

Error control and adaptivity in numerical simulations

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Outline

- 1 Introduction: numerical approximation of partial differential equations
- 2 Laplace equation: error control and mesh adaptivity
 - A posteriori error estimates: error control
 - Potential reconstruction
 - Flux reconstruction
 - A posteriori error estimates: mesh adaptivity
- 3 Nonlinear Laplace equation: error control and solver adaptivity
 - A posteriori error estimates: error control
 - A posteriori error estimates: solver adaptivity
- 4 Reaction–diffusion equation: robustness wrt parameters
- 5 Heat equation: robustness wrt final time and space–time localization
- 6 Eigenvalue problems
- 7 Conclusions

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Numerical approximations of PDEs:

Setting

- u : unknown exact PDE solution
- u_h : known numerical approximation on mesh \mathcal{T}_h

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- $u_h^{n,k,i}$: known numerical approximation on mesh \mathcal{T}_h , time step n , linearization step k , and linear solver step i

Numerical approximations of PDEs: 3 crucial questions

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Crucial questions

- ① How **large** is the overall **error** between u and $u_h^{n,k,i}$?

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- ① How **large** is the overall **error** between u and $u_h^{n,k,i}$?
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- ③ Can we **decrease** it **efficiently**?

Numerical approximations of PDEs: 3 crucial questions & suggested answers

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Suggested answers

- ① Computable **a posteriori** error **estimates**.

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Suggested answers

- ① Computable **a posteriori** error **estimates**.
- ② Identification of **error components**.

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- ① How **large** is the overall **error** between u and $u_h^{n,k,i}$?
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- ③ Can we **decrease** it **efficiently**?

Suggested answers

- ① Computable **a posteriori** error **estimates**.
- ② Identification of **error components**.
- ③ **Balancing** error components, **adaptivity** (working where needed).

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A posteriori error estimates: error control

Laplace equation in $\Omega \subset \mathbb{R}^d$, $d = 2, 3$, $f \in L^2(\Omega)$

$$\begin{aligned} -\Delta u &= f \quad \text{in } \Omega, \\ u &= 0 \quad \text{on } \partial\Omega \end{aligned}$$

Guaranteed error upper bound (reliability) ($u_h \in \mathcal{P}_p(\mathcal{T}_h) \cap H_0^1(\Omega)$, $p \geq 1$, FEs)

$$\underbrace{\|\nabla(u - u_h)\|}_{\text{unknown error}} \quad \underbrace{\eta(u_h)}_{\text{computable estimator}}$$

error lower bound (efficiency, $f \in \mathcal{P}_{p-1}(\mathcal{T}_h)$)

$$\eta(u_h) \leq C_{\text{eff}} \|\nabla(u - u_h)\|$$

- C_{eff} a generic constant only dependent on shape regularity of \mathcal{T}_h and thus independent of Ω , u , u_h , h , p

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Computing the error estimator $\eta(u_h)$ is the key step.

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Local error lower bound (efficiency, $f \in \mathcal{P}_{p-1}(\mathcal{T}_h)$)

$$\eta_K(u_h) \leq C_{\text{eff}} \|\nabla(u - u_h)\|_{\omega_K} \quad \forall K \in \mathcal{T}_h$$

- C_{eff} a generic constant only dependent on shape regularity of \mathcal{T}_h and thus independent of Ω , u , u_h , h , p
- computable bound on C_{eff} available, $C_{\text{eff}} \approx 5$

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→ Dörfler (1996), Verfürth (1991), Babuška & Rheinboldt (1974).

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How large is the overall error?

(model pb, known smooth solution)

h	p	$\eta(u_h)$	rel. error estimate $\frac{\eta(u_h)}{\ \nabla u_h\ }$	$\ \nabla(u - u_h)\ $	rel. error $\frac{\ \nabla(u - u_h)\ }{\ \nabla u\ } = \frac{\ \nabla(u - u_h)\ }{\ \nabla u_h\ }$	$\ u - u_h\ $
h_0	1	1.25	28%	1.07	24%	1.1
$\approx h_0/2$						
$\approx h_0/4$						
$\approx h_0/8$						
$\approx h_0/16$						
$\approx h_0/32$						
$\approx h_0/64$						
$\approx h_0/128$						

How large is the overall error? (model pb, known smooth solution)

h	p	$\eta(\mathbf{u}_h)$	rel. error estimate $\frac{\eta(\mathbf{u}_h)}{\ \nabla \mathbf{u}_h\ }$	$\ \nabla(\mathbf{u} - \mathbf{u}_h)\ $	rel. error $\frac{\ \nabla(\mathbf{u} - \mathbf{u}_h)\ }{\ \nabla \mathbf{u}\ }$	$\mathcal{E} = \frac{\eta(\mathbf{u}_h)}{\ \nabla \mathbf{u}\ }$
h_0	1	1.25	28%	1.07	24%	13%
$\approx h_0/2$		6.07×10^{-1}				
$\approx h_0/4$		3.10×10^{-1}				
$\approx h_0/8$		1.45×10^{-1}				
$\approx h_0/16$		4.23×10^{-2}				
$\approx h_0/32$		2.62×10^{-2}				
$\approx h_0/64$		1.260×10^{-2}				

Estimated error vs. true error
 Estimated error vs. true error (log-log scale)

How large is the overall error? (model pb, known smooth solution)

h	p	$\eta(\mathbf{u}_h)$	rel. error estimate $\frac{\eta(\mathbf{u}_h)}{\ \nabla \mathbf{u}_h\ }$	$\ \nabla(\mathbf{u} - \mathbf{u}_h)\ $	rel. error $\frac{\ \nabla(\mathbf{u} - \mathbf{u}_h)\ }{\ \nabla \mathbf{u}_h\ }$	$\text{ref} = \frac{\eta(\mathbf{u}_h)}{\ \nabla(\mathbf{u} - \mathbf{u}_h)\ }$
h_0	1	1.25	28%	1.07	24%	1.17
$\approx h_0/2$		6.07×10^{-1}				
$\approx h_0/4$		3.10×10^{-1}				
$\approx h_0/8$		1.45×10^{-1}				
$\approx h_0/16$		4.23×10^{-2}				
$\approx h_0/32$		2.62×10^{-2}				
$\approx h_0/64$		1.26×10^{-2}				

How large is the overall error? (model pb, known smooth solution)

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h_0	1	1.25	28%	1.07	24%	1.17
$\approx h_0/2$		6.07×10^{-1}	14%	5.56×10^{-1}		
$\approx h_0/4$		3.10×10^{-1}	7%	2.92×10^{-1}		
$\approx h_0/8$		1.45×10^{-1}	3.5%	1.39×10^{-1}		
$\approx h_0/16$		4.23×10^{-2}	1.1%	4.07×10^{-2}		
$\approx h_0/32$		2.62×10^{-2}	0.7%	2.60×10^{-2}		
$\approx h_0/64$		2.60×10^{-2}	0.7%	2.58×10^{-2}		

