

Localized Model Order Reduction via Multiscale-Spectral Generalized Finite Elements

Robert Scheichl

Institute for Mathematics & Interdisciplinary Center for Scientific Computing



UNIVERSITÄT
HEIDELBERG
ZUKUNFT
SEIT 1386

Collaborators: Chupeng Ma (Great Bay Univ.), Jean Bénézech (ONERA),
Christian Alber, Peter Bastian, Lukas Holbach, Arne Strehlow (HD),
Markus Bachmayr, Huqing Yang (RWTH Aachen), ...

“Reduced Order & Surrogate Modelling for Digital Twins”, **IMSI**, Chicago

Motivation

Many scientific/engineering problems involve multiscale phenomena:

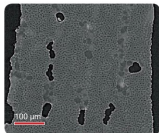
- Flow and transport in **porous media**
- Structural mechanics in **composites**
- **Geodynamics** (e.g. crystal-melt in earth mantel)
- **High-frequency** waves in heterogeneous media



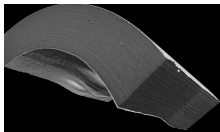
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Ply with individual fibres



Coupon with defect

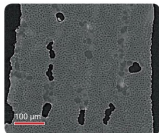


wing spar

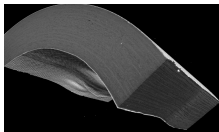
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- Coefficients vary on many (unseparated) scales in a complicated way, often **depending on time, the solution or a (high-dim.) parameter y**



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Key Questions

- How to set up a digital twin for such multiscale problems?
- How to make it computational feasible?
- How to deal with the inherent high dimensionality?
- How to build reduced order models or surrogates **with theory**?

Challenges and Aims (e.g. for diffusion)

Challenges for classical FEs: e.g. for $a(u, v) = \int_{\Omega} A(y; x) \nabla u \cdot \nabla v \, dx$

$$\|u - u_H\|_{H^1(\Omega)} \leq C_A \inf_{v \in V_H} \|u - v\|_{H^1(\Omega)} \quad (\text{Cea's lemma}).$$

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- **Aim 1** Use fine mesh and solve efficiently, using a multilevel solver **robust** w.r.t. mesh size h + w.r.t. coefficient variation $A(y; x)$!

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- **Aim 1** Use fine mesh and solve efficiently, using a multilevel solver
robust w.r.t. mesh size h + w.r.t. coefficient variation $A(y; x)$!
- **Aim 2** Simulate on coarse mesh where $A(y; x)$ is **not resolved** !
need to find **bespoke** (adapted) A -dependent space $V_H(y)$

Key Question (for both): **Robust coarse space** $V_H(y)$ or $\overline{V}_H$

Multiscale methods

Multiscale methods are effective techniques to reduce computational cost by **incorporating fine-scale information into coarse model/space**.

Traditionally: Asymptotic homogenization (Lions, Oleinik, Allaire,...)

Various multiscale methods (focussing only on related ones):

- 1 Multiscale Finite Element Method (MsFEM) (Hou, Wu, Efendiev,...)
- 2 Generalized Multiscale FE Method (GMsFEM) (Hou, Efendiev,...)
- 3 Localized Orthogonal Decomposition (LOD) (Peterseim, Malqvist,...)
- 4 *Multiscale Spectral Generalized FE Method (MS-GFEM)*
[Babuska & Lipton, *Multiscale Model Sim (SIAM)* **9**, 2011], ...

Based on enriching **FE space** V_H with **pre-computed multiscale basis fcts.** containing **fine-scale information**

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Based on enriching **FE space** V_H with **pre-computed multiscale basis fcts.** containing **fine-scale information** $\longleftrightarrow$ **localized model order reduction**

Some context

- Setup is expensive! Without **reuse** (multiple times) **no clear gains** over **efficient, scalable multilevel parallel solver!**
- For **wave problems** **efficient solvers** (w. theory) still hot topic!!
- Can use **MS-GFEM** coarse space in **multilevel iterative meth.**
- Can use for **localized model reduction** [Smetana, Patera, 2016], ...
- Embed all in efficient offline/online, parallel, adaptive scheme.

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THIS TALK: Localized model reduction via GFEM + new analysis!

Coefficient-robust theory for **multiscale approximation** (continuous & discrete), **wavenumber-explicit** theory for **Helmholtz** + extension to nonsym./indef. PDEs **AND** exponential convergence in space+parameter via **Grassmann interpolation**

Generalized Finite Element Methods (GFEM)

- Developed by Babuska & Melenk [[Melenk, PhD Thesis, 1995](#)], ...
- **Extension** of standard FEMs based on a **domain decomposition technique** and the **partition of unity (POU)** approach.
- **Generalised FE methods (GFEM)** consist of three steps:
 - 1 Construct **local spaces** with good approximation properties;
 - 2 Glue together **local spaces** by PoU to form global approximation;
 - 3 Solve the **problem** over the global approximation space.

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 - 1 Construct **local spaces** with good approximation properties;
 - 2 Glue together **local spaces** by PoU to form global approximation;
 - 3 Solve the **problem** over the global approximation space.
- **Global error** fully determined by local approximation errors.
- Can design **special approximation spaces tailored to problem**:

Multiscale-Spectral Generalized FE Method (**MS-GFEM**)

[Babuska & Lipton, 2011], [Ma, **RS**, Dodwell, 2022], [Ma, 2025],...

Types of Problems – Abstract Formulation

Find $u^e \in \mathcal{H}_0(\Omega) \subset \mathcal{H}(\Omega) \subset \mathcal{L}(\Omega)$ Hilbert on $\Omega \subset \mathbb{R}^d$ bdd. Lipschitz s.t.

$$a(u^e, v) = F(v), \quad \forall v \in \mathcal{H}_0(\Omega).$$

with $a : \mathcal{H}(\Omega) \times \mathcal{H}(\Omega) \rightarrow \mathbb{C}$ sesquilinear.

