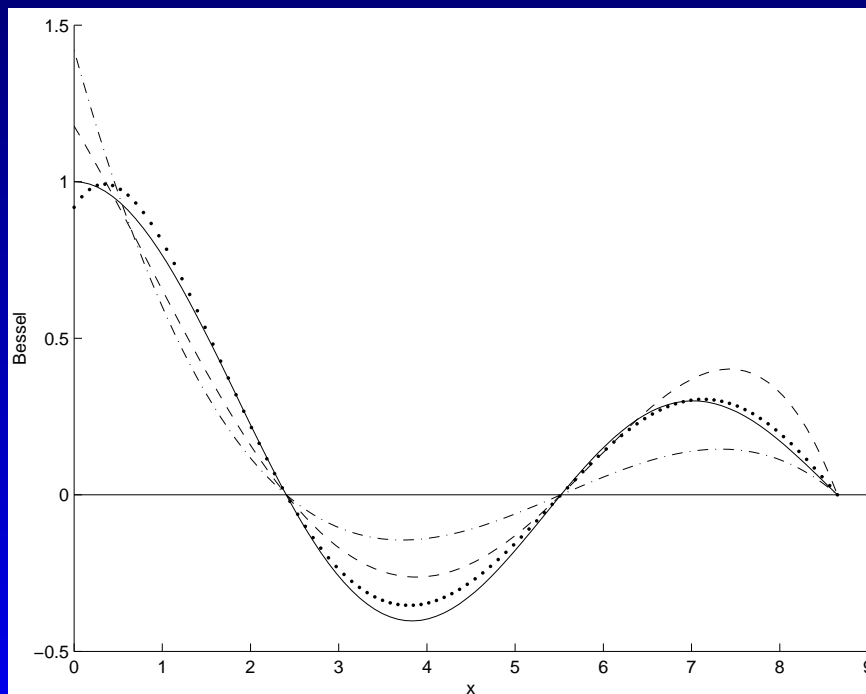
$$s_1 = j_{0,1}, \quad s_2 = j_{0,2}, \quad s_3 = j_{0,3}; \quad p(s_j) = 0, \quad 1 \leq j \leq 3$$

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constrained least squares $n = 3, 4, 5$



Demo #7

Example (cont')

additional constraints (m=5)

$$p(0) = 1, \quad p'(0) = 0$$

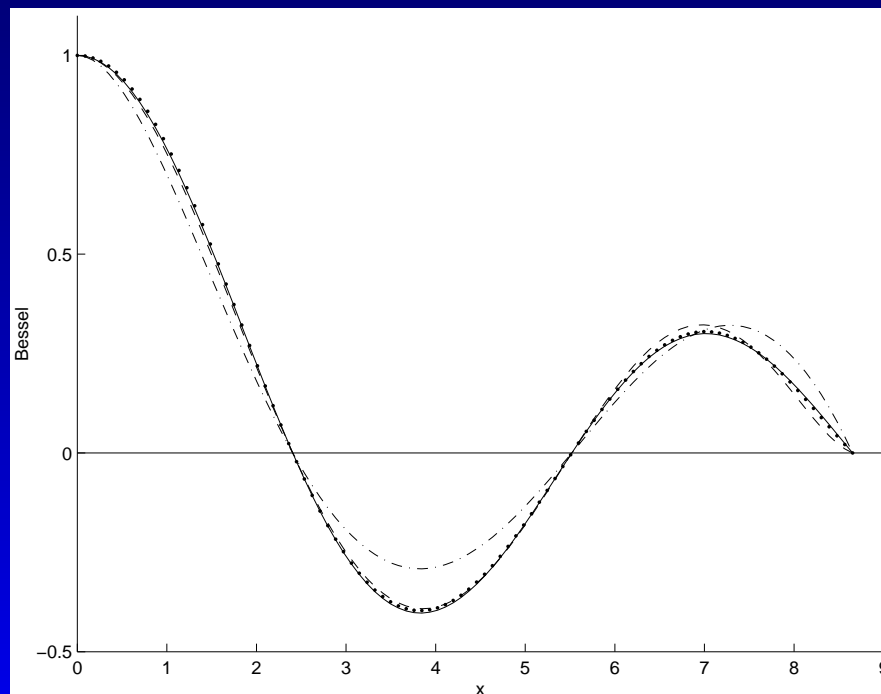
Demo #7

Example (cont')

additional constraints (m=5)

$$p(0) = 1, \quad p'(0) = 0$$

derivative-constrained least squares $n = 5, 6, 7$



L_2 approximation in Sobolev spaces

Problem

$$\text{minimize : } \sum_{\sigma=0}^s \sum_{k=1}^N w_k^{(\sigma)} [p^{(\sigma)}(t_k) - f_k^{(\sigma)}]^2, \quad p \in \mathbb{P}_n$$

