

Perspectives of discontinuous Galerkin method for the numerical solution of computational fluid dynamics problems

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Programy a algoritmy numerické matematiky 17
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Computational fluid dynamics (CFD)

- WIKI: CFD uses numerical methods to solve and analyze problems involving fluid flows,
- turbomachinery, aeroacoustic, aeronautics, car industry, biomedical, electronics, environmental protection,
- problems are described by partial differential equations (PDEs).

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How to achieve the main goal

- suitable discretization:
numerical method & domain partition $\mathcal{T}_h, \tau_k,$
- efficient solution of arising algebraic systems
- accurate and efficient error estimates.

Requirements

- numerical method: accurate, robust, parallelizable
- algebraic solver: iterative, stopping criteria
- a posterior error analysis: accurate and fast approximation of error, algebraic error
- mesh adaptation: h, hp variants, anisotropy
- time step adaptation: explicit/implicit, order adaptation

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- “CFD software spectral method” – 168 000 links
- “CFD software discontinuous Galerkin method” – 25 000 links

www.cfd-online.com – list of CFD codes (public and commercial)

- finite element methods (FEM) – 50%
- finite volume methods (FVM) – 40%
- spectral methods (SM) – 10%
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FEM – piecewise polynomial continuous approximation

- high order of accuracy supported by theory
- efficient for problems with continuous solutions

FVM – piecewise constant discontinuous approximation

- low order of accuracy (commercial codes at most 2nd order)
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1D convection-diffusion problem

$$-\varepsilon u'' + u' = 1 \quad \text{in } \Omega := (0, 1), \quad u(0) = u(1) = 0,$$

$0 < \varepsilon \ll 1$ convection dominating problem

\Rightarrow boundary layer at $x = 1$ proportional to ε .

Numerical tests

- FEM with continuous P_1 approximation with $h = 1/32$,
- FVM piecewise constant approximation with $h = 1/32$,
- DGM using P_4 approximation with $h = 1/8$.

\Rightarrow 32 degrees of freedom for all cases.

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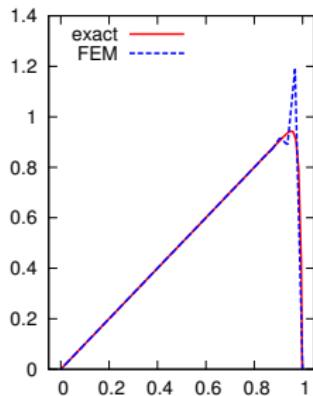
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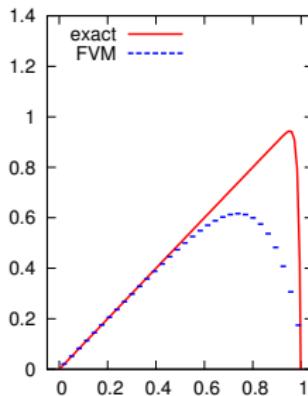
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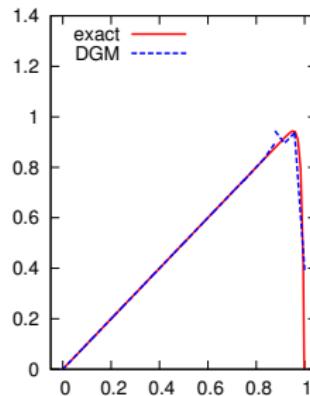
Comparison of FVM, FEM and DGM with $\varepsilon = 10^{-2}$



FEM

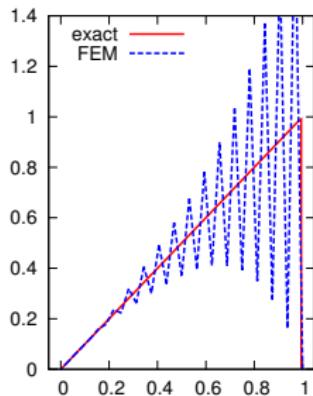


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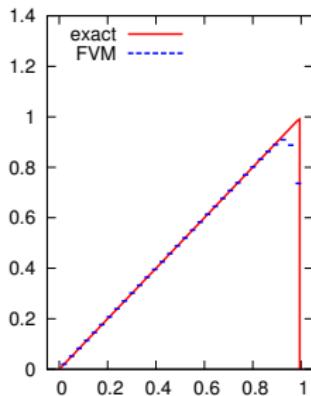


DGM

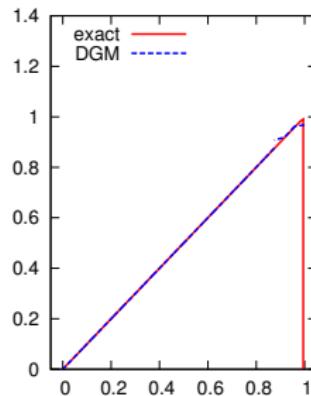
Comparison of FVM, FEM and DGM with $\varepsilon = 10^{-3}$



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DGM

Why higher order approximation?

the aim is $\|u - u_h\| \leq \omega$ & DOF minimal

Theoretical as well as experimental results

$$\|u - u_h\| \approx Ch^{p+1}, h \approx (\#\mathcal{T}_h)^{1/d}, d = 2, 3$$

$$p = \text{polyn. degree, } \text{DOF} \approx \frac{1}{d!}(p+1)\dots(p+d)\#\mathcal{T}_h$$

number of DOF necessary to fulfil $\|u - u_h\| \leq \omega$:

d	ω	P_1	P_2	P_3	P_4	P_5	P_6
2	1.00E-02	301	130	101	95	98	105
	1.00E-03	3001	601	317	238	211	202
	1.00E-04	30001	2785	1001	598	453	390
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$$\|u - u_h\| \approx Ch^{p+1}, h \approx (\#\mathcal{T}_h)^{1/d}, d = 2, 3$$

$$p = \text{polyn. degree}, \quad \text{DOF} \approx \frac{1}{d!}(p+1)\dots(p+d)\#\mathcal{T}_h$$

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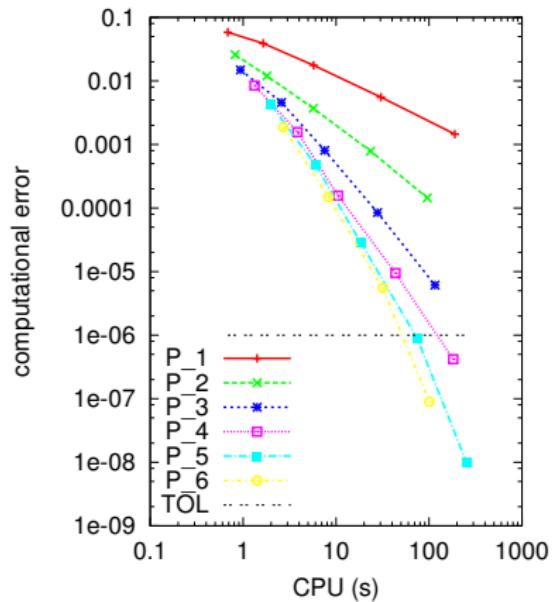
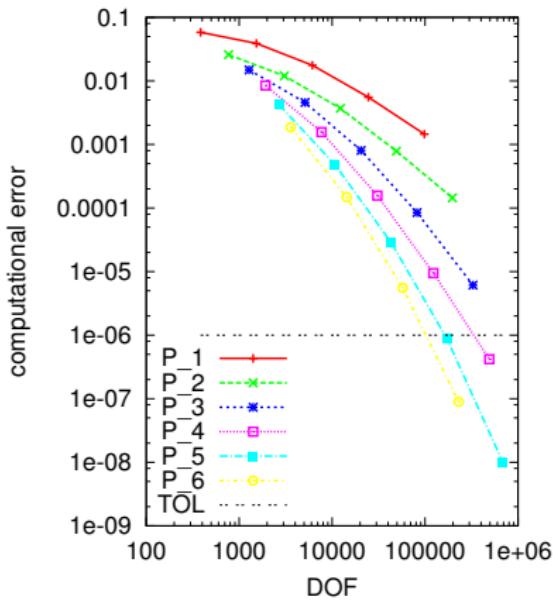
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Practical demonstration of the efficiency

- scalar linear convection-diffusion equation solved by DGM



1 Introduction

2 DGM for problems of CFD

3 Solution strategies

4 Mesh adaptation

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$$\frac{\partial \mathbf{w}}{\partial t} + \sum_{s=1}^d \frac{\partial}{\partial x_s} \mathbf{f}_s(\mathbf{w}) = \sum_{s=1}^d \frac{\partial}{\partial x_s} \mathbf{R}_s(\mathbf{w}, \nabla \mathbf{w}), \quad (1)$$

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- closing relations, e.g., from thermodynamic, BC + IC.

compressible Navier-Stokes equations, shallow water equations, etc.

Space of piecewise polynomial functions

$$S_h^p := \{v; v \in L^2(\Omega), v|_K \in P_p(K) \forall K \in \mathcal{T}_h\}, \quad \mathbf{S}_{hp} := (S_h^p)^N.$$

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$$\frac{1}{\tau_k} (\mathbf{w}_h^k - \mathbf{w}_h^{k-1}, \boldsymbol{\varphi}_h) + \mathbf{c}_h(\mathbf{w}_h^k, \boldsymbol{\varphi}_h) = 0 \quad \forall \boldsymbol{\varphi}_h \in \mathbf{S}_{hp}, \quad k = 1, 2, \dots$$

$$\begin{aligned} \mathbf{c}_h(\mathbf{w}_h, \boldsymbol{\varphi}_h) &= \sum_{K \in \mathcal{T}_h} \int_K \sum_{s=1}^d \mathbf{R}_s(\mathbf{w}_h, \nabla \mathbf{w}_h) \frac{\partial \boldsymbol{\varphi}_h}{\partial x_s} \, dx \\ &\quad - \sum_{\Gamma \in \mathcal{F}_h} \int_{\Gamma} \sum_{s=1}^d \langle \mathbf{R}_s(\mathbf{w}_h, \nabla \mathbf{w}_h) \rangle n_s[\boldsymbol{\varphi}_h] \, dS + \eta \sum_{\Gamma \in \mathcal{F}_h} \int_{\Gamma} \sum_{s=1}^d \langle \mathbf{R}_s(\mathbf{w}_h, \nabla \boldsymbol{\varphi}_h) \rangle n_s[\mathbf{w}_h] \, dS \\ &\quad - \sum_{K \in \mathcal{T}_h} \int_K \sum_{s=1}^d \mathbf{f}_s(\mathbf{w}_h) \frac{\partial \boldsymbol{\varphi}_h}{\partial x_s} \, dx + \sum_{\Gamma \in \mathcal{F}_h} \int_{\Gamma} \mathbf{H}(\mathbf{w}_h|_{\Gamma}^{(L)}, \mathbf{w}_h|_{\Gamma}^{(R)}, \mathbf{n}_{\Gamma}) [\boldsymbol{\varphi}_h]_{\Gamma} \, dS \\ &\quad + \sum_{\Gamma \in \mathcal{F}_h} \int_{\Gamma} \sigma[\mathbf{w}_h] [\boldsymbol{\varphi}_h] \, dS \end{aligned}$$

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finite volume method

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finite element method

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only DGM

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Numerical analysis

Asymptotical order of convergence

Poisson problem & scalar nonlinear convection-diffusion equation

$$|u - u_h|_{H^1(\Omega)} = O(h^p), \quad \|u - u_h\|_{L^2(\Omega)} = O(h^{p+1})$$

the same order of convergence as for FEM

Number of degrees of freedom (DOF)

let $d = 2$, $M = \#\mathcal{T}_h$

p	1	2	3	4	5	6
FEM	$\frac{1}{2}M$	$2M$	$\frac{9}{2}M$	$8M$	$\frac{25}{2}M$	$18M$
DGM	$3M$	$6M$	$10M$	$15M$	$21M$	$28M$
ratio = $\frac{\text{DGM}}{\text{FEM}}$	6	3	2.22	1.875	1.68	1.55

DGM is more expensive than FEM, the ratio is smaller for larger p

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1 Introduction

2 DGM for problems of CFD

3 Solution strategies

4 Mesh adaptation

Algebraic representation

Space-time discretization

$$\frac{1}{\tau_k} (\mathbf{w}_h^k - \mathbf{w}_h^{k-1}, \varphi_h) + \mathbf{c}_h(\mathbf{w}_h^k, \varphi_h) = 0 \quad \forall \varphi_h \in \mathbf{S}_{hp}, \quad k = 1, \dots \quad (2)$$

- system of nonlinear algebraic equations for each k ,
let $\mathbf{w}_h^k \in \mathbf{S}_{hp} \leftrightarrow \boldsymbol{\xi}_k \in \mathbb{R}^{\text{DOF}}$, $\text{DOF} = \dim \mathbf{S}_{hp}$, (2) is equivalent to

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- Newton-like method uses $\mathbf{F}(\boldsymbol{\xi}_k) \approx \mathbf{C}(\boldsymbol{\xi}_k) \boldsymbol{\xi}_k - \mathbf{b}(\boldsymbol{\xi}_k)$,
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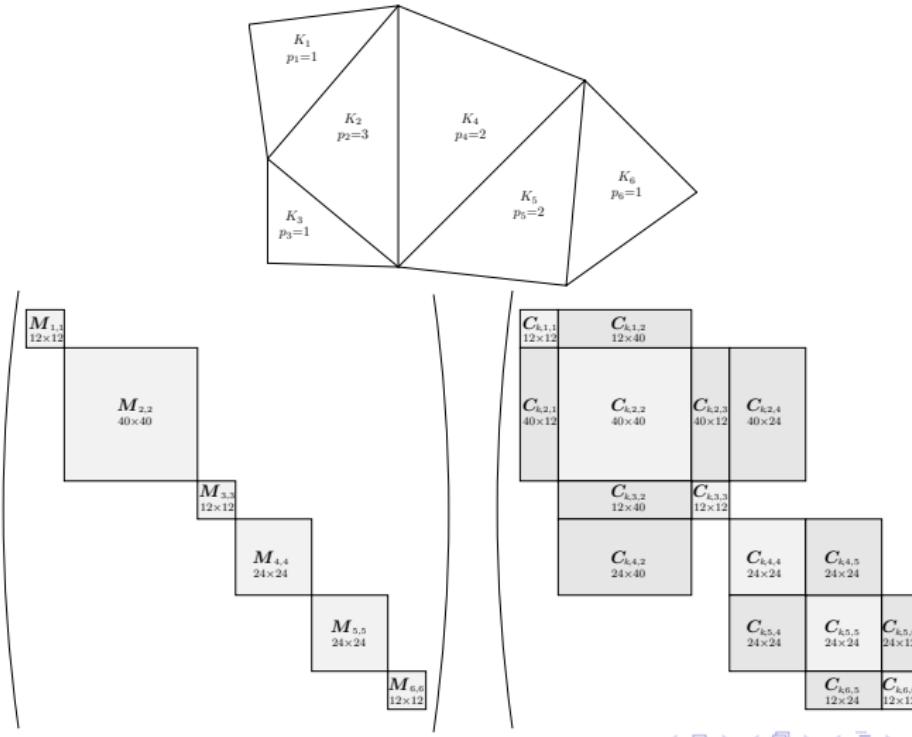
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- Newton-like method uses $\mathbf{F}(\boldsymbol{\xi}_k) \approx \mathbf{C}(\boldsymbol{\xi}_k) \boldsymbol{\xi}_k - \mathbf{b}(\boldsymbol{\xi}_k)$,
- \mathbf{M} and \mathbf{C} sparse block-structure matrices

