

# Leja interpolation for matrix functions

Peter Kandolf

Innovative Time Integrators

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# Aim

## Problem

Exponential integrator schemes require the evaluation or approximation of a matrix function acting on vectors. We denote this action by

$$\phi(A)v, \quad A \in \mathbb{R}^{d \times d}, \quad v \in \mathbb{R}^d,$$

for some analytic function  $\phi$ .

## Ansatz

Polynomial interpolation with Leja points.

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- 1 Polynomial interpolation with Newton's scheme
- 2 Introduction to Leja points
- 3 Extension to the matrix case
- 4 Computation
- 5 Future work

# Newton interpolation

## Ansatz

Let  $f$  be a function, analytic in an open set  $K \subset \mathbb{C}$  and  $\{\xi_i\}_{i=0}^n$  points in  $K$ . The Newton interpolation uses the ansatz

$$p(x) = a_0 + a_1(x - \xi_0) + a_2(x - \xi_0)(x - \xi_1) + \dots \\ \dots + a_n(x - \xi_0) \cdots (x - \xi_n).$$

## Divided differences

We define the divided differences  $f[\xi_j, \dots, \xi_k]$  of  $f$  at the points  $\{\xi_i\}_{i=0}^n$  as

$$f[\xi_j, \dots, \xi_k] := \frac{f[\xi_{j+1}, \dots, \xi_k] - f[\xi_j, \dots, \xi_{k-1}]}{\xi_k - \xi_j}, \quad f[\xi_i] = f(\xi_i).$$

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# Newton interpolation 2

## Rewritten

With the divided differences the scheme can be written in a more stable and compact form (reduction of round-off errors)

$$p_n(x) = f[\xi_0] + \sum_{j=1}^n f[\xi_0, \dots, \xi_j] \prod_{k=0}^{j-1} (x - \xi_k).$$

## Remark

- *It is easy to compute  $p_{n+1}$  from  $p_n$ .*
- *Optimally conditioned interpolation for Chebyshev points.*

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# Definition of Leja points

## Aim

Define a sequence of points with same convergence properties as Chebyshev points, but computational advantages

## Definition (Leja points)

Let  $K \subset \mathbb{C}$  be a compact set then the sequence of Leja points  $\{\xi_i\}_{i=0}^{\infty}$  for  $K$  is defined recursively as:

- $\xi_0$  can be chosen arbitrary, normally  $|\xi_0| = \max_{z \in K} |z|$
- $\xi_m$  is then defined as

$$\xi_m \in \arg \max_{z \in K} \prod_{i=0}^{m-1} |z - \xi_i|, \quad m > 0.$$

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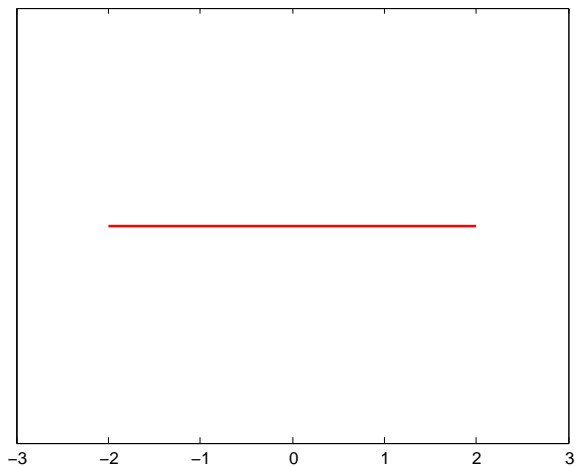
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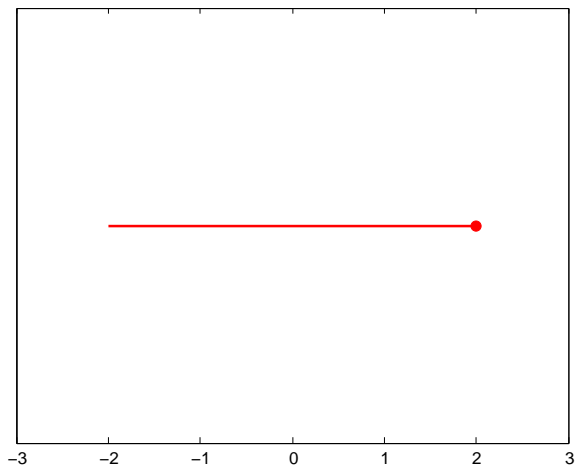
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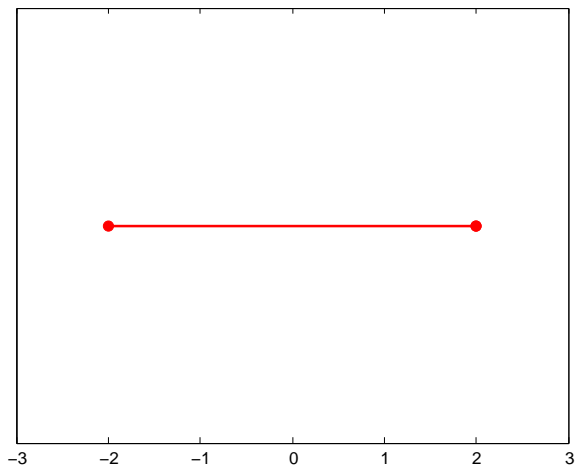


