

Multigrid methods for Isogeometric analysis

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joint work with
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Outline

- 1 Introduction
- 2 Abstract multigrid theory
- 3 Approximation error and inverse estimates
- 4 A robust multigrid solver
- 5 Numerical results

Model problem

Elliptic model problem: Find $u \in H^1(\Omega)$:

$$-\Delta u + u = f \text{ in } \Omega, \quad \frac{\partial u}{\partial n} = 0 \text{ on } \partial\Omega$$

Variational formulation: Find $u \in V$:

$$a(u, v) = \langle f, v \rangle \quad \forall v \in V$$

where

$$a(u, v) = \int_{\Omega} (\nabla u \cdot \nabla v + uv) \, dx, \quad \langle f, v \rangle = \int_{\Omega} fv \, dx.$$

Or as a linear system:

$$Au = f.$$

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Isogeometric Analysis

What is Isogeometric Analysis?

- **Idea:** One method that can be used for design (CAD) and numerical simulation
- **Technical:** B-spline (NURBS) based FEM



T.J.R. Hughes, J.A. Cottrell, Y. Bazilevs.

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B-spline basis functions

Let $m \in \mathbb{N}$, $h = 1/m$ and let

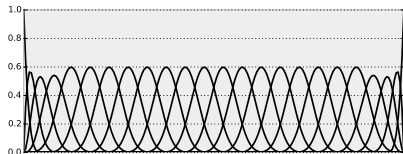
$$S_{p,h} := \{u \in C^{p-1}(0,1) : u|_{((j-1)h,jh)} \in \mathcal{P}^p \quad \forall j = 1, \dots, m\},$$

denote the **spline space** over $[0,1]$ with degree p , maximum continuity C^{p-1} , and mesh size h .

We denote the standard **B-spline basis functions** by

$$S_{p,h} = \text{span}(\mathcal{B}), \quad \mathcal{B} = \{\phi_1, \dots, \phi_n\},$$

where $n = \dim S_{p,h} = m + p$.



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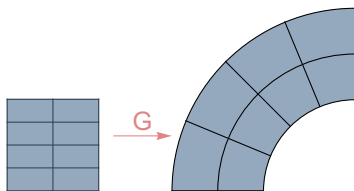
where $n = \dim S_{p,h} = m + p$.

In higher dimensions, we form **tensor product** spline spaces:

$$S_{p,h}^2 = S_{p,h} \otimes S_{p,h}, \quad \phi_{j_1, j_2}(x, y) := \phi_{j_1}(x) \phi_{j_2}(y).$$

Isogeometric Analysis

Global geometry transformation

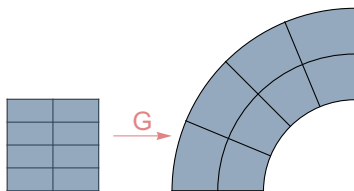


More complicated domains:

- Multi-patch discretization with tensor-product patches

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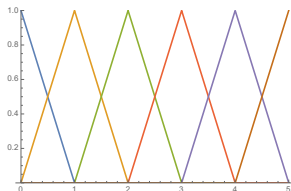
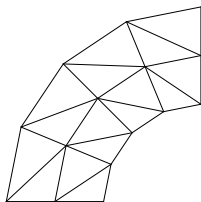


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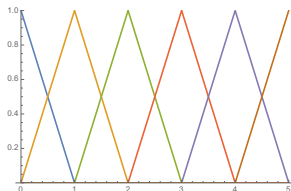
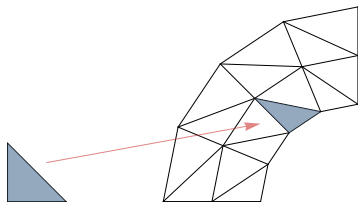
Finite element method

Courant element



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Properties of the B-spline basis

- **Non-negativity:** $\phi_i(x) \geq 0$
- Partition of unity: $\sum_i \phi_i(x) = 1$
- Approximation power:

$$\|u - u_h\|_{L_2} \leq C_p h^p |u|_{H^p}$$

- $\dim S_{p,h} = n + p$, unlike $\dim S_{p,0,h} = n p + 1$
- Condition number (of the basis):

$$\kappa(M_{p,h}) = \mathcal{O}(2^{pd}) \quad \kappa(K_{p,h}) = \mathcal{O}(h^{-2} 2^{pd}),$$

where $M_{p,h}$ is the mass matrix and $K_{p,h}$ is the stiffness matrix.