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We assume

$$|a(u, v)| \leq C_a \|u\|_{\mathcal{H}} \|v\|_{\mathcal{H}} \quad \forall u, v \in \mathcal{H}(\Omega) \quad (\text{Boundedness})$$

$$C_1 \|u\|_{\mathcal{H}}^2 - C_0 \|u\|_{\mathcal{L}}^2 \leq |a(u, u)| \quad \forall u \in \mathcal{H}(\Omega) \quad (\text{Gårding Ineq.})$$

(If a coercive $\Rightarrow C_0 = 0$. If a symmetric $\Rightarrow$ choose $\|u\|_{\mathcal{H}} = \sqrt{a(u, u)}$.)

In addition, we assume unique solvability and stability:

$$\|u^e\|_{\mathcal{H}} + \|w^e\|_{\mathcal{H}} \leq C_{\text{stab}} \|F\|_{\mathcal{L}} \quad \forall F \in \mathcal{L}(\Omega)$$

where $w^e \in \mathcal{H}_0(\Omega)$ is the adjoint solution s.t. $a(v, w^e) = F(v)$, $\forall v \in \mathcal{H}_0(\Omega)$.

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Examples

- (High-Peclet) Convection-Diffusion:

$$a_y(u, v) = \int_{\Omega} A(x, y) \nabla u \cdot \nabla v + v \mathbf{b}(x, y) \cdot \nabla u \, dx$$

- (Non-)Linear Elasticity: $a_y(\mathbf{u}, \mathbf{v}) = \int_{\Omega} \mathbf{C}(x, y) \epsilon(\mathbf{u}) : \epsilon(\mathbf{v}) \, dx$

- (High-frequency) Helmholtz:

$$a_y(u, v) = \int_{\Omega} (A(x, y) \nabla u \cdot \nabla \bar{v} - k^2 V^2(x, y) u \bar{v}) \, dx - ik \int_{\partial\Omega} \beta(x, y) u \bar{v} \, ds$$

- Heterogeneous Stokes:

$$a_y(u, v) = \int_{\Omega} \nu(x, y) \nabla \mathbf{u} \cdot \nabla \mathbf{v} + \gamma \nu(x, y) \operatorname{div} \mathbf{u} \operatorname{div} \mathbf{v} \, dx$$

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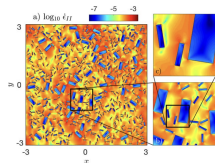
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Multiscale coefficients varying on many scales



Global Approximation Theorem (coercive case)

Theorem (Ma, RS, Dodwell, 2022)

For each $i = 1 \dots N$ let $u_i^p \in \mathcal{H}(\omega_i^*)$ be a particular function (satisfying BCs & RHS on ω_i^*) and let $S_{n_i}(\omega_i^*) \subset \mathcal{H}(\omega_i^*)$ be an n_i -dimensional subspace s.t.

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$$\|u^e - u^F\|_a \leq \kappa \max_{i=1}^N \varepsilon_i \|u^e\|_a.$$

Here we assume that each point $\mathbf{x} \in \Omega$ belongs to at most κ subdomains ω_i^* .

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Global Approximation Theorem (non-coercive case)

Theorem (Ma, FoCM, 2025)

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$$\|u^e - u^G\|_{a^+} \leq \kappa \frac{2C_a}{C_1} \max_{i=1}^N \varepsilon_i \|u^e\|_{a^+}.$$

with a suitable inner product $a^+(\cdot, \cdot)$ (+ under some resolution condition).

- **Particular solution** u_i^P with artificial BC $u_i^P|_{\partial\omega_i^*} = 0$ s.t. locally

$$a_{\omega_i^*}(u_i^P, v) = F_{\omega_i^*}(v) \quad v \in \mathcal{H}_0(\omega_i^*).$$

- The '**remainder**' $u|_{\omega_i^*} - u_i^P$ is **locally a-harmonic** and lies in

$$\mathcal{H}_a(\omega_i^*) = \{v \in \mathcal{H}(\omega_i^*) : a_{\omega_i^*}(v, \varphi) = 0 \quad \forall \varphi \in \mathcal{H}_0(\omega_i^*)\}.$$

- Consider the **PoU operator** $P_i : \mathcal{H}_a(\omega_i^*) \rightarrow \mathcal{H}_0(\omega_i)$ s.t.

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Crucial observation: P_i is **compact**. Optimal local approximation space $\mathcal{S}_{n_i}(\omega_i^*)$ can be computed via **SVD** in the a^+ -inner product.

Key Tools: **Cacciopoli inequality** and a weak approximation property

Local Particular Solution & Approximation Space

Theorem (Ma, RS, Dodwell, 2022; Ma, 2025)

Local particular solutions u_i^P & local approximation spaces defined as

$$S_n(\omega_i^*) := \text{span}\{v_1, \dots, v_n\},$$

where $v_k \in \mathcal{H}_a(\omega_i^)$ denotes k -th eigenfunction of the eigenproblem*

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*similar to **GenEO**-eigenproblem, but in $\mathcal{H}_a(\omega_i^*)$ and with $\text{supp} \chi_i \subsetneq \omega_i^*$*

[Spillane, Dolean, Hauret, Nataf, Pechstein, RS, 2014]

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If $\text{supp} \chi_i \subsetneq \omega_i^$ then $\lambda_{n+1}^{1/2} = \mathcal{O}(e^{-cn^{1/d}})$ for all the examples above.*

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continuous & discrete

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Main computational cost in earlier works: Building (discrete) $\mathcal{H}_a^h(\omega_i^*)$

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- [Calo et al '16; Chen et al '20] random sampling techniques
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Idea [Ma, RS, 2022]: Eigensolver based on mixed formulation

Find $\lambda \in \mathbb{R}$, $v \in V_h(\omega_i^*)$ and $\overbrace{p \in V_{h,0}(\omega_i^*)}^{\text{Lagrange multiplier}}$ such that

$$\begin{aligned} a_{\omega_i^*}^+(v, \varphi) + a_{\omega_i^*}(\varphi, p) &= \lambda^{-1} a_{\omega_i^*}^+(\chi_i v, \chi_i \varphi) & \forall \varphi \in V_h(\omega_i^*), \\ a_{\omega_i^*}(v, \xi) &= 0 & \forall \xi \in V_{h,0}(\omega_i^*). \end{aligned}$$

Note. The a -harmonic constraint is incorporated into the eigenproblem.