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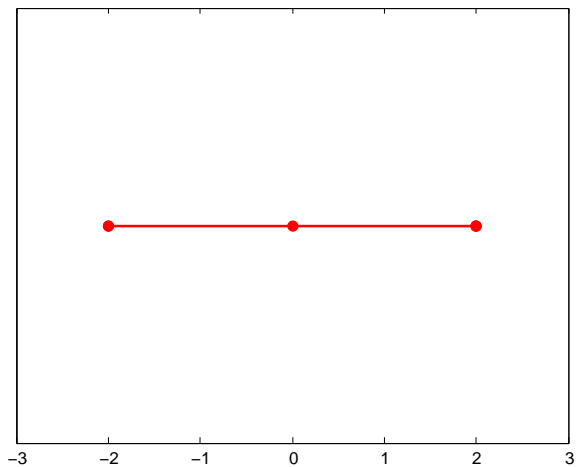




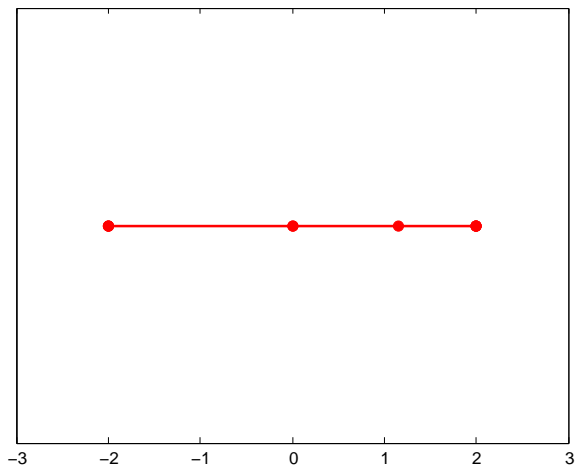
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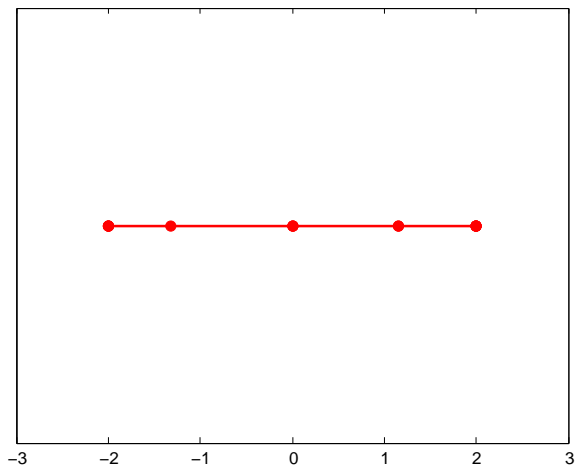
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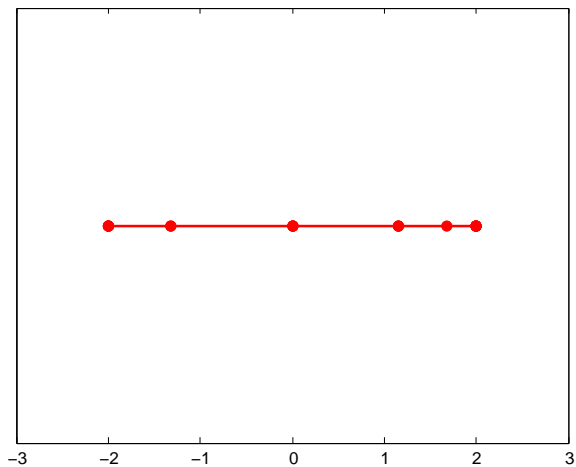
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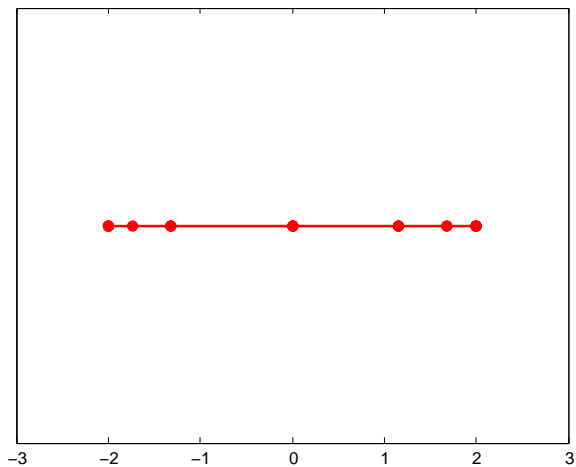
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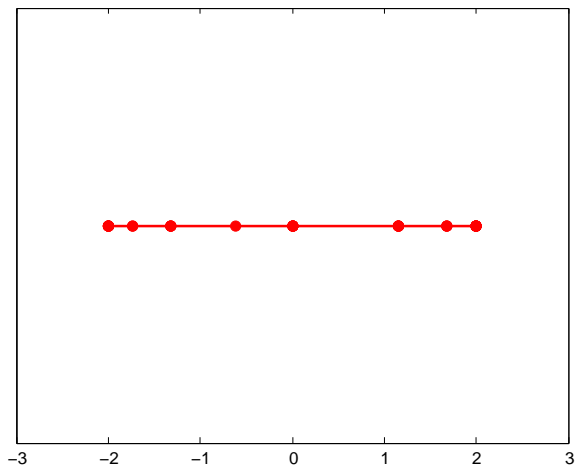