Estimated error vs. reference error
 Estimated error vs. exact error

How large is the overall error? (model pb, known smooth solution)

h	p	$\eta(\mathbf{u}_h)$	rel. error estimate $\frac{\eta(\mathbf{u}_h)}{\ \nabla \mathbf{u}_h\ }$	$\ \nabla(\mathbf{u} - \mathbf{u}_h)\ $	rel. error $\frac{\ \nabla(\mathbf{u} - \mathbf{u}_h)\ }{\ \nabla \mathbf{u}_h\ }$	$\text{f}^{\text{eff}} = \frac{\eta(\mathbf{u}_h)}{\ \nabla(\mathbf{u} - \mathbf{u}_h)\ }$
h_0	1	1.25	28%	1.07	24%	1.17
$\approx h_0/2$		6.07×10^{-1}	14%	5.56×10^{-1}	13%	
$\approx h_0/4$		3.10×10^{-1}	7.0%	2.92×10^{-1}	6.6%	
$\approx h_0/8$		1.45×10^{-1}	3.3%	1.39×10^{-1}	3.1%	
$\approx h_0/16$		4.23×10^{-2}	0.8%	4.07×10^{-2}	0.8%	
$\approx h_0/32$		2.62×10^{-2}	0.4%	2.60×10^{-2}	0.4%	
$\approx h_0/64$		2.60×10^{-2}	0.2%	2.58×10^{-2}	0.2%	

How large is the overall error? (model pb, known smooth solution)

h	p	$\eta(\mathbf{u}_h)$	rel. error estimate $\frac{\eta(\mathbf{u}_h)}{\ \nabla \mathbf{u}_h\ }$	$\ \nabla(\mathbf{u} - \mathbf{u}_h)\ $	rel. error $\frac{\ \nabla(\mathbf{u} - \mathbf{u}_h)\ }{\ \nabla \mathbf{u}_h\ }$	$I^{\text{eff}} = \frac{\eta(\mathbf{u}_h)}{\ \nabla(\mathbf{u} - \mathbf{u}_h)\ }$
h_0	1	1.25	28%	1.07	24%	1.17
$\approx h_0/2$		6.07×10^{-1}	14%	5.56×10^{-1}	13%	1.09
$\approx h_0/4$		3.10×10^{-1}	7.0%	2.92×10^{-1}	6.6%	1.06
$\approx h_0/8$		1.45×10^{-1}	3.3%	1.39×10^{-1}	3.1%	1.04
$\approx h_0/16$		4.23×10^{-2}	0.8%	4.07×10^{-2}	0.9%	1.03
$\approx h_0/32$		2.62×10^{-2}	0.4%	2.60×10^{-2}	0.4%	1.02
$\approx h_0/64$		2.60×10^{-2}	0.2%	2.58×10^{-2}	0.2%	1.01

Estimated error: 1.39×10^{-1} (from $\eta(\mathbf{u}_h) = 1.45 \times 10^{-1}$)

Actual error: 1.39×10^{-1} (from $\|\nabla(\mathbf{u} - \mathbf{u}_h)\| = 1.39 \times 10^{-1}$)

Relative error: 3.1%

How large is the overall error? (model pb, known smooth solution)

h	p	$\eta(\mathbf{u}_h)$	rel. error estimate $\frac{\eta(\mathbf{u}_h)}{\ \nabla \mathbf{u}_h\ }$	$\ \nabla(\mathbf{u} - \mathbf{u}_h)\ $	rel. error $\frac{\ \nabla(\mathbf{u} - \mathbf{u}_h)\ }{\ \nabla \mathbf{u}_h\ }$	$I^{\text{eff}} = \frac{\eta(\mathbf{u}_h)}{\ \nabla(\mathbf{u} - \mathbf{u}_h)\ }$
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$\approx h_0/8$		1.45×10^{-1}	3.3%	1.39×10^{-1}	3.1%	1.04
$\approx h_0/2$	2	4.23×10^{-2}	$9.5 \times 10^{-1}\%$	4.07×10^{-2}	$9.2 \times 10^{-1}\%$	1.04
$\approx h_0/4$		2.62×10^{-2}	5.9%	2.60×10^{-2}	$5.9 \times 10^{-2}\%$	1.0
$\approx h_0/8$		1.260×10^{-2}	3.1%	1.258×10^{-2}	$3.1 \times 10^{-2}\%$	1.0

Estimated error: $\|\nabla(\mathbf{u} - \mathbf{u}_h)\| \approx 1.258 \times 10^{-2}$
 Estimated overall error: $I^{\text{eff}} \approx 1.0$

How large is the overall error? (model pb, known smooth solution)

h	p	$\eta(\mathbf{u}_h)$	rel. error estimate $\frac{\eta(\mathbf{u}_h)}{\ \nabla \mathbf{u}_h\ }$	$\ \nabla(\mathbf{u} - \mathbf{u}_h)\ $	rel. error $\frac{\ \nabla(\mathbf{u} - \mathbf{u}_h)\ }{\ \nabla \mathbf{u}_h\ }$	$I^{\text{eff}} = \frac{\eta(\mathbf{u}_h)}{\ \nabla(\mathbf{u} - \mathbf{u}_h)\ }$
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$\approx h_0/4$	3	2.62×10^{-3}	$5.9 \times 10^{-3}\%$	2.60×10^{-3}	$5.9 \times 10^{-3}\%$	1.01
$\approx h_0/8$	4	2.66×10^{-4}	$5.9 \times 10^{-4}\%$	2.58×10^{-4}	$5.8 \times 10^{-4}\%$	1.01

Estimated error vs. exact error
 Estimated error vs. numerical error

How large is the overall error? (model pb, known smooth solution)

h	p	$\eta(u_h)$	rel. error estimate $\frac{\eta(u_h)}{\ \nabla u_h\ }$	$\ \nabla(u - u_h)\ $	rel. error $\frac{\ \nabla(u - u_h)\ }{\ \nabla u_h\ }$	$I^{\text{eff}} = \frac{\eta(u_h)}{\ \nabla(u - u_h)\ }$
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A. Ern, M. Vohralík, SIAM Journal on Numerical Analysis (2015)