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Fast solver for $Au = f$

Requirements:

- Fast solver must be robust in h
- Should behave well in p

We know from finite element world:

- Multigrid converges robustly in h .
- Use $S_{p,H} \subset S_{p,h}$ for $H = 2h$, setup a h -multigrid with fixed p

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Multigrid with Gauss-Seidel smoother

$\ell \setminus p$	1	2	3	4	5	6	7	8	≥ 9
8	10	12	37	127	462	1762	6531	21657	>50k
7	10	12	37	127	488	1856	7247	23077	>50k
6	10	12	39	131	485	1883	6723	23897	>50k

V-cycle multigrid, $\nu_{pre} + \nu_{post} = 1 + 1$, stopping criterion: ℓ^2 norm of the initial residual is reduced by a factor of $\epsilon = 10^{-8}$

Observations and problems

- Obtain h -robustness of the method

$$\kappa(A) = \mathcal{O}(h^{-2}), \quad \kappa(M) = \mathcal{O}(1)$$

- In p : bad condition number of the mass matrix:

$\kappa(A)$ and $\kappa(M)$ grow exponentially in p

- Idea:

Basis-independent method (mass-smoother)

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Multigrid framework

One step of the multigrid method applied to iterate $u^{(0,0)} = u^{(0)}$ and right-hand-side f to obtain $u^{(1)}$ is given by:

- Apply ν **smoothing steps**

$$u^{(0,m)} = u^{(0,m-1)} + \tau L^{-1}(f - Au^{(0,m-1)})$$

for $m = 1, \dots, \nu$.

- Apply **coarse-grid correction**

- Compute defect and restrict to coarser grid
- Solve problem on coarser grid
- Prolongate and add result

If realized exactly (two-grid method):

$$u^{(1)} = u^{(0,\nu)} + I_H^h A_H^{-1} I_h^H (f - Au^{(0,\nu)})$$

- Two-grid convergence \Rightarrow multigrid (W-cycle) convergence

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Multigrid setup

- **Nested spaces:** $S_{p,H}(\Omega) \subset S_{p,h}(\Omega)$
- The prolongation I_H^h is the canonical embedding
- The restriction is its transpose: $I_h^H = (I_H^h)^T$
- Hackbusch-like analysis: smoothing property and approximation property
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A p -robust estimate for high smoothness

$$\tilde{S}_{p,h}(0,1) := \left\{ u \in S_{p,h}(0,1) : \begin{array}{l} \frac{\partial^{2i+1}}{\partial x^{2i+1}} u(0) = 0 \\ \frac{\partial^{2i+1}}{\partial x^{2i+1}} u(1) = 0 \end{array} \forall i \in \mathbb{Z} \text{ with } 1 \leq 2i+1 < p \right\}$$

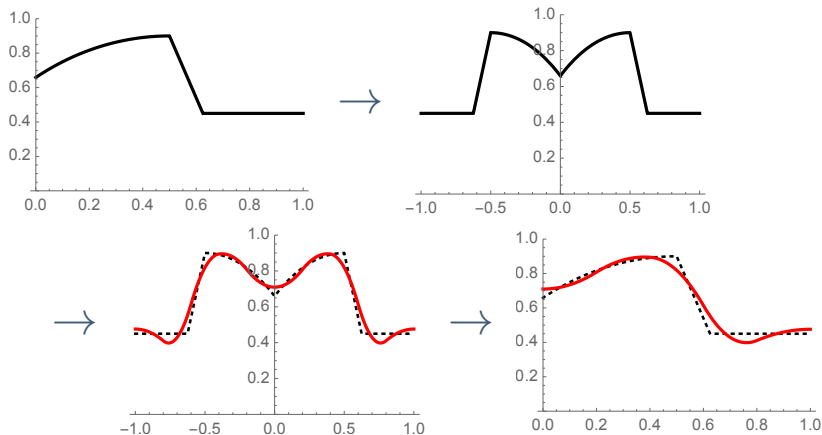
Theorem (T., Takacs 2016)

For each $u \in H^1(\Omega)$, each $p \in \mathbb{N}$ and each h ,

$$\|(I - \Pi)u\|_{L^2(\Omega)} \leq \sqrt{2} h |u|_{H^1(\Omega)}$$

is satisfied for Π being the H^1 -orthogonal projection into $\tilde{S}_{p,h}(\Omega)$.