Sobolev inner product and norm

$$(u, v)_S = \sum_{\sigma=0}^s \sum_{k=1}^N w_k^{(\sigma)} u^{(\sigma)}(t_k) v^{(\sigma)}(t_k), \quad \|u\|_S = \sqrt{(u, u)_S}$$

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$\pi_i \dots$ Sobolev orthogonal polynomials

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Matlab

`[phat, c]=least_squares_sob(n, f, xw, B)`

Demo #8

Example $f(t) = e^{t^2} \operatorname{erfc} t = \frac{2}{\sqrt{\pi}} e^{t^2} \int_t^\infty e^{-u^2} du, \quad 0 \leq t \leq 2$

$$N = 5, \quad t_k = 2\frac{k-1}{N-1}, \quad w_k^{(\sigma)} = \frac{1}{N}, \quad k = 1, 2, \dots, N$$

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s	τ_1	\hat{E}_n	$E_{n,0}^\infty$	$E_{n,1}^\infty$	$E_{n,2}^\infty$
2	0	1.153(+00)	4.759(-01)	1.128(+00)	2.000(+00)
	2	7.356(-01)	8.812(-02)	2.860(-01)	1.411(+00)
	4	1.196(-01)	1.810(-02)	5.434(-02)	1.960(-01)
	9	2.178(-05)	4.710(-06)	3.011(-05)	3.159(-04)
	14	3.653(-16)	1.130(-09)	1.111(-08)	1.966(-07)
0	0	2.674(-01)	4.759(-01)	1.128(+00)	2.000(+00)
	2	2.245(-02)	3.865(-02)	3.612(-01)	1.590(+00)
	4	1.053(-16)	3.516(-03)	5.160(-02)	4.956(-01)
	9	1.053(-16)	5.409(-03)	8.124(-02)	7.959(-01)
	14	1.053(-16)	5.478(-03)	8.226(-02)	8.057(-01)

Moment-preserving spline approximation

splines of degree 0 (piecewise constant) on \mathbb{R}_+

$$s_n(t) = \sum_{\nu=1}^n a_\nu H(t_\nu - t), \quad t \in \mathbb{R}_+$$

where $a_\nu \in \mathbb{R}$, $0 < t_1 < t_2 < \dots < t_n$, and

$$H(u) = \begin{cases} 1 & \text{if } u \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

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Problem Given $f \in C^1(\mathbb{R}_+)$, determine $a_\nu \in \mathbb{R}$ and $0 < t_1 < t_2 < \dots < t_n$ such that

$$\int_0^\infty s_n(t) t^j dt = \mu_j, \quad j = 0, 1, \dots, 2n - 1,$$

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Solution Gauss quadrature relative to the measure

$$d\lambda(t) := -t f'(t) dt \quad \text{on } \mathbb{R}_+$$

Theorem (G., 1984)

If the first $2n$ moments μ_j , $j = 0, 1, \dots, 2n - 1$, exist and $f(t) = o(t^{-2n})$ as $t \rightarrow \infty$, then the problem has a unique solution if and only if the measure $d\lambda(t) = -tf'(t)dt$ admits a Gaussian quadrature formula

$$\int_0^\infty g(t) d\lambda(t) = \sum_{\nu=1}^n \lambda_\nu^G g(\tau_\nu^G), \quad g \in \mathbb{P}_{2n-1},$$

satisfying $0 < \tau_1^G < \tau_2^G < \dots < \tau_n^G$. If so, then

$$t_\nu = \tau_\nu^G, \quad a_\nu = \frac{\lambda_\nu^G}{\tau_\nu^G}, \quad \nu = 1, 2, \dots, n. \quad \square$$

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Remark If $f' < 0$ on \mathbb{R}_+ , then $d\lambda(t) \geq 0$.