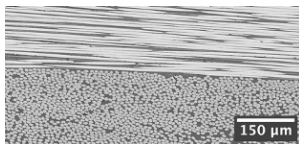
Example 1: (Non-)linear elasticity

Carbon fibre aerospace composites (C heterog./anisotropic) [Benezech et al, 2024]

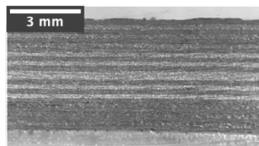
$$a(\mathbf{u}, \mathbf{v}) := \int_{\Omega} \mathbf{C}(\mathbf{x}) \varepsilon(\mathbf{u}) : \varepsilon(\mathbf{v}) \, d\mathbf{x} = \int_{\Omega} \mathbf{f} \cdot \mathbf{v} \, d\mathbf{x} + \int_{\Gamma} (\boldsymbol{\sigma} \cdot \mathbf{n}) \cdot \mathbf{v} \, d\mathbf{x} \quad \forall \mathbf{v} \in V$$



Carbon fibres



inner ply scale (microscopic)

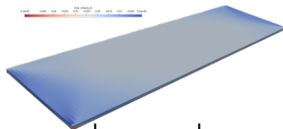


inner structure (mesoscopic)

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beam under compression
(laminate: 3 layers + thin interlayers)

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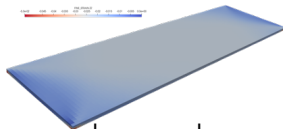
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Theory [Ma, 2025]:

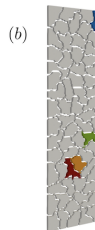
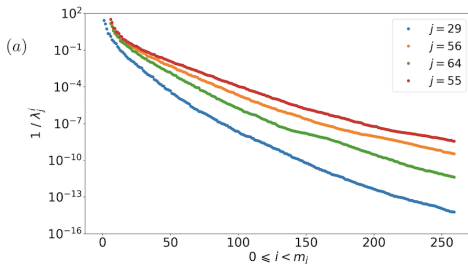
$$\frac{\|u - u^G\|_a}{\|u\|_a} \leq \kappa \max_{j=1, \dots, M} (\lambda_j^{m_j+1})^{-1/2}$$

(can be extended to nonlinear case)

(laminate: 3 layers + thin interlayers)

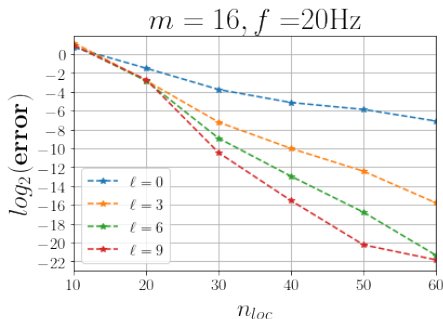
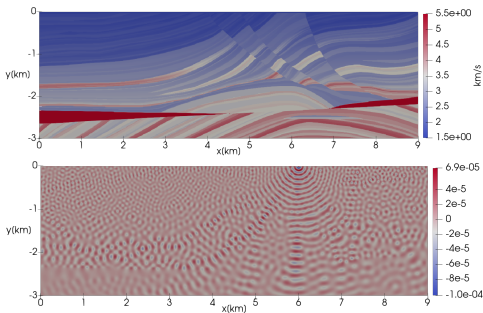


beam under compression



Example 2: High-frequency heterogeneous Helmholtz

Marmousi benchmark model with $A \equiv I$ and V^{-1} below [Ma, Alber, RS, 2023]

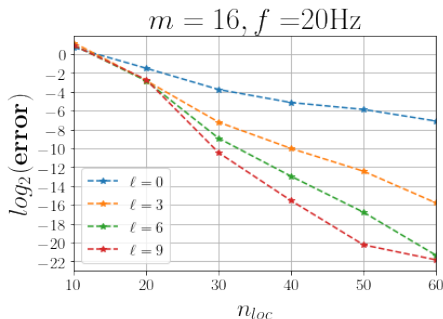
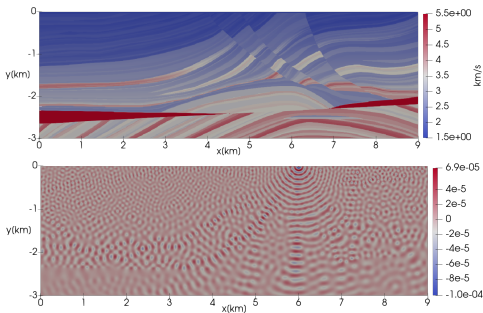


23000 basis functions $\longrightarrow$ **error** $< 10^{-3}$ ($m = 16$, $\ell = 9$, $n_{loc} = 30$)

Fully coefficient robust! No pollution effect!
 (quasi-optimal convergence for $H = \mathcal{O}(1/k)$)

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Crucial: Cacciopoli-ineq., generalized 'Helmholtz'-harmonic eigenproblem

