

A posteriori error estimation in the FEniCSx finite element software and application to the fractional Laplacian.

Raphaël Bulle

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DRIVEN



Background

2010-2013 **Bachelor in Mathematics**

at Université de Bourgogne Franche-Comté (FR).

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2014 **CAPES** (competitive exam)
of Mathematics.

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2016 **Agrégation** (competitive exam)
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2015-2017 **Master in Advanced Mathematics**

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Background

- 2017-2022 PhD student in Computational Engineering and Applied Mathematics**
at University of Luxembourg and Université de Bourgogne Franche-Comté
Supervision: S. P. A. Bordas, F. Chouly, J. S. Hale and A. Lozinski.
- 2015-2017 Master in Advanced Mathematics**
at Université de Bourgogne Franche-Comté.
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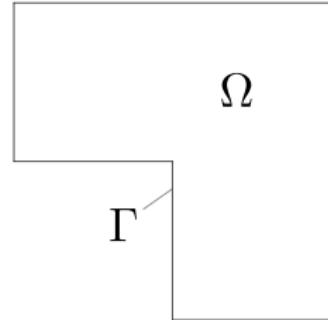
The Bank–Weiser estimator

The Bank–Weiser estimator

A reaction diffusion problem

Let $f \in L^2(\Omega)$ and $a \in \mathbb{R}^{+*}$, we look for u s.t.

$$u - a\Delta u = f \text{ in } \Omega, \quad u = 0 \text{ on } \Gamma.$$



The Bank–Weiser estimator

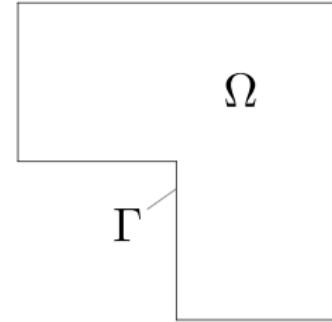
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In weak formulation, find u in $H_0^1(\Omega)$ such that

$$\int_{\Omega} uv + a \int_{\Omega} \nabla u \cdot \nabla v = \int_{\Omega} fv, \quad \forall v \in H_0^1(\Omega).$$



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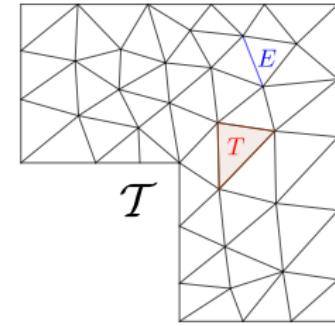
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Lagrange finite element discretization of order k , find u_k in V^k such that

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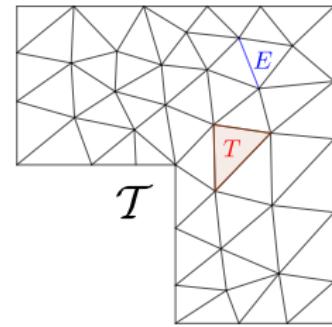
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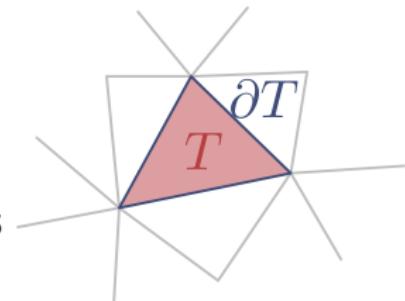
Goal: estimate $\eta_{\text{err}} = \|u_k - u\|_{\Omega}$ i.e. find a computable quantity η_{bw} such that $\eta_{\text{bw}} \approx \eta_{\text{err}}$.



The Bank–Weiser estimator

Definition

On a cell T , the Bank–Weiser problem is given by: find e_T^{bw} in V_T^{bw} such that

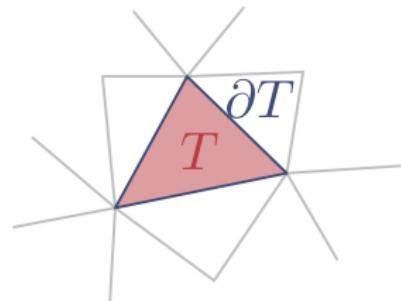


$$\int_T e_T^{\text{bw}} v_T^{\text{bw}} + a \int_T \nabla e_T^{\text{bw}} \cdot \nabla v_T^{\text{bw}} = \int_T r_T v_T^{\text{bw}} + \sum_{E \in \partial T} \frac{1}{2} \int_E J_E v_T^{\text{bw}} \quad \forall v_T^{\text{bw}} \in V_T^{\text{bw}}.$$

The Bank–Weiser estimator

Definition

On a cell $\textcolor{red}{T}$, the Bank–Weiser problem is given by: find $e_{\textcolor{red}{T}}^{\text{bw}}$ in $V_{\textcolor{red}{T}}^{\text{bw}}$ such that



$$\int_{\textcolor{red}{T}} e_{\textcolor{red}{T}}^{\text{bw}} v_{\textcolor{red}{T}}^{\text{bw}} + a \int_{\textcolor{red}{T}} \nabla e_{\textcolor{red}{T}}^{\text{bw}} \cdot \nabla v_{\textcolor{red}{T}}^{\text{bw}} = \int_{\textcolor{red}{T}} r_{\textcolor{red}{T}} v_{\textcolor{red}{T}}^{\text{bw}} + \sum_{E \in \partial T} \frac{1}{2} \int_E J_E v_{\textcolor{red}{T}}^{\text{bw}} \quad \forall v_{\textcolor{red}{T}}^{\text{bw}} \in V_{\textcolor{red}{T}}^{\text{bw}}.$$

The Bank–Weiser estimator is defined as

$$\eta_{\text{bw}}^2 := \sum_{\textcolor{red}{T} \in \mathcal{T}} \eta_{\text{bw}, \textcolor{red}{T}}^2, \quad \eta_{\text{bw}, \textcolor{red}{T}} := ||| e_{\textcolor{red}{T}}^{\text{bw}} |||_{\textcolor{red}{T}}.$$

The Bank–Weiser estimator

Definition

What is V_T^{bw} ?