Proof Integration by parts

$$\int_0^T f(t)t^j dt = \frac{1}{j+1} t^{j+1} f(t) \Big|_0^T - \frac{1}{j+1} \int_0^T f'(t)t^{j+1} dt$$

letting $T \rightarrow \infty$ and recalling $-t f'(t) dt =: d\lambda(t)$

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on the other hand

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moment matching

$$\sum_{\nu=1}^n (a_\nu t_\nu) t_\nu^j = \int_0^\infty t^j d\lambda(t), \quad j = 0, 1, \dots, 2n - 1$$



Example Maxwell distribution (Calder & Laframboise, 1986)

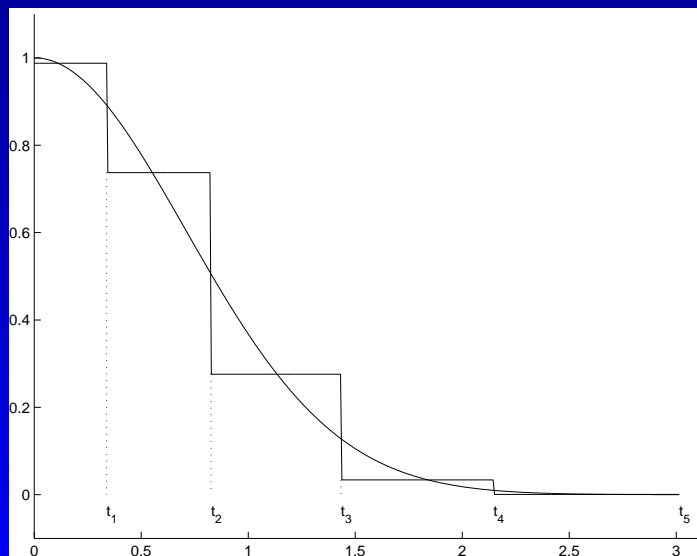
$$f(t) = e^{-t^2}, \quad d\lambda(t) = 2t^2 e^{-t^2} dt \text{ on } \mathbb{R}_+$$

The recurrence coefficients $\alpha_k(d\lambda)$, $\beta_k(d\lambda)$, $k \leq n - 1$, and hence the Gauss quadrature rule for $d\lambda$, can be obtained by twice modifying the **half-range Hermite measure** by a linear factor t (two applications of `chr1`).

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spline function of degree $m > 0$

$$s_{n,m}(t) = \sum_{\nu=1}^n a_{\nu} (t_{\nu} - t)_{+}^m, \quad t \in \mathbb{R}_{+}$$

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$$u_{+} = uH(u) = \begin{cases} u & \text{if } u \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

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Solution Gauss quadrature relative to

$$d\lambda^{[m]}(t) = \frac{(-1)^{m+1}}{m!} t^{m+1} f^{(m+1)}(t) dt \quad \text{on } \mathbb{R}_{+}$$

Remark If f is completely monotonic on \mathbb{R}_{+} , then $d\lambda^{[m]} \geq 0$

Example Maxwell distribution

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existence and accuracy of spline approximant

n	$m = 1$	$m = 2$	$m = 3$	n	$m = 1$	$m = 2$	$m = 3$
1	6.9(-2)	1.8(-1)	2.6(-1)	11	—	1.1(-3)	1.1(-4)
2	8.2(-2)	—	2.3(-1)	12	—	—	*
3	—	1.1(-2)	2.5(-3)	13	7.8(-3)	6.7(-4)	*
4	3.5(-2)	6.7(-3)	2.2(-3)	14	8.3(-3)	5.6(-4)	8.1(-5)
5	2.6(-2)	—	1.6(-3)	15	7.7(-3)	—	7.1(-5)
6	2.2(-2)	3.1(-3)	*	16	—	4.9(-4)	7.8(-5)
7	—	2.4(-3)	*	17	—	3.8(-4)	3.8(-5)
8	1.4(-2)	—	3.4(-4)	18	5.5(-3)	3.8(-4)	*
9	1.1(-2)	1.7(-3)	2.5(-4)	19	5.3(-3)	—	*
10	9.0(-3)	1.1(-3)	—	20	5.4(-3)	3.1(-4)	*