Corollary: Two-Level Hybrid Restricted Additive Schwarz

Aim 1 Robust and scalable preconditioner for (discretised) $A\mathbf{u} = \mathbf{b}$

$$P := R_0^T A_0^{-1} R_0 \left(I - \sum_i R_i^T X_i A_i^{-1} R_i \right) + \sum_i R_i^T X_i A_i^{-1} R_i$$

Theorem (Strehlow, Ma, RS, 2024; Ma, Alber, RS, Zhang, 2024)

Let $\Lambda := \kappa \frac{2C_a}{C_1} \max_i \lambda_{i,n+1}^{1/2} < 1$. The sequence $\{\mathbf{u}^j\}_{j \geq 1}$ of approximations generated by preconditioned GMRES (in the b -inner product) satisfies

$$\|PA(\mathbf{u} - \mathbf{u}^j)\|_b \leq \Lambda^j \left(\frac{1 + \Lambda}{1 - \Lambda} \right) C \|PA(\mathbf{u} - \mathbf{u}^0)\|_b, \quad \forall j \geq 1$$

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Recall. $\lambda_{i,n+1}^{1/2} = \mathcal{O}(e^{-cn^{1/d}}) \implies$ **Tuneable convergence rate!**

see also [Chartier, Falgout et al, *Spectral AMGe*, SISC, 2003]

Example 3: 3D convection-diffusion (high Peclet number)

Iterative MS-GFEM (parallel RAS preconditioner) [Bastian, Holbach, **RS**, 2025]

$$a(u, v) = \int_{\Omega} \mathbf{A} \nabla u \cdot \nabla v + v \mathbf{b} \cdot \nabla u \, dx$$

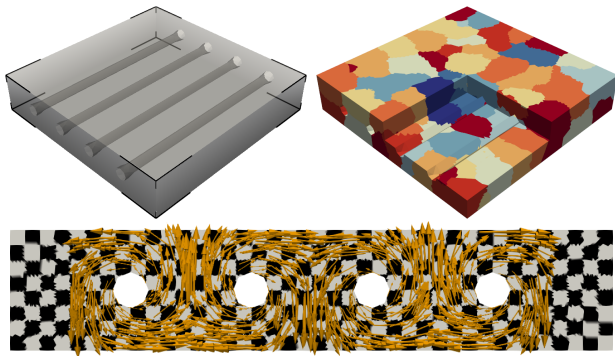
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- 64 subdomains, 2016 256 dofs
- $u = 0$ on $\partial\Omega$
- $80 \times 40 \times 8$ checkerboard diffusion ($a_{\max} = 1$)
- rotating velocity field around holes

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$a_{\min}$	GAMG		BoomerAMG		PoU (cst+lin)		MS-GFEM		
	#IT	t_{total}	#IT	t_{total}	#IT	t_{total}	#IT	t_{setup}	t_{total}
10^{-3}	2061	52.7	165	5.7	179	70.9	13	78.1	81.6
10^{-4}	-	-	-	-	365	134.3	13	77.1	80.7
10^{-5}	-	-	-	-	-	-	12	77.4	80.4
10^{-6}	-	-	-	-	-	-	13	77.6	81.5

- Preconditioned GMRES, MPI-parallel on dual AMD474 EPYC 7713
- 2 layers overlap + 1 oversampling (3 overlap for PoU coarse space)

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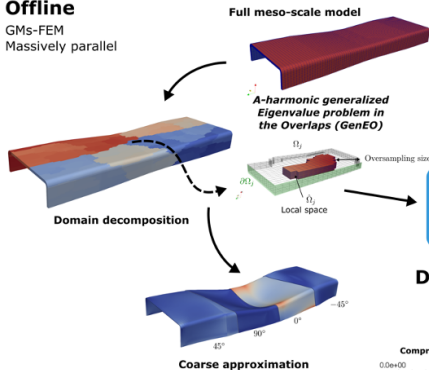
- Preconditioned GMRES, MPI-parallel on dual AMD474 EPYC 7713
- 2 layers overlap + 1 oversampling (3 overlap for PoU coarse space)
- Setup cost can be significantly reduced by formulating *eigenproblems on rings* instead of full subdomains $\leadsto$ **speed-up by factor 10!**

[Alber, Bastian, Hauck, **RS**, 2025]

Offline–Online Method for UQ

Offline

GMs-FEM
Massively parallel

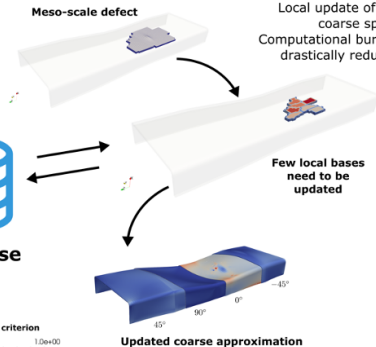


Database



Online

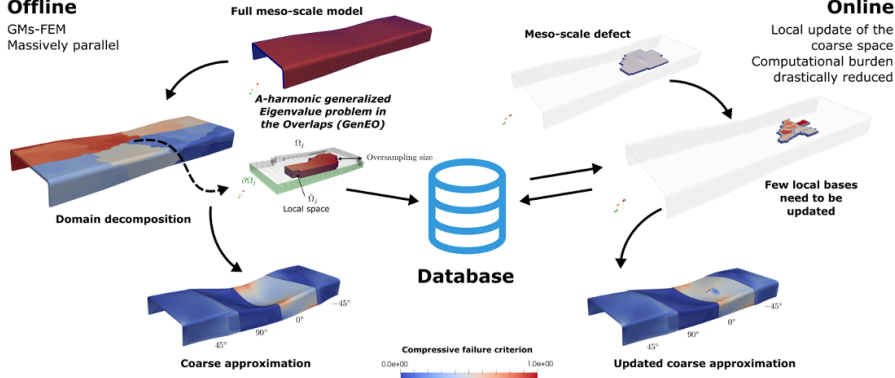
Local update of the
coarse space
Computational burden
drastically reduced



Offline–Online Method for UQ

Offline

GMs-FEM
Massively parallel



Can use now to study **localised wrinkling defects**



Studying Impact of Localised Wrinkling Defects

Strain field variations (pristine vs. defective)

On **1 CPU core**: **2-3min** to recompute local bases & **16s** for coarse solve

Parametric Setting – Localized MOR

BUT in a **digital twin** (or in many other target applications):

- Do not want to compute $V_H(y)$ again for **each new** value of y (solving an eigenproblem in each ω_i^* is **very costly**).
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- **Utopian?** Maybe not!

