

# A symbolic-numeric validation algorithm for linear ODEs with Newton-Picard method

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Florent Bréhard<sup>1</sup>, Nicolas Brisebarre<sup>2</sup>, Mioara Joldes<sup>3</sup>

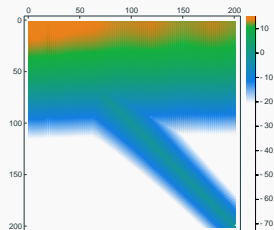
ACA 2023, Warsaw

July 20, 2023

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<sup>3</sup> LAAS-CNRS, Toulouse



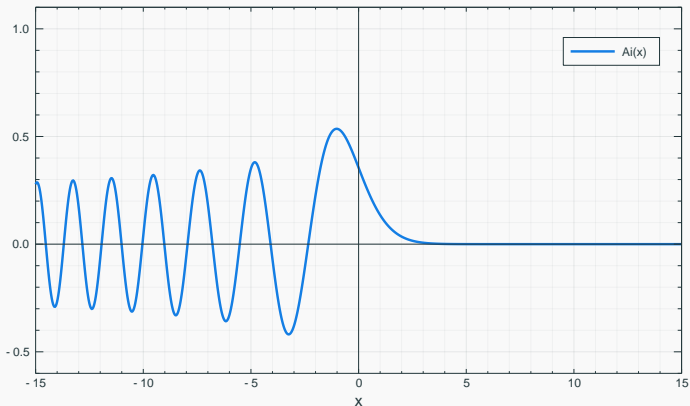
## Introduction

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# An Example: Airy Function

○  $\text{Ai}(x) = \frac{1}{\pi} \int_0^{+\infty} \cos\left(\frac{t^3}{3} + xt\right) dt$

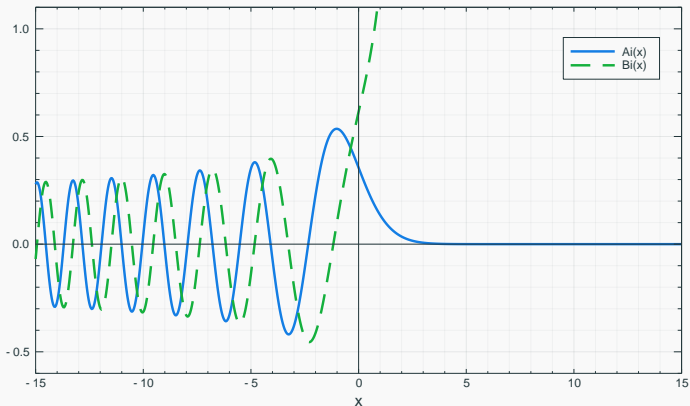
○ **Linear** Initial Value Problem:  $y''(x) - xy(x) = 0,$   $\begin{cases} y(0) = \frac{1}{3^{\frac{2}{3}} \Gamma(\frac{2}{3})} \\ y'(0) = -\frac{1}{3^{\frac{1}{3}} \Gamma(\frac{1}{3})} \end{cases}$



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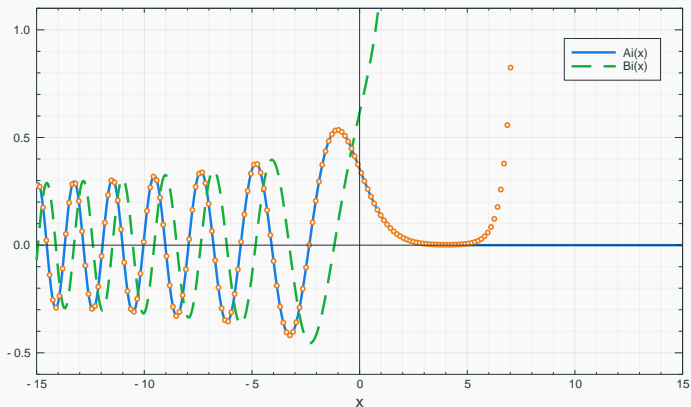
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- Higher order methods proposed in the literature:
  - *Makino & Berz (1998–), CAPD, VNODE-LP*: Taylor methods
  - *Ultra-arithmetic (1982–), Benoit & Joldes & Mezzarobba (2017), Dzetkulič (2015)* : Picard iterations
  - *Zgliczynski (2002), Wilczak & Zgliczynski (2011)*: Lohner methods
  - *Kedem (1981), Plum (1991)*: Resolvent kernel/Green function based methods
  - *Mezzarobba (2011)*: Majorant series (for D-finite functions)
  - *Yamamoto (1998), Lessard & Mireles James & van den Berg & al. (2014–), Bréhard & Brisebarre & Joldes (2018)*: Newton-like a posteriori validated spectral methods  
→ a.k.a. **Newton-Galerkin**