Idea behind $\tilde{S}_{\rho,h}(0,1)$



Inverse inequality

- A p -robust inverse inequality does not exist for $S_{p,h}(\Omega)$:

$$|u|_{H^1(\Omega)} \leq C h^{-1} \|u\|_{L^2(\Omega)} \rightarrow \text{not true for all } u \in S_{p,h}(\Omega)$$

- Choose $u^*(x) := \max\{0, h - x\}^p$
- What about the space $\tilde{S}_{p,h}(\Omega)$?

Theorem (T., Takacs 2016)

For each $p \in \mathbb{N}$ and each h ,

$$|u|_{H^1} \leq 2\sqrt{3}h^{-1} \|u\|_{L^2}$$

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Robust multigrid for IgA

How to choose the smoother L such that the two-grid/multigrid method **converges robustly** in h and p ?

- Standard smoothers (e.g., **Gauss-Seidel**) achieve h -robustness but scale poorly with p .
- Our previous concept: **mass smoother with low-rank boundary correction** is robust in h and p , but only efficient up to 2D. (*Hofreither, T., Zulehner, CMAME 2016*)
- New idea: stable splitting of the spline space – **subspace correction**. Robust and efficient in arbitrary dimension.
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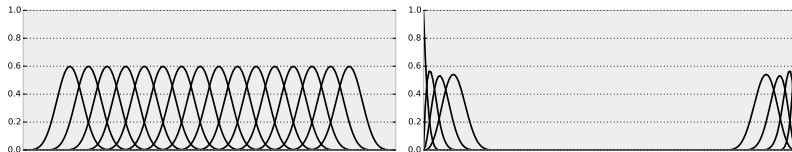
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Splittings of spline spaces

Any spline $u \in S_{p,h}(0,1)$ can be split into $u_I \in S'_{p,h}(0,1)$ and $u_\Gamma \in S^\Gamma_{p,h}(0,1)$:

$$u = u_I + u_\Gamma$$



Have: Inverse inequality: $\|v\|_1 \leq ch^{-1}\|v\|_0 \quad \forall v \in S'_{p,h}(0,1)$.

Problem: Splitting is not stable.

$$c^{-1}\|u\|_1 \leq \|u_I\|_1 + \|u_\Gamma\|_1 \leq c\|u\|_1 \quad \forall u \in S_{p,h}(0,1) \rightarrow \text{wrong!}$$

The subspace $\tilde{S}_{p,h}(0, 1)$

We have seen that for $\tilde{S}_{p,h}(0, 1)$,

- an **approximation error estimate** and
- an **inverse inequality** holds.

Define:

$$V := S_{p,h}(0, 1)$$

$$V_0 := \tilde{S}_{p,h}(0, 1)$$

V_1 is the L^2 -orthogonal complement of V_0 in V

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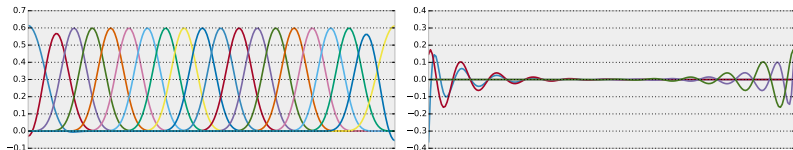
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Stability of the splitting based on V_0

Any spline $u \in V$ can be split into $u_0 \in V_0, u_1 \in V_1: u = u_0 + u_1$



Due to orthogonality, we have: $\|u\|_0^2 = \|u_0\|_0^2 + \|u_1\|_0^2 \quad \forall u \in V.$

Theorem (Hofreither, T. 2016)

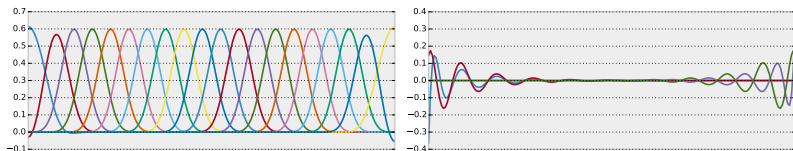
Stability of the splitting

$$c^{-1} \|u\|_1^2 \leq \|u_0\|_1^2 + \|u_1\|_1^2 \leq c \|u\|_1^2 \quad \forall u \in V$$

holds, where c does not depend on h or p .