V. Dolejší, A. Ern, M. Vohralík, SIAM Journal on Scientific Computing (2016)

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h	p	$\eta(\mathbf{u}_h)$	rel. error estimate $\frac{\eta(\mathbf{u}_h)}{\ \nabla \mathbf{u}_h\ }$	$\ \nabla(\mathbf{u} - \mathbf{u}_h)\ $	rel. error $\frac{\ \nabla(\mathbf{u} - \mathbf{u}_h)\ }{\ \nabla \mathbf{u}_h\ }$	$I^{\text{eff}} = \frac{\eta(\mathbf{u}_h)}{\ \nabla(\mathbf{u} - \mathbf{u}_h)\ }$
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$\approx h_0/4$		3.10×10^{-1}	7.0%	2.92×10^{-1}	6.6%	1.06
$\approx h_0/8$		1.45×10^{-1}	3.3%	1.39×10^{-1}	3.1%	1.04
$\approx h_0/2$	2	4.23×10^{-2}	$9.5 \times 10^{-1}\%$	4.07×10^{-2}	$9.2 \times 10^{-1}\%$	1.04
$\approx h_0/4$	3	2.62×10^{-4}	$5.9 \times 10^{-3}\%$	2.60×10^{-4}	$5.9 \times 10^{-3}\%$	1.01
$\approx h_0/8$	4	2.60×10^{-7}	$5.9 \times 10^{-6}\%$	2.58×10^{-7}	$5.8 \times 10^{-6}\%$	1.01

A. Ern, M. Vohralík, SIAM Journal on Numerical Analysis (2015)
V. Dolejší, A. Ern, M. Vohralík, SIAM Journal on Scientific Computing (2016)

How large is the overall error? (model pb, known smooth solution)

h	p	$\eta(\mathbf{u}_h)$	rel. error estimate $\frac{\eta(\mathbf{u}_h)}{\ \nabla \mathbf{u}_h\ }$	$\ \nabla(\mathbf{u} - \mathbf{u}_h)\ $	rel. error $\frac{\ \nabla(\mathbf{u} - \mathbf{u}_h)\ }{\ \nabla \mathbf{u}_h\ }$	$I^{\text{eff}} = \frac{\eta(\mathbf{u}_h)}{\ \nabla(\mathbf{u} - \mathbf{u}_h)\ }$
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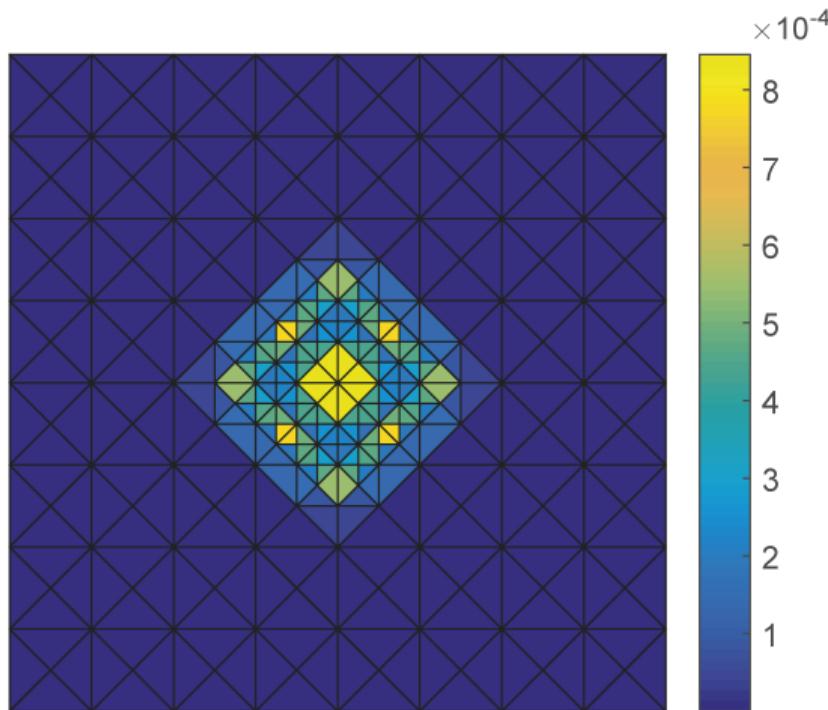
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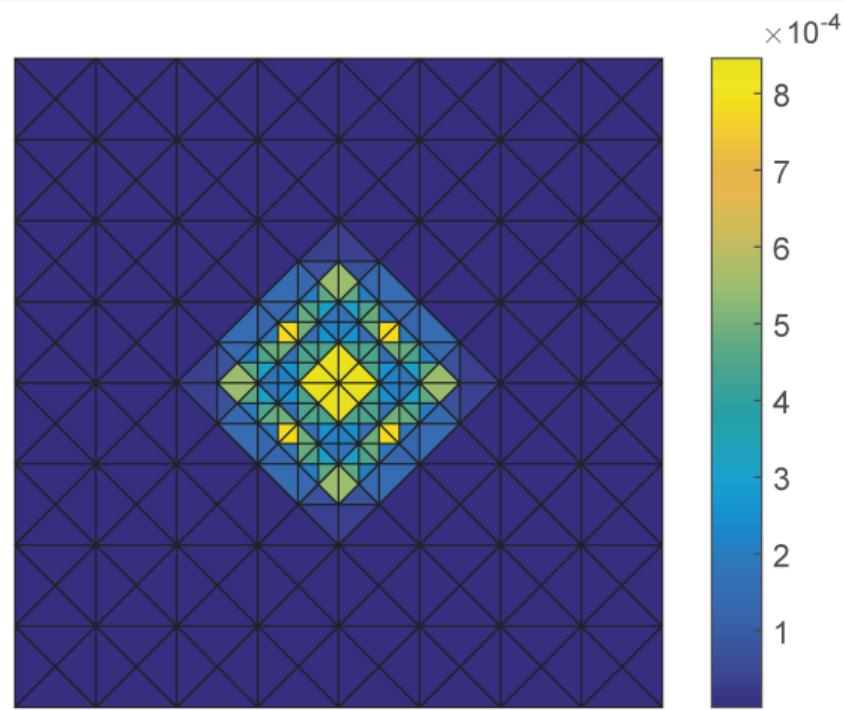
h	p	$\eta(u_h)$	rel. error estimate $\frac{\eta(u_h)}{\ \nabla u_h\ }$	$\ \nabla(u - u_h)\ $	rel. error $\frac{\ \nabla(u - u_h)\ }{\ \nabla u_h\ }$	$I^{\text{eff}} = \frac{\eta(u_h)}{\ \nabla(u - u_h)\ }$
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A. Ern, M. Vohralík, SIAM Journal on Numerical Analysis (2015)
V. Dolejší, A. Ern, M. Vohralík, SIAM Journal on Scientific Computing (2016)

Where (in space) is the error **localized**? (known smooth solution)



Estimated error distribution $\eta_K(u_h)$



Exact error distribution $\|\nabla(u - u_h)\|_K$

P. Daniel, A. Ern, I. Smears, M. Vohralík, Computers & Mathematics with Applications (2018)

Error characterization

Theorem (Error characterization)