Let $V_T^- \subsetneq V_T^+$ be two finite element spaces and

$$\mathcal{L}_T : V_T^+ \longrightarrow V_T^-,$$

be the local Lagrange interpolation operator,

$$V_T^{\text{bw}} := \ker(\mathcal{L}_T) = \{v_T^+ \in V_T^+, \mathcal{L}_T(v_T^+) = 0\}.$$

The Bank–Weiser estimator

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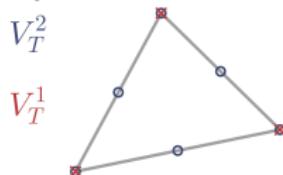
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Examples:



The Bank–Weiser estimator

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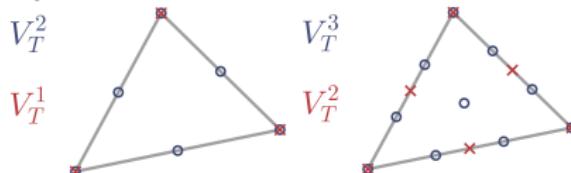
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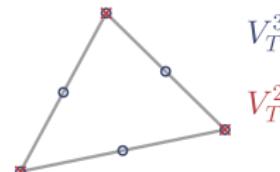
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Examples:

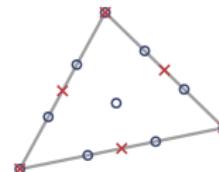
$$V_T^2$$

$$V_T^1$$



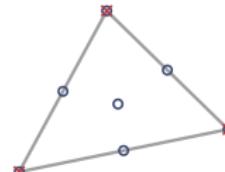
$$V_T^3$$

$$V_T^2$$



$$V_T^3 + \text{Span}\{\psi_T\}$$

$$V_T^1$$



The Bank–Weiser estimator

Implementation

We need to compute the matrix A_T^{bw} and vector b_T^{bw} from

$$\int_T e_T^{\text{bw}} v_T^{\text{bw}} + a \int_T \nabla e_T^{\text{bw}} \cdot \nabla v_T^{\text{bw}} = \int_T r_T v_T^{\text{bw}} + \sum_{E \in \partial T} \frac{1}{2} \int_E J_E v_T^{\text{bw}} \quad \forall v_T^{\text{bw}} \in V_T^{\text{bw}}.$$

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Problem: the space V_T^{bw} is not provided by DOLFIN/x.

The Bank–Weiser estimator

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Problem: the space V_T^{bw} is not provided by DOLFIN/x.

Idea: we rely on the matrix A_T^+ and vector b_T^+ from

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since V_T^+ is provided by DOLFIN/x

The Bank–Weiser estimator

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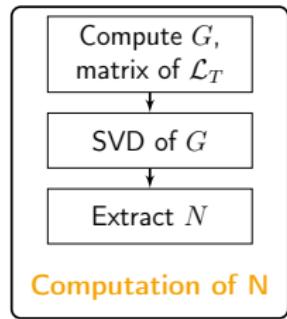
$$\int_T e_T^+ v_T^+ + a \int_T \nabla e_T^+ \cdot \nabla v_T^+ = \int_T r_T v_T^+ + \sum_{E \in \partial T} \frac{1}{2} \int_E J_E v_T^+ \quad \forall v_T^+ \in V_T^+,$$

since V_T^+ is provided by DOLFIN/x and we look for a matrix N such that:

$$A_T^{\text{bw}} = N^t A_T^+ N, \quad \text{and} \quad b_T^{\text{bw}} = N^t b_T^+.$$

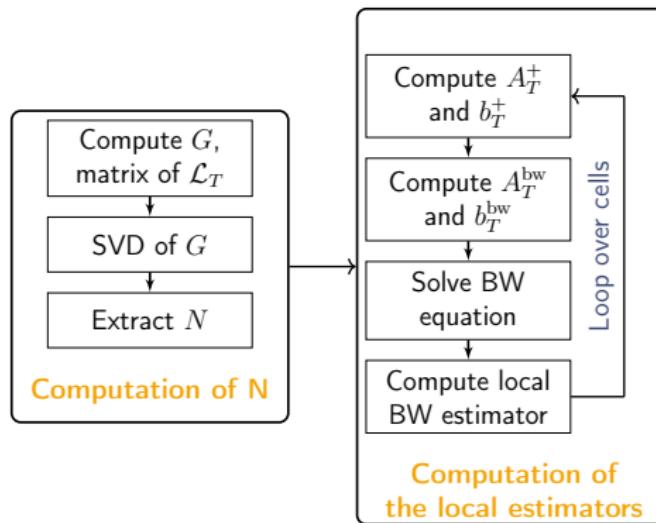
The Bank–Weiser estimator

Implementation



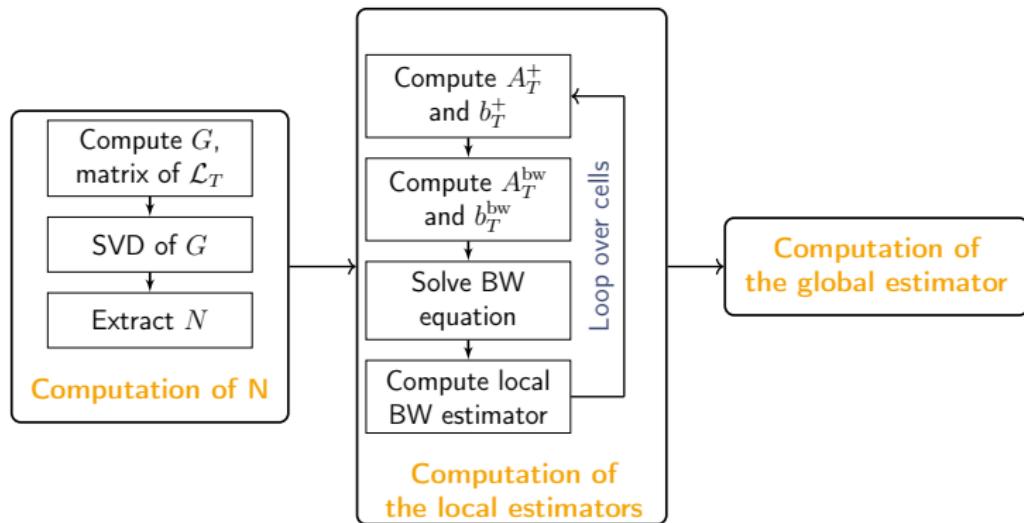
The Bank–Weiser estimator

Implementation



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Implementation



The Bank–Weiser estimator

Pros and cons

Pros

Cons



The Bank–Weiser estimator

Pros and cons

Pros

Local efficiency

$\eta_{\text{bw},T} \leq C\eta_{\text{err},T} + \text{h.o.t.}|_T$
[Bank and Weiser, 1985, Nochetto, 1993,
Verfürth, 1994].

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The Bank–Weiser estimator

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[Bank and Weiser, 1985, Nocettono, 1993,
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Reliability $\eta_{\text{err}} \leq c\eta_{\text{bw}} + \text{h.o.t.}$
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[Bank and Weiser, 1985, Nocettono, 1993,
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Flexible & Robust w.r.t. parameters of
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Not asymptotically exact in general
[Duran and Rodriguez, 1992, Ainsworth, 1994].