Block structure of \mathbb{M} and \mathbb{C}



Iterative solvers

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Linear multigrid

- h -multigrid is based on hierarchy of grids \mathcal{T}_h , $h \in \{h_0, h_1, \dots\}$
- let \mathcal{T}_h and \mathcal{T}_H be two grids, $H > h$,
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$$S_h^{P-l} := \{v; v \in L^2(\Omega), v|_K \in P_{p-l}(K) \forall K \in \mathcal{T}_h\}, \quad l = 0, 1, \dots$$
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Solution of complex problems requires parallelization

- suitable discretization technique
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- DGM allows to distribute efficiently the computation and required memory among the processors
- interchange of data among processors is minimal
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Parallelization

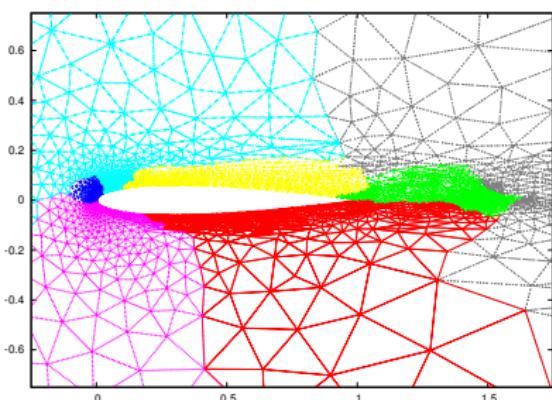
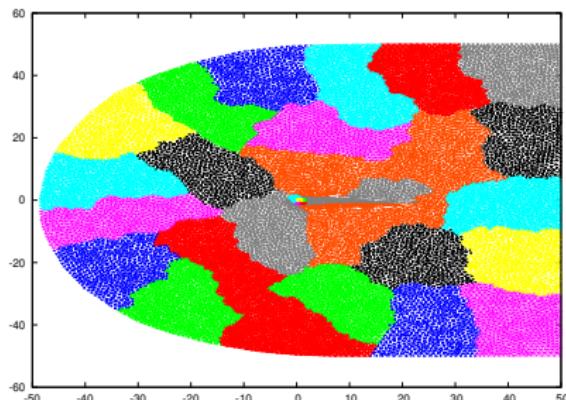
Solution of complex problems requires parallelization

- suitable discretization technique
- suitable algebraic solvers

Parallelization of DGM

- DGM perfectly suits for parallelization
- DGM allows to distribute efficiently the computation and required memory among the processors
- interchange of data among processors is minimal
- evaluation of one block-row requires data from neighbouring elements only from **adjacent faces**

Mesh decomposition [V. Šíp, Master thesis 2011]



mesh decomposition among 32 processors

Efficiency of parallelization [V. Šíp, Master thesis 2011]

mesh	# \mathcal{T}	P_1 DOF	P_3 DOF
\mathcal{T}_{h1}	6 876	82 512	275 040
\mathcal{T}_{h2}	29 040	348 480	1 161 600

π -number of processors, (1,2,4,8,16,32),
 $S_\pi = T_1/T_\pi$ - acceleration,
 $E_\pi = S_\pi/\pi$ - efficiency,
ideal case: $S_\pi = \pi$ & $E_\pi = 1$

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		T_π	S_π	E_π	T_π	S_π	E_π
P_1	1	102.43 s	1.00	1.00	539.73 s	1.00	1.00
	2	50.75 s	2.02	1.01	258.16 s	2.09	1.05
	4	25.90 s	3.95	0.99	131.49 s	4.10	1.03
	8	15.07 s	6.80	0.85	65.80 s	8.20	1.03
	16	9.79 s	10.46	0.65	35.21 s	15.33	0.96
	32	7.77 s	13.19	0.41	26.75 s	20.18	0.63
P_3	1	1278.27 s	1.00	1.00	5988.53 s	1.00	1.00
	2	651.42 s	1.96	0.98	3026.76 s	1.98	0.99
	4	310.50 s	4.12	1.03	1526.50 s	3.92	0.98
	8	156.58 s	8.16	1.02	760.79 s	7.87	0.98
	16	87.28 s	14.65	0.92	395.66 s	15.13	0.94
	32	50.07 s	25.53	0.80	206.64 s	28.98	0.91

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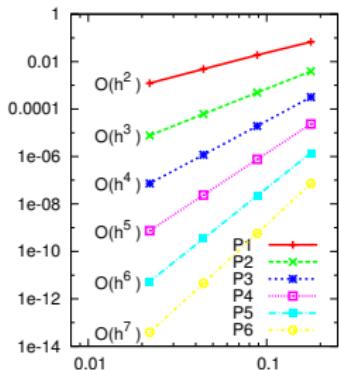
1 Introduction

2 DGM for problems of CFD

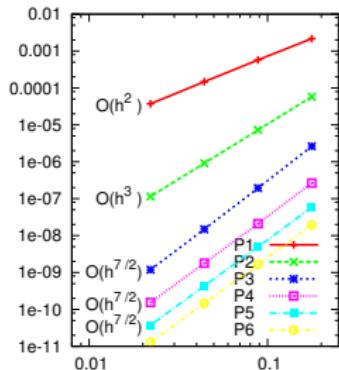
3 Solution strategies

4 Mesh adaptation

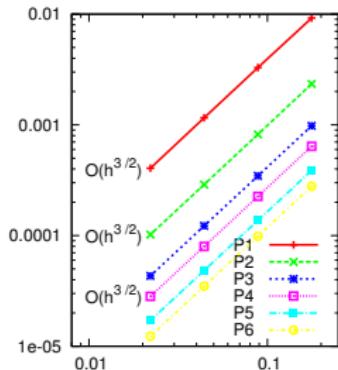
Orders of convergence



$$u \in C^\infty(\Omega)$$



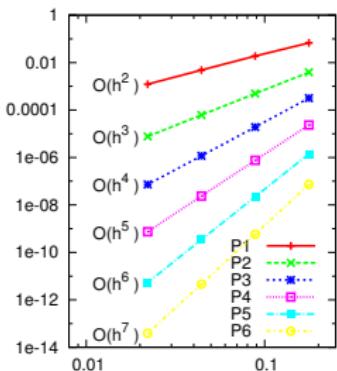
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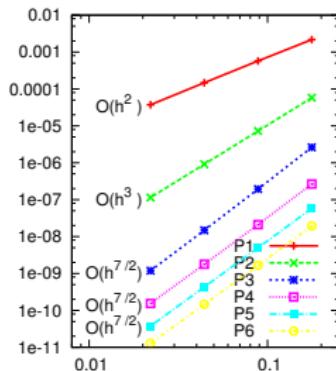
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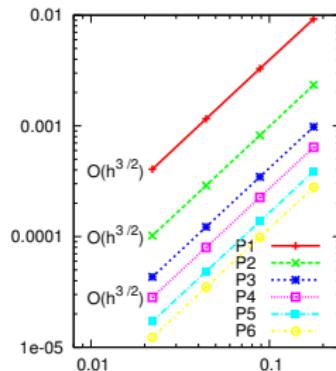
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 - BUT only if the exact solution is sufficiently regular
 - $\|u - u_h\|_{L^2} = O(h^\mu)$, $\mu = \min(p + 1, s)$, $u_h \in S_{hp}$, $u \in H^s(\Omega)$



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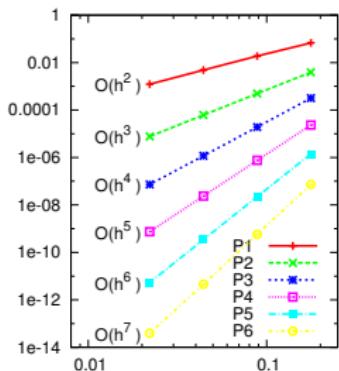
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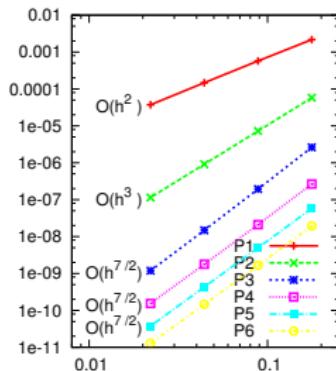
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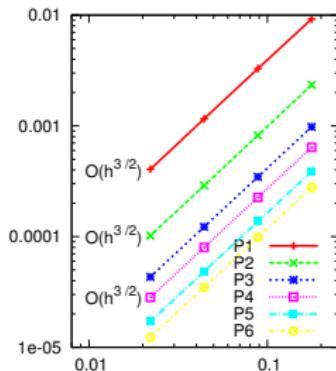
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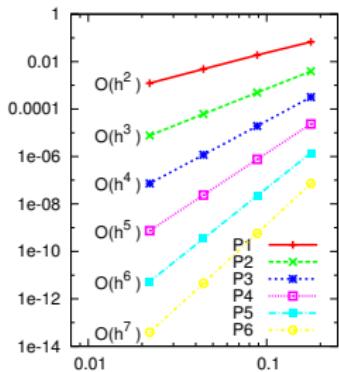


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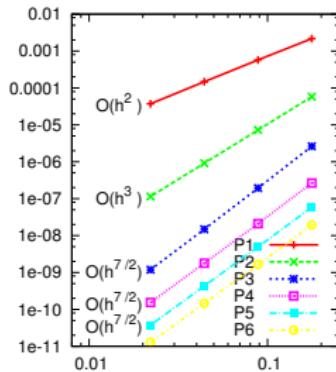


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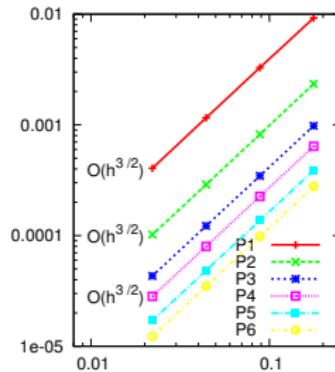
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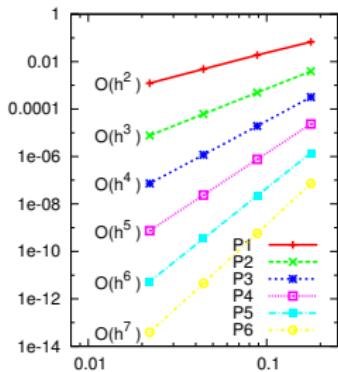
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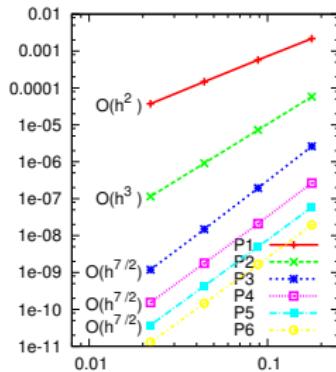
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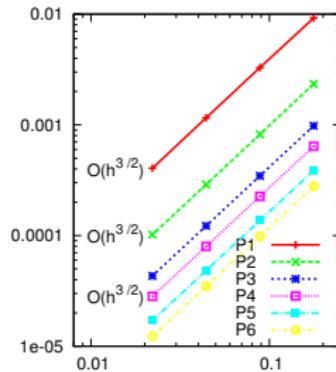
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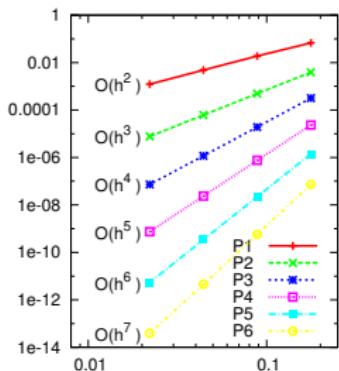
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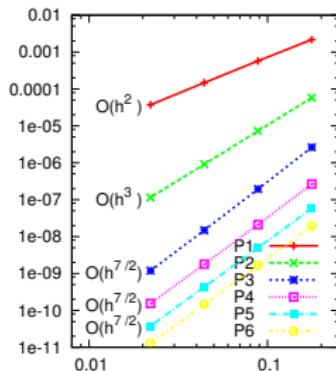
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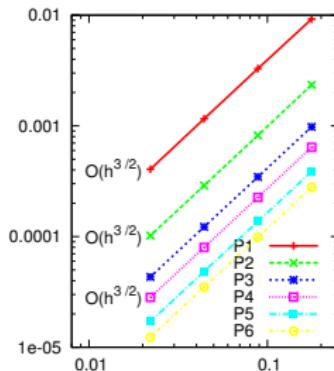
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hp-DGM

Idea of *hp*-methods

- p -refinement in subdomains where solution is regular,
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Technical aspects

- marking of elements for refinement (based on error estimates)
- decide if p or h adaptation
- many (more or less heuristic) techniques

[Demkowicz, Georgoulis, Houston, Melenk, Schwab, Šolín, Süli, ...]

Implementation aspects of *hp*-DGM

- basis of S_h^P : local and discontinuous
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[Demkowicz, Georgoulis, Houston, Melenk, Schwab, Šolín, Süli, ...]

Implementation aspects of *hp*-DGM

- basis of S_h^P : local and discontinuous
 - ⇒ NO implementation obstacle

hp-DGM

Idea of *hp*-methods

- p -refinement in subdomains where solution is regular,
- h -refinement in subdomains where solution is not regular,

Technical aspects

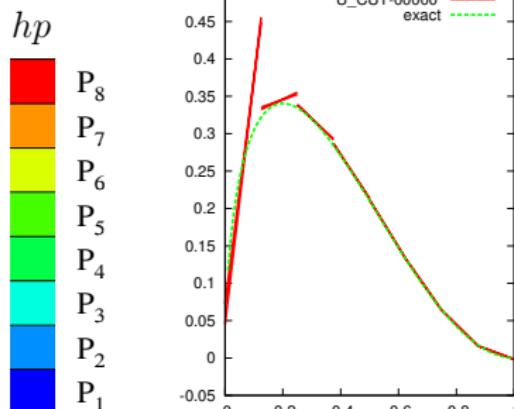
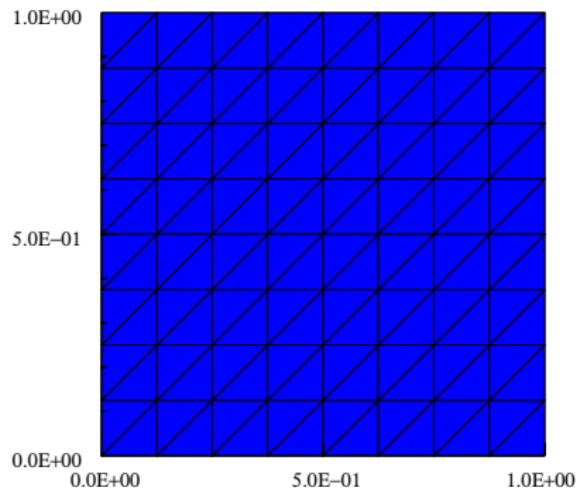
- marking of elements for refinement (based on error estimates)
- decide if p or h adaptation
- many (more or less heuristic) techniques
[Demkowicz, Georgoulis, Houston, Melenk, Schwab, Šolín, Süli, ...]