# A Brief Review of Functional Analytic Validation Methods for ODEs

- Higher order methods proposed in the literature:
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→ a.k.a. **Newton-Galerkin**
- Comparison of **Newton-Picard** and **Newton-Galerkin**:
  - **Newton-Galerkin**: truncate integral operators (Galerkin projections) to design Newton operators
  - **Newton-Picard**: inspired by Picard iterations to design Newton operators

# A Posteriori Validation Paradigm

○  $\mathbf{L}y = 0, \{y^{(i)}(0) = v_i\}_{i=0}^{r-1}$  linear IVP

Step 1 ○ Numerical approximation method: Spectral method

- *Polynomial approximations in Chebyshev basis*
- *Floating-point operations*

$\tilde{y}$

Step 2 ○ A posteriori validation: **Newton-Galerkin** vs **Newton-Picard**

- *Interval operations + RPAs*
- *Newton-like fixed-point operator*

$\varepsilon$

**Rigorous Polynomial Approximation (RPA) for  $y$**

= pair  $(\tilde{y}, \varepsilon)$  s.t.  $\|\tilde{y} - y\| \leq \varepsilon$



# **Chebyshev Approximations using Spectral Methods**

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## From Differential Equations to Integral Equations (1)

- $L\{y\} = y^{(r)} + a_{r-1}(x)y^{(r-1)} + \cdots + a_1(x)y' + a_0(x)y = h(x),$   
with initial conditions:  $y^{(i)}(0) = v_i$  for  $0 \leq i < r$ ,  $\deg a_i \leq s$

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- $f = y^{(r)} \Rightarrow y^{(i)}(x) = \int_0^x \int_0^{t_1} \dots \int_0^{t_{r-1-i}} f(t_{r-i}) dt_{r-i} \dots t_1 + \sum_{j=i}^{r-1} \frac{x^{j-i}}{(j-i)!} v_j$

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$\Rightarrow$  Integral equation  $f + K\{f\} = g$ ,  $K\{f\}(x) = \int_0^x \mathfrak{K}(x,t) f(t) dt$

$$\mathfrak{K}(x,t) = \sum_{i=0}^{r-1} a_i(x) \frac{(x-t)^{r-1-i}}{(r-1-i)!} \quad g(x) = h(x) - \sum_{i=0}^{r-1} a_i(x) \sum_{j=i}^{r-1} \frac{x^{j-i}}{(j-i)!} v_j$$

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### Example (Airy)

$$y'' - xy = 0 \quad \Rightarrow \quad f + \int_0^x (xt - x^2) f(t) dt = v_0 x + v_1 x^2 \quad f = Ai''$$

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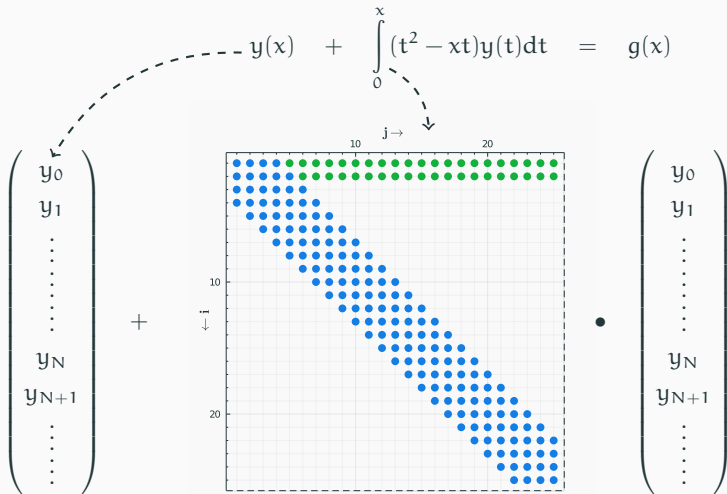
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# Spectral Method for Airy Function

$$\begin{pmatrix} y_0 \\ y_1 \\ \vdots \\ \vdots \\ y_N \\ y_{N+1} \\ \vdots \\ \vdots \end{pmatrix} + y(x) + \int_0^x (t^2 - xt)y(t)dt = g(x)$$