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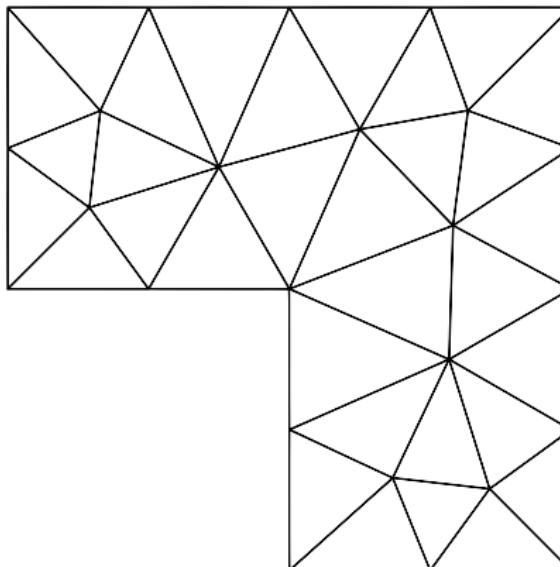
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No convergence proof when used for
adaptive mesh refinement
[Carstensen et al., 2014].

The Bank–Weiser estimator

Numerical results

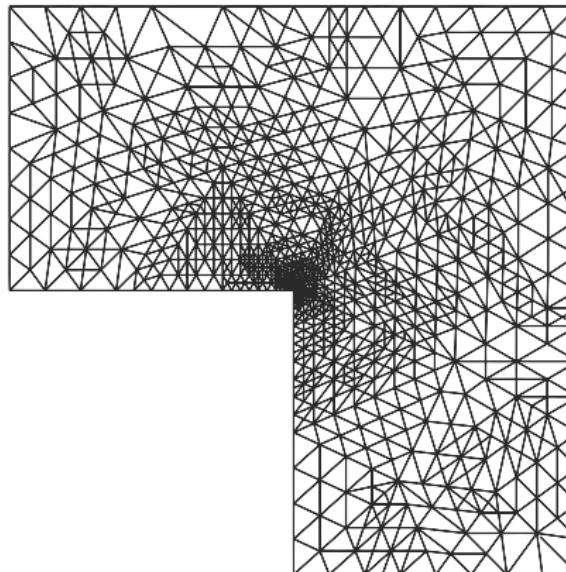
Adaptive finite elements for a Poisson problem:
 $-\Delta u = 0$ in Ω , $u = u_D$ on Γ . Linear finite elements.



The Bank–Weiser estimator

Numerical results

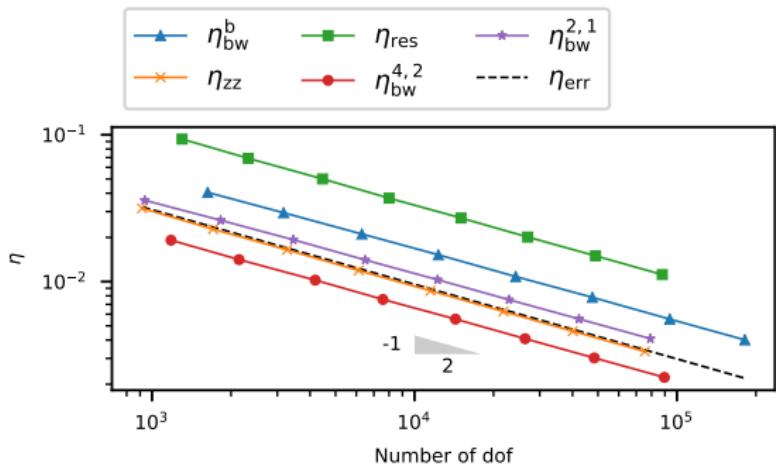
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The Bank–Weiser estimator

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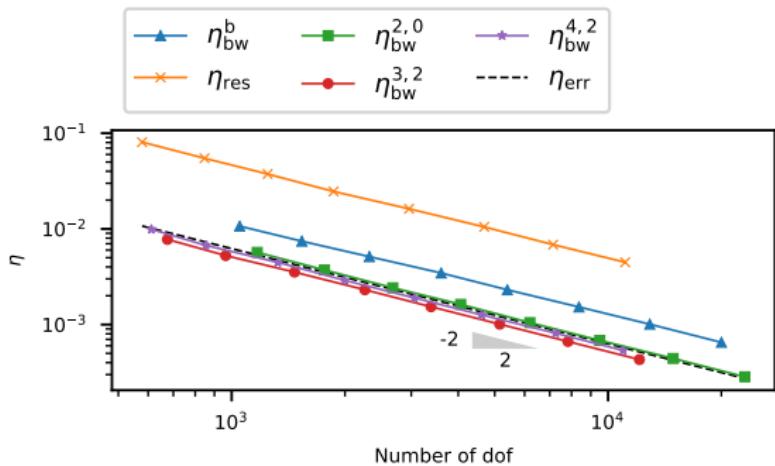
Notation	V_T^+	V_T^-
$\eta_{bw}^{k_+, k_-}$	$V_T^{k_+}$	$V_T^{k_-}$
η_{bw}^b	$V_T^2 + \text{bubble}$	V_T^1

The Bank–Weiser estimator

Numerical results

Adaptive finite elements for a Poisson problem:

$-\Delta u = 0$ in Ω , $u = u_D$ on Γ . Quadratic finite elements.



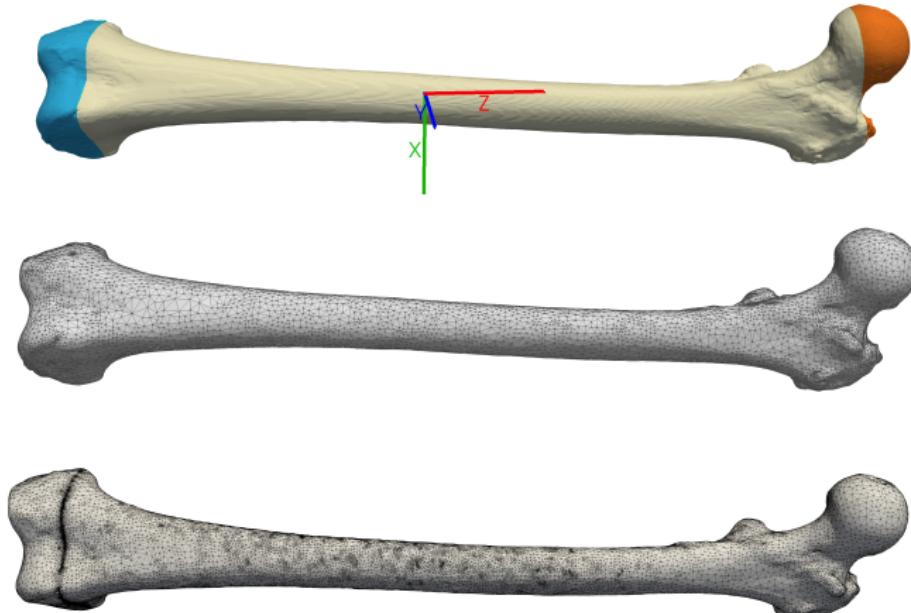
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The Bank–Weiser estimator

Numerical results

GO AFEM for a linear elasticity problem:

we used a technique from [Khan et al., 2019] and [Becker et al., 2011] to compute the estimators. The goal functional is defined by $J(\mathbf{u}, p) := \int_{\Gamma} \mathbf{u} \cdot \mathbf{n} c$, where c is a Gaussian weight centered on the middle of the bone.