Let $u \in H_0^1(\Omega)$ be the weak solution and let $u_h \in H^1(\mathcal{T}_h)$ be arbitrary. Then

$$\|\nabla(u - u_h)\|^2 = \underbrace{\min_{\substack{\sigma \in \mathbf{H}(\text{div}, \Omega) \\ \nabla \cdot \sigma = f}} \|\nabla u_h + \sigma\|^2}_{= \max_{\substack{\varphi \in H_0^1(\Omega) \\ \|\nabla \varphi\| = 1}} [(f, \varphi) - (\nabla u_h, \nabla \varphi)]^2} + \min_{s \in H_0^1(\Omega)} \|\nabla(u_h - s)\|^2.$$

Comments

- It is enough to choose suitable (discrete, piecewise polynomial) $\sigma_h \in \mathbf{H}(\text{div}, \Omega)$ with $\nabla \cdot \sigma_h = f$ and $s_h \in H_0^1(\Omega)$ to get a guaranteed upper bound.

→ Theorem of Babuška-Brezzi

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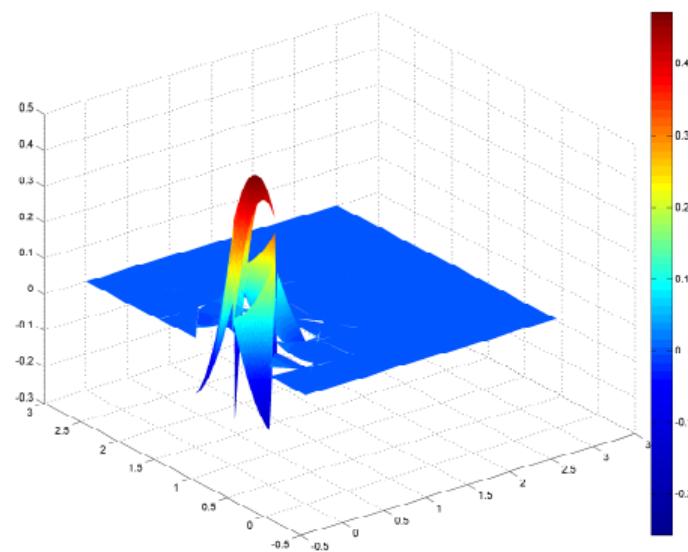
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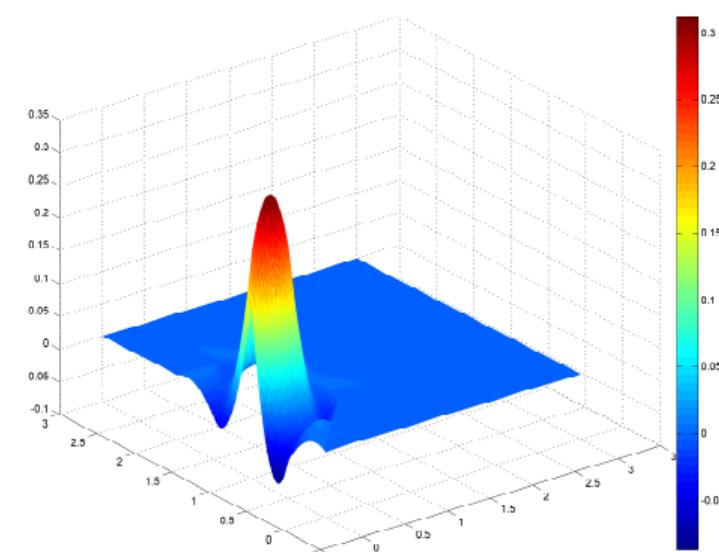
Outline