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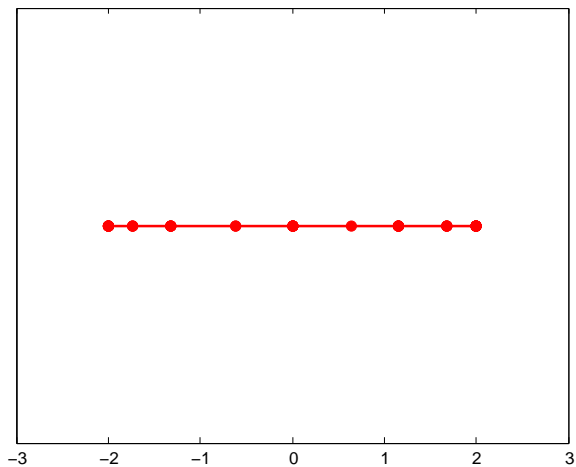
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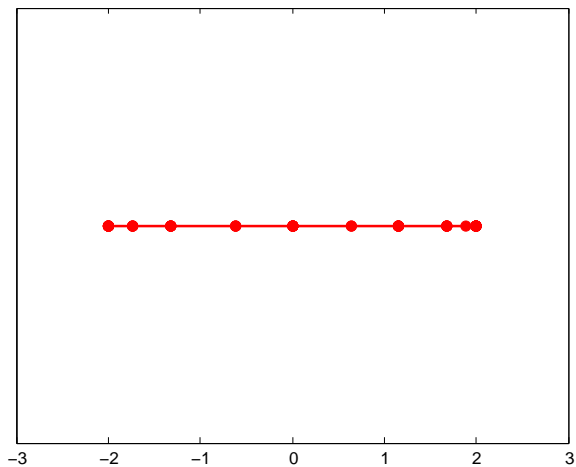


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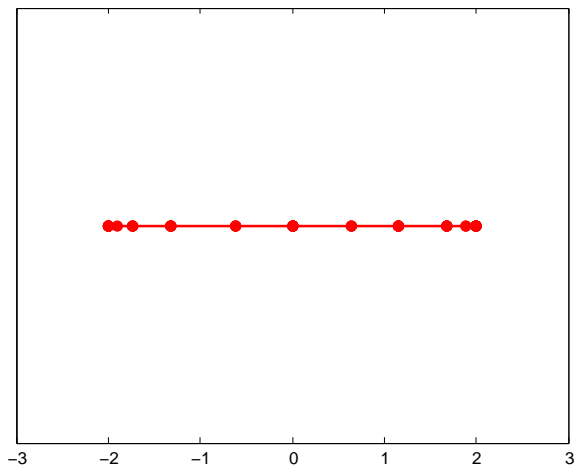




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## Computation of Leja points

- For  $K \subset \mathbb{C}$  compact,  $\{\xi_j\} \in \partial K$ .
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# Convergence and stability

## Convergence

For entire functions super-linear convergence can be shown.