# Spectral Method for Airy Function



$\mathbf{K}$  : almost-banded, compact

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 $\vdots$   
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 $y_{N+1}$   
 $\vdots$

$y_0$   
 $y_1$   
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$\mathbf{K}^{[N]}$  : truncated operator

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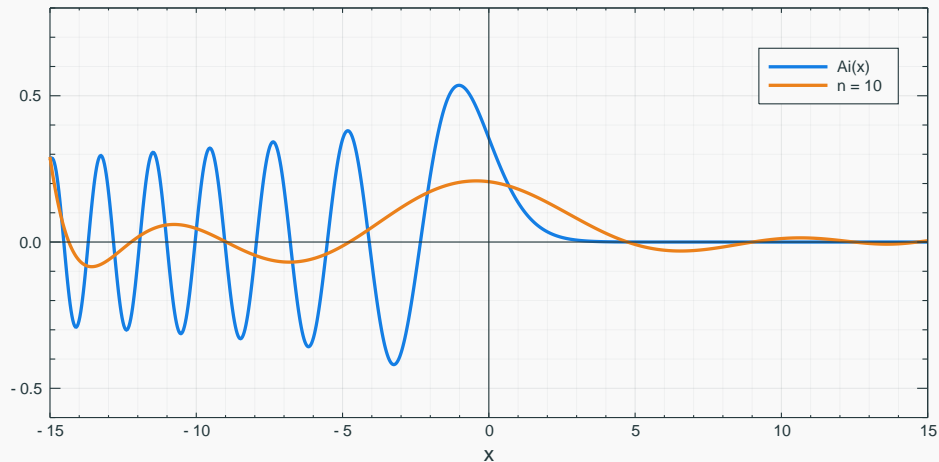
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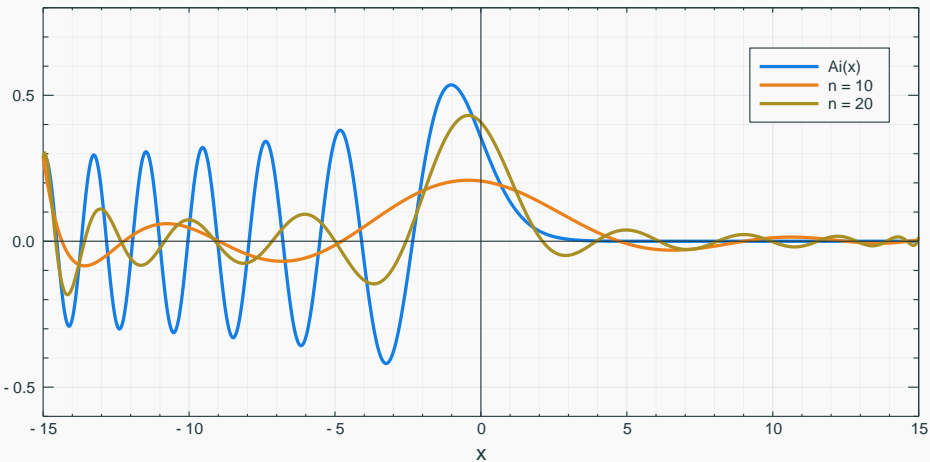
- o Solution in  $\mathcal{O}((r + s)^2 N)$  arith. op. with **Olver and Townsend's QR algorithm**