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Potential reconstruction



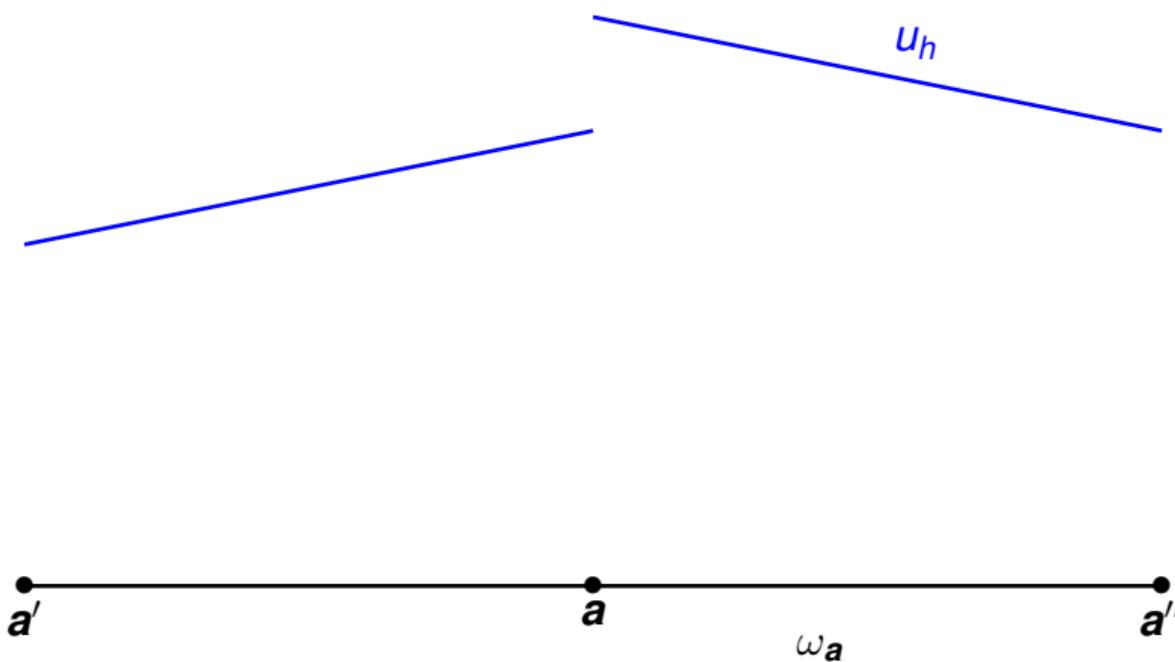
Potential u_h



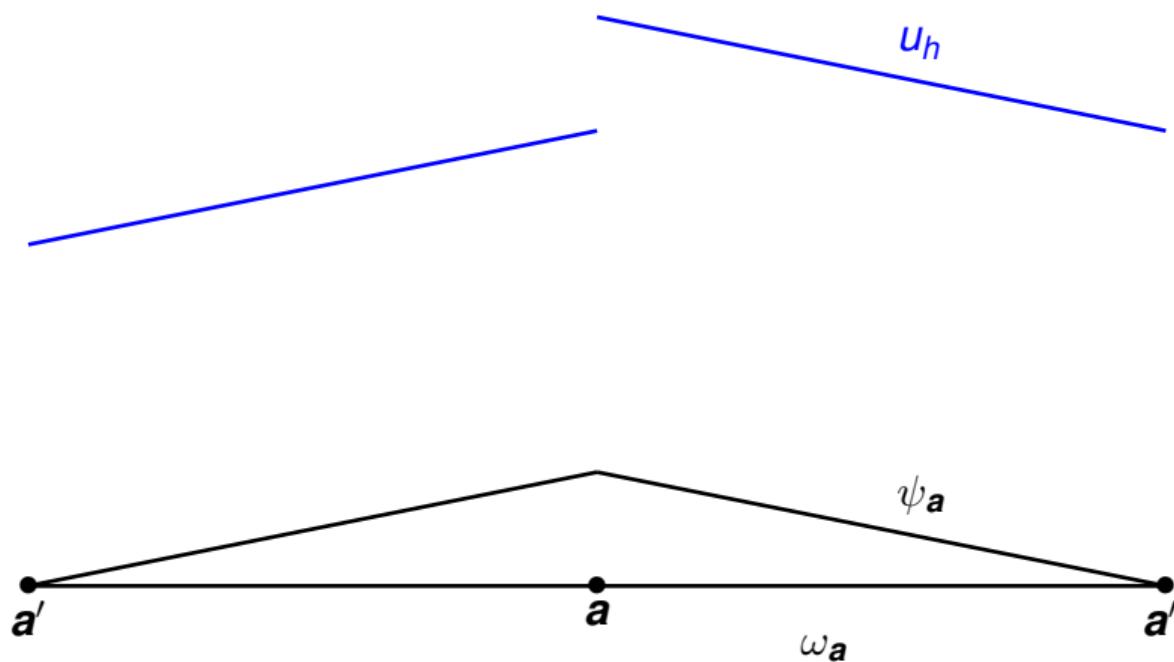
Potential reconstruction s_h

$$u_h \in \mathcal{P}_p(\mathcal{T}_h) \rightarrow s_h \in \mathcal{P}_{p+1}(\mathcal{T}_h) \cap H_0^1(\Omega)$$

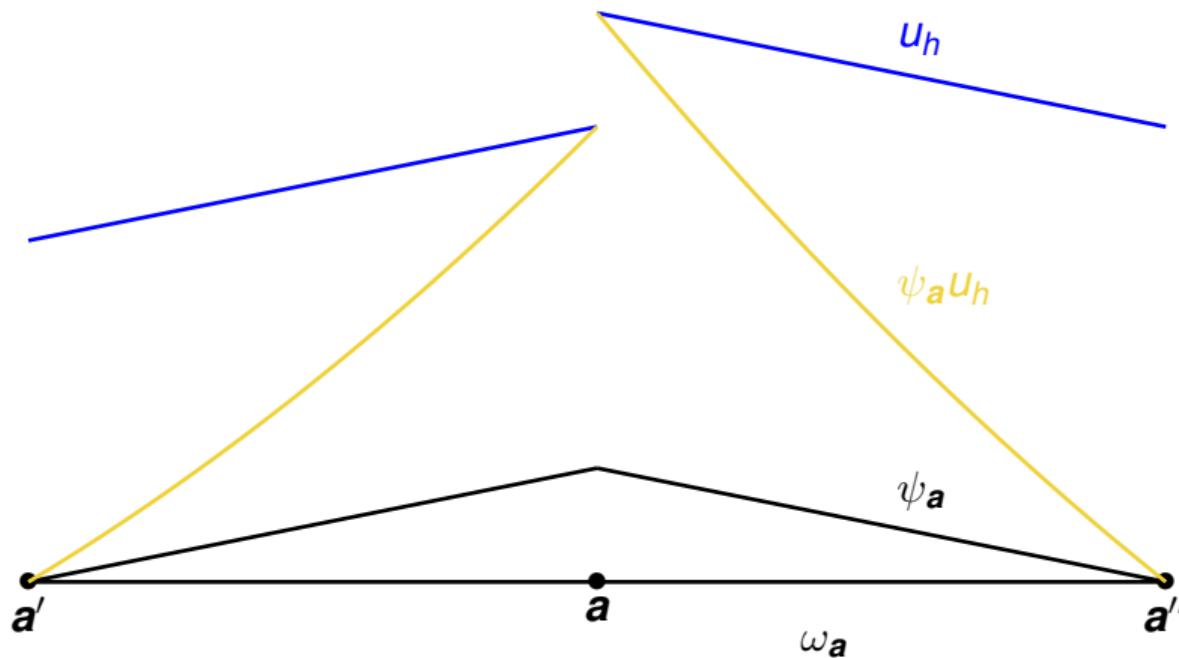
Potential reconstruction in 1D, $p = 1$



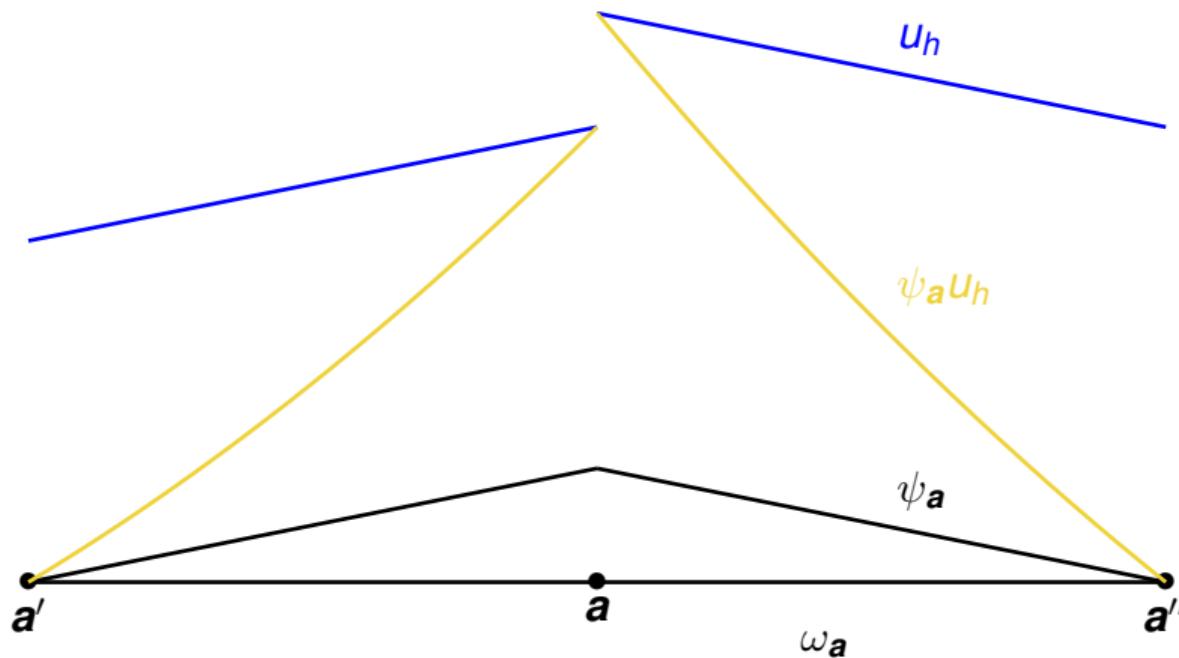
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Definition (Construction of s_h Ern & V. (2015), \approx Carstensen and Merdon (2013))