Implementation aspects of *hp*-DGM

- basis of S_h^P : local and discontinuous
 \implies NO implementation obstacle

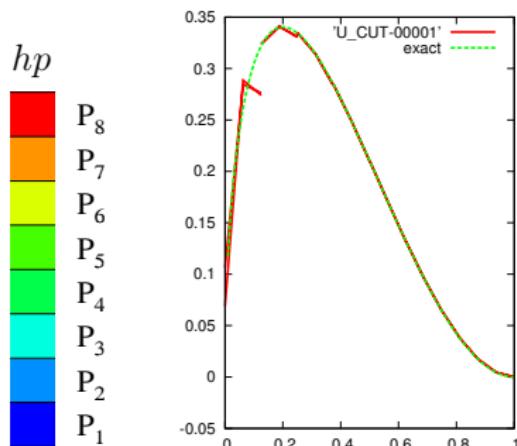
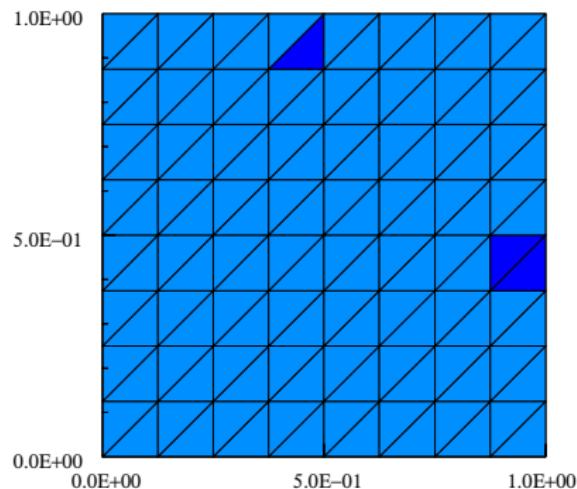
Performance of the *hp*-DGM

nonlinear convection-diffusion equation with a corner singularity



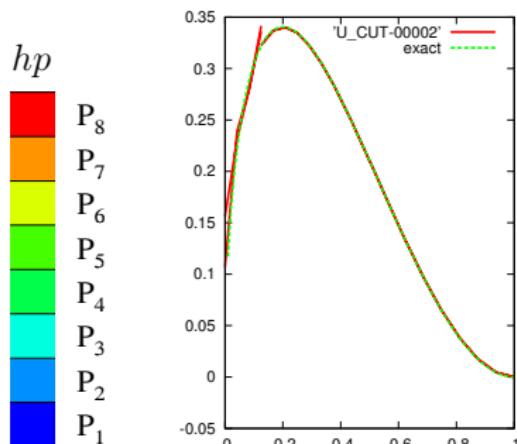
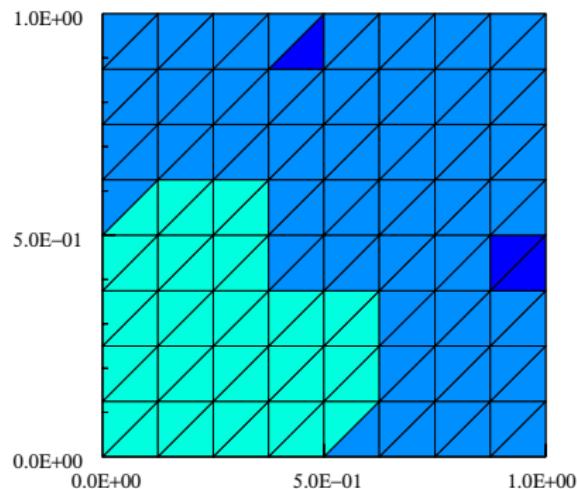
Performance of the *hp*-DGM

nonlinear convection-diffusion equation with a corner singularity



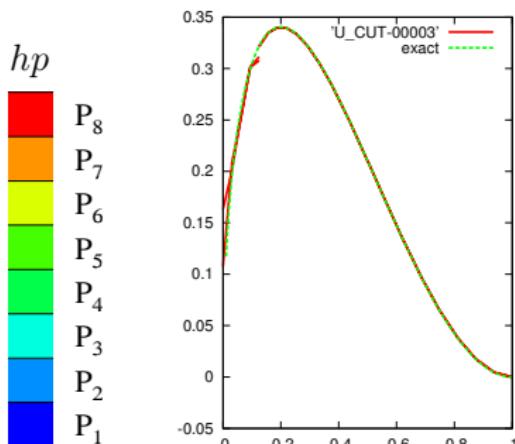
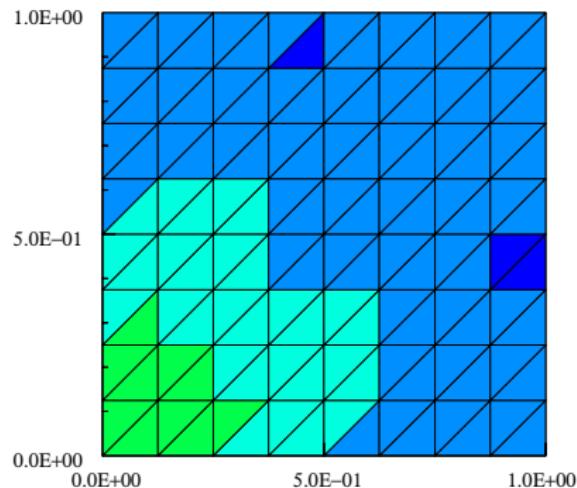
Performance of the *hp*-DGM

nonlinear convection-diffusion equation with a corner singularity



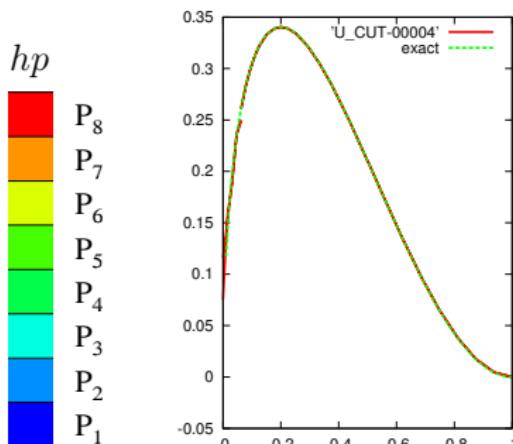
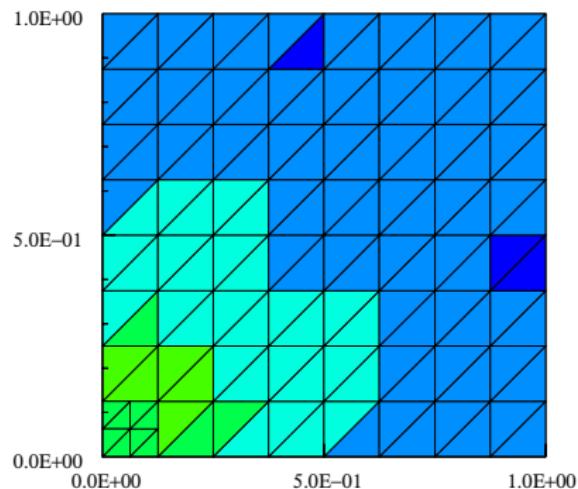
Performance of the *hp*-DGM

nonlinear convection-diffusion equation with a corner singularity



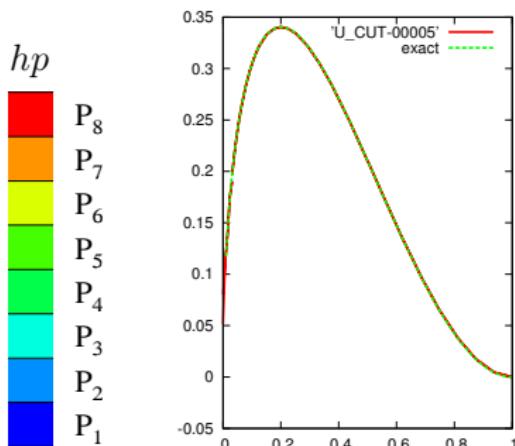
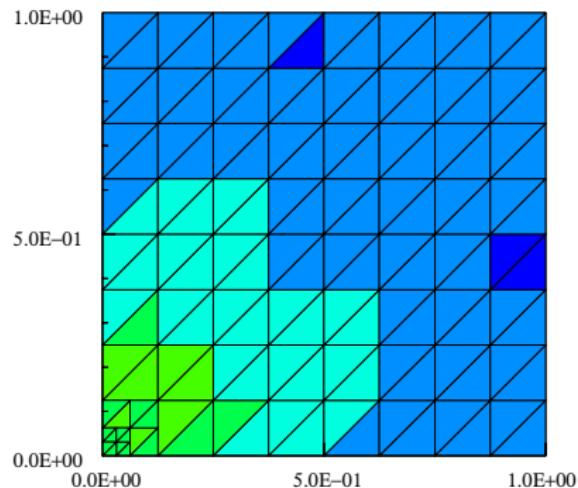
Performance of the *hp*-DGM

nonlinear convection-diffusion equation with a corner singularity



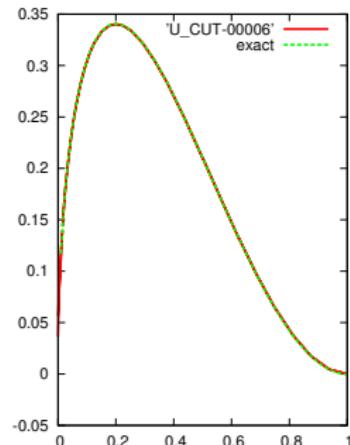
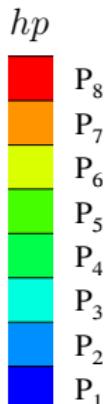
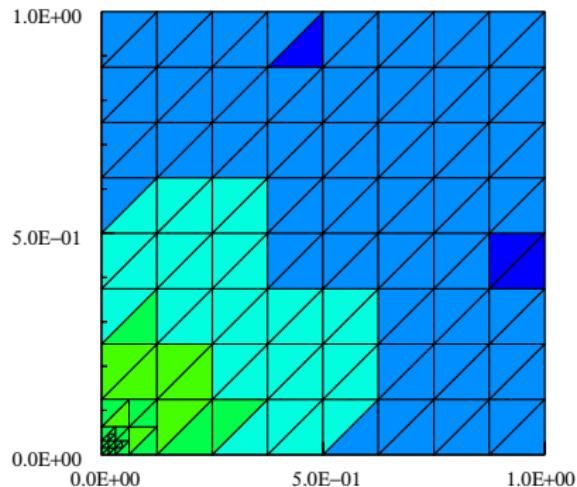
Performance of the *hp*-DGM

nonlinear convection-diffusion equation with a corner singularity



Performance of the *hp*-DGM

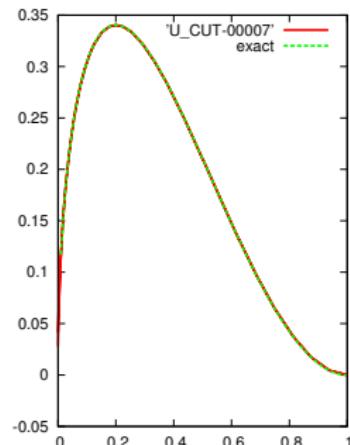
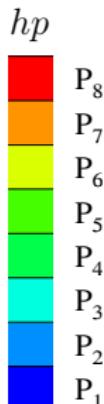
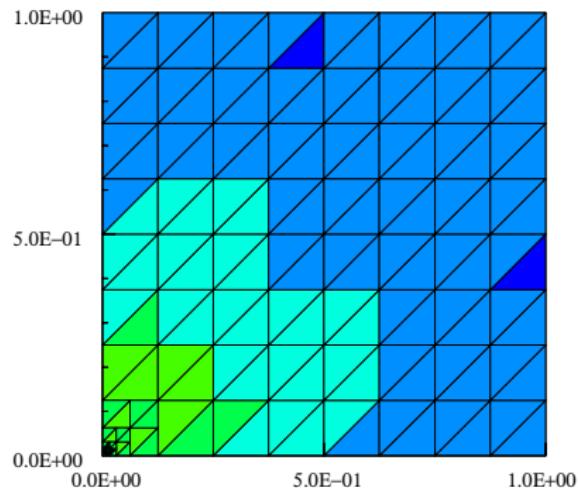
nonlinear convection-diffusion equation with a corner singularity



adaptation level = 06

Performance of the *hp*-DGM

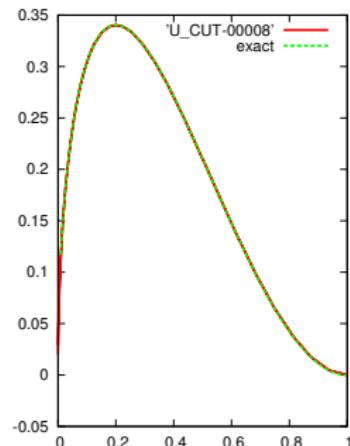
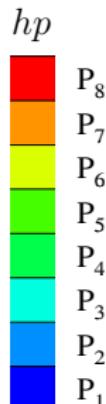
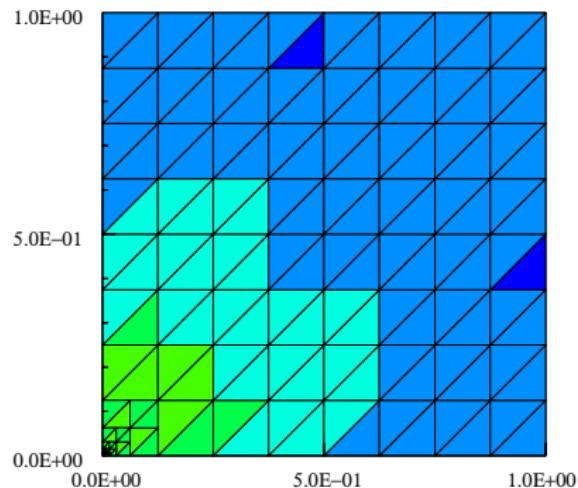
nonlinear convection-diffusion equation with a corner singularity



adaptation level = 07

Performance of the *hp*-DGM

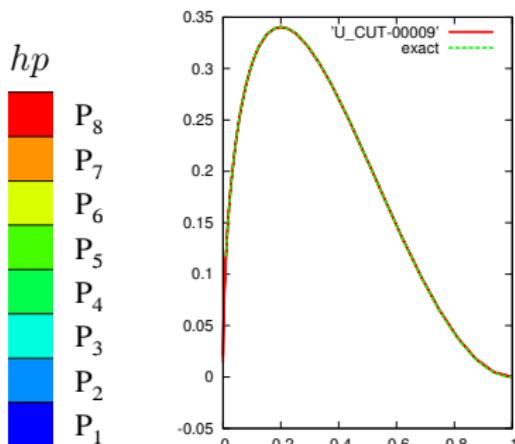
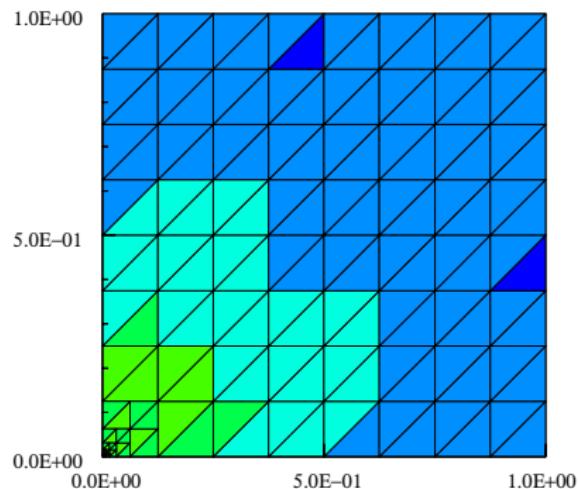
nonlinear convection-diffusion equation with a corner singularity