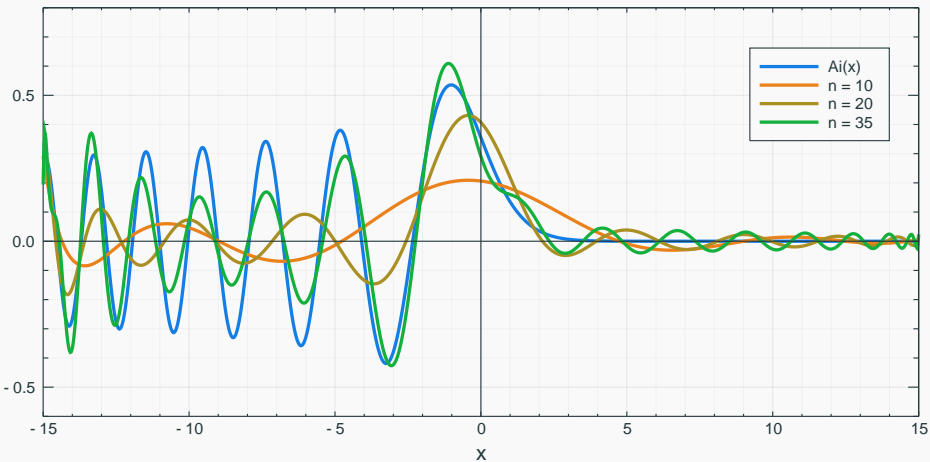
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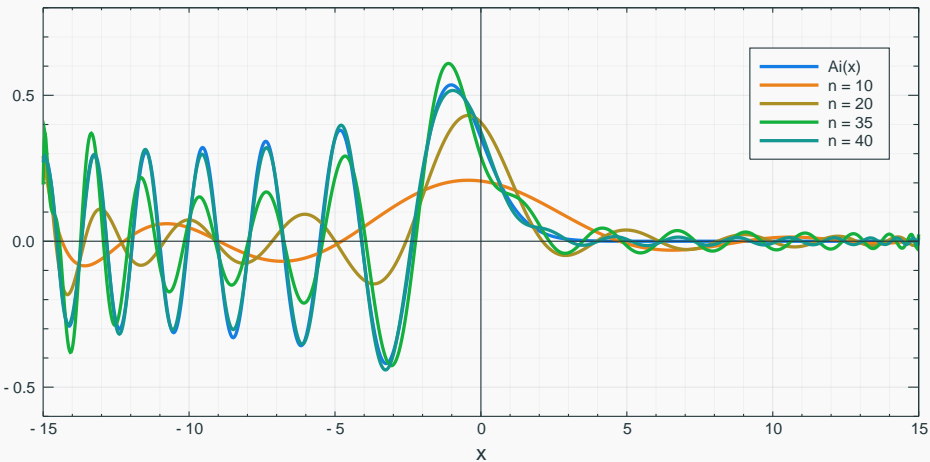
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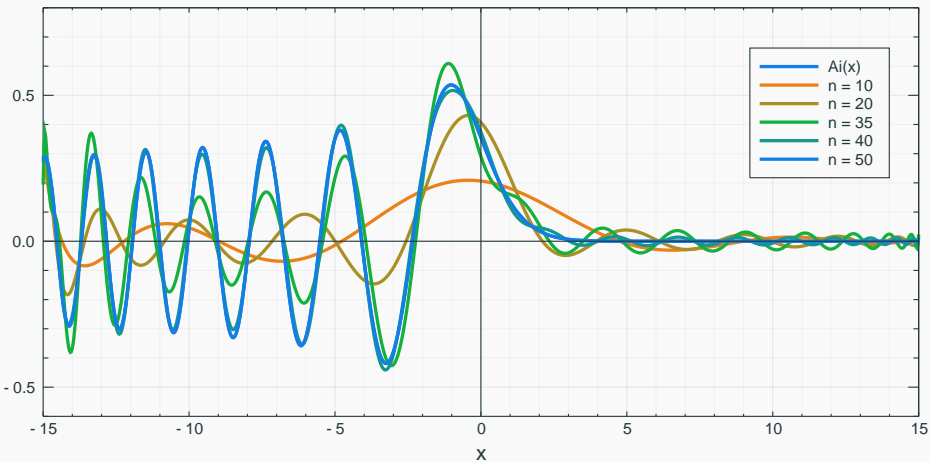
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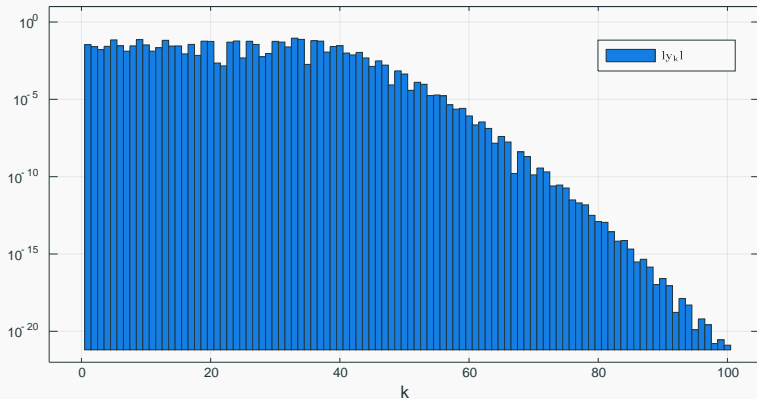