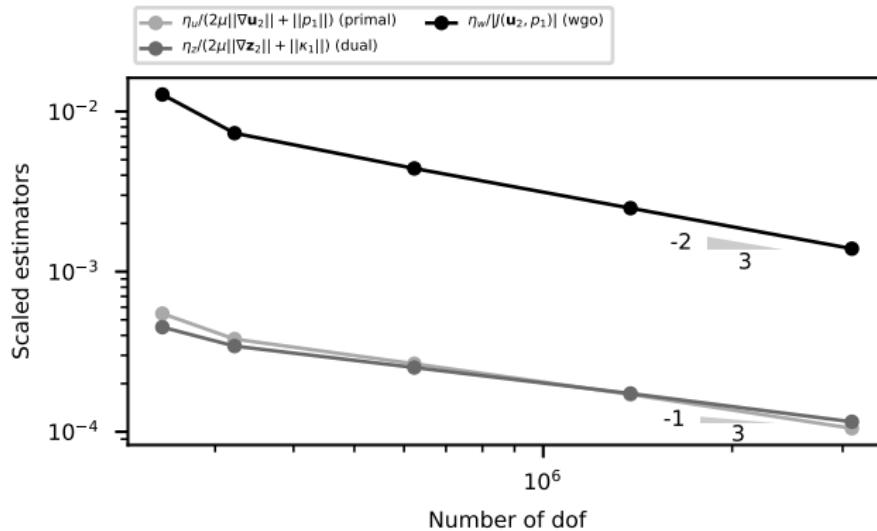


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The Bank–Weiser estimator

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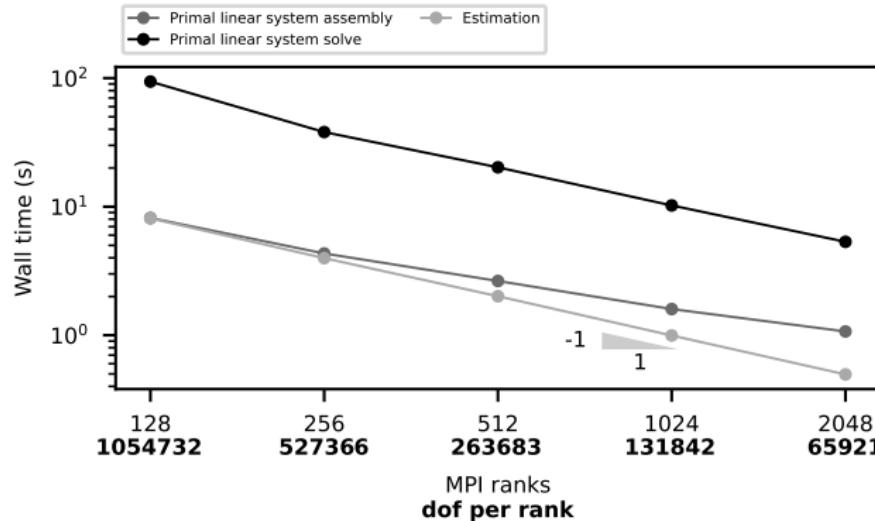
Timescale study:

strong scaling study on the Uni Lu cluster [Varrette et al., 2014].

$-\Delta u = f$ on $[0, 1]^3$, $u = 0$ on Γ . \mathcal{P}_2 Lagrange elements.

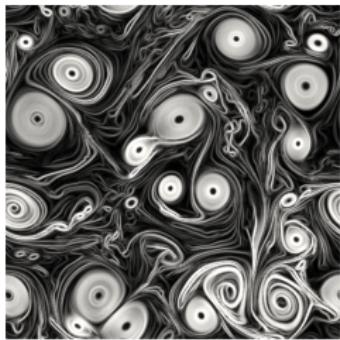
The Bank–Weiser estimator is $\eta_{\text{bw}}^{3,2}$.

The problem size is fixed around 135 million dof.

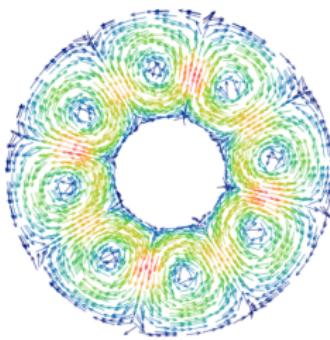


The spectral fractional Laplacian

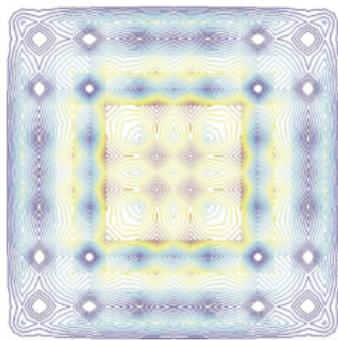
The spectral fractional Laplacian



[Bonito and Nazarov, 2021]



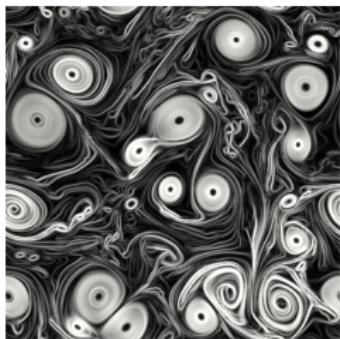
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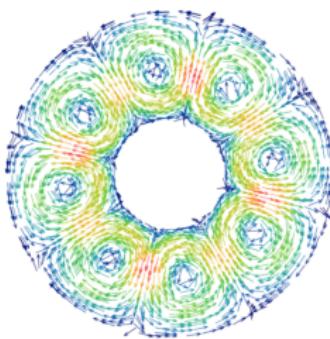
[Sumelka, 2015]

Fractional models are more and more popular and are used in a wide range of fields such as statistics, hydrogeology, finance, physics...