approximation on the interval $[0, 1]$

spline function of degree $m \geq 0$

$$s_{n,m}(t) = p(t) + \sum_{\nu=1}^n a_{\nu} (t_{\nu} - t)_{+}^m, \quad p \in \mathbb{P}_m, \quad 0 \leq t \leq 1$$

where $a_{\nu} \in \mathbb{R}$, $0 < t_1 < t_2 < \cdots < t_n < 1$

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Problem I Find $s_{n,m}$ such that

$$\int_0^1 s_{n,m}(t) t^j dt = \mu_j, \quad j = 0, 1, \dots, 2n + m$$

approximation on the interval $[0, 1]$

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Problem II Find $s_{n,m}$ such that

$$\int_0^1 s_{n,m}(t) t^j dt = \mu_j, \quad j = 0, 1, \dots, 2n - 1$$

and

$$s_{n,m}^{(\mu)}(1) = f^{(\mu)}(1), \quad \mu = 0, 1, \dots, m$$

Solution of Problem I (Frontini, G., and Milovanović, 1987)
generalized Gauss-Lobatto quadrature

$$d\lambda^{[m]}(t) = \frac{(-1)^{m+1}}{m!} f^{(m+1)}(t)dt \quad \text{on } [0, 1]$$

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 generalized Gauss-Lobatto quadrature

$$d\lambda^{[m]}(t) = \frac{(-1)^{m+1}}{m!} f^{(m+1)}(t) dt \quad \text{on } [0, 1]$$

$$\int_0^1 g(t) d\lambda^{[m]}(t) = \sum_{\mu=0}^m [\lambda_0^{(\mu)} g^{(\mu)}(0) + (-1)^\mu \lambda_{n+1}^{(\mu)} g^{(\mu)}(1)] \\ + \sum_{\nu=1}^n \lambda_\nu^L g(\tau_\nu^L), \quad g \in \mathbb{P}_{2n+2m+1}$$

if this exists with $0 < \tau_1^L < \dots < \tau_n^L < 1$, then

$$t_\nu = \tau_\nu^L, \quad a_\nu = \lambda_\nu^L, \quad \nu = 1, 2, \dots, n$$

and p is uniquely determined by

$$p^{(\mu)}(1) = f^{(\mu)}(1) + (-1)^\mu m! \lambda_{n+1}^{(m-\mu)}, \quad \mu = 0, 1, \dots, m$$

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complete monotonicity of f implies $d\lambda \geq 0$

Solution of Problem II (Frontini, G., and Milovanović, 1987)
generalized Gauss-Radau quadrature

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Solution of Problem II (Frontini, G., and Milovanović, 1987)
generalized Gauss-Radau quadrature

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$$\int_0^1 g(t) d\lambda^{[m]}(t) = \sum_{\mu=0}^m \lambda_0^{(\mu)} g^{(\mu)}(0) + \sum_{\nu=1}^n \lambda_{\nu}^R g(\tau_{\nu}^R), \quad g \in \mathbb{P}_{2n}$$

if this exists with $0 < \tau_1^R < \dots < \tau_n^R < 1$, then

$$t_{\nu} = \tau_{\nu}^R, \quad a_{\nu} = \lambda_{\nu}^R, \quad \nu = 1, 2, \dots, n$$

and (trivially)

$$p(t) = \sum_{\mu=0}^m \frac{f^{(\mu)}(1)}{\mu!} (t-1)^{\mu}$$

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Slowly convergent series

series generated by a **Laplace transform**

$$S = \sum_{k=1}^{\infty} a_k, \quad a_k = (\mathcal{L} f)(k), \quad k = 1, 2, 3, \dots$$

where

$$(\mathcal{L} f)(s) = \int_0^{\infty} e^{-st} f(t) dt$$

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reduction to a **quadrature** problem

$$\begin{aligned} S &= \sum_{k=1}^{\infty} \int_0^{\infty} e^{-kt} f(t) dt \\ &= \int_0^{\infty} \sum_{k=1}^{\infty} e^{-(k-1)t} \cdot e^{-t} f(t) dt \\ &= \int_0^{\infty} \frac{1}{1-e^{-t}} e^{-t} f(t) dt \\ &= \int_0^{\infty} \frac{t}{1-e^{-t}} \frac{f(t)}{t} e^{-t} dt \end{aligned}$$