adaptation level = 08

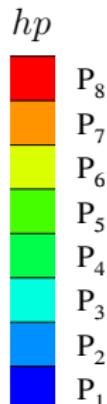
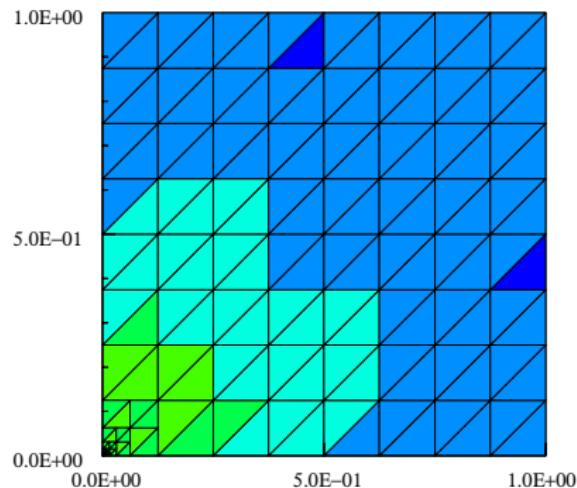
Performance of the *hp*-DGM

nonlinear convection-diffusion equation with a corner singularity

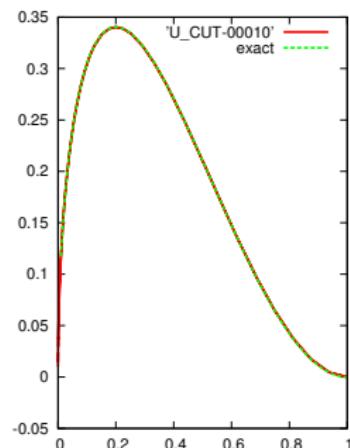


Performance of the *hp*-DGM

nonlinear convection-diffusion equation with a corner singularity

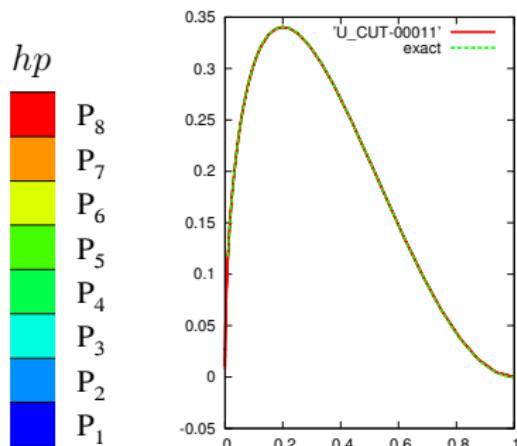
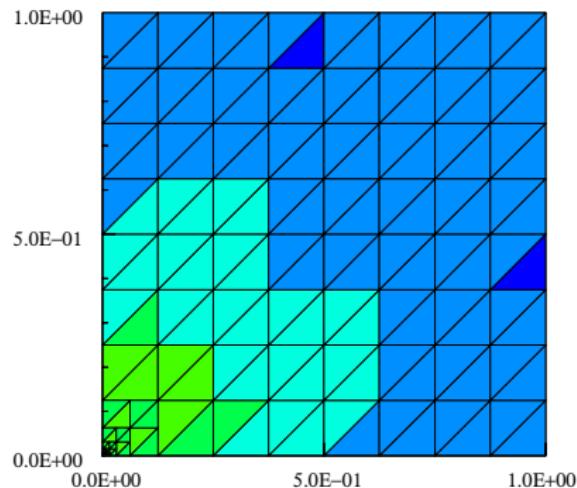


adaptation level = 10



Performance of the *hp*-DGM

nonlinear convection-diffusion equation with a corner singularity

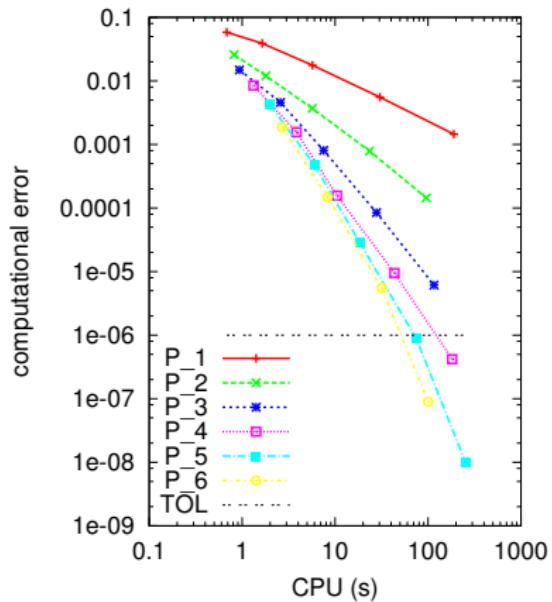
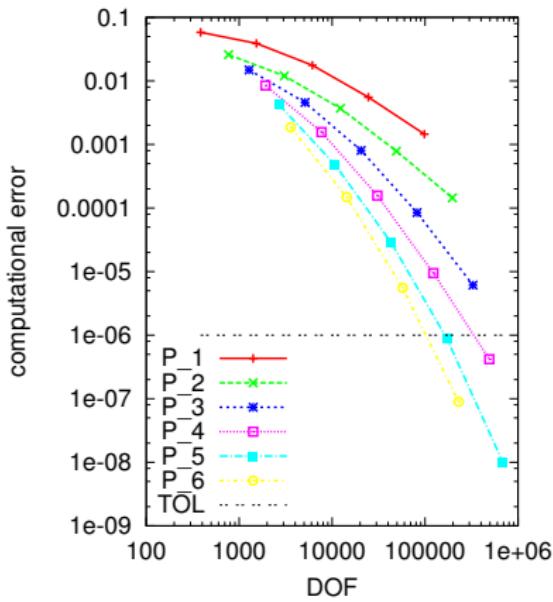


Practical demonstration of the efficiency of *hp*-DGM

- scalar linear convection-diffusion equation solved by DGM

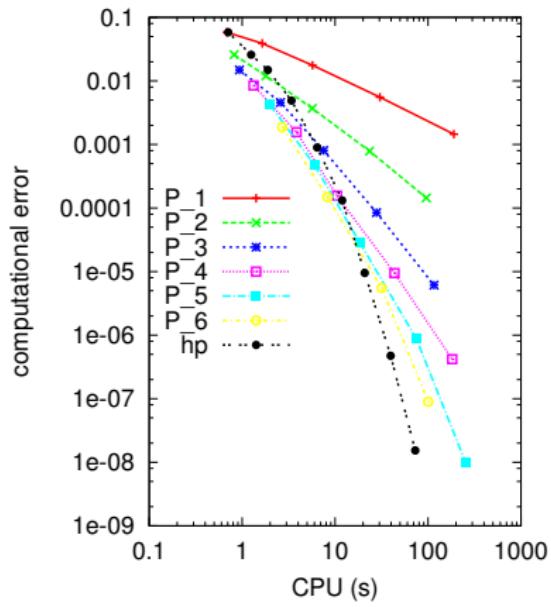
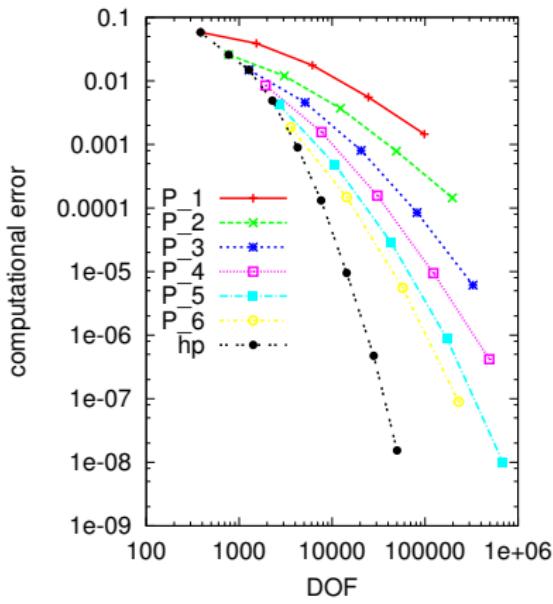
Practical demonstration of the efficiency of *hp*-DGM

- scalar linear convection-diffusion equation solved by DGM



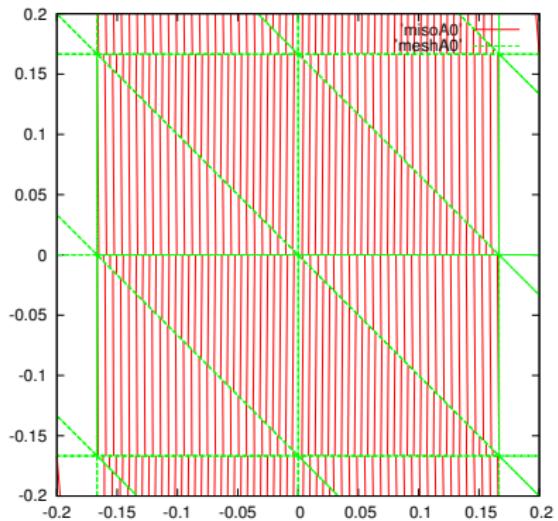
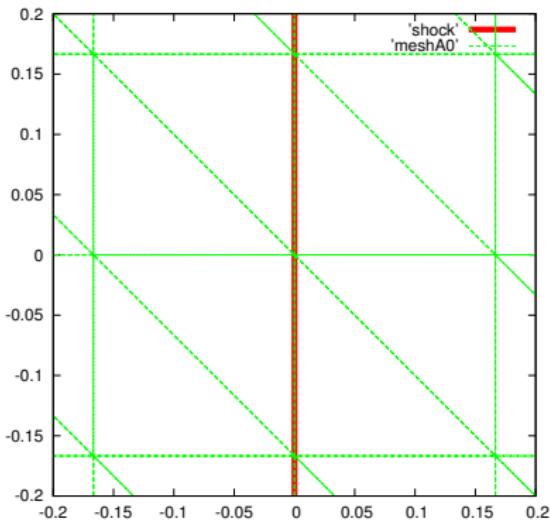
Practical demonstration of the efficiency of *hp*-DGM

- scalar linear convection-diffusion equation solved by DGM



h-refinement for interior and boundary layers problems

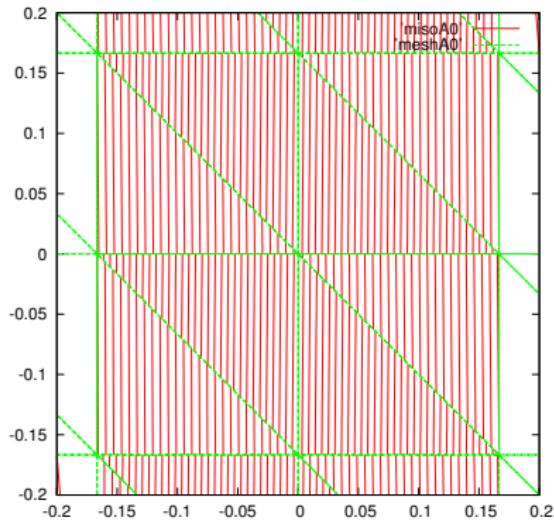
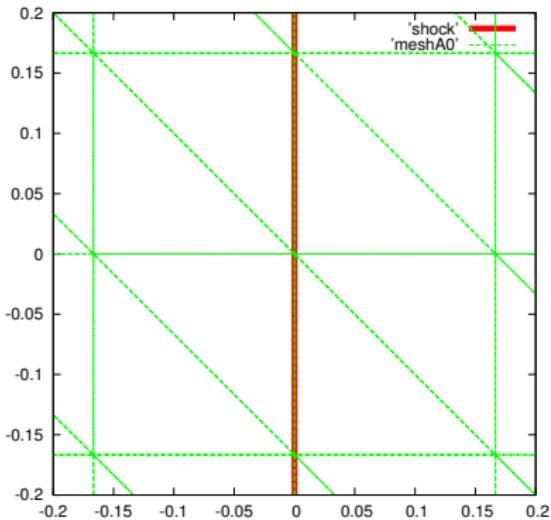
- isotropic *h*-refinement – not efficient
- anisotropic mesh adaptation – more efficient



adaptation level = 0

h -refinement for interior and boundary layers problems

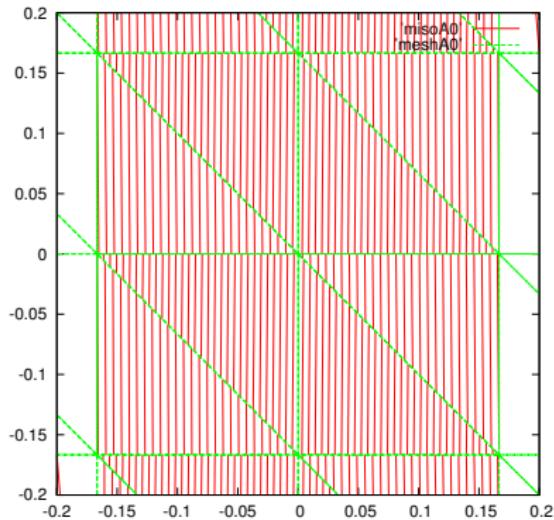
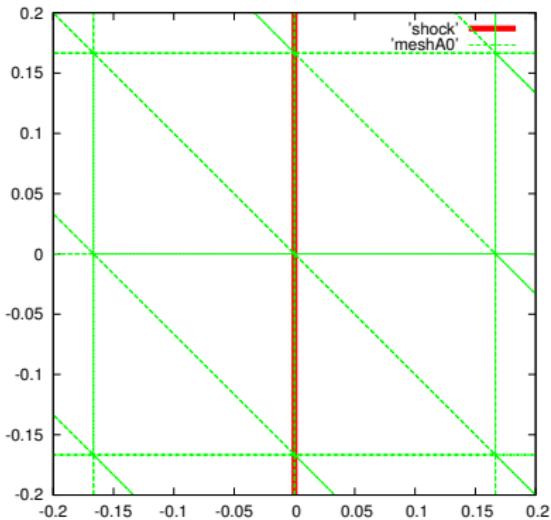
- isotropic h -refinement – not efficient
- anisotropic mesh adaptation – more efficient



adaptation level = 0

h -refinement for interior and boundary layers problems

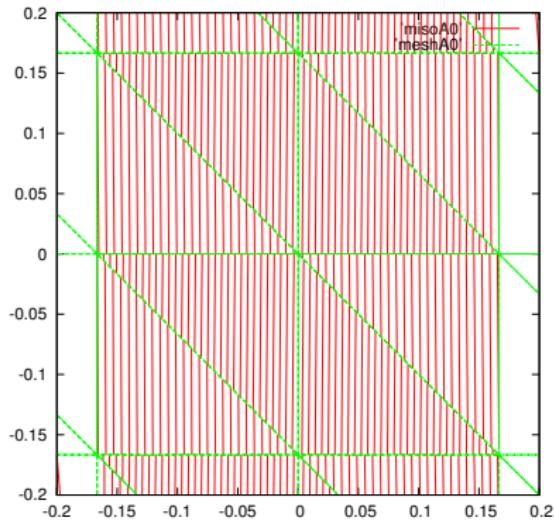
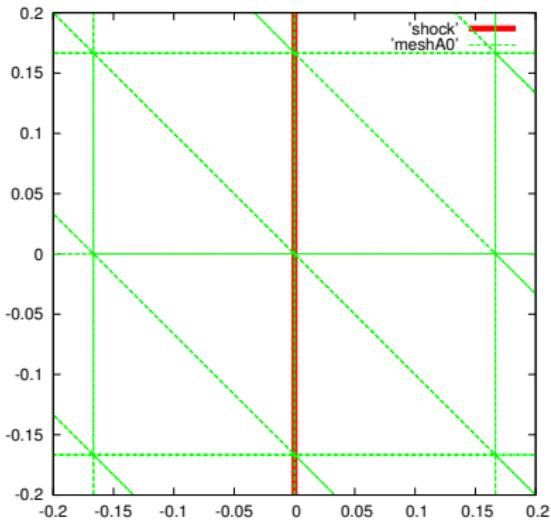
- isotropic h -refinement – not efficient
- anisotropic mesh adaptation – more efficient