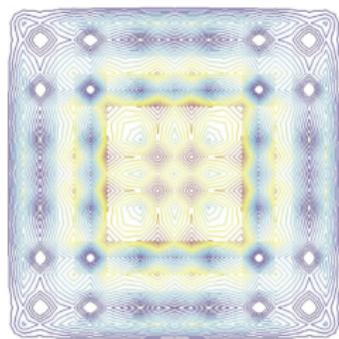
The spectral fractional Laplacian



[Bonito and Nazarov, 2021]



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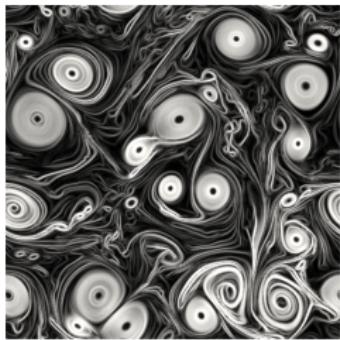


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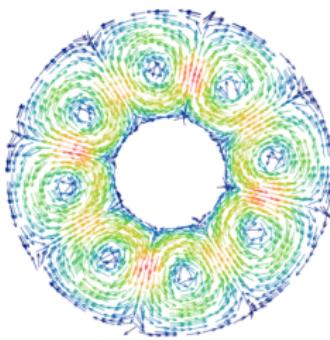
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- **Main advantage:** they are nonlocal.

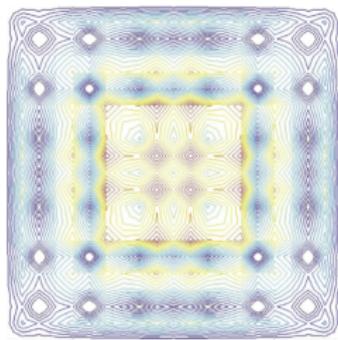
The spectral fractional Laplacian



[Bonito and Nazarov, 2021]



[Bonito and Wei, 2020]



[Sumelka, 2015]

Fractional models are more and more popular and are used in a wide range of fields such as statistics, hydrogeology, finance, physics...

- **Main advantage:** they are nonlocal.
- **Main drawback:** they are nonlocal.

The spectral fractional Laplacian

Problem setting

Let $\Omega \subset \mathbb{R}^d$, $s \in (0, 1)$ and $f \in L^2(\Omega)$.

$$(-\Delta)^s u = f \quad \text{in } \Omega, \quad u = 0 \quad \text{on } \Gamma.$$

The spectral fractional Laplacian

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The solution u is defined by

$$u := \sum_{i=1}^{+\infty} \lambda_i^{-s} (f, \psi_i)_{L^2},$$

where $\{\psi_i, \lambda_i\}_{i=1}^{+\infty} \subset L^2(\Omega) \times \mathbb{R}^+$ is the spectrum of $-\Delta$.

The spectral fractional Laplacian

Problem setting

The natural space associated with this problem is

$$\mathbb{H}^s(\Omega) := \left\{ v \in L^2(\Omega), \sum_{i=1}^{+\infty} \lambda_i^s (v, \psi_i)_{L^2}^2 < +\infty \right\},$$

of norm $\|v\|_{\mathbb{H}^s}^2 := \sum_{i=1}^{+\infty} \lambda_i^s (v, \psi_i)_{L^2}^2.$

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Especially, $\mathbb{H}^0(\Omega) = L^2(\Omega)$ and $\mathbb{H}^1(\Omega) = H_0^1(\Omega).$

If $f \in L^2(\Omega)$, then $u \in \mathbb{H}^{2s}(\Omega)$ and

$$\|u\|_{\mathbb{H}^{2s}}^2 = \|f\|_{L^2}^2.$$

The spectral fractional Laplacian

Discretization

$$(-\Delta)^s u = f \quad \text{in } \Omega, \quad u = 0 \quad \text{on } \Gamma.$$

How to solve this equation numerically ?

The spectral fractional Laplacian

Discretization

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$$u := (-\Delta)^{-s} f = \sum_{i=1}^{+\infty} \lambda_i^{-s} (f, \psi_i)_{L^2},$$

we use a rational approximation

$$\lambda^{-s} \simeq \mathcal{Q}_s^N(\lambda) := C_s(N) \sum_{l=1}^N a_l (1+b_l \lambda)^{-1}, \quad \forall \lambda \in [\lambda_1, +\infty),$$

where $(a_l)_l$ and $(b_l)_l$ are positive coefficients and $C_s(N)$ is independent of λ .

The spectral fractional Laplacian

Discretization

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The spectral fractional Laplacian

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$$\begin{aligned} u = (-\Delta)^{-s} f &= \sum_{i=1}^{+\infty} \lambda_i^{-s} (f, \psi_i)_{L^2} \\ &\simeq \sum_{i=1}^{+\infty} \mathcal{Q}_s^N(\lambda_i) (f, \psi_i)_{L^2} \end{aligned}$$

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The spectral fractional Laplacian

Discretization

For $l = 1, \dots, N$,

$$\begin{aligned} (-\Delta)^s u &= f, & \text{in } \Omega, \\ u &= 0, & \text{on } \Gamma. \end{aligned} \quad \longrightarrow \quad \begin{aligned} u_l - b_l \Delta u_l &= f, & \text{in } \Omega, & (1) \\ u_l &= 0, & \text{on } \Gamma. & (2) \end{aligned}$$

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The spectral fractional Laplacian

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$$\int_{\Omega} u_l v + b_l \int_{\Omega} \nabla u_l \cdot \nabla v = \int_{\Omega} f v, \quad \forall v \in H_0^1(\Omega), \quad \forall l \in \llbracket 1, N \rrbracket,$$

The spectral fractional Laplacian

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and write its FE discretization

$$\int_{\Omega} u_{l,k} v_k + b_l \int_{\Omega} \nabla u_{l,k} \cdot \nabla v_k = \int_{\Omega} f v_k, \quad \forall v_k \in V^k, \quad \forall l \in \llbracket 1, N \rrbracket.$$

The spectral fractional Laplacian

Discretization

Solving these classical FE problems we finally get a fully discrete approximation of u

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The spectral fractional Laplacian

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Advantages of this method:

- it is easily parallelizable,
- it involves “standard” FE machinery,
- it is well-suited to three-dimensional problems.

The spectral fractional Laplacian

Error estimation

How can we bound the discretization error ?

$$\|u - u_{\mathcal{Q}_s^N}^k\| \leq \|u - u_{\mathcal{Q}_s^N}\| + \|u_{\mathcal{Q}_s^N} - u_{\mathcal{Q}_s^N}^k\|.$$

where $\|\cdot\| = \|\cdot\|_{L^2}$, or $\|\cdot\|_{\mathbb{H}^s}$.