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Localized Model Order Reduction

e.g., survey paper [Buhr, Iapichino, Ohlberger, Rave, Schindler, Smetana, 2021]
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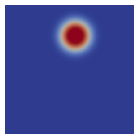
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[Patera, Smetana, 2016], [Buhr, Smetana, 2019]

- + Significantly reduce effective dimension + cost (locally active params.)
- One “average” space $\overline{V}_H$ (size?) + **no full** theoretical guarantees!

Example Diffusion $a_y(u, v) = \int_{\Omega} A(y; x) \nabla u \cdot \nabla v \, dx$

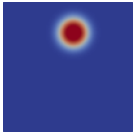
$$A(y; x)|_{\omega_i^*} =$$



$$\max_x A = 10^4, \quad \min_x A = 1$$

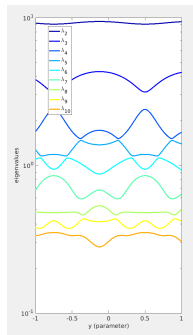
$$S_n(\omega_i^*) = \text{span} \left\{ \mathbf{1}_{\omega_i^*}, \quad \text{[gradient image]}, \quad \text{[smooth variation image]}, \quad \dots \right\}$$

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Now **vary parameter** $y = \text{location of Gaussian bump}$:

Eigenvalues



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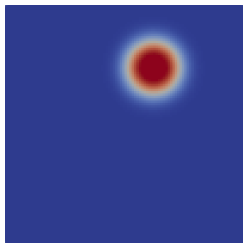
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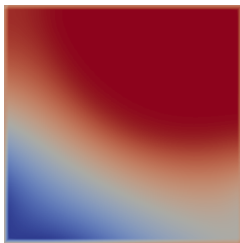
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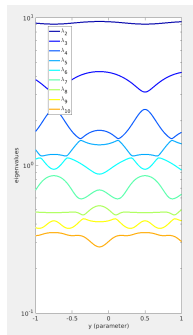
Coefficient



Dominant eigenfunction



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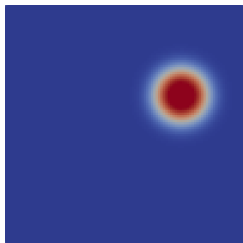
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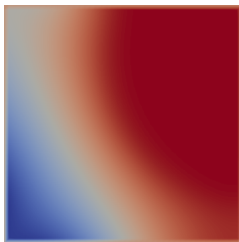
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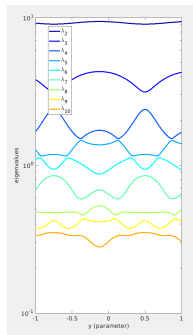
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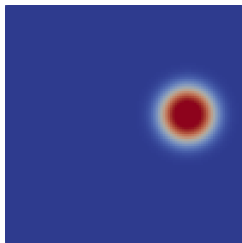
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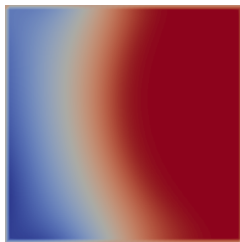
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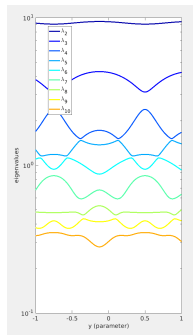
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Eigenvalues

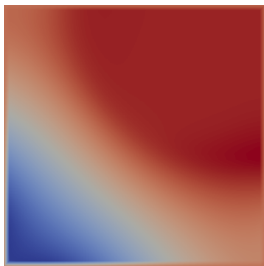


Comparison of Projection Errors (diffusion example)

How does $S_2(\omega_i^*)$ vary with y ? Can we approximate it from snapshots?

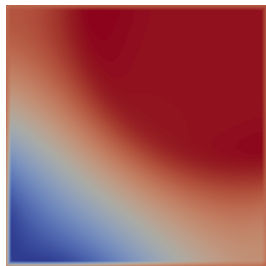
2 snapshots / interpolation points

PCA (dim=3)



$$\|(I - \Pi_{\tilde{S}})v_2\|_a / \|v_2\|_a = 0.908$$

Grassmannian interpol. (dim=2)



$$\|(I - \Pi_{\tilde{S}})v_2\|_a / \|v_2\|_a = 0.951$$

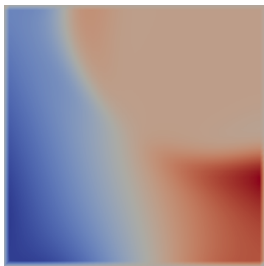
$\Pi_{\tilde{S}}$ = projection to approximate space $\tilde{S}$, v_2 = exact 2nd eigenfunction

Comparison of Projection Errors (diffusion example)

How does $S_2(\omega_i^*)$ vary with y ? Can we approximate it from snapshots?

4 snapshots / interpolation points

PCA (dim=5)



$$\|(I - \Pi_{\tilde{S}})v_2\|_a / \|v_2\|_a = 0.304$$

Grassmannian interpol. (dim=2)



$$\|(I - \Pi_{\tilde{S}})v_2\|_a / \|v_2\|_a = 0.498$$

$\Pi_{\tilde{S}}$ = projection to approximate space $\tilde{S}$, v_2 = exact 2nd eigenfunction

Comparison of Projection Errors (diffusion example)

How does $S_2(\omega_i^*)$ vary with y ? Can we approximate it from snapshots?