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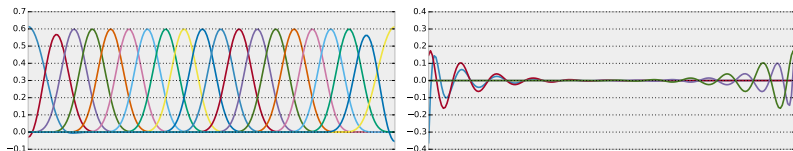
Stability of the splitting

$$c^{-1} \|u\|_1^2 \leq \|u_0\|_1^2 + \|u_1\|_1^2 \leq c \|u\|_1^2 \quad \forall u \in V$$

holds, where c does not depend on h or p .

Stability of the splitting based on V_0

Any spline $u \in V$ can be split into $u_0 \in V_0, u_1 \in V_1: u = u_0 + u_1$



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Setting up the splitting in 1D

- Construction of V_0 and V_1 is local process on the boundary
- Basis functions away from the boundary are directly taken as basis functions in V_0
- For the first and last p basis functions, we can use a SVD (for two $p \times p$ matrices) to set up the ℓ^2 -orthogonal splitting representing the basis functions for V_0 and V_1 as linear combination of the ϕ_i
- The vectors representing the basis functions on V_1 are pre-multiplied with M^{-1} to obtain L^2 -orthogonality

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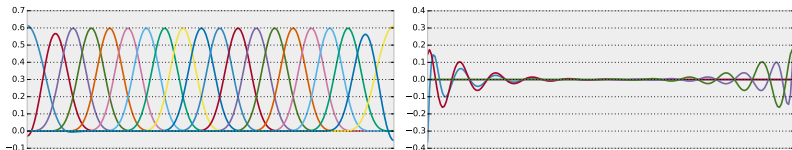
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Stability of the splitting based on V_0 (once more)

Any spline $u \in V$ can be split into $u_0 \in V_0, u_1 \in V_1: u = u_0 + u_1$



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Theorem (Hofreither, T. 2016)

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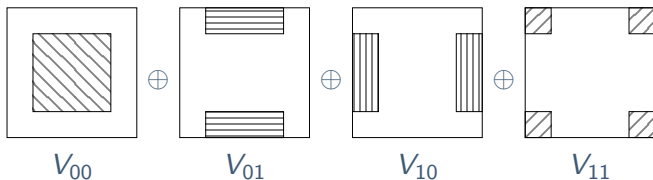
$$c^{-1} \|u\|_1^2 \leq \|u_0\|_1^2 + \|u_1\|_1^2 \leq c \|u\|_1^2 \quad \forall u \in V$$

holds, where c does not depend on h or p .

A stable splitting in 2D

The 2D tensor product spline space is given by

$$\begin{aligned}
 V^2 &= V \otimes V \\
 &= (V_0 \oplus V_1) \otimes (V_0 \oplus V_1) \\
 &= (V_0 \otimes V_0) \oplus (V_0 \otimes V_1) \oplus (V_1 \otimes V_0) \oplus (V_1 \otimes V_1) \\
 &= V_{00} \oplus V_{01} \oplus V_{10} \oplus V_{11}.
 \end{aligned}$$



A stable splitting in 2D

Let

$$Q_0 : V \rightarrow V_0, \quad Q_1 : V \rightarrow V_1$$

denote the L_2 -orthogonal projectors into V_0 and V_1 . Then

$$Q_{\alpha_1, \alpha_2} := Q_{\alpha_1} \otimes Q_{\alpha_2} \quad : \quad V^2 \rightarrow V_{\alpha_1, \alpha_2}$$

is the L_2 -orthogonal projector into V_{α_1, α_2} .

Theorem (Hofreither, T. 2016)

For any tensor product spline $u \in V^2$, we have

$$c^{-1} \|u\|_1^2 \leq \sum_{(\alpha_1, \alpha_2) = (0,0)}^{(1,1)} \|Q_{\alpha_1, \alpha_2} u\|_1^2 \leq c \|u\|_1^2$$

with a constant c which does not depend on h or p .

Stable splitting in arbitrary dimensions

For a multiindex $\alpha \in \{0, 1\}^d$, we define projectors

$$Q_\alpha := Q_{\alpha_1} \otimes \dots \otimes Q_{\alpha_d} \quad : \quad V^d \rightarrow V_{\alpha_1} \otimes \dots \otimes V_{\alpha_d} =: V_\alpha$$

into the 2^d subspaces V_α .