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The spectral fractional Laplacian

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The spectral fractional Laplacian

Error estimation

Quantification of the rational approximation error $\|u - u_{\mathcal{Q}_s^N}\|.$

The spectral fractional Laplacian

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Quantification of the rational approximation error $\|u - u_{\mathcal{Q}_s^N}\|.$

If there exists $\varepsilon_s(N) \xrightarrow[N \rightarrow +\infty]{} 0$ such that

$$|\lambda^{-s} - \mathcal{Q}_s^N(\lambda)| \leq \varepsilon_s(N), \quad \forall \lambda \in [\lambda_1, +\infty),$$

then, [Bonito and Pasciak, 2015]

$$\|u - u_{\mathcal{Q}_s^N}\|_{L^2} \leq \varepsilon_s(N) \|f\|_{L^2}.$$

The spectral fractional Laplacian

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Quantification of the rational approximation error $\|u - u_{\mathcal{Q}_s^N}\|.$

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Moreover, if $f \in \mathbb{H}^s(\Omega)$ then [Bonito and Pasciak, 2016]

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The spectral fractional Laplacian

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$$\|u - u_{\mathcal{Q}_s^N}\|_{\mathbb{H}^s} \leq \varepsilon_s(N) \|f\|_{\mathbb{H}^s}.$$

In particular, there exists an approximation \mathcal{Q}_s^N such that $\varepsilon_s(N)$ is fully computable and [Bonito and Pasciak, 2015]

$$\varepsilon_s(N) = \mathcal{O}_{N \rightarrow +\infty} \left(e^{-(\pi^2/2\sqrt{2})\sqrt{N}} \right).$$

The spectral fractional Laplacian

Error estimation

Quantification of the rational approximation error $\|u - u_{\mathcal{Q}_s^N}\|.$

Conjecture: $\|u - u_{\mathcal{Q}_s^N}\|_{\mathbb{H}^s} \leq \varepsilon_s(N) \|f\|_{L^2}.$

The spectral fractional Laplacian

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Quantification of the rational approximation error $\|u - u_{\mathcal{Q}_s^N}\|.$

Conjecture: $\|u - u_{\mathcal{Q}_s^N}\|_{\mathbb{H}^s} \leq \varepsilon_s(N) \|f\|_{L^2}.$

What we can prove [Bulle, 2022]:

$$\|u - u_{\mathcal{Q}_s^N}\|_{\mathbb{H}^s} \leq \tilde{\varepsilon}_s(N) \|f\|_{L^2},$$

where $\tilde{\varepsilon}_s(N) \xrightarrow[N \rightarrow +\infty]{} 0$ with a possibly slower convergence rate than $\varepsilon_s.$

The spectral fractional Laplacian

Error estimation

Quantification of the finite element error $\|u_{\mathcal{Q}_s^N} - u_{\mathcal{Q}_s^N}^k\|.$

The spectral fractional Laplacian

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The spectral fractional Laplacian

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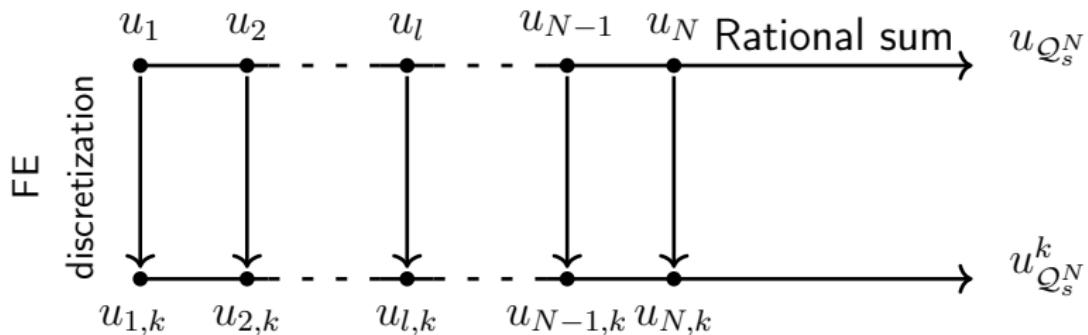
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- A posteriori error estimate for $\|\cdot\|_{\mathbb{H}^s}$ is an ongoing work.

The spectral fractional Laplacian

Error estimation

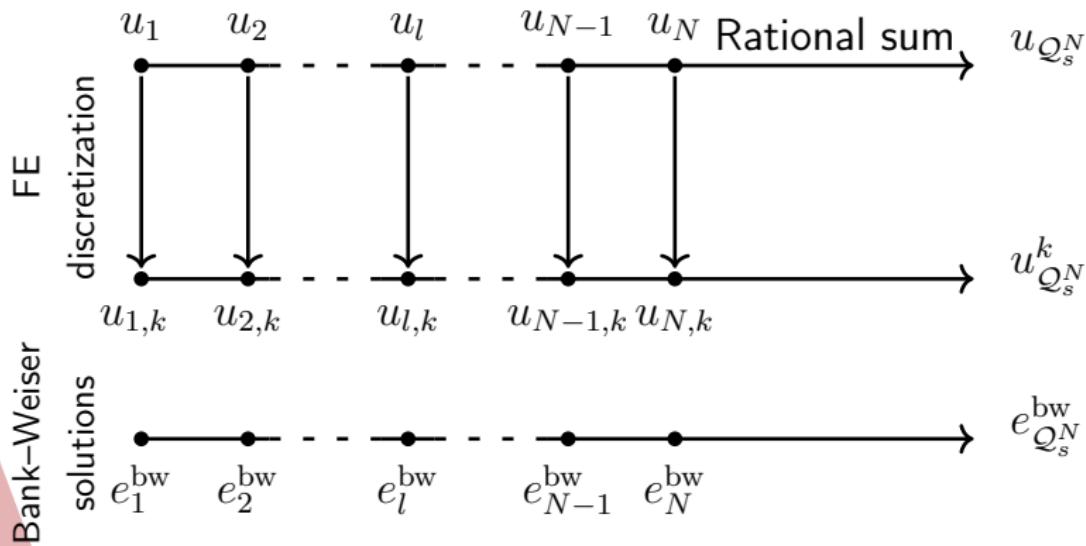
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The spectral fractional Laplacian

Error estimation

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The spectral fractional Laplacian

Error estimation

Quantification of the finite element error $\|u_{\mathcal{Q}_s^N} - u_{\mathcal{Q}_s^N}^k\|.$