6 snapshots / interpolation points

PCA (dim=7)



$$\|(I - \Pi_{\tilde{S}})v_2\|_a / \|v_2\|_a = 0.077$$

Grassmannian interpol. (dim=2)



$$\|(I - \Pi_{\tilde{S}})v_2\|_a / \|v_2\|_a = 0.134$$

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Comparison of Projection Errors (diffusion example)

How does $S_2(\omega_i^*)$ vary with y ? Can we approximate it from snapshots?

8 snapshots / interpolation points

PCA (dim=9)



$$\|(I - \Pi_{\tilde{S}})v_2\|_a / \|v_2\|_a = 0.010$$

Grassmannian interpol. (dim=2)



$$\|(I - \Pi_{\tilde{S}})v_2\|_a / \|v_2\|_a = 0.017$$

$\Pi_{\tilde{S}}$ = projection to approximate space $\tilde{S}$, v_2 = exact 2nd eigenfunction

Comparison of Projection Errors (diffusion example)

How does $S_2(\omega_i^*)$ vary with y ? Can we approximate it from snapshots?

10 snapshots / interpolation points

PCA (dim=11)



$$\|(I - \Pi_{\tilde{\mathcal{S}}})v_2\|_a / \|v_2\|_a = 0.007$$

Grassmannian interpol. (dim=2)



$$\|(I - \Pi_{\tilde{\mathcal{S}}})v_2\|_a / \|v_2\|_a = 0.011$$

Exploiting holomorphic dependence on y !

Grassmannian Interpolation of ROMs

[Amsallem, Farhat, AIAA Journal, 2008]

Parametric family M of all n -dimensional local approximation spaces is the so-called Grassmannian manifold.

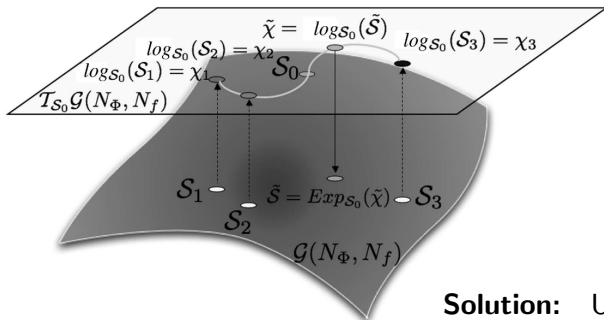
Main problem: M is not a linear vector space. How to interpolate on M ?

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Solution: Use the tangent space to M at a basepoint S_0 to interpolate (use $\log_{S_0}$ / $\exp_{S_0}$ to move between them)

Rigorous Error Analysis: A Roadmap (coercive case)

[Alber, Bachmayr, RS, Yang, 2025+]

Assume gap in the spectrum $\lambda_{n+1}/\lambda_n \leq \sigma < 1$ uniform in y .

- 1 In that case, extension to higher dimensions of perturbation theory in [Kato, 2013] gives holomorphic dependence of $S_n(\omega_i^*)$ on y .
- 2 Polynomial interpolation of holomorphic functions (in tangent space = vector space) converges exponentially in 1D [Trefethen, 2019]

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[Alber, Bachmayr, RS, Yang, 2025+]

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- 5 Additional interpolation error can be estimated using cosine of angle between subspaces [Lipton, Sinz, Stübner, 2022].

Local approximation error

Theorem (Alber, Bachmayr, **RS**, Yang, 2025+)

[Informal]

Assume that $\lambda_{n+1}/\lambda_n \geq \sigma > 1$ uniformly in y and let

$$\cos^2(\beta^a(y)) := \inf_{v \in S_n(y)} \frac{a_{\omega_i^*}(v, \Pi_{\tilde{S}(y)}^a v)}{a_{\omega_i^*}(v, v)},$$

such that $\beta^a(y)$ is the angle (w.r.t. $a_{\omega_i^*}$) between the interpolated and the local approximation subspace. Then

$$\sup_{u \in H_{A(y)}(\omega_i^*)} \inf_{v \in \tilde{S}(y)} \frac{\|u - v\|_{a, \omega_i^*}}{\|u\|_{a, \omega_i^*}} \leq \left(1 + \frac{1}{\cos \beta^a(y)}\right) \lambda_{n+1}^{1/2} \lesssim \left(1 + e^{-bN^\alpha}\right) e^{-cn^{1/d}}$$

where N is the number of interpolation points.

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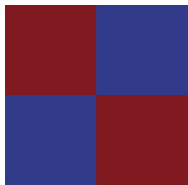
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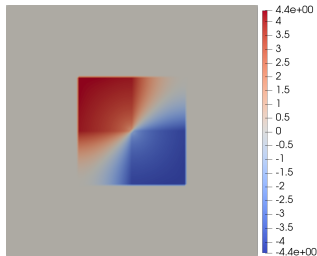
Note that for the theory we had to change the MS-GFEM eigenproblem slightly and use $P_i : H^{1/2}(\partial\omega_i^*) \rightarrow H_0^1(\omega_i)$ defined by $u \mapsto \chi_i E_a u$, where E_a is the a -harmonic extension from $H^{1/2}(\partial\omega_i^*)$ to $H_a(\omega_i^*)$.