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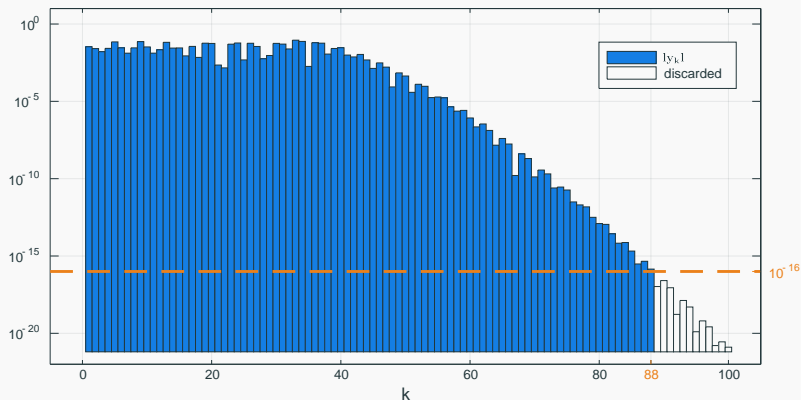
# Chebyshev Coefficients of Airy Function

- Super-algebraic decay of Chebyshev coefficients for analytic functions



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- Heuristic truncation methods in Chebfun, ...
- Need for validation algorithms

## **Fixed-Point Based Validation**

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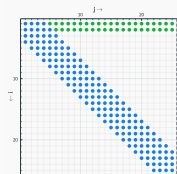
# A Posteriori Validation Paradigm

Step 1 ○ Numerical approximation method

- complexity
- numerical stability
- asymptotic convergence

$\tilde{y}$

Step 2 ○ A posteriori validation algorithm



Rigorous Polynomial Approximation (RPA) for  $y$

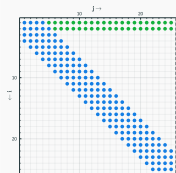
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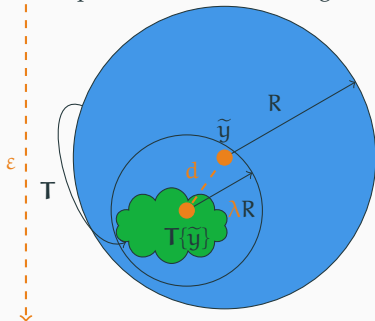
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Banach Fixed-Point Theorem

$$\frac{d}{1+\lambda} \leq \|\tilde{y} - y\| \leq \frac{d}{1-\lambda}$$

$$d = \|\mathbf{T}\{\tilde{y}\} - \tilde{y}\|$$

Rigorous Polynomial Approximation (RPA) for  $y$

$$= \text{pair } (\tilde{y}, \varepsilon) \text{ s.t. } \|\tilde{y} - y\| \leq \varepsilon$$

## **Fixed-Point Based Validation**

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### **Newton-Galerkin Algorithm**

## Newton-Galerkin Validation Algorithm

○ Newton:  $\mathbf{y} + \mathbf{K}\{\mathbf{y}\} = \mathbf{g} \quad \Leftrightarrow \quad \mathbf{T}\{\mathbf{y}\} = \mathbf{y} \quad \begin{cases} \mathbf{T}\{\mathbf{y}\} := \mathbf{y} - \mathbf{A}\{\mathbf{y} + \mathbf{K}\{\mathbf{y}\} - \mathbf{g}\} \\ \mathbf{A} \approx (\mathbf{I} + \mathbf{K})^{-1} \end{cases}$