adaptation level = 0

h -refinement for interior and boundary layers problems

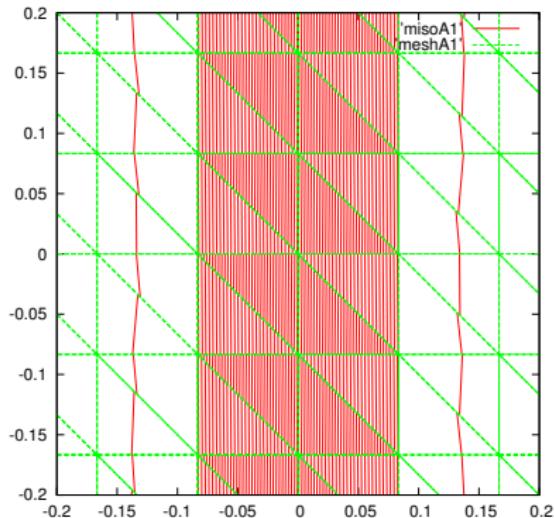
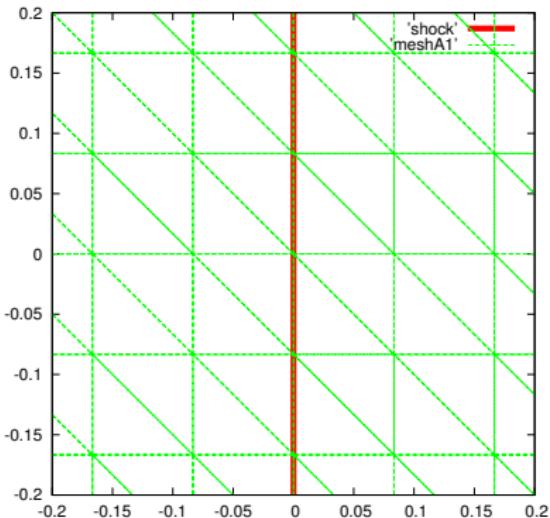
- isotropic h -refinement – not efficient
- anisotropic mesh adaptation – more efficient



adaptation level = 0

h -refinement for interior and boundary layers problems

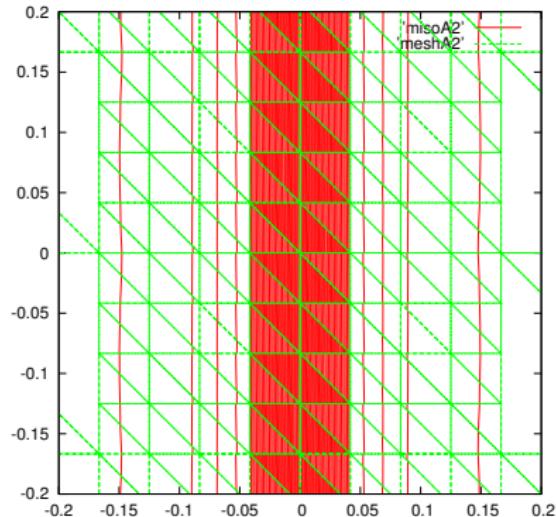
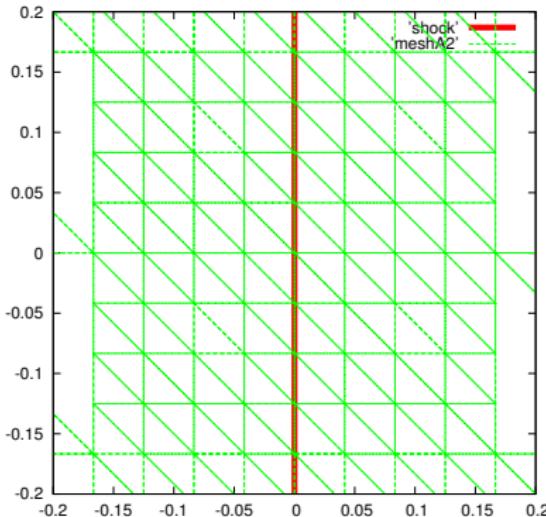
- isotropic h -refinement – not efficient
- anisotropic mesh adaptation – more efficient



adaptation level = 1

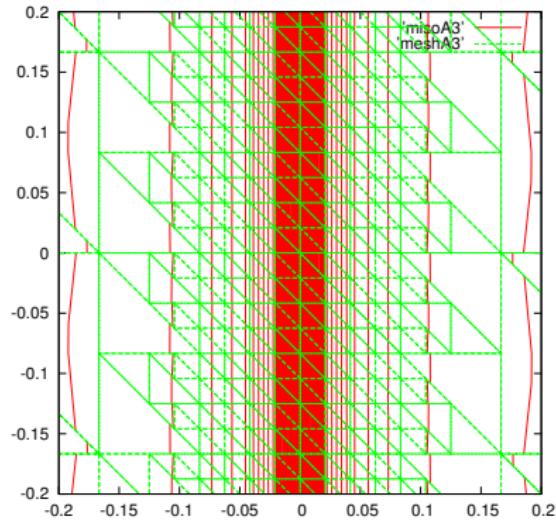
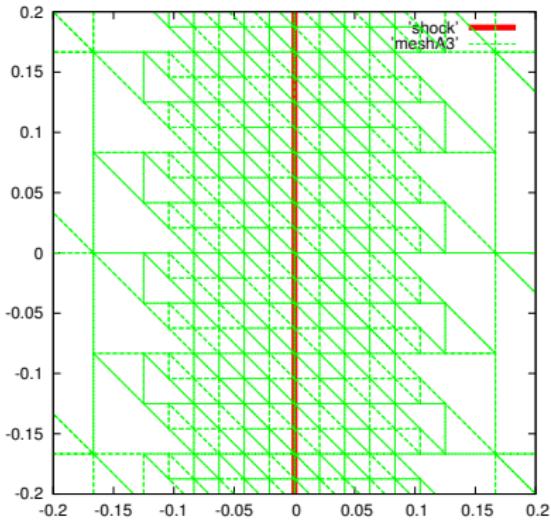
h -refinement for interior and boundary layers problems

- isotropic h -refinement – not efficient
- anisotropic mesh adaptation – more efficient



h -refinement for interior and boundary layers problems

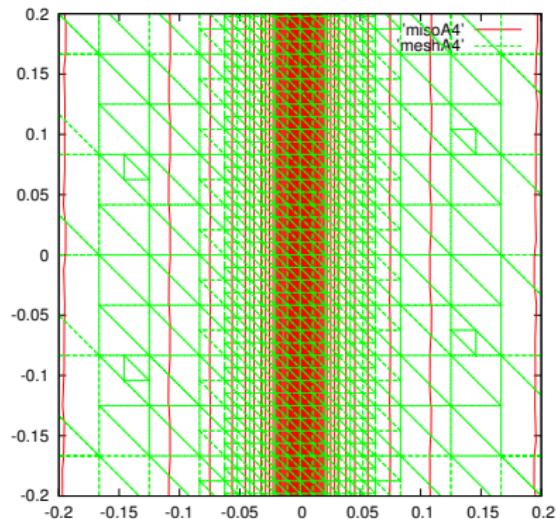
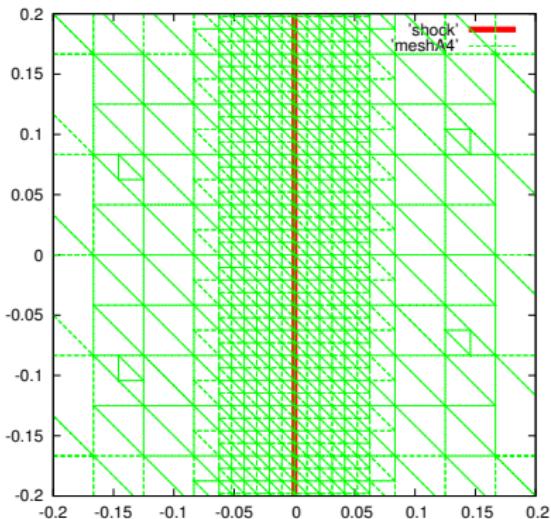
- isotropic h -refinement – not efficient
- anisotropic mesh adaptation – more efficient



adaptation level = 3

h -refinement for interior and boundary layers problems

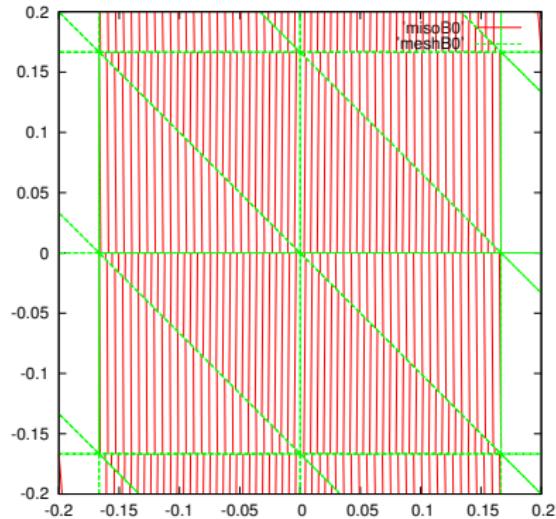
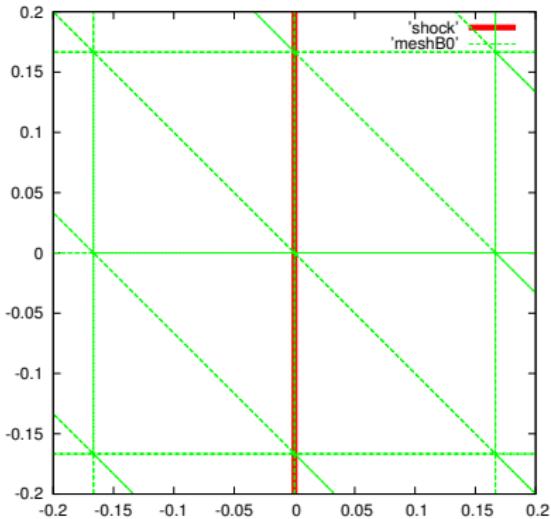
- isotropic h -refinement – not efficient
- anisotropic mesh adaptation – more efficient



adaptation level = 4

h -refinement for interior and boundary layers problems

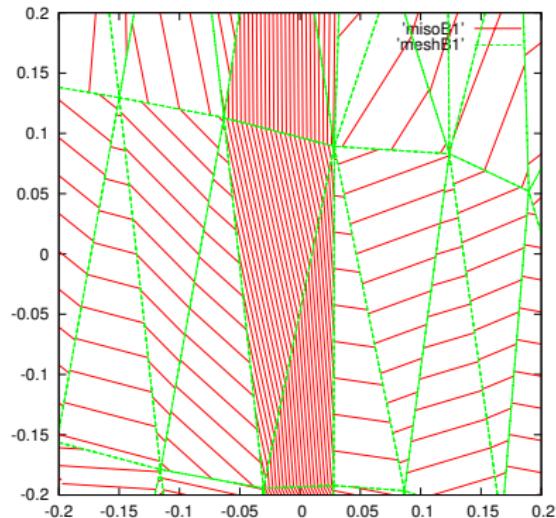
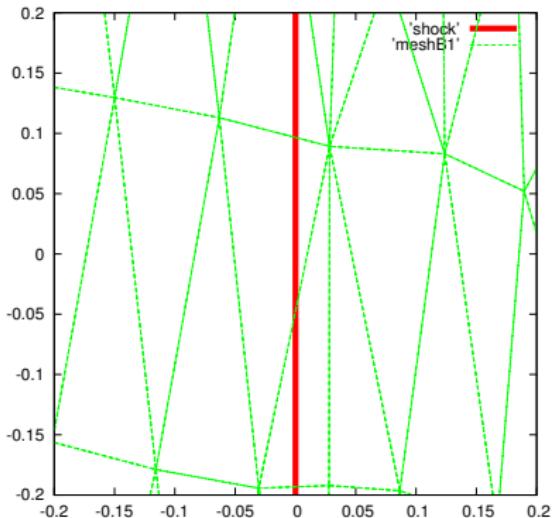
- isotropic h -refinement – not efficient
- anisotropic mesh adaptation – more efficient



AMA adaptation level = 0

h -refinement for interior and boundary layers problems

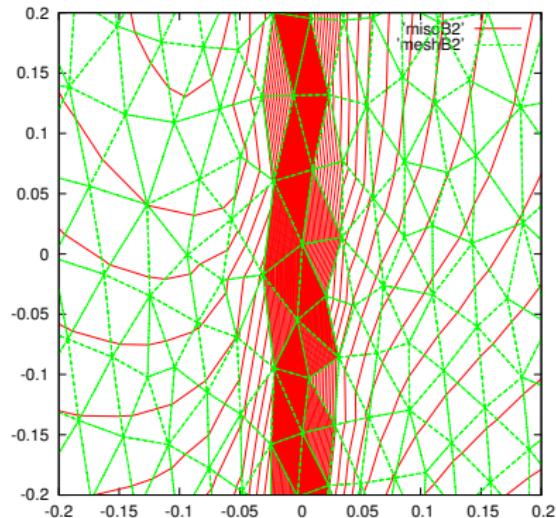
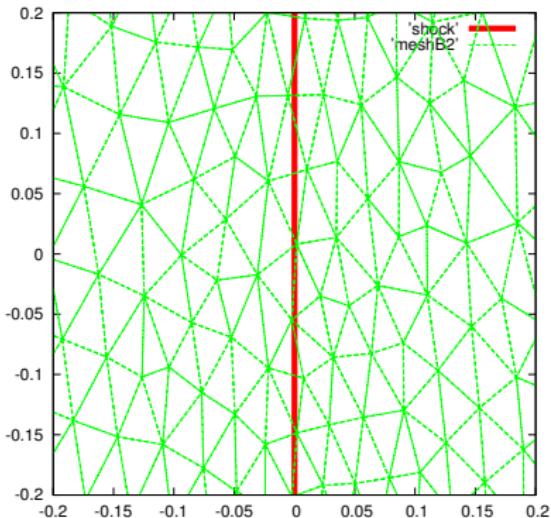
- isotropic h -refinement – not efficient
- anisotropic mesh adaptation – more efficient



AMA adaptation level = 1

h -refinement for interior and boundary layers problems

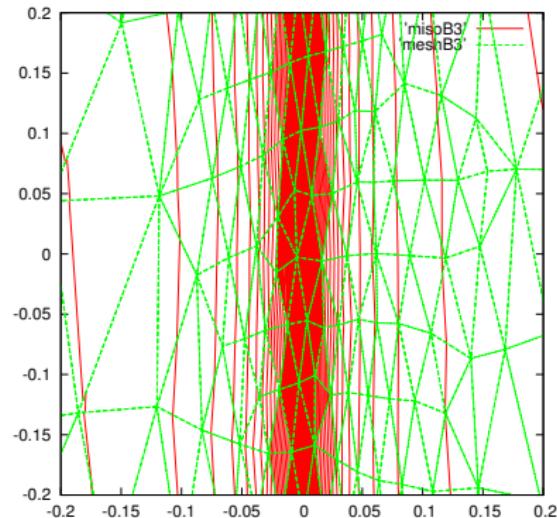
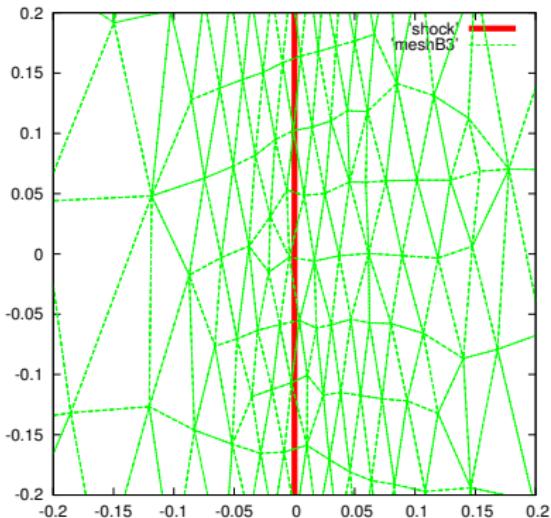
- isotropic h -refinement – **not efficient**
- **anisotropic** mesh adaptation – more efficient