$$S = \int_0^{\infty} \frac{t}{1-e^{-t}} \frac{f(t)}{t} e^{-t} dt$$

quadrature methods

- Gauss-Laguerre $d\lambda(t) = e^{-t} dt$ on \mathbb{R}_+
- rational/polynomial Gauss-Laguerre
- Gauss-Einstein $d\lambda(t) = \frac{t}{e^t-1} dt$

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Example Theodorus constant (P.J. Davis, 1993)

$$S = \sum_{k=1}^{\infty} \frac{1}{k^{3/2} + k^{1/2}} = 1.860025 \dots$$

here

$$\frac{1}{s^{3/2} + s^{1/2}} = s^{-1/2} \frac{1}{s+1} = \left(\mathcal{L} \frac{1}{\sqrt{\pi t}} * e^{-t} \right) (s)$$

\uparrow
 convolution

$$f(t) = \frac{2}{\sqrt{\pi}} F(\sqrt{t}), \quad F(x) := e^{-x^2} \int_0^x e^{t^2} dt$$

Demo #9 Theodorus constant

$$\begin{aligned} S &= \frac{2}{\sqrt{\pi}} \int_0^{\infty} \frac{t}{1 - e^{-t}} \frac{F(\sqrt{t})}{\sqrt{t}} t^{-1/2} e^{-t} dt \\ &= \frac{2}{\sqrt{\pi}} \int_0^{\infty} \frac{F(\sqrt{t})}{\sqrt{t}} t^{-1/2} \frac{t}{e^t - 1} dt \end{aligned}$$

Demo #9 Theodorus constant

$$S = \frac{2}{\sqrt{\pi}} \int_0^{\infty} \frac{t}{1 - e^{-t}} \frac{F(\sqrt{t})}{\sqrt{t}} t^{-1/2} e^{-t} dt$$

$$= \frac{2}{\sqrt{\pi}} \int_0^{\infty} \frac{F(\sqrt{t})}{\sqrt{t}} t^{-1/2} \frac{t}{e^t - 1} dt$$

n	Gauss-Laguerre	rational Gauss-Laguerre	Gauss-Einstein
1	9.6799(-03)	1.5635(-02)	1.3610(-01)
4	5.5952(-06)	1.1893(-08)	2.1735(-04)
7	4.0004(-08)	5.9689(-16)	3.3459(-07)
10	5.9256(-10)		5.0254(-10)
15	8.2683(-12)		9.4308(-15)
20	8.9175(-14)		4.7751(-16)
	timing: 10.8	timing: 8.78	timing: 10.4

Example Hardy-Littlewood function

$$H(x) = \sum_{k=1}^{\infty} \frac{1}{k} \sin \frac{x}{k}, \quad x > 0$$

inverse Laplace transform of $\frac{1}{s} \sin \frac{x}{s}$

$$f(t; x) = \frac{1}{2i} [I_0(2\sqrt{ixt}) - I_0(2\sqrt{-ixt})]$$

integral representation for H

$$H(x) = \int_0^{\infty} \frac{t}{1-e^{-t}} \frac{f(t;x)}{t} e^{-t} dt = \int_0^{\infty} \frac{f(t;x)}{t} \frac{t}{e^t-1} dt$$

Example Hardy-Littlewood function

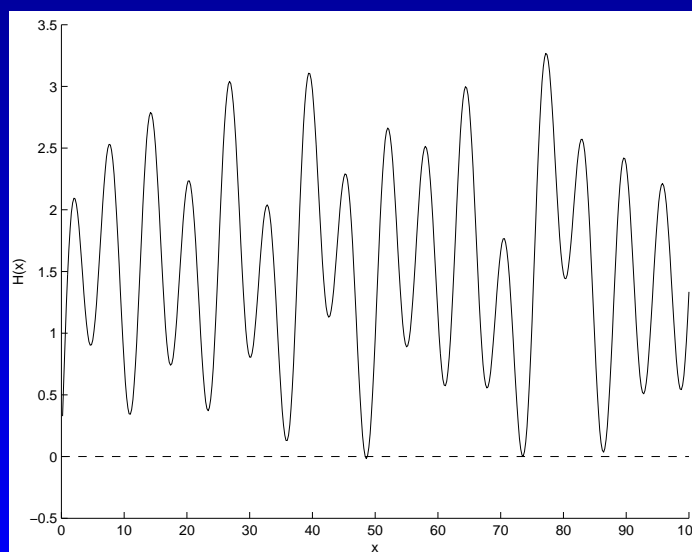
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“alternating” series generated by a **Laplace transform**