## Stability

Let  $T : \mathbb{C}^{m+1} \rightarrow \mathbb{P}_m$  map a sequence of points  $\{\xi_i\}$  to the interpolation polynomial in Newton form.

- $\text{cond}(T)$  grows exponentially for arbitrary points.
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Nodes	equidistant	rand. chosen	Chebyshev	Leja
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# Convergence for matrix functions

## Preliminaries

- Let  $f$  be analytic in  $K = B(0, R_{max}) \subset \mathbb{C}$
- Let  $\{p_m\} \in \mathbb{P}_m$  be the polynomial interpolation to  $f$  in the Leja points of  $K$

The sequence  $\{p_m\}$  converges asymptotically like the best uniform approximation polynomial to  $f$  in  $K$ .



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Let  $A \in \mathbb{R}^{n \times n}$ ,  $v \in \mathbb{R}^n$  and  $\sigma(A) \subset B(0, R)$  for some  $0 < R < R_{max}$ . Then  $\{p_m(A)v\}$  converges to  $f(A)v$ .

## Corollary

For an entire functions  $f$  this means that

$$\limsup_{m \rightarrow \infty} \|f(A)v - p_m(A)v\|_2^{1/m} = 0$$

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# Computation of $\varphi$ -functions

## Problem

We want to compute  $\varphi_k(hA)v$  for the entire functions

$$\varphi_k(\tau z) = \tau^{-k} \int_0^\tau e^{(\tau-s)z} \frac{s^{k-1}}{(k-1)!} ds, \quad k \geq 1.$$

up to a specified tolerance.

# Algorithm

## Leja interpolation of $\varphi$ -functions

Input:  $A, v, h, tol, k$

Compute rough estimate of spectrum  $h\sigma(A)$ :

$$(-a, -ib), (0, -ib), (0, ib), (a, ib) \quad a, b \geq 0$$

If:  $a \geq b$  Newton interpolation on real Leja points in  $[-a, 0]$

$a < b$  Newton interpolation on conjugate pairs of Leja points in  $D = \{z \in D : \Re z = -a/2, \Im z \in [-b, b]\}$   
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Computation of divided differences  $d_i$  at shifted  $\varphi_k(h(c - \gamma\xi_i))$ .

Initialise:  $q_0 = v$ ,  $p_0(hA)v = d_0q_0$

while:  $\|e_m\| \leq tol$

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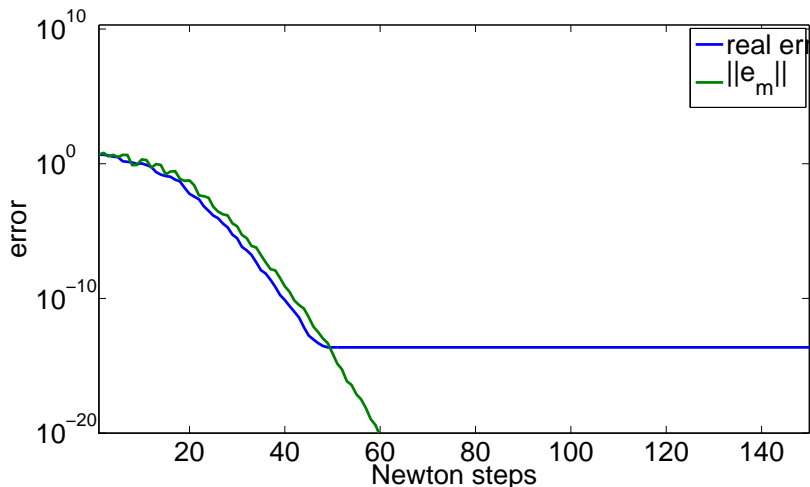
## Example (2D advection-diffusion)