AMA adaptation level = 2

h -refinement for interior and boundary layers problems

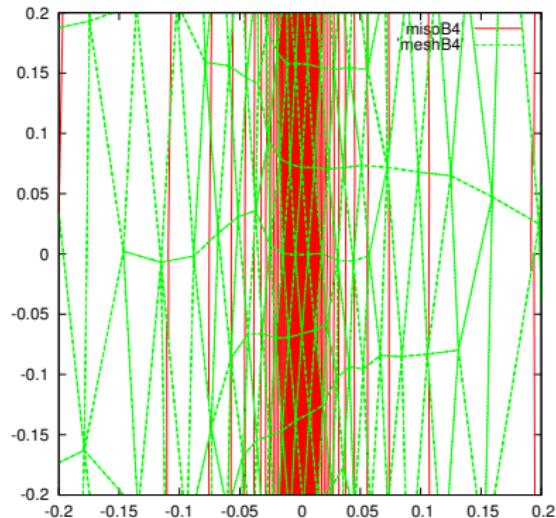
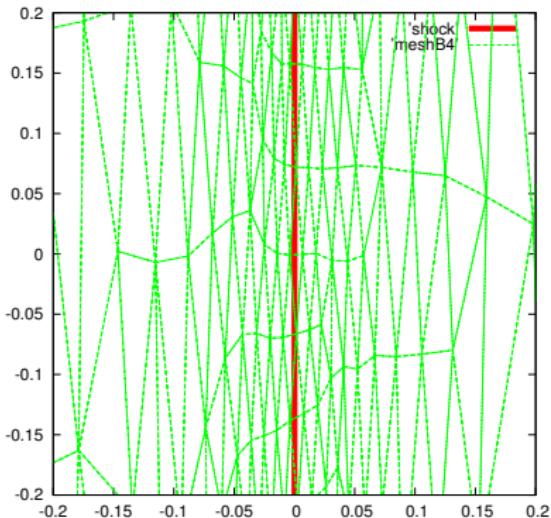
- isotropic h -refinement – **not efficient**
- **anisotropic** mesh adaptation – more efficient



AMA adaptation level = 3

h -refinement for interior and boundary layers problems

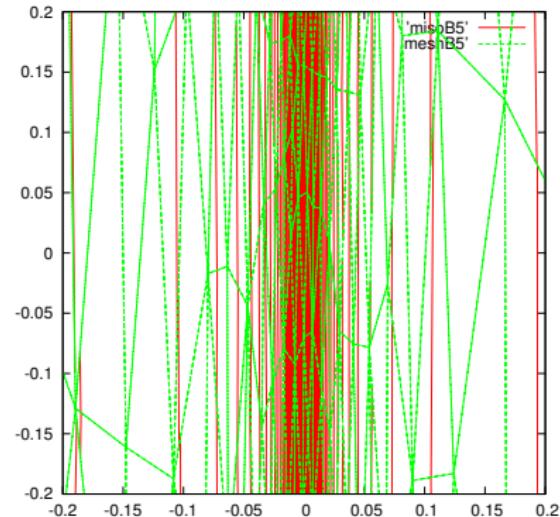
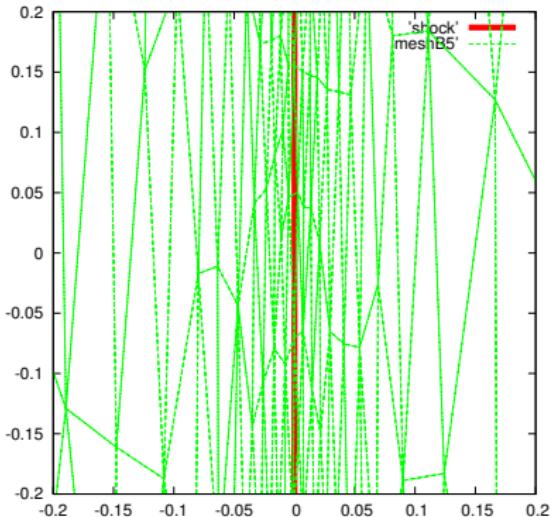
- isotropic h -refinement – **not efficient**
- **anisotropic** mesh adaptation – more efficient



AMA adaptation level = 4

h -refinement for interior and boundary layers problems

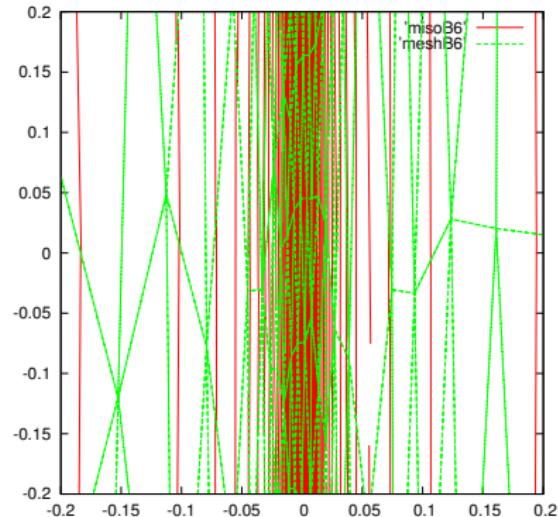
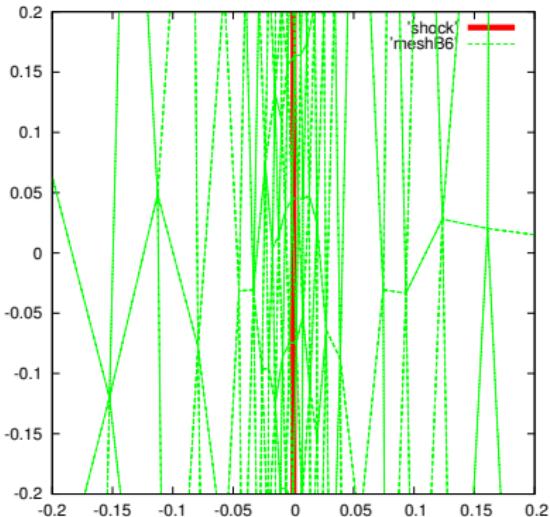
- isotropic h -refinement – **not efficient**
- **anisotropic** mesh adaptation – more efficient



AMA adaptation level = 5

h -refinement for interior and boundary layers problems

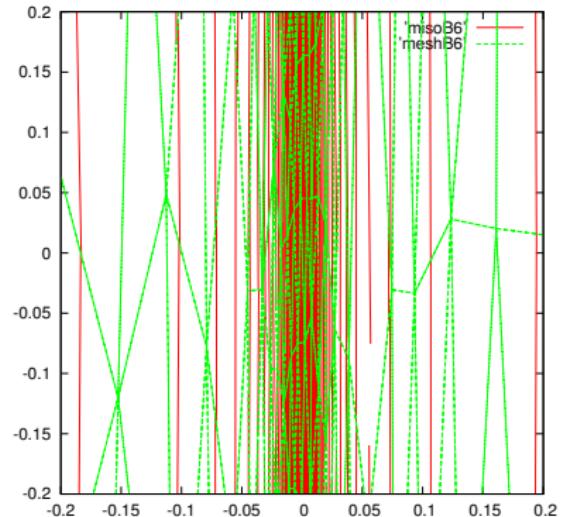
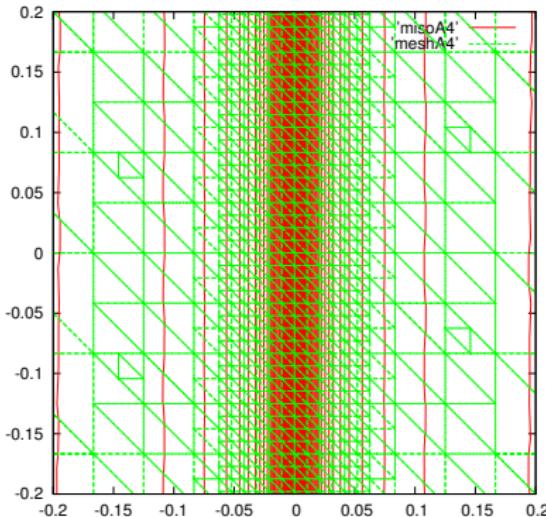
- isotropic h -refinement – **not efficient**
- **anisotropic** mesh adaptation – more efficient



AMA adaptation level = 6

h -refinement for interior and boundary layers problems

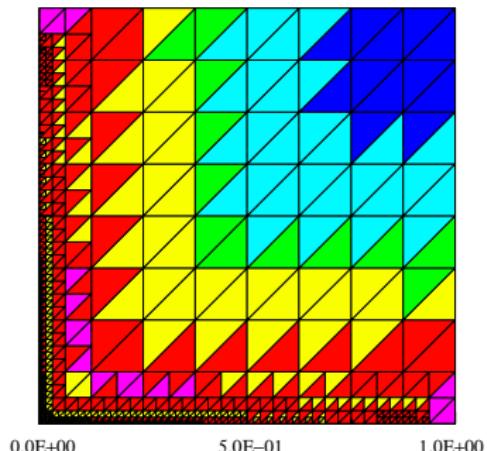
- isotropic h -refinement – **not efficient**
- **anisotropic** mesh adaptation – more efficient



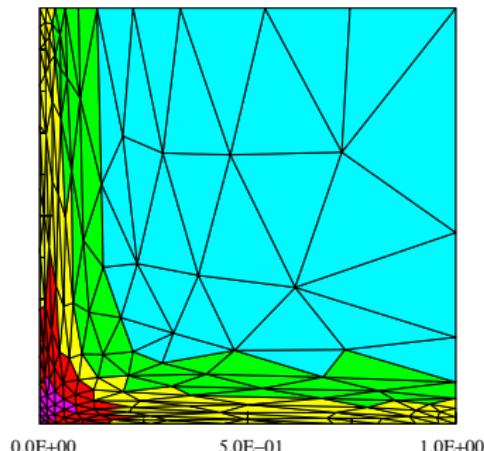
comparison: isotropic (5649 elems) – anisotropic (432 elems)

Anisotropic *hp*-DGM

hp-DGM & anisotropic mesh adaptation



isotropic *hp*-mesh



anisotropic *hp*-mesh

Anisotropic *hp*-DGM

Basic idea [D. APNUM 2014]

- let $u : \Omega \rightarrow \mathbb{R}$, $q > 1$ and $\omega > 0$ be given,
- we seek mesh \mathcal{T}_h and the corresponding space S_{hp} such that
 - $\|u - \Pi_{hp}u\|_{L^q(\Omega)} \leq \omega$,
 - $\dim S_{hp}$ is minimal,
- Π_{hp} is the L^2 -orthogonal projection into S_{hp} .

Practical realization

- for each $x \in \Omega$ and $p \in \mathbb{N}$, we seek optimal shape of $K_{x,p}$ minimizing $\|u - \Pi_{hp}u\|_{L^q(K)}$,
- from $\|u - \Pi_{hp}u\|_{L^q(K)}^q \leq \omega^q \frac{|K|}{|\Omega|}$, we set size of $K_{x,p}$
- we set optimal p for $x \implies$ “optimal” S_{hp} .

Anisotropic *hp*-DGM

Basic idea [D. APNUM 2014]

- let $u : \Omega \rightarrow \mathbb{R}$, $q > 1$ and $\omega > 0$ be given,
- we seek mesh \mathcal{T}_h and the corresponding space S_{hp} such that
 - $\|u - \Pi_{hp} u\|_{L^q(\Omega)} \leq \omega$,
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Anisotropic *hp*-DGM

Basic idea [D. APNUM 2014]

- let $u : \Omega \rightarrow \mathbb{R}$, $q > 1$ and $\omega > 0$ be given,
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Anisotropic *hp*-DGM

Basic idea [D. APNUM 2014]

- let $u : \Omega \rightarrow \mathbb{R}$, $q > 1$ and $\omega > 0$ be given,
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Anisotropic *hp*-DGM

Basic idea [D. APNUM 2014]

- let $u : \Omega \rightarrow \mathbb{R}$, $q > 1$ and $\omega > 0$ be given,
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- for each $x \in \Omega$ and $p \in \mathbb{N}$, we seek optimal shape of $K_{x,p}$ minimizing $\|u - \Pi_{hp} u\|_{L^q(K)}$,
- from $\|u - \Pi_{hp} u\|_{L^q(K)}^q \leq \omega^q \frac{|K|}{|\Omega|}$, we set size of $K_{x,p}$
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Anisotropic *hp*-DGM

Basic idea [D. APNUM 2014]