For each vertex $a \in \mathcal{V}_h$, solve the local minimization problem

$$s_h^a := \arg \min_{v_h \in V_h^a} \|\nabla(\psi_a u_h - v_h)\|_{\omega_a}$$

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Equivalent form: conforming FEs

Find $s_h^a \in V_h^a$ such that

$$(\nabla s_h^a, \nabla v_h)_{\omega_a} = (\nabla(\psi_a u_h), \nabla v_h)_{\omega_a} \quad \forall v_h \in V_h^a.$$

Key points

- localization to patches \mathcal{T}_h^a
- cut-off by hat basis functions ψ_a
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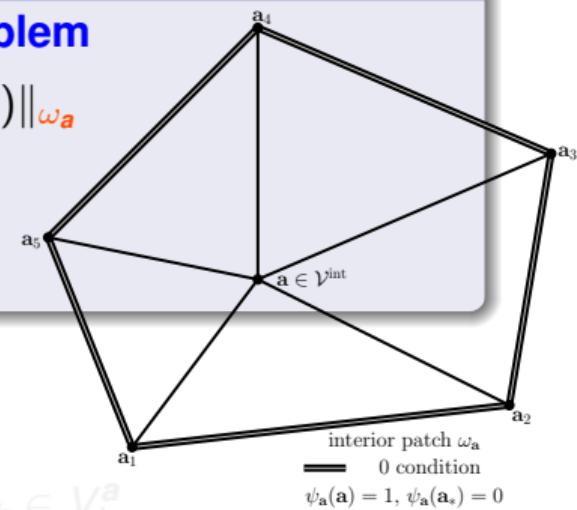
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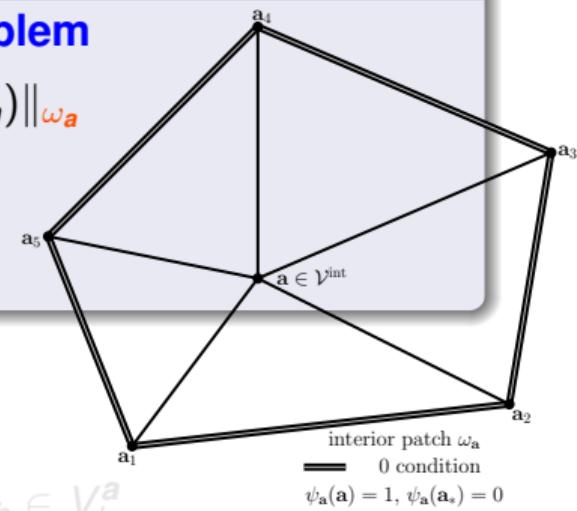
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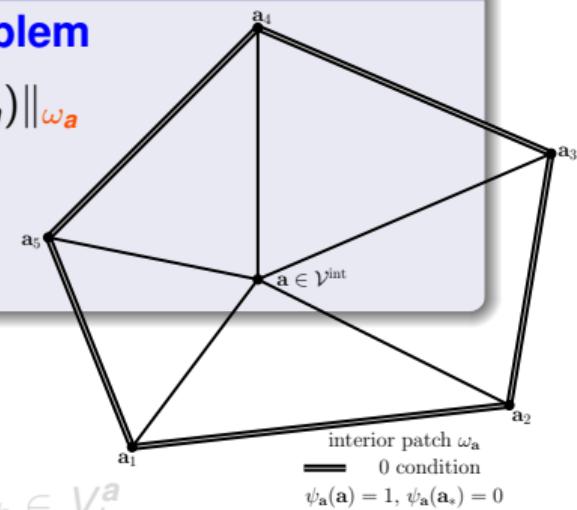