*Computation of  $e^{hA}v$  with polynomial interpolation in Leja points for:*

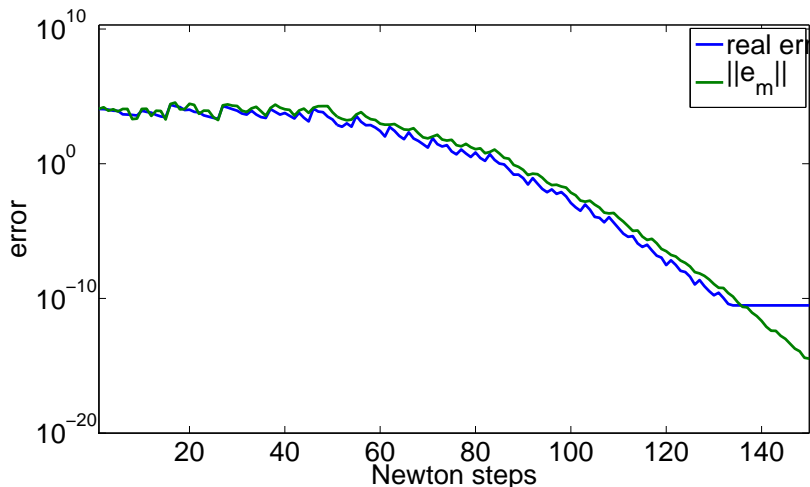
- *dimension of  $A$ :  $10.000 \times 10.000$ ,*
- *Peclet number 0.303,*
- *$v = [1, \dots, 1]^T$ ,*
- *$h = 5e-4$ ,*
- *tolerance  $1e-12$ .*



# Example - 2D advection-diffusion, $h = 5e-4$



# Example - 2D advection-diffusion, $h = 30e-4$



# Substepping

## Substeps

To overcome the hump problem we compute  $L$  substeps and recover  $\varphi_k(hA)v$  from  $\varphi_k(\tau hA)v$  with  $\tau = 1/L$ .

## Example

$y = v$

for  $j = 1 : L$

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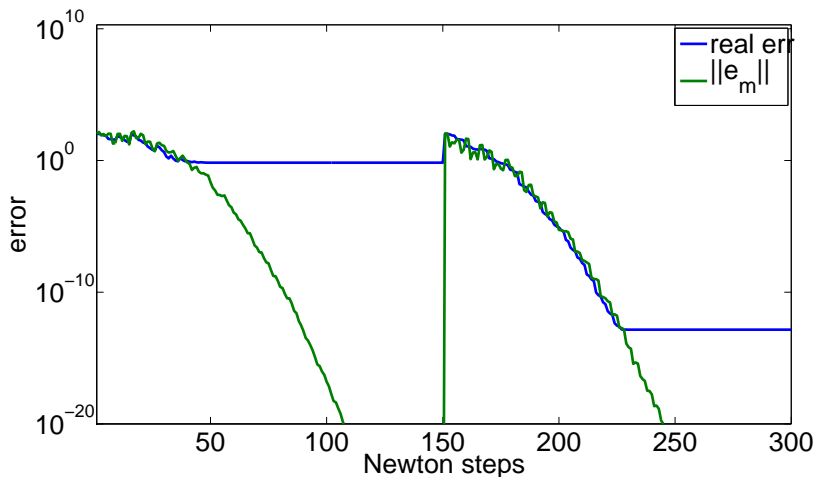
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- 3 Extension to the matrix case
- 4 Computation
- 5 Future work**

# Future work

## New error estimate

Develop a new error estimate that:

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- obtains the accurate number of substeps,
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### Parallelisation on GPU:

- primary matrix-vector multiplications
- multiply-accumulate functionality
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# Computation of divided differences

## Standard computation

$$f[\xi_j, \dots, \xi_k] := \frac{f[\xi_{j+1}, \dots, \xi_k] - f[\xi_j, \dots, \xi_{k-1}]}{\xi_k - \xi_j}, \quad f[\xi_i] = f(\xi_i).$$

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# Stable dd via matrix function [M. Caliari 2007]

## Matrix computation

Divided differences  $\{d_i\}$  of  $f(h(c + \gamma\xi_i))$  at  $\xi_i \in [-2, 2]$  are the first column of the matrix function  $f(H_m)$  for

$$H_m = h(cI_{m+1} + \gamma T_m), \quad T_m = \begin{bmatrix} \xi_0 & & & & & \\ 1 & \xi_2 & & & & \\ & 1 & \ddots & & & \\ & & \ddots & \ddots & & \\ & & & 1 & \xi_m & \\ & & & & & \end{bmatrix}.$$

# Stable dd via matrix function [M. Caliari 2007]

## Computation of $\varphi(H_m)$

- scale  $H_m$  by  $\tau = 1/L$  s.t.  $\max_i |\tau x_i| < 1.59$  for  $x_i = h(c + \gamma \xi_i)$ ,
- compute  $\varphi(\tau H_m)$  by Taylor expansion,
- recover, in  $L$  steps,  $\varphi(H_m)e_1$  via recurrence relation.

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Thank you for your attention. Enjoy the wine!



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