$$S = \sum_{k=1}^{\infty} a_k, \quad a_k = (-1)^{k-1} (\mathcal{L} f)(k), \quad k = 1, 2, 3, \dots$$

$$S = \int_0^{\infty} \frac{1}{1+e^{-t}} f(t) e^{-t} dt = \int_0^{\infty} f(t) \frac{1}{e^t+1} dt$$

Gauss-Laguerre, rat/pol Gauss-Laguerre, or Gauss-Fermi

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Gauss-Laguerre, rat/pol Gauss-Laguerre, or Gauss-Fermi

Example $\sum_{k=1}^{\infty} (-1)^{k-1} k^{-1} e^{-1/k}, f(t) = J_0(2\sqrt{t})$

n	Gauss-Laguerre	rational Gauss-Laguerre	Gauss-Fermi
1	1.6961(-01)	1.0310(-01)	5.6994(-01)
4	4.4754(-03)	4.6605(-05)	9.6454(-07)
7	1.7468(-04)	1.8274(-09)	9.1529(-15)
10	3.7891(-06)	1.5729(-13)	2.8163(-16)
15	2.6569(-07)	1.5490(-15)	
20	8.6155(-09)		
40	1.8066(-13)		
	timing: 12.7	timing: 19.5	timing: 4.95

series generated by the **derivative** of a **Laplace transform**

$$S = \sum_{k=1}^{\infty} a_k, \quad a_k = -\frac{d}{ds}(\mathcal{L}f)(s) \Big|_{s=k}, \quad k = 1, 2, 3, \dots$$

$$S = \int_0^{\infty} \frac{t}{1-e^{-t}} f(t) e^{-t} dt = \int_0^{\infty} f(t) \frac{t}{e^t-1} dt$$

Gauss-Laguerre, rat/pol Gauss-Laguerre, or Gauss-Einstein

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Gauss-Laguerre, rat/pol Gauss-Laguerre, or Gauss-Einstein

Example $\sum_{k=1}^{\infty} \left(\frac{3}{2} + 1\right) k^{-2} (k+1)^{-3/2}, f(t) = \frac{\operatorname{erf}\sqrt{t}}{\sqrt{t}} \cdot t^{1/2}$

n	Gauss-Laguerre	rational Gauss-Laguerre	Gauss-Einstein
1	4.0125(-03)	5.1071(-02)	8.1715(-02)
4	1.5108(-05)	4.5309(-08)	1.6872(-04)
7	4.6576(-08)	1.3226(-13)	3.1571(-07)
10	3.0433(-09)	1.2087(-15)	5.4661(-10)
15	4.3126(-11)		1.2605(-14)
20	7.6664(-14)		
30	3.4533(-16)		
	timing: 6.50	timing: 10.8	timing: 1.58

Slowly convergent series occurring in plate contact problems

$$R_p(z) = \sum_{k=0}^{\infty} \frac{z^{2k+1}}{(2k+1)^p}, \quad z \in \mathbb{C}, |z| \leq 1, p = 2 \text{ or } 3$$