- let $u : \Omega \rightarrow \mathbb{R}$, $q > 1$ and $\omega > 0$ be given,
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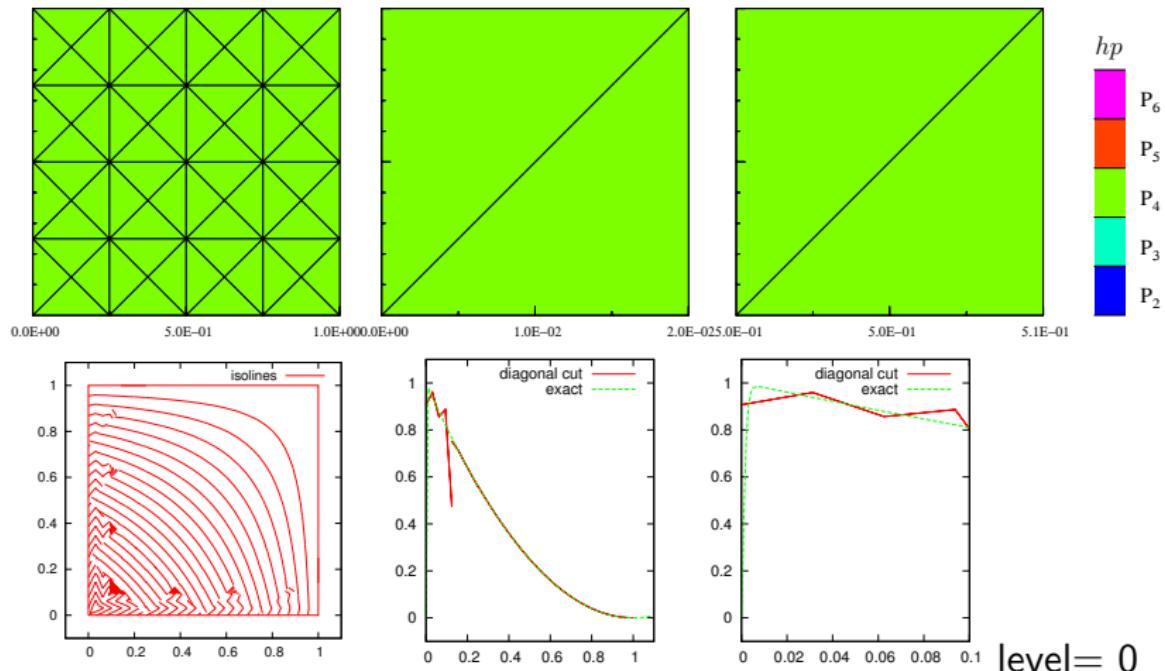
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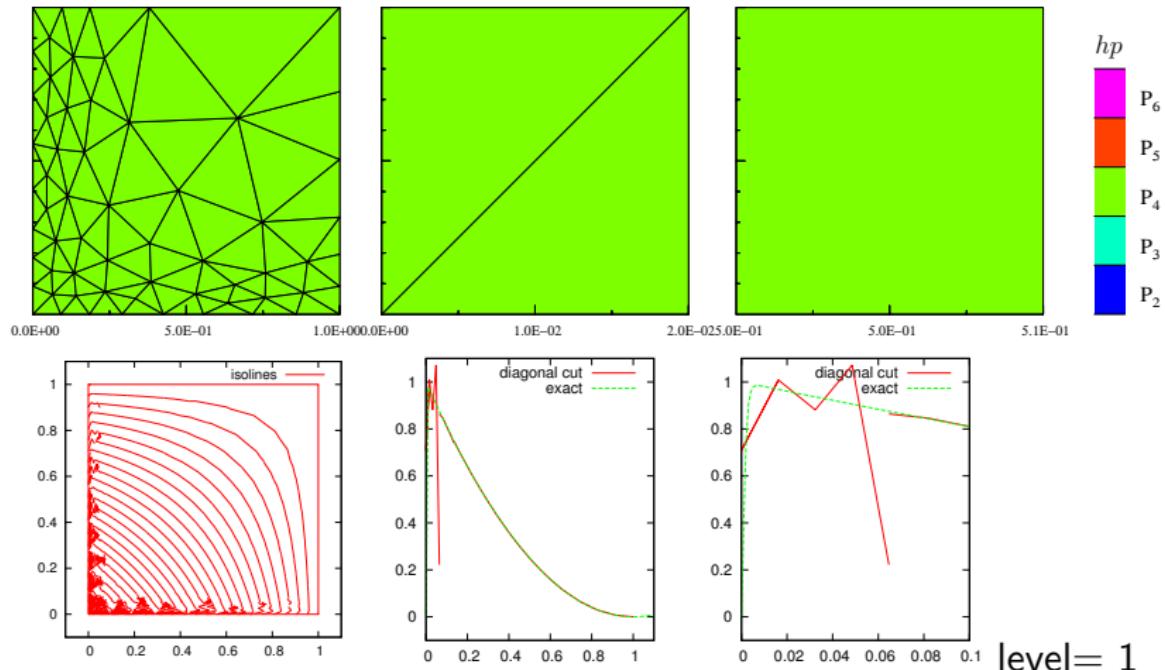
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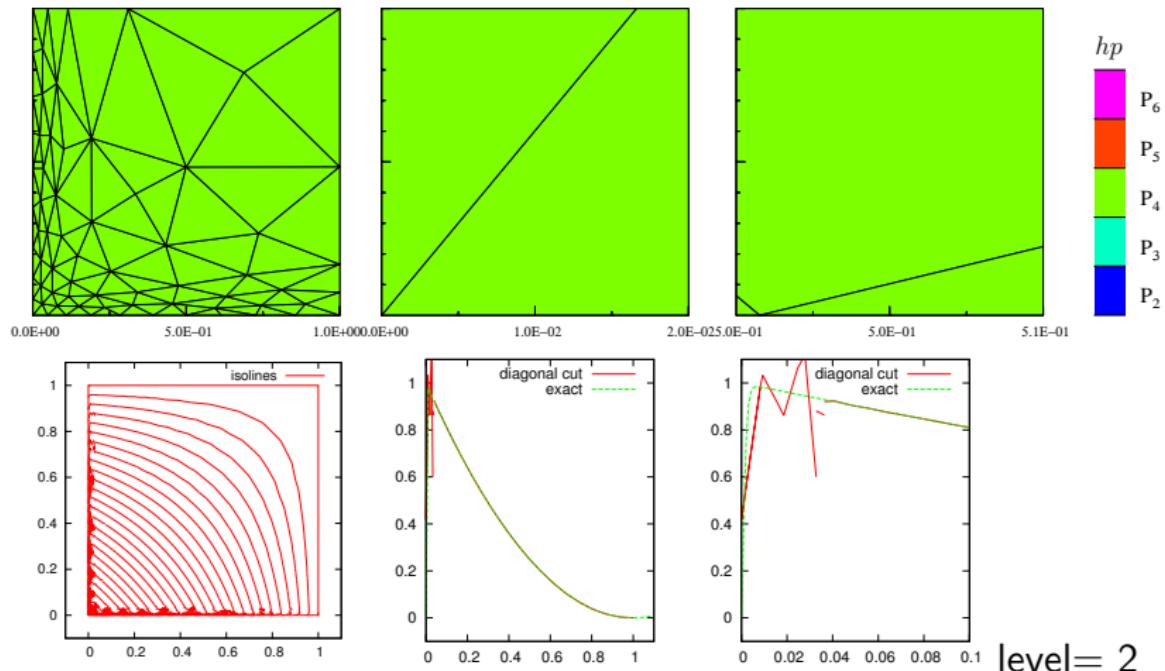
Boundary layers with $\varepsilon = 10^{-3}$ – performance



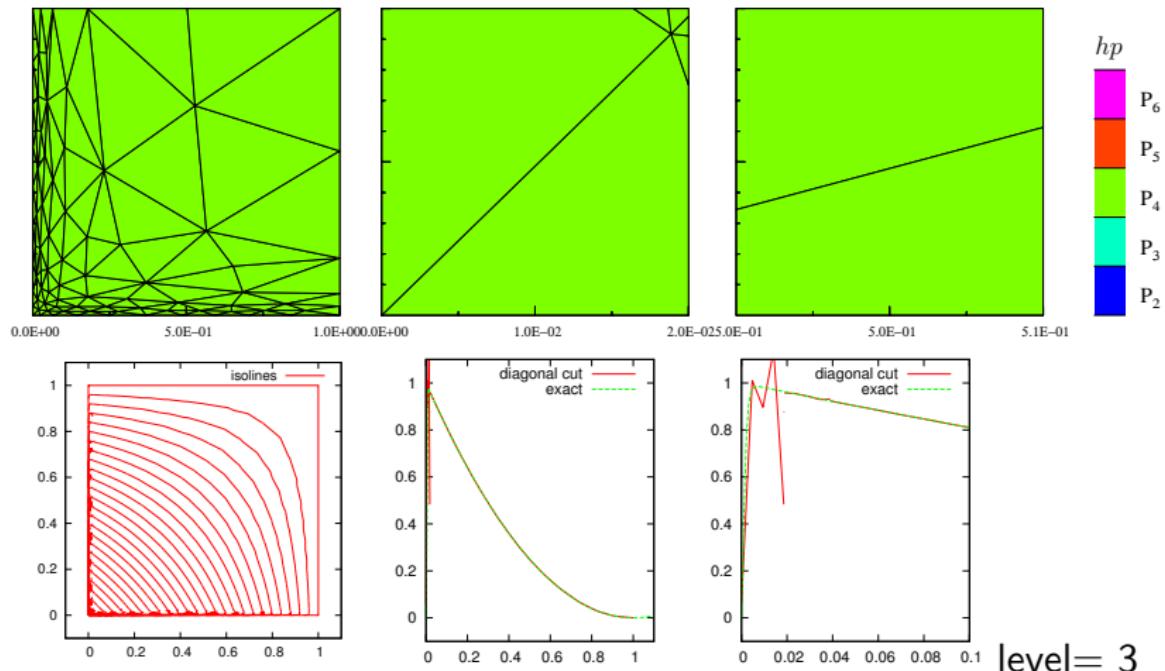
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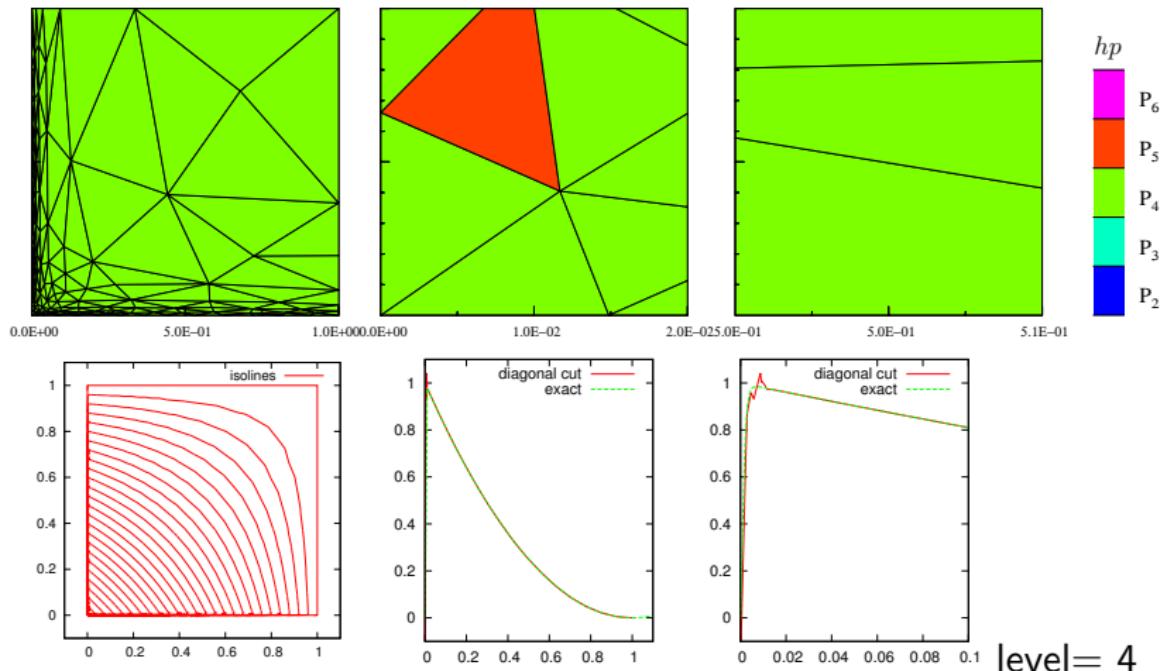
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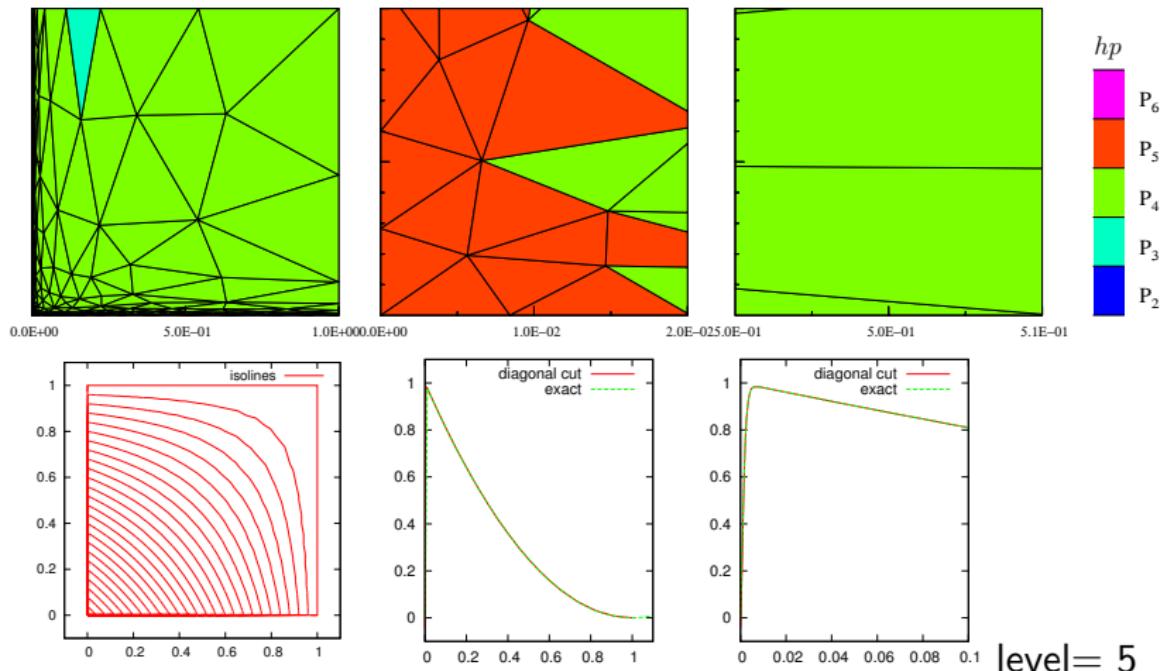
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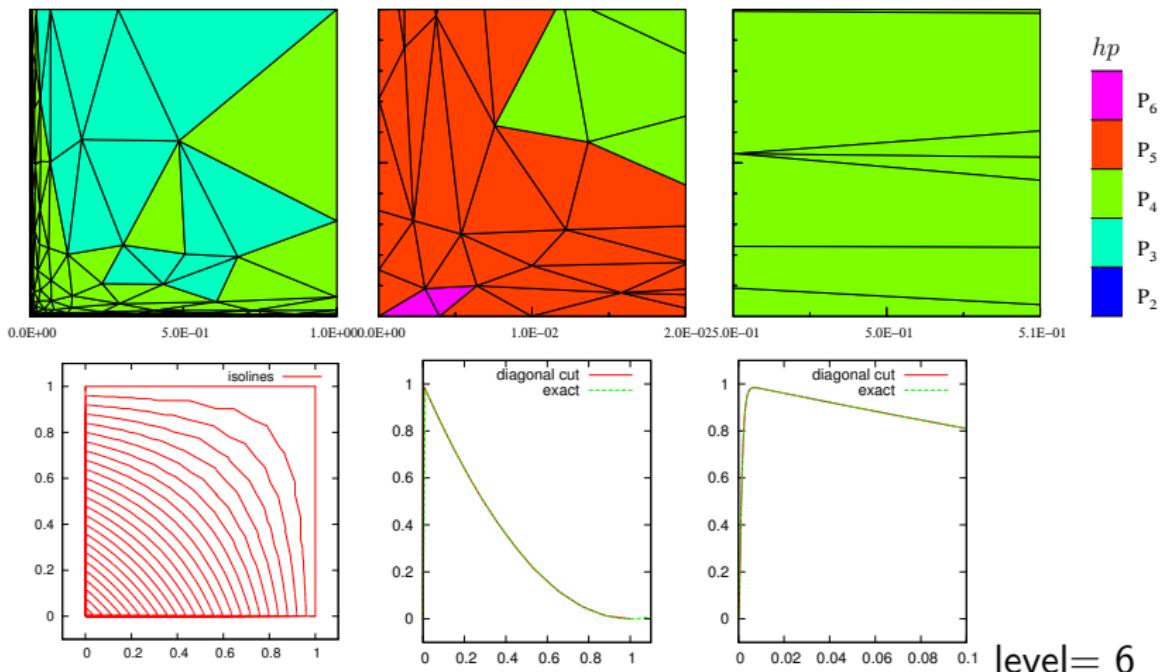
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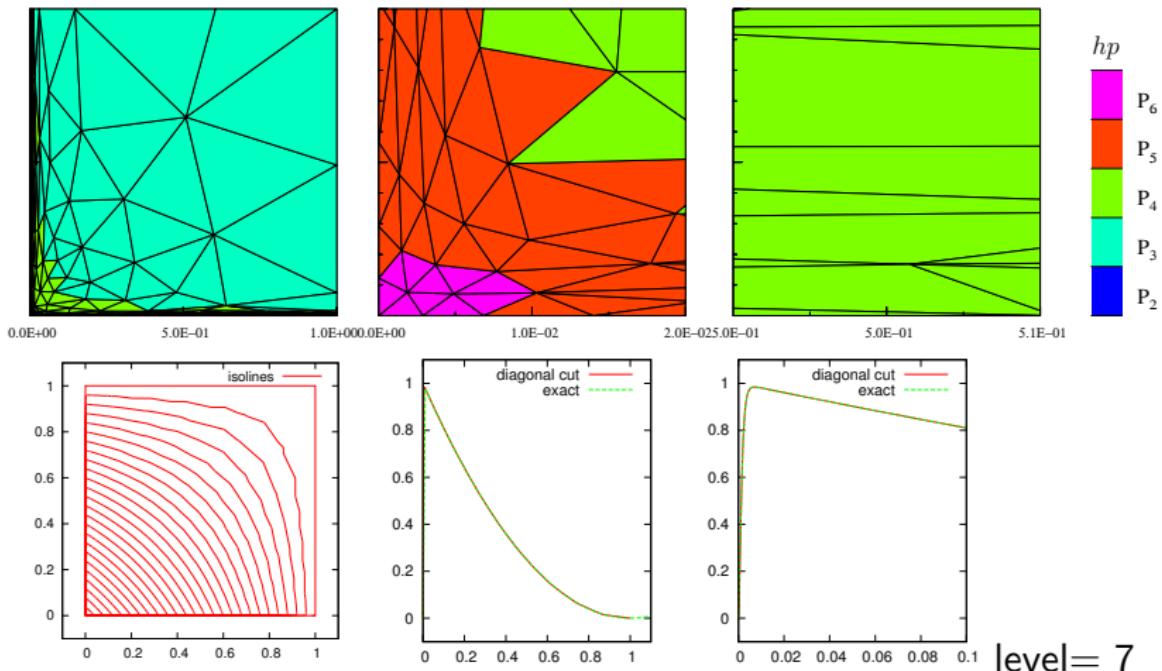
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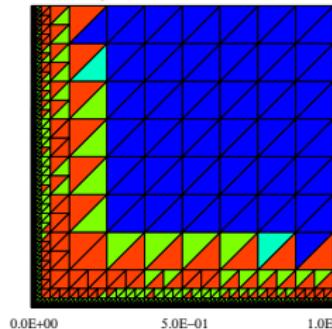