Theorem (Hofreither, T. 2016)

For any d -dimensional tensor product spline $u \in V^d$, we have

$$c^{-1} \|u\|_1^2 \leq \sum_{\alpha=(0,\dots,0)}^{(1,\dots,1)} \|Q_\alpha u\|_1^2 \leq c \|u\|_1^2$$

with a constant c which does not depend on h or p .

A smoother based on subspace correction

In each subspace V_α , we apply a local smoothing operator $L_\alpha : V_\alpha \rightarrow V'_\alpha$. The overall operator is

$$L = \sum_{\alpha} Q'_\alpha L_\alpha Q_\alpha.$$

Theorem (a variant of Hackbusch's analysis)

Assume that we have an appropriate approximation error estimate and

$$\langle Av, v \rangle \leq c \langle Lv, v \rangle \quad \forall v \in V$$

and

$$\langle Lv, v \rangle \leq c \langle (A + h^{-2}M^d)v, v \rangle \quad \forall v \in V.$$

Then the two-grid method with smoother based on L converges with a rate which depends only on c .

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Theorem (Hofreither, T. 2016)

Assume that we have an appropriate approximation error estimate and for every $\alpha \in \{0, 1\}^d$ we have

and

$$\langle A_\alpha v_\alpha, v_\alpha \rangle \leq c \langle L_\alpha v_\alpha, v_\alpha \rangle \quad \forall v_\alpha \in V_\alpha$$

$$\langle L_\alpha v_\alpha, v_\alpha \rangle \leq c \langle (A_\alpha + h^{-2} M_\alpha^d) v_\alpha, v_\alpha \rangle \quad \forall v_\alpha \in V_\alpha.$$

Then the two-grid method with smoother based on L converges with a rate which depends only on c .

Construction of the subspace smoothers (2D)

Let M and K denote the 1D mass and stiffness operators. Then

$$A = K \otimes M + M \otimes K + M \otimes M.$$

The restriction to the subspace V_{α_1, α_2} is

$$A_\alpha = K_{\alpha_1} \otimes M_{\alpha_2} + M_{\alpha_1} \otimes K_{\alpha_2} + M_{\alpha_1} \otimes M_{\alpha_2}.$$

The robust inverse inequality in V_0 states that

$$K_0 \leq ch^{-2}M_0.$$

We want

$$c^{-1}A_\alpha \leq L_\alpha \leq c(A_\alpha + h^{-2}M_\alpha^d).$$

Construction of the subspace smoothers (2D)

Using $K_0 \leq ch^{-2}M_0$, we estimate:

$$A_{00} = K_0 \otimes M_0 + M_0 \otimes K_0 + M_0 \otimes M_0 \lesssim h^{-2}M_0 \otimes M_0$$

$$A_{01} = K_0 \otimes M_1 + M_0 \otimes K_1 + M_0 \otimes M_1 \lesssim M_0 \otimes (h^{-2}M_1 + K_1)$$

$$A_{10} = K_1 \otimes M_0 + M_1 \otimes K_0 + M_1 \otimes M_0 \lesssim (h^{-2}M_1 + K_1) \otimes M_0$$

So we choose

$$L_{00} := h^{-2}M_0 \otimes M_0 \qquad L_{01} := M_0 \otimes (h^{-2}M_1 + K_1)$$

$$L_{10} := (h^{-2}M_1 + K_1) \otimes M_0 \qquad L_{11} := A_{11}$$

L_{00}, L_{01}, L_{10} have tensor product structure. Invert using

$$(A \otimes B)^{-1} = A^{-1} \otimes B^{-1}.$$

L_{11} lives in the small space V_{11} ($\mathcal{O}(p^2)$ dofs) – invert directly.

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Robust convergence

By construction, the subspace smoothers satisfy

$$\langle A_\alpha v_\alpha, v_\alpha \rangle \leq c \langle L_\alpha v_\alpha, v_\alpha \rangle \quad \forall v_\alpha \in V_\alpha$$

and

$$\langle L_\alpha v_\alpha, v_\alpha \rangle \leq c \langle (A_\alpha + h^{-2} M_\alpha^d) v_\alpha, v_\alpha \rangle \quad \forall v_\alpha \in V_\alpha.$$

In both cases, c does not depend on h or p .

Theorem (Hofreither, T. 2016)

The two-grid method with the subspace correction smoother L converges with a rate which does not depend on h or p .

The extension to W-cycle multigrid is standard.