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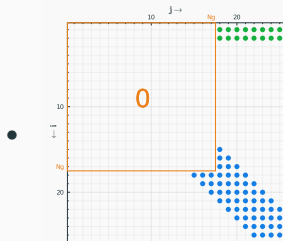
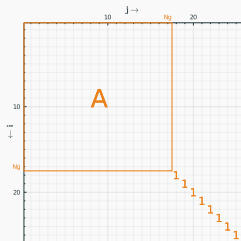
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$$\bullet \quad \|\tilde{\mathbf{y}} - \mathbf{y}\| \leq \|\mathbf{T}\{\tilde{\mathbf{y}}\} - \tilde{\mathbf{y}}\| / (1 - \lambda)$$

**Theorem (Bréhard, Brisebarre, Joldes)** — ACM Trans. Math. Softw.

Validating a degree  $N$  approximation  $\tilde{\mathbf{y}}$  requires:

$$\mathcal{O}(N_g^2(r+s) + (N_g + r + s)N) \quad \text{arithmetic operations}$$



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## Bound the operator norm of $\mathbf{T}$

$$\begin{aligned} \lambda &:= \|\mathbf{DT}\| = \|\mathbf{I} - \mathbf{A}(\mathbf{I} + \mathbf{K})\| \\ &\leq \underbrace{\|\mathbf{I} - \mathbf{A}(\mathbf{I} + \mathbf{K}^{[N_g]})\|}_{\text{approximation error}} + \underbrace{\|\mathbf{A}(\mathbf{K} - \mathbf{K}^{[N_g]})\|}_{\text{truncation error}} \end{aligned}$$

$$\bullet \quad \|\tilde{\mathbf{y}} - \mathbf{y}\| \leq \|\mathbf{T}\{\tilde{\mathbf{y}}\} - \tilde{\mathbf{y}}\| / (1 - \lambda)$$

**Theorem (Bréhard, Brisebarre, Joldes)** — ACM Trans. Math. Softw.

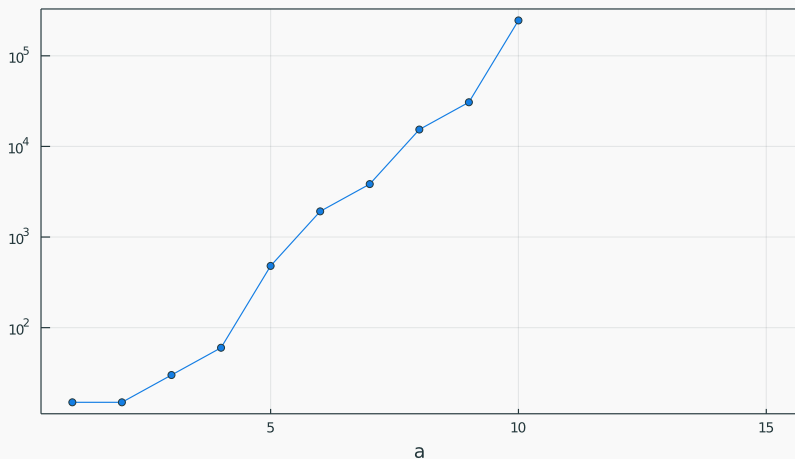
Validating a degree  $N$  approximation  $\tilde{\mathbf{y}}$  requires:

$$\mathcal{O}(N_g^2(r+s) + (N_g + r + s)N) \quad \text{arithmetic operations}$$

...but  $N_g$  may be exponential w.r.t. the  $\|a_i\|$  !

## Newton-Galerkin Validation on Airy Example

- Newton-Galerkin method for Airy function over  $[-a, a]$



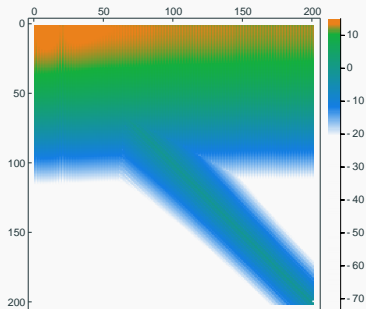
⇒ Truncation index  $N_g$  grows exponentially fast!