Slowly convergent series occurring in plate contact problems

$$R_p(z) = \sum_{k=0}^{\infty} \frac{z^{2k+1}}{(2k+1)^p}, \quad z \in \mathbb{C}, |z| \leq 1, p = 2 \text{ or } 3$$

let

$$\frac{1}{(k+\frac{1}{2})^p} = (\mathcal{L}f)(k), \quad f(t) = \frac{1}{(p-1)!} t^{p-1} e^{-t/2}$$

then

$$\begin{aligned} R_p(z) &= \frac{z}{2^p} \sum_{k=0}^{\infty} \frac{z^{2k}}{(k+\frac{1}{2})^p} \\ &= \frac{z}{2^p} \sum_{k=0}^{\infty} z^{2k} \int_0^{\infty} e^{-kt} \cdot \frac{t^{p-1} e^{-t/2}}{(p-1)!} dt \\ &= \frac{z}{2^p (p-1)!} \int_0^{\infty} \sum_{k=0}^{\infty} (z^2 e^{-t})^k \cdot t^{p-1} e^{-t/2} dt \\ &= \frac{z}{2^p (p-1)!} \int_0^{\infty} \frac{1}{1 - z^2 e^{-t}} t^{p-1} e^{-t/2} dt \end{aligned}$$

$$R_p(z) = \frac{z}{2^p(p-1)!} \int_0^\infty \frac{t^{p-1} e^{t/2}}{e^t - z^2} dt, \quad z^{-2} \in \mathbb{C} \setminus [0, 1]$$

change of variables $e^{-t} \mapsto t$

$$R_p(z) = \frac{1}{2^p(p-1)!z} \int_0^1 \frac{t^{-1/2} [\ln(1/t)]^{p-1}}{z^{-2} - t} dt$$

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$$R_p(z) = \frac{1}{2^p(p-1)!z} \int_0^1 \frac{t^{-1/2} [\ln(1/t)]^{p-1}}{z^{-2} - t} dt$$

Cauchy integral of $d\lambda^{[p]}(t) = t^{-1/2} [\ln(1/t)]^{p-1} dt$

continued fraction algorithm in combination with modified Chebyshev algorithm to generate recurrence coefficients of $d\lambda^{[p]}$

Example

$R_p(x)$, $p = 2$ and 3 , $x = .8, .9, .95, .99, .999$ and 1.0

r	$R_2(r)$	$R_3(r)$
.8	0.87728809392147	0.82248858052014
.9	1.02593895111111	0.93414857586540
.95	1.11409957792905	0.99191543992243
.99	1.20207566477686	1.03957223187364
.999	1.22939819733	1.05056774973
1.000	1.233625	1.051795

for $x \geq .999$ full accuracy cannot be achieved with $\text{numax}=100$ recurrence coefficients

Example

$R_p(e^{i\alpha})$, $p = 2$ and 3 , $\alpha = \omega\pi/2$,
 $\omega = .2, .1, .05, .01, .001$ and 0.0

p	ω	$\text{Re}(R_p(z))$	$\text{Im}(R_p(z))$
2	.2	0.98696044010894	0.41740227008596
3		0.96915102126252	0.34882061265337
2	0.1	1.11033049512255	0.27830297928558
3		1.02685555765937	0.18409976778928
2	0.05	1.17201552262936	0.16639152396897
3		1.04449411539672	0.09447224926029
2	0.01	1.22136354463481	0.04592009281744
3		1.05140829197388	0.01928202831056
2	0.001	1.232466849	0.006400460
3		1.051794454	0.001936923
2	0.000	1.2336	0.0000
3		1.0518	0.0000

Series involving ratios of hyperbolic cosines

$$T_p(x; b) = \sum_{k=0}^{\infty} \frac{1}{(2k+1)^p} \frac{\cosh(2k+1)x}{\cosh(2k+1)b}, \quad 0 \leq x \leq b, \quad b > 0, \quad p = 2, 3$$

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same **Laplace transform** technique, but after expanding

$$\begin{aligned} & \frac{\cosh(2k+1)x}{\cosh(2k+1)b} \\ &= \sum_{n=0}^{\infty} (-1)^n \left\{ e^{-(2k+1)[(2n+1)b-x]} + e^{-(2k+1)[(2n+1)b+x]} \right\} \end{aligned}$$

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result

$$T_p(x, b) = \frac{1}{2^p (p-1)!} \sum_{n=0}^{\infty} (-1)^n e^{(2n+1)b} [\varphi_n(-x) + \varphi_n(x)]$$

where

$$\varphi_n(s) = e^s \int_0^1 \frac{d\lambda^{[p]}(t)}{e^{2[(2n+1)b+s]t}}, \quad -b \leq s \leq b,$$

continued fraction algorithm for $d\lambda^{[p]}$