For each cell $T \in \mathcal{T}_h$ and each parametric problem $l \in \llbracket 1, N \rrbracket$, we solve the Bank–Weiser equation to estimate the difference

$$u_{l|_T} - u_{l,k|_T} \simeq e_{l,T}^{\text{bw}}.$$

The spectral fractional Laplacian

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Then,

$$\left(u_{\mathcal{Q}_s^N} - u_{\mathcal{Q}_s^N}^k \right)_{|_T} = C_s(N) \sum_{l=1}^N a_l (\underline{u}_l - u_{l,k}) \simeq C_s(N) \sum_{l=1}^N a_l e_{l,T}^{\text{bw}} =: e_{\mathcal{Q}_s^N, T}^{\text{bw}},$$

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and finally, we expect that:

$$\|u_{\mathcal{Q}_s^N} - u_{\mathcal{Q}_s^N}^k\|_{L^2}^2 \simeq \|e_{\mathcal{Q}_s^N}^{\text{bw}}\|_{L^2}^2 = \sum_{T \in \mathcal{T}} \|e_{\mathcal{Q}_s^N, T}^{\text{bw}}\|_{L^2(T)}^2.$$

The spectral fractional Laplacian

Adaptive mesh refinement

Fractional Laplacian problems show a particular sensibility to **boundary layers effect**. Thus, even for smooth data, the mesh might need to be adaptively refined near the boundary Γ [Banjai et al., 2019].

The spectral fractional Laplacian

Adaptive mesh refinement

Fractional Laplacian problems show a particular sensibility to **boundary layers effect**. Thus, even for smooth data, the mesh might need to be adaptively refined near the boundary Γ [Banjai et al., 2019].

We can use the Bank–Weiser error estimator to steer an adaptive refinement algorithm.

The spectral fractional Laplacian

Adaptive mesh refinement

Choose a tolerance $\delta > 0$, an initial mesh $\mathcal{T}_{n=0}$ and N such that $\varepsilon_s(N) \|f\|_{L^2} \ll \delta$

Generate the rational approximation \mathcal{Q}_s^N coefficients

Initialize the estimator $\eta_{\mathcal{Q}_s^N}^{\text{bw}} = \delta + 1$

The spectral fractional Laplacian

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While $\eta_{\mathcal{Q}_s^N}^{\text{bw}} > \delta$:

 Initialize the solution $u_{\mathcal{Q}_s^N, k} = 0$

 Initialize the local Bank–Weiser solutions $\{e_{\mathcal{Q}_s^N, T}^{\text{bw}} = 0\}_T$

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For each parametric problem $l \in \llbracket 1, N \rrbracket$:

 Solve parametric problem on \mathcal{T}_n to obtain $u_{l,k}$

 Add $u_{\mathcal{Q}_s^N, k} + C_s(N) a_l u_{l,k}$

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For each cell T of \mathcal{T}_n :

 Solve BW local parametric problem on T to obtain $e_{l,T}^{\text{bw}}$

 Add $e_{\mathcal{Q}_s^N, T}^{\text{bw}} + C_s(N) a_l e_{l,T}^{\text{bw}}$

The spectral fractional Laplacian

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Choose a tolerance $\delta > 0$, an initial mesh $\mathcal{T}_{n=0}$ and N such that $\varepsilon_s(N) \|f\|_{L^2} \ll \delta$

Generate the rational approximation \mathcal{Q}_s^N coefficients

Initialize the estimator $\eta_{\mathcal{Q}_s^N}^{\text{bw}} = \delta + 1$

While $\eta_{\mathcal{Q}_s^N}^{\text{bw}} > \delta$:

 Initialize the solution $u_{\mathcal{Q}_s^N, k} = 0$

 Initialize the local Bank–Weiser solutions $\{e_{\mathcal{Q}_s^N, T}^{\text{bw}} = 0\}_T$

For each parametric problem $l \in \llbracket 1, N \rrbracket$:

 Solve parametric problem on \mathcal{T}_n to obtain $u_{l,k}$

 Add $u_{\mathcal{Q}_s^N, k} + C_s(N) a_l u_{l,k}$

For each cell T of \mathcal{T}_n :

 Solve BW local parametric problem on T to obtain $e_{l,T}^{\text{bw}}$

 Add $e_{\mathcal{Q}_s^N, T}^{\text{bw}} + C_s(N) a_l e_{l,T}^{\text{bw}}$

 Compute $\{\eta_{\mathcal{Q}_s^N, T}^{\text{bw}} = \|e_{\mathcal{Q}_s^N, T}^{\text{bw}}\|_{L^2(T)}\}_T$

 Take the square root of the sum of $\{\eta_{\mathcal{Q}_s^N, T}^{\text{bw}}\}_T^2$ to obtain $\eta_{\mathcal{Q}_s^N}^{\text{bw}}$

The spectral fractional Laplacian

Adaptive mesh refinement

Choose a tolerance $\delta > 0$, an initial mesh $\mathcal{T}_{n=0}$ and N such that $\varepsilon_s(N) \|f\|_{L^2} \ll \delta$

Generate the rational approximation \mathcal{Q}_s^N coefficients

Initialize the estimator $\eta_{\mathcal{Q}_s^N}^{\text{bw}} = \delta + 1$

While $\eta_{\mathcal{Q}_s^N}^{\text{bw}} > \delta$:

 Initialize the solution $u_{\mathcal{Q}_s^N, k} = 0$

 Initialize the local Bank–Weiser solutions $\{e_{\mathcal{Q}_s^N, T}^{\text{bw}} = 0\}_T$

For each parametric problem $l \in \llbracket 1, N \rrbracket$:

 Solve parametric problem on \mathcal{T}_n to obtain $u_{l,k}$

 Add $u_{\mathcal{Q}_s^N, k} + C_s(N) a_l u_{l,k}$

For each cell T of \mathcal{T}_n :

 Solve BW local parametric problem on T to obtain $e_{l,T}^{\text{bw}}$

 Add $e_{\mathcal{Q}_s^N, T}^{\text{bw}} + C_s(N) a_l e_{l,T}^{\text{bw}}$

 Compute $\{\eta_{\mathcal{Q}_s^N, T}^{\text{bw}} = \|e_{\mathcal{Q}_s^N, T}^{\text{bw}}\|_{L^2(T)}\}_T$

 Take the square root of the sum of $\{\eta_{\mathcal{Q}_s^N, T}^{\text{bw}}\}_T^2$ to obtain $\eta_{\mathcal{Q}_s^N}^{\text{bw}}$

If $\eta_{\mathcal{Q}_s^N}^{\text{bw}} > \delta$:

 Mark the mesh using $\{\eta_{\mathcal{Q}_s^N, T}^{\text{bw}}\}_T$

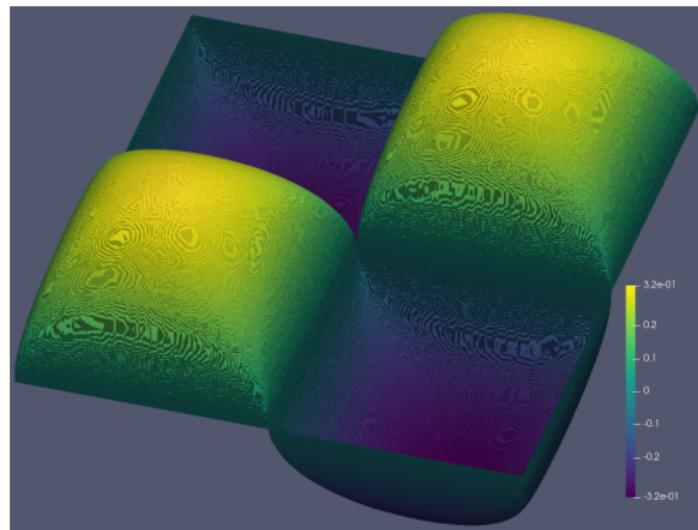
 Refine the mesh and replace \mathcal{T}_n by \mathcal{T}_{n+1}

The spectral fractional Laplacian

Numerical results

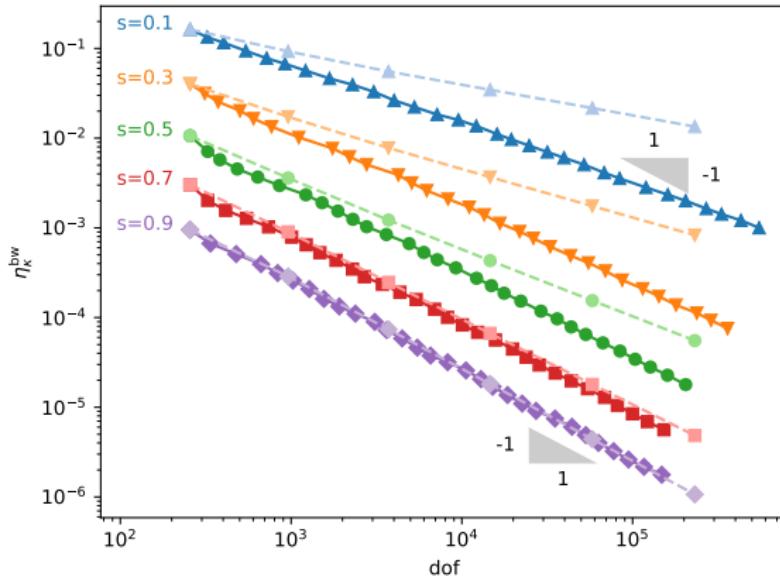
$(-\Delta)^s u = f$, in $[0, 1]^2$, $u = 0$, on Γ ,
with $f(x, y) = 1$ in $[0, 0.5]^2 \cup [0.5, 1]^2$, -1 otherwise.

We assume the rational approximation is negligible, i.e. $u = u_{Q_s^N}$.



The spectral fractional Laplacian

Numerical results



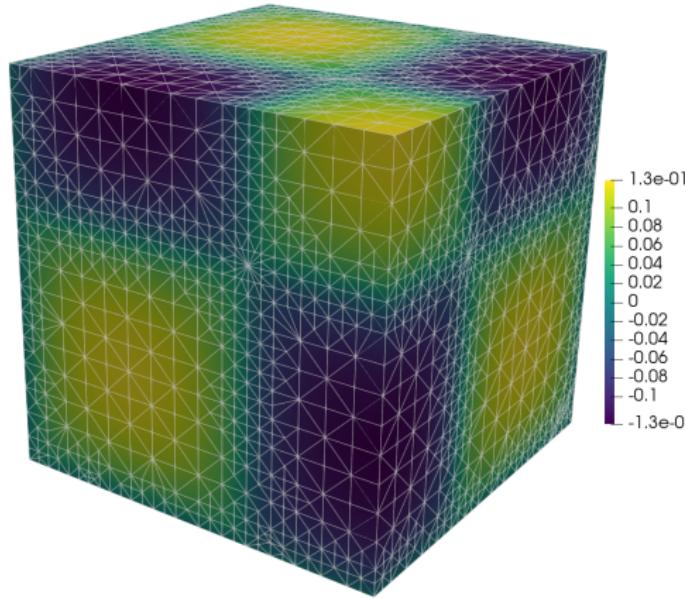
Frac. power	0.1	0.3	0.5	0.7	0.9
Theory [Bonito and Pasciak, 2015]	-0.35	-0.55	-0.75	-0.95	-1.00
Est. (unif.)	-0.35	-0.55	-0.76	-0.95	-1.00
Est. (adapt.)	-0.65	-0.84	-0.93	-0.97	-1.01

The spectral fractional Laplacian

Numerical results

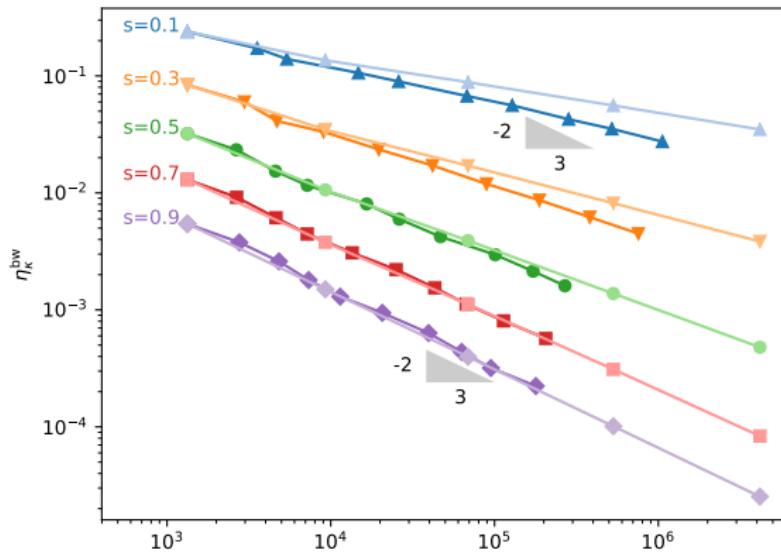
$$(-\Delta)^s u = f, \text{ in } [0, 1]^3, \quad u = 0, \text{ on } \Gamma.$$

We assume the rational approximation is negligible, i.e. $u = u_{Q_s^N}$.



The spectral fractional Laplacian

Numerical results



Frac. power	0.1	0.3	0.5	0.7	0.9
Theory [Bonito and Pasciak, 2015]	-0.23	-0.37	-0.50	-0.63	-0.67
Est. (unif.)	-0.24	-0.38	-0.52	-0.62	-0.67
Est. (adapt.)	-0.33	-0.46	-0.55	-0.65	-0.68

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Thank you for your attention!



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