## **Fixed-Point Based Validation**

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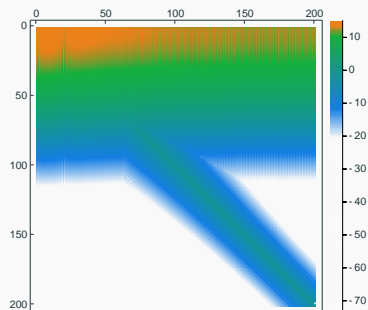
### **Newton-Picard Algorithm**

# Almost Banded Approximate Inverses



- $(\mathbf{I} + \mathbf{K})^{-1}$  is “asymptotically almost-banded”

# Almost Banded Approximate Inverses

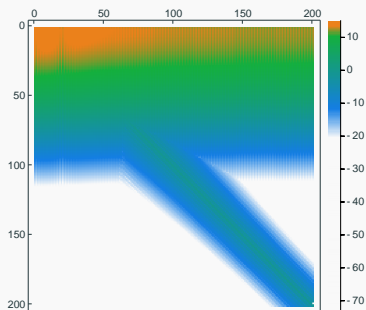


○  $(\mathbf{I} + \mathbf{K})^{-1}$  is “asymptotically almost-banded”

... because of Picard iterations:

$$(\mathbf{I} + \mathbf{K})^{-1} = \mathbf{I} - \mathbf{K} + \mathbf{K}^2 - \dots + (-1)^n \mathbf{K}^n + \dots$$

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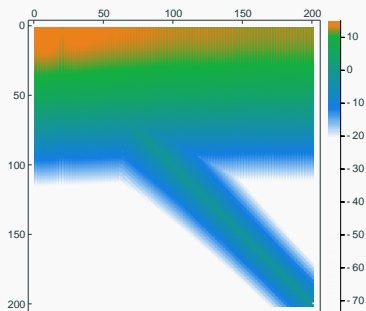
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$$\left. \begin{array}{l} \mathbf{K} \rightsquigarrow \mathfrak{K}(x, t) \\ \mathbf{L} \rightsquigarrow \mathfrak{L}(x, t) \end{array} \right\} \Rightarrow \mathbf{KL} \rightsquigarrow \mathfrak{K} * \mathfrak{L} \quad \text{where} \quad (\mathfrak{K} * \mathfrak{L})(x, t) := \int_t^x \mathfrak{K}(x, s) \mathfrak{L}(s, t) ds$$

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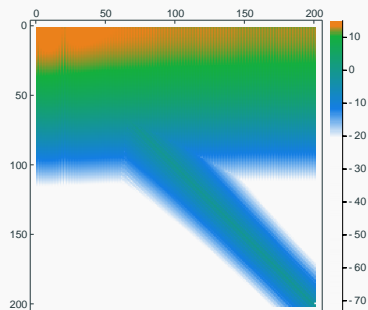
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## Iterated Kernels and Resolvent Kernel

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$$\begin{aligned}(\mathbf{I} + \mathbf{K})^{-1} &= \mathbf{I} - \mathbf{K} + \mathbf{K}^2 - \dots + (-1)^n \mathbf{K}^n + \dots \\ &= \mathbf{I} + \mathbf{R} \quad \text{where } \mathbf{R} \rightsquigarrow \mathfrak{R}(x, t)\end{aligned}$$

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## Newton-Picard Validation Algorithm

Validating a candidate approximation  $\tilde{y}$ :

1. Compute  $\mathbf{I} + \tilde{\mathbf{R}} \approx (\mathbf{I} + \mathbf{K})^{-1}$  with  $\tilde{\mathbf{R}} \rightsquigarrow \tilde{\mathfrak{R}}(x, t) \approx \mathfrak{R}(x, t)$  polynomial

$$\text{Newton operator: } \quad \mathbf{T}\{\mathbf{y}\} := \mathbf{y} - (\mathbf{I} + \tilde{\mathbf{R}})\{\mathbf{y} + \mathbf{K}\{\mathbf{y}\} - \mathbf{g}\}$$

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$$-D\mathbf{T} = (\mathbf{I} + \tilde{\mathbf{R}})(\mathbf{I} + \mathbf{K}) - \mathbf{I} = \mathbf{K} + \tilde{\mathbf{R}} + \tilde{\mathbf{R}}\mathbf{K} \quad \rightsquigarrow \quad \mathfrak{K} + \tilde{\mathfrak{R}} + \tilde{\mathfrak{R}} * \mathfrak{K} =: \mathfrak{E}$$

$$\text{with } \quad \lambda \geq T \sup_{0 \leq t \leq x \leq T} |\mathfrak{E}(x, t)|$$

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How to efficiently approximate  $\mathfrak{R}(x, t)$ ?