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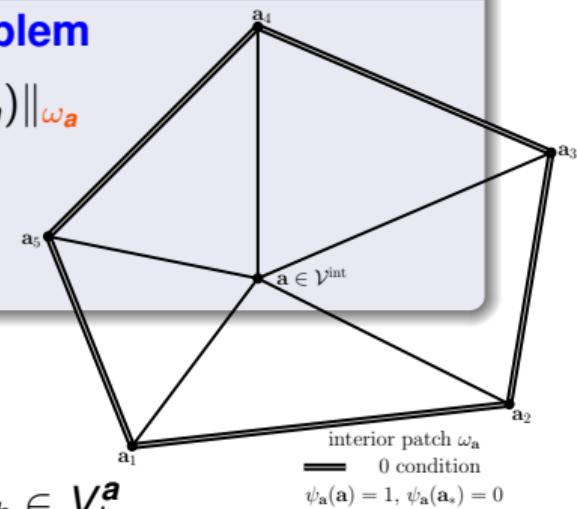
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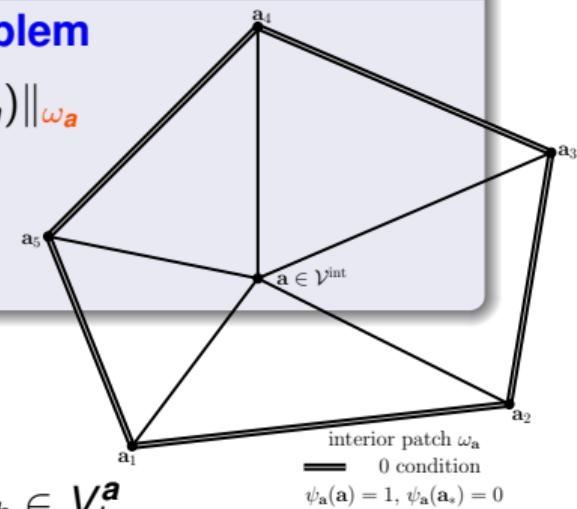
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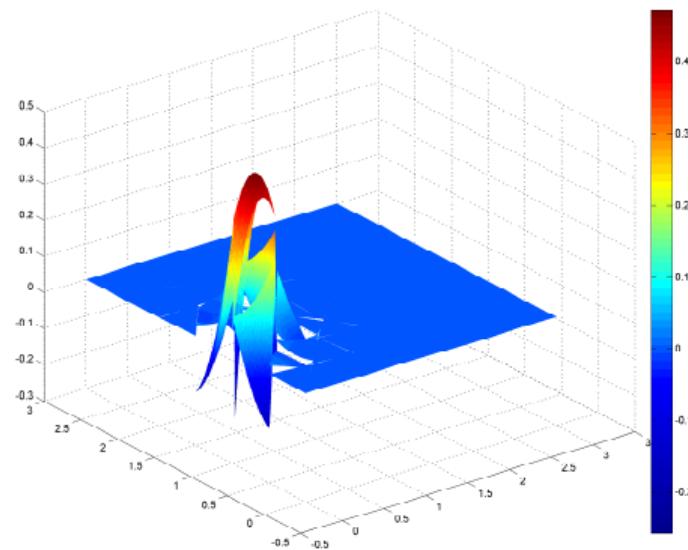
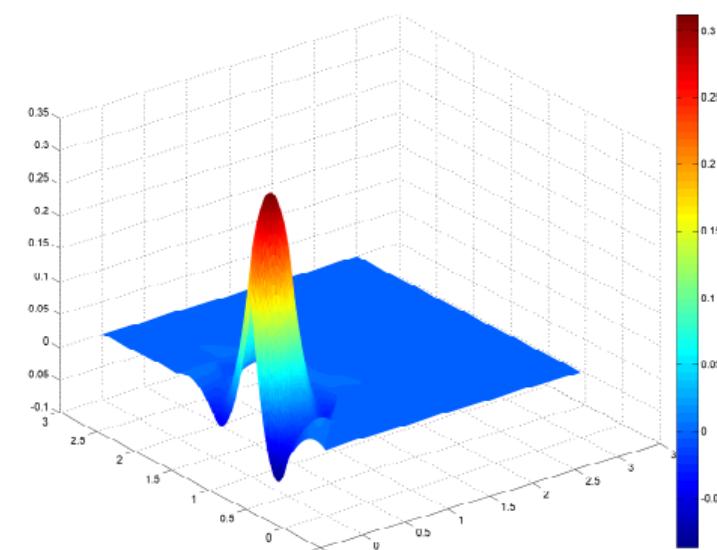
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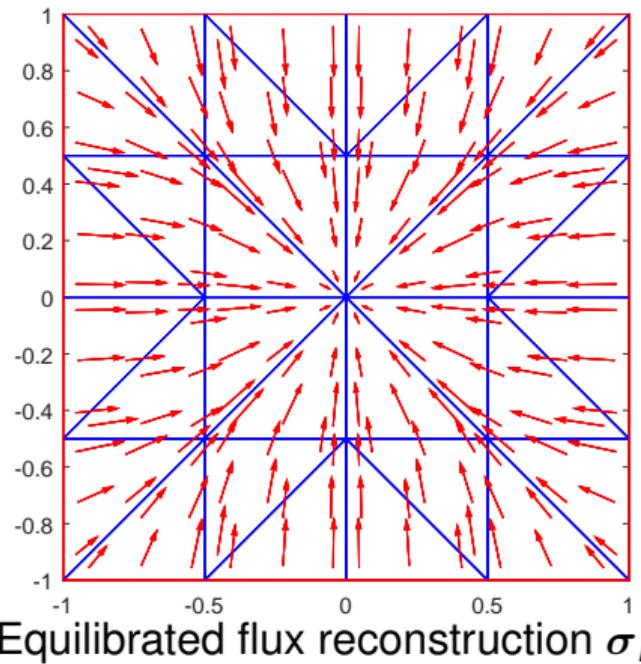
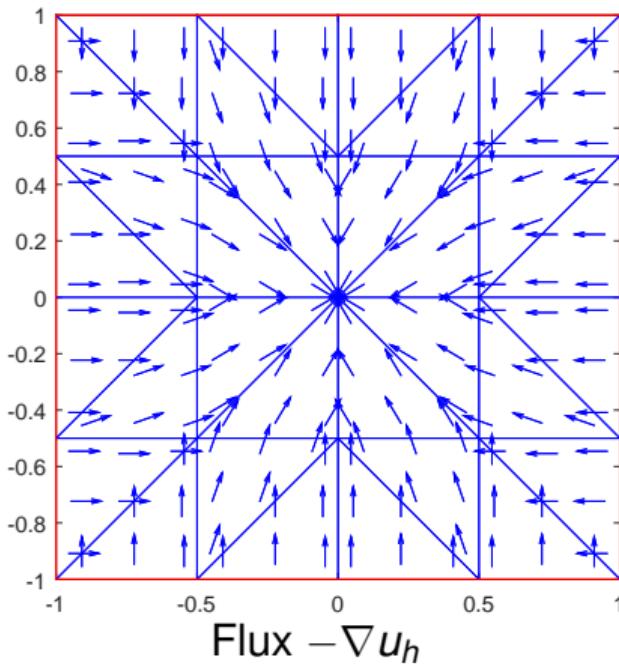
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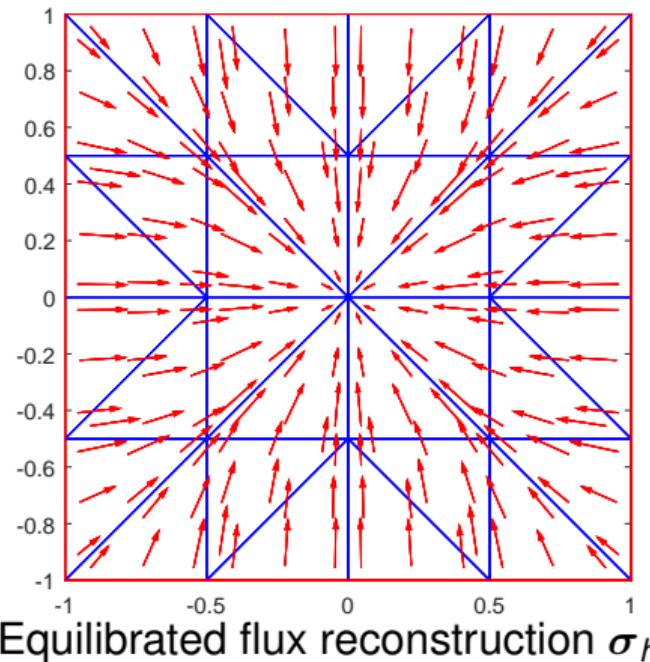
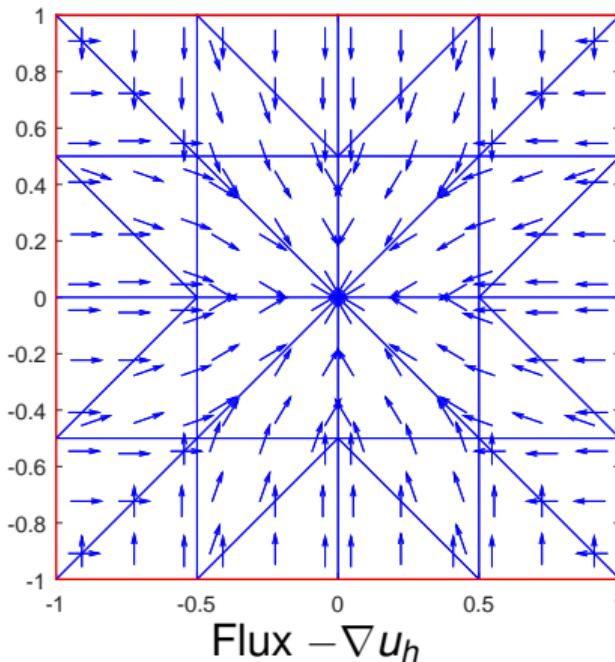
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Equilibrated flux reconstruction