Numerical Experiment (diffusion example with cross point)

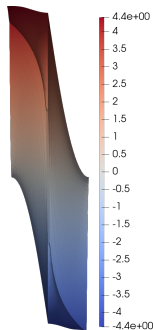


with $A(y; x)|_{\omega_i^*} = \begin{cases} 1 - 0.99y, & \text{in red squares,} \\ 1 + 0.99y, & \text{in blue squares.} \end{cases}$

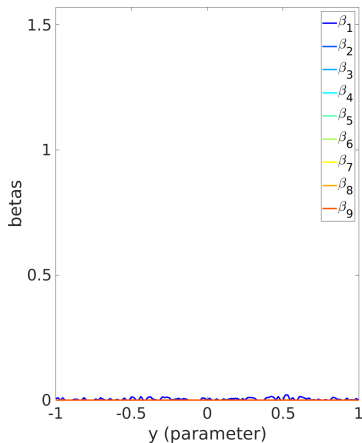
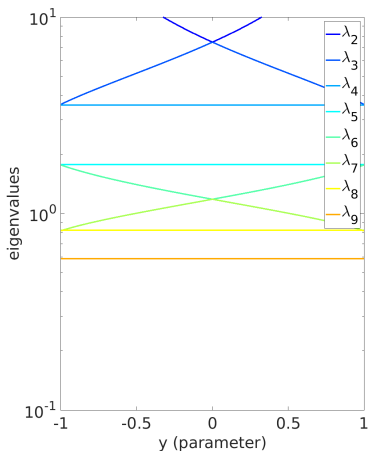
$v_2(-1) =$



$=$

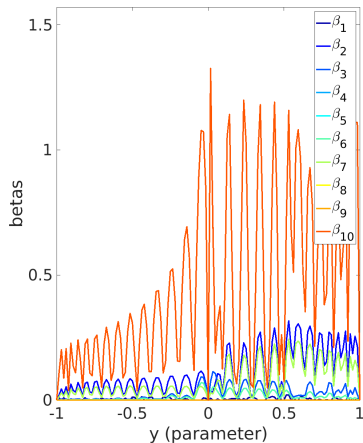
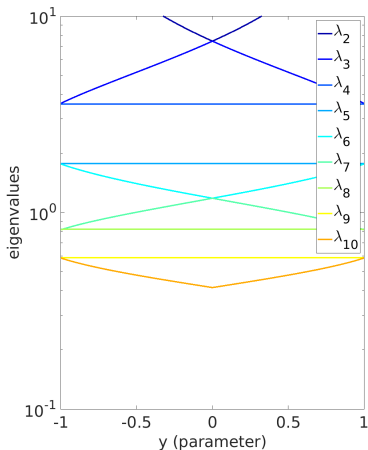


Numerical Experiment (diffusion example with cross point)



Angles for $S_9(\omega_i^*)$ (uniform gap between λ_9 and λ_{10})
(base point $S_n(\omega_i^*)$ at $y = -1$)

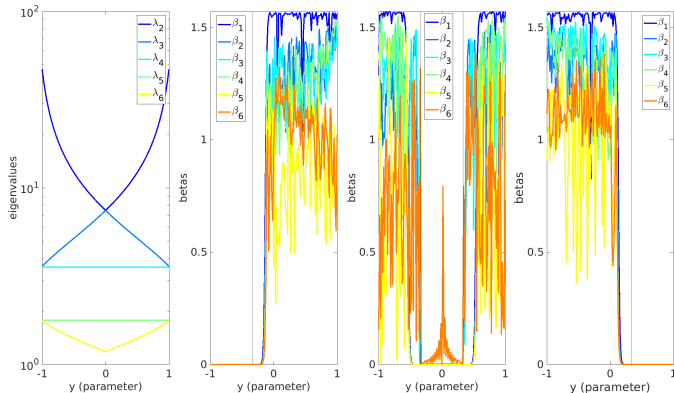
Numerical Experiment (diffusion example with cross point)



Angles for $S_{10}(\omega_i^*)$ (no uniform gap between λ_{10} and λ_{11})
 (base point $S_n(\omega_i^*)$ at $y = -1$)

Numerical Experiment (diffusion example with cross point)

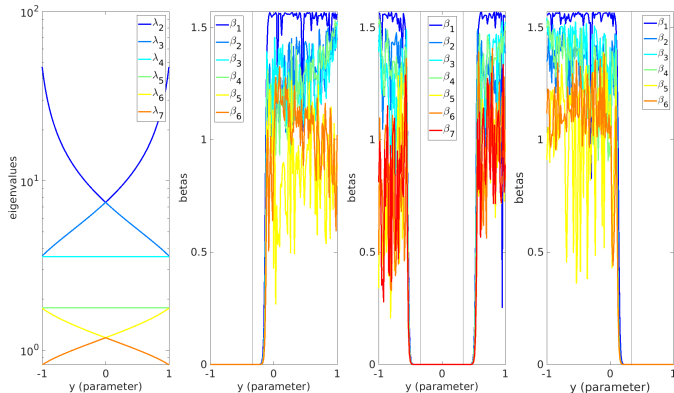
To deal with **eigenvalue crossings** use **multiple base points**



Angles for $S_6(\omega_i^*)$ (**no** uniform eigenvalue gap in middle)
(base points at $y = -1, 0, 1$)

Numerical Experiment (diffusion example with cross point)

To deal with **eigenvalue crossings** use **multiple base points** + **variable n** :

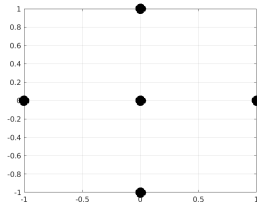
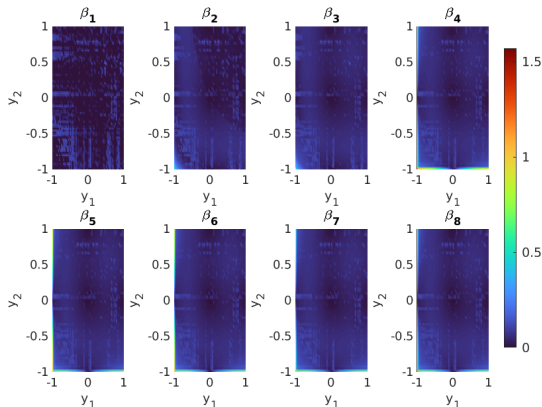


Angles for $S_6(\omega_i^*)$, $S_7(\omega_i^*)$, $S_6(\omega_i^*)$ (uniform eigenvalue gaps)
(base points at $y = -1, 0, 1$)

Numerical Experiment (two parameter cross point)



with $A(y; x)|_{\omega_i^*} = \begin{cases} 1, & \text{in red squares,} \\ 1 + 0.99y_1, & \text{in top right,} \\ 1 + 0.99y_2, & \text{in bottom left.} \end{cases}$



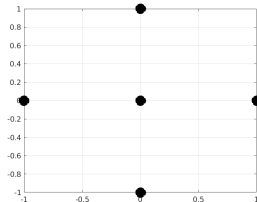
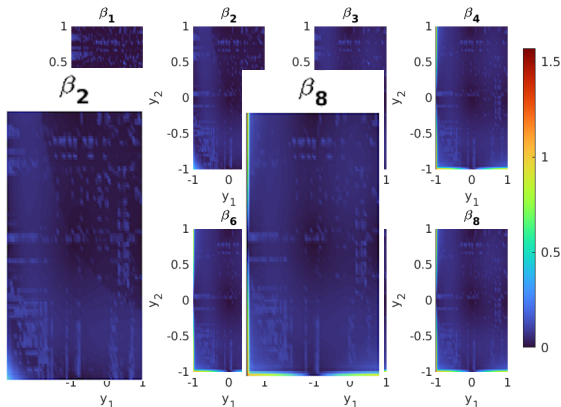
Clenshaw-Curtis
sparse grid

$$S_8(\omega_i^*)$$

Numerical Experiment (two parameter cross point)



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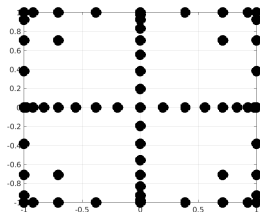
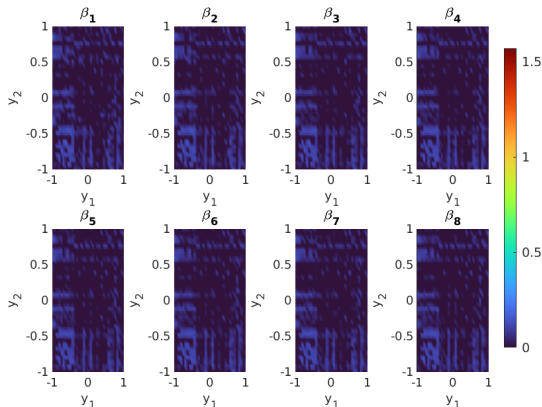
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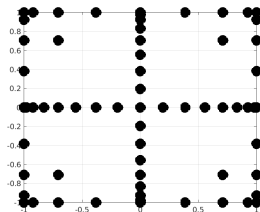
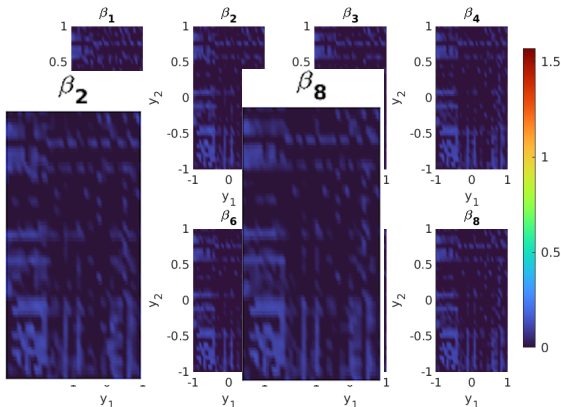
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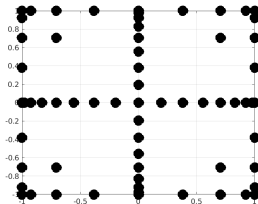
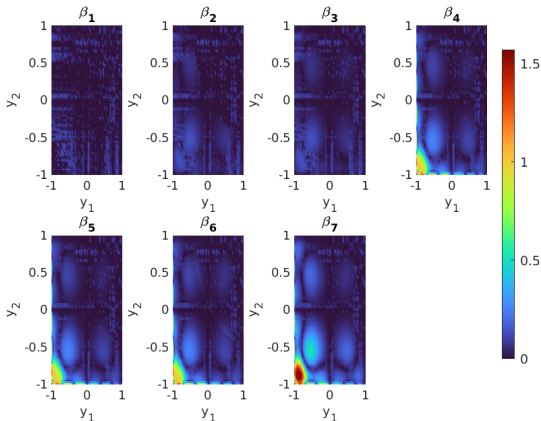
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Clenshaw-Curtis
sparse grid

$S_7(\omega_i^*)$

Conclusions and Further Comments

- **Robust multiscale coarse space** via **generalised FEM** and **optimal spectral local approximation spaces** (w/o a priori regularity assumptions)
- **Crucial** to use **oversampling** and **α -harmonicity** (weakly enforced)
- Rigorous analysis for many generic **heterogeneous** PDEs, incl.
 - (non-)linear elasticity in composites [Benezech et al, 2024 & 2025+]
 - (high-Peclet) convection-diffusion [Bastian, Holbach, RS, 2025+]
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Current and Future Work

- Nonlinear problems [Benezech et al, 2025+]
- Efficient Offline/Online implementation (e.g. for UQ) and adaptivity
- Complete theory for Grassmann interpolation [Alber et al, 2025+]
- Operator learning-based surrogates (again enforcing geometry)