## Formulas for Resolvent Kernel Approximation

- $\mathbf{L} = \partial^r + a_{r-1}(x)\partial^{r-1} + \cdots + a_0(x) \rightsquigarrow \mathbf{K}$  acting on  $f = y^{(r)}$

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- Approximations using spectral methods to some degree  $N_{\mathfrak{R}}$
- The idea is very close to the fast algorithm for power series solutions to ODEs, but in a symbolic-numeric setting  
(*Bostan, Chyzak, Ollivier, Salvy, Schost, Sedoglavic – 2006*)

# Complexity Analysis of Newton-Picard Validation Algorithm

Validating a candidate approximation  $\tilde{y}$  of degree  $N$ :

1. Choose a validation degree  $N_{\mathfrak{R}}$  and

compute 
$$\tilde{\mathfrak{R}}(x, t) := \sum_{i=0}^{r-1} \tilde{\varphi}_i^{(r)}(x) \tilde{\psi}_i(t) \approx \sum_{i=0}^{r-1} \varphi_i^{(r)}(x) \psi_i(t) =: \mathfrak{R}(x, t)$$

2. Bound the norm of  $\mathfrak{E} := \mathfrak{K} + \tilde{\mathfrak{R}} + \tilde{\mathfrak{R}} * \mathfrak{K}$

3. Compute defect  $\|\mathbf{T}\{\tilde{y}\} - \tilde{y}\| = \|(\mathbf{I} + \tilde{\mathbf{R}})\{\tilde{y} + \mathbf{K}\{\tilde{y}\} - g\}\|$

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$$\text{complexity: } \mathcal{O}((r+s)^2 N_{\mathfrak{R}}) \quad \begin{cases} r = \text{order of } L \\ s = \max \deg a_i \end{cases}$$

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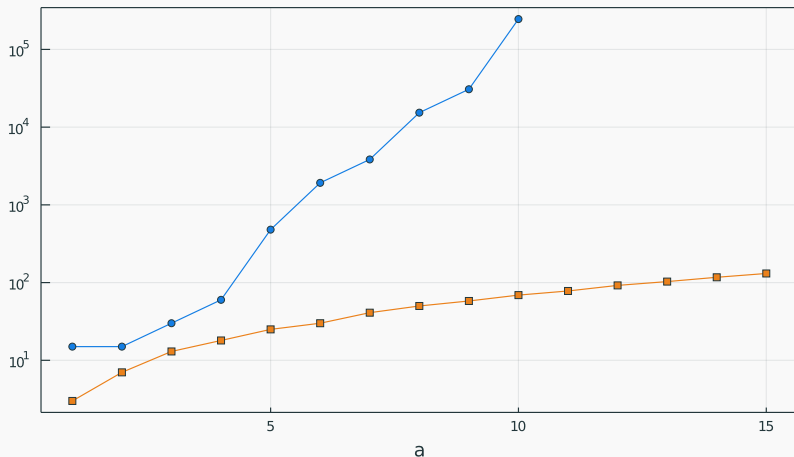
Newton-Galerkin's  $N_{\mathfrak{G}}$  vs Newton-Picard's  $N_{\mathfrak{R}}$  ?

$$\circ N_{\mathfrak{G}} = \mathcal{O}\left(\sum_i \|\varphi_i^{(r)}\| \|\psi_i\|\right) \rightsquigarrow \text{exponential in the } \|a_i\|$$

$$\circ N_{\mathfrak{R}} = \mathcal{O}\left(\log\left(\sum_i \|\varphi_i^{(r)}\| \|\psi_i\|\right)\right) \rightsquigarrow \text{polynomial in the } \|a_i\|$$

# Newton-Galerkin vs Newton-Picard on Airy Example

- Validation for Airy function over  $[-a, a]$



- $N_g \rightsquigarrow$  exponential in the  $\|a_i\|$
- $N_{gp} \rightsquigarrow$  polynomial in the  $\|a_i\|$