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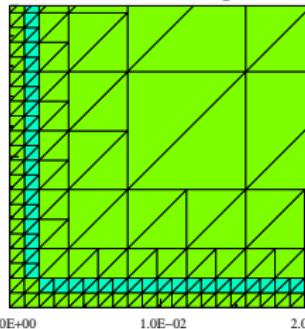


Boundary layers with $\varepsilon = 10^{-3}$ – comparison

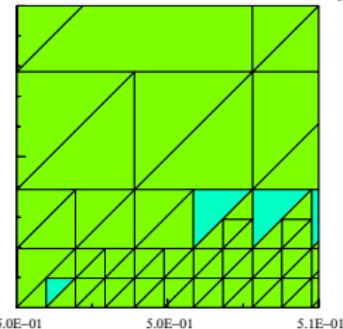
isotropic: total



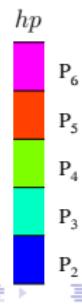
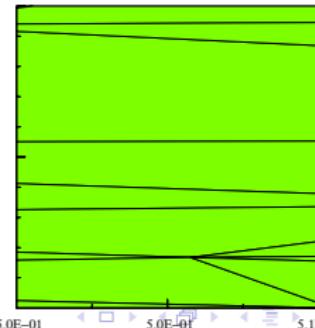
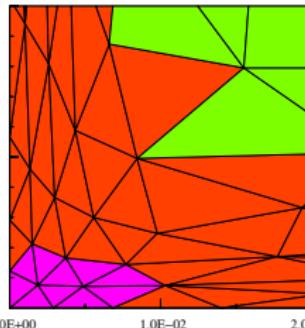
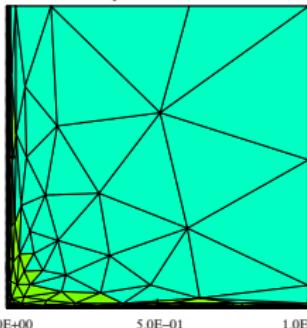
zoom 50 of origin



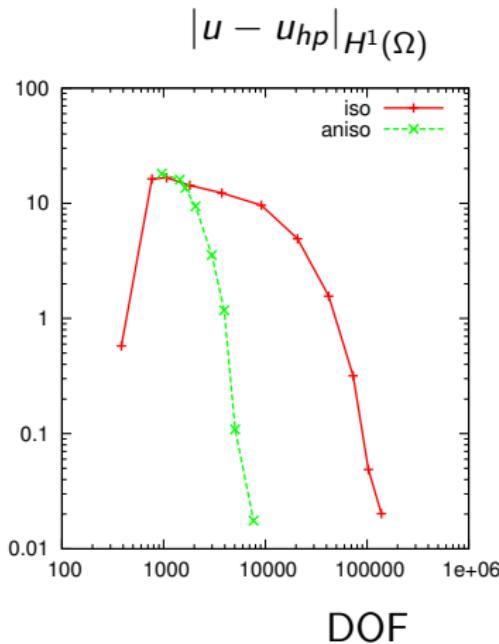
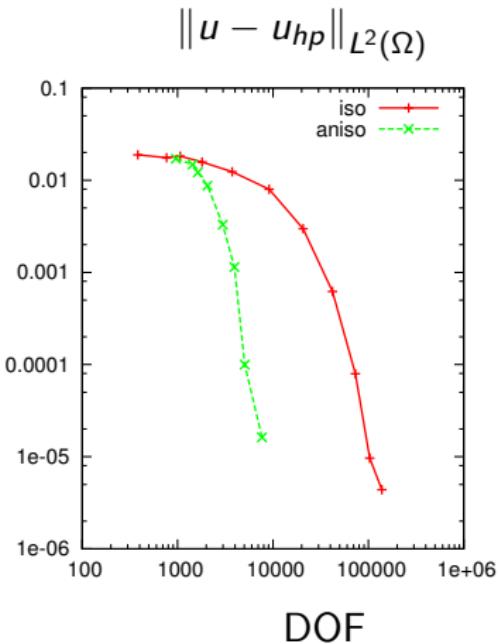
zoom 100 of boundary layer



anisotropic



Boundary layers with $\varepsilon = 10^{-3}$ – comparison



Anisotropic *hp*-DGM for compressible flow simulation

Viscous compressible flow around NACA 0012

$M_{\text{inlet}} = 0.5$, $\alpha = 3^\circ$, $\text{Re} = 5\,000$,

Reference values of aerodynamical coefficients

$c_D = 0.057701$, $c_L = 0.052737$, $c_M = -0.022987$

The goal: compute aerodynamical coefficients

with tolerances: 1% for c_D , 5% for c_L , 2% for c_M

Adaptive techniques

- isotropic *hp*-refinement
- P_1 and P_2 anisotropic mesh refinement
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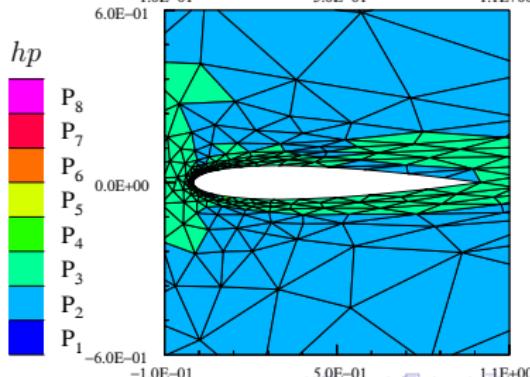
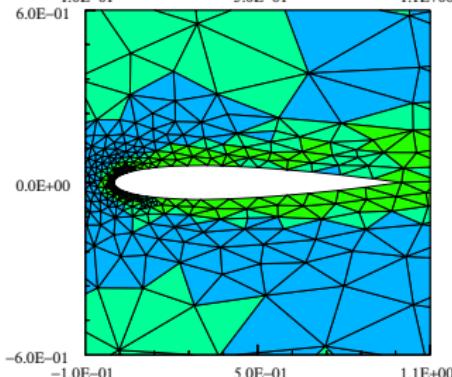
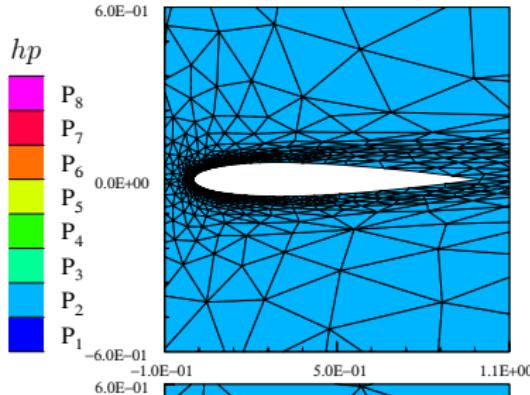
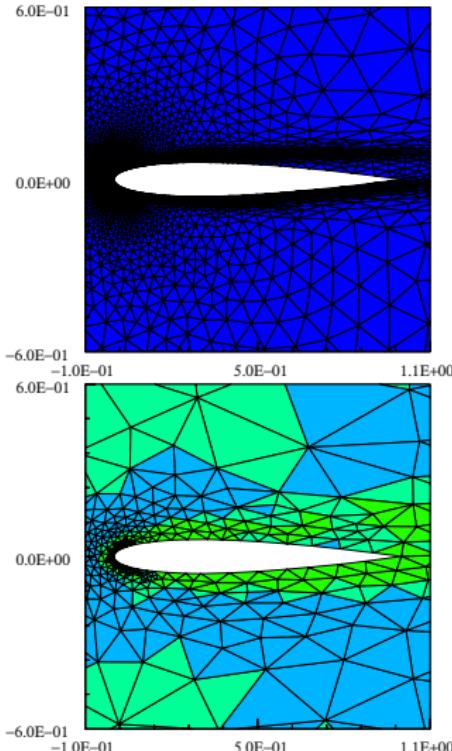
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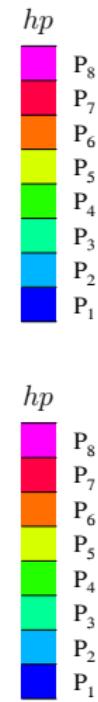
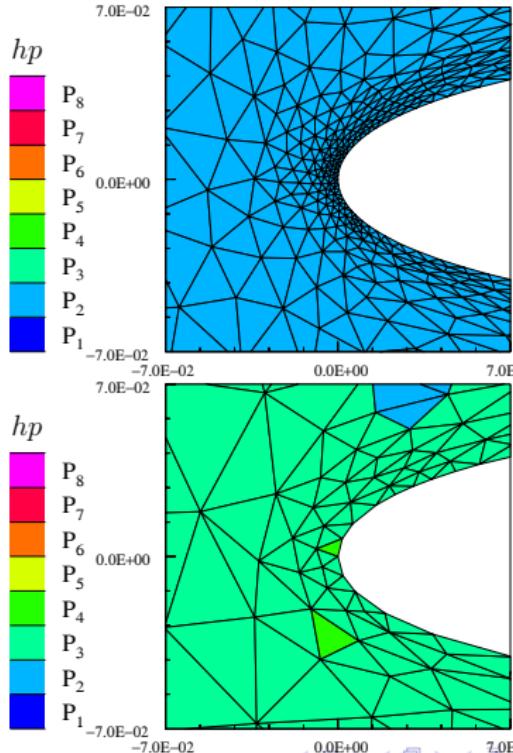
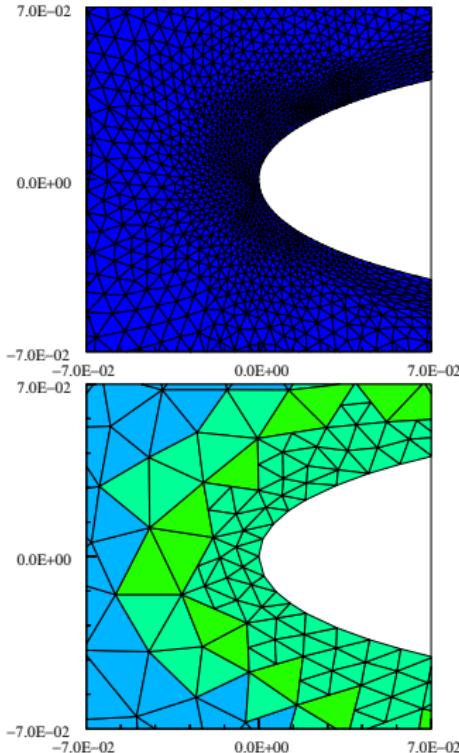
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Comparison of DOF and CPU

method	$\#\mathcal{T}_h$	DOF	CPU(s)
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AMA P_2	1618	38832	107
iso hp	885	31488	91
hp -AMA	595	18488	80

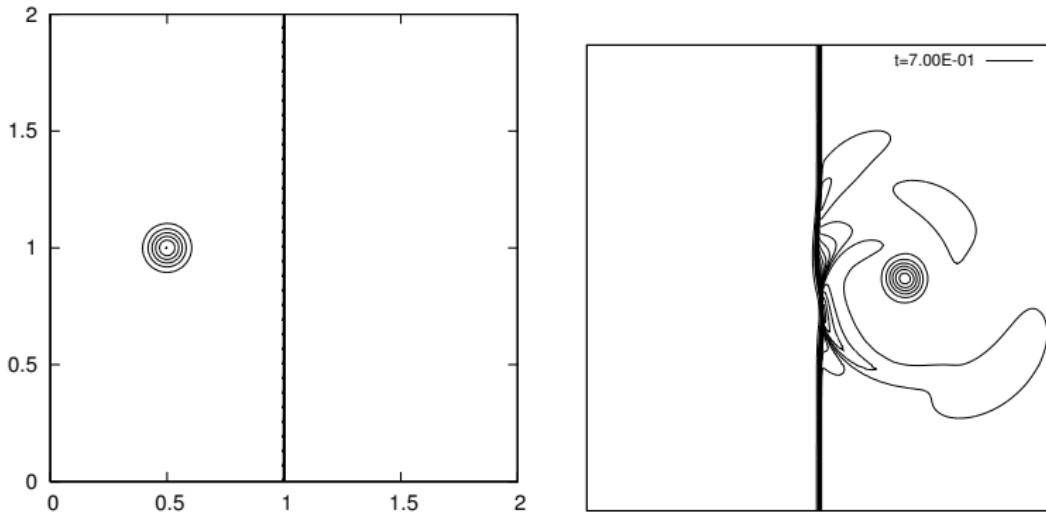
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Viscous shock-vortex interaction - preliminary results



Viscous shock-vortex interaction – adaptive refinement

A posteriori error estimates

State of the art

- many theoretical works for **scalar linear** problems,
- **nonlinear problems**: significantly smaller number of results
- most results estimates of $\|\mathbf{w} - \mathbf{w}_h\|$ in a suitable norm
- It is really our goal?

A posteriori error estimates of the quantity of interest

- quantity of interest: a linear functional $J(\mathbf{w})$,
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YES, if we employ all benefits of DGM which allows:

- high polynomial degrees of approximation
- anisotropic *hp*-grids
- *p*-multigrid techniques
- efficient parallelization

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