$$\underbrace{-\nabla u_h \in \mathcal{RT}_{p-1}(\mathcal{T}_h), f \in L^2(\Omega)}_{(f, \psi_a)_{\omega_a} - (\nabla u_h, \nabla \psi_a)_{\omega_a} = 0 \quad \forall a \in \mathcal{V}_h^{\text{int}}} \rightarrow \sigma_h \in \mathcal{RT}_p(\mathcal{T}_h) \cap H(\text{div}, \Omega), \nabla \cdot \sigma_h = \Pi_p f$$

Equilibrated flux reconstruction



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Flux reconstruction: $-\nabla u_h \in \mathcal{RT}_{p-1}(\mathcal{T}_h)$, $p \geq 1$, $f \in L^2(\Omega)$

Assumption (Orthogonality wrt hat functions)

There holds $(f, \psi_a)_{\omega_a} - (\nabla u_h, \nabla \psi_a)_{\omega_a} = 0 \quad \forall a \in \mathcal{V}_h^{\text{int}}$.

Definition (Construction of σ_h , Destuynder and Métivet (1999) & Braess and Schöberl (2008))

For each $a \in \mathcal{V}_h$, solve the **local constrained minimization pb**

$$\sigma_h^a := \arg \min_{\substack{\mathbf{v}_h \in \mathcal{V}_h^a \\ \nabla \cdot \mathbf{v}_h =}} \|\psi_a \nabla u_h + \mathbf{v}_h\|_{\omega_a}$$

• σ_h^a is unique

Key points

- homogeneous Neumann BC on $\partial \omega_a$: $\sigma_h \in \mathcal{RT}_p(\mathcal{T}_h) \cap H(\text{div}, \Omega)$
- equilibrium $\nabla \cdot \sigma_h = \sum_{a \in \mathcal{V}_h} \nabla \cdot \sigma_h^a = \sum_{a \in \mathcal{V}_h} \Pi_p(f \psi_a - \nabla u_h \cdot \nabla \psi_a) = \Pi_p f$

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$$\sigma_h^{\mathbf{a}} := \arg \min_{\begin{array}{c} \mathbf{v}_h \in \mathcal{V}_h^{\mathbf{a}} - \mathcal{RT}_p(\mathcal{T}^*) \cap H_0(\text{div}, \omega_{\mathbf{a}}) \\ \nabla \cdot \mathbf{v}_h = 0 \text{ on } \partial\omega_{\mathbf{a}} \cup \partial\Omega \end{array}} \|\psi_{\mathbf{a}} \nabla u_h + \mathbf{v}_h\|_{\omega_{\mathbf{a}}}$$

• $\sigma_h^{\mathbf{a}} \in \mathcal{RT}_p(\mathcal{T}_h)$

Key points

- homogeneous Neumann BC on $\partial\omega_{\mathbf{a}}$: $\sigma_h \in \mathcal{RT}_p(\mathcal{T}_h) \cap H(\text{div}, \Omega)$
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Flux reconstruction: $-\nabla u_h \in \mathcal{RT}_{p-1}(\mathcal{T}_h)$, $p \geq 1$, $f \in L^2(\Omega)$

Assumption (Orthogonality wrt hat functions)

There holds $(f, \psi_a)_{\omega_a} - (\nabla u_h, \nabla \psi_a)_{\omega_a} = 0 \quad \forall a \in \mathcal{V}_h^{\text{int}}$.

Definition (Construction of σ_h , Destuynder and Métivet (1999) & Braess and Schöberl (2008))

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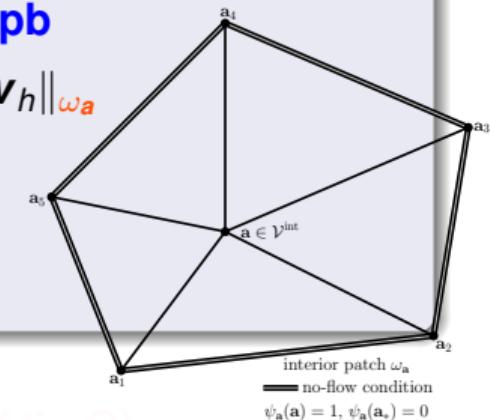
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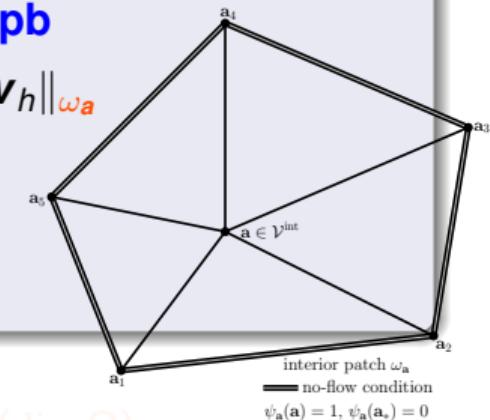
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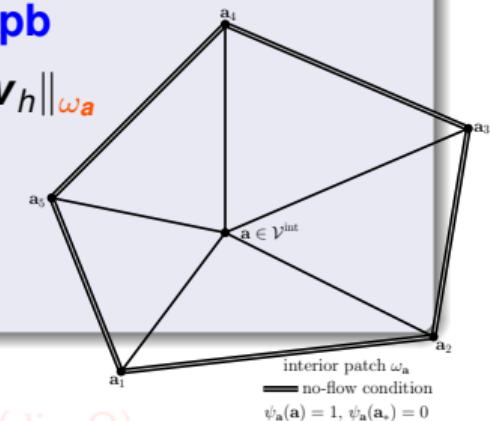
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