Computational costs

Construction is easily extended to d dimensions.

Complexity analysis:

Setup costs	$\mathcal{O}(np^2 + p^{3d})$
Application costs	$\mathcal{O}(n^d p + \max_{k=0, \dots, d} n^k p^{2(d-k)})$ $= \mathcal{O}(n^d p + p^{2d})$
Stiffness matrix costs	$\mathcal{O}(n^d p^d)$

For $d \geq 2$ and $p^2 \lesssim n$, both setup and application of the smoother are **not more expensive** than applying the stiffness matrix.

Outline

- 1 Introduction
- 2 Abstract multigrid theory
- 3 Approximation error and inverse estimates
- 4 A robust multigrid solver
- 5 Numerical results**

Iteration numbers: $d = 1$

$\ell \setminus p$	1	2	3	4	5	6	7	8	9	10
9	27	33	34	34	33	33	33	32	31	31
8	27	33	34	34	32	33	33	31	30	30
7	27	33	34	34	32	33	33	31	28	30

V-cycle multigrid, $\nu_{pre} + \nu_{post} = 1 + 1$, stopping criterion: ℓ^2 norm of the initial residual is reduced by a factor of $\epsilon = 10^{-8}$

Iteration numbers: $d = 2$

$l \setminus p$	1	2	3	4	5	6	7	8	9	10
8	34	38	39	39	39	38	38	37	37	36
7	34	38	39	39	38	38	37	36	36	34
6	34	38	38	38	37	37	35	34	34	32
5	34	36	37	34	34	32	30	28	26	24
4	34	33	32	28	25	21	19	16	13	11
3	38	25	21	15	11	9	7	-	-	-

Iteration numbers using standard Gauss-Seidel smoother:

$l \setminus p$	1	2	3	4	5	6	≥ 7
8	10	12	37	127	462	1762	$>5k$

Iteration numbers: $d = 3$

$l \setminus p$	2	3	4	5
5	44	43	42	39
4	39	36	32	29
3	30	42	18	23
2	16	23	-	-
1	-	-	-	-

Iteration numbers using standard Gauss-Seidel smoother:

$l \setminus p$	2	3	4	≥ 5
5	38	240	1682	$>5k$

Multigrid solver

- Single-patch solver (some DD approach might be used for multi-patch domains)
- Robust convergence rates, robust number of smoothing steps
- Optimal computational complexity in the sense: “same complexity as the multiplication with the stiffness matrix A ”
- Mild dependence of the rates on d (not fully analyzed)
- Rigorous analysis

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C. Hofreither, S. Takacs and W. Zulehner.

A Robust Multigrid Method for Isogeometric Analysis using Boundary Correction.

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Robust Multigrid for Isogeometric Analysis using Subspace Correction.

In preparation, 2016.

Thanks for your attention!

Construction of the subspace smoothers (3D)

Using $K_0 \leq ch^{-2}M_0$, we estimate:

$$\begin{aligned} A_{000} &= K_0 \otimes M_0 \otimes M_0 + M_0 \otimes K_0 \otimes M_0 + M_0 \otimes M_0 \otimes K_0 + M_0 \otimes M_0 \otimes M_0 \\ &\lesssim h^{-2}M_0 \otimes M_0 \otimes M_0 =: L_{000} \end{aligned}$$

$$\begin{aligned} A_{100} &= K_1 \otimes M_0 \otimes M_0 + M_1 \otimes K_0 \otimes M_0 + M_1 \otimes M_0 \otimes K_0 + M_1 \otimes M_0 \otimes M_0 \\ &\lesssim (K_1 + h^{-2}M_1) \otimes M_0 \otimes M_0 =: L_{100} \end{aligned}$$

$$\begin{aligned} A_{110} &= K_1 \otimes M_1 \otimes M_0 + M_1 \otimes K_1 \otimes M_0 + M_1 \otimes M_1 \otimes K_0 + M_1 \otimes M_1 \otimes M_0 \\ &\lesssim (K_1 \otimes M_1 + M_1 \otimes K_1 + h^{-2}M_1 \otimes M_1) \otimes M_0 =: L_{110} \end{aligned}$$

$$\begin{aligned} A_{111} &= K_1 \otimes M_1 \otimes M_1 + M_1 \otimes K_1 \otimes M_1 + M_1 \otimes M_1 \otimes K_1 + M_1 \otimes M_1 \otimes M_1 \\ &=: L_{111} \end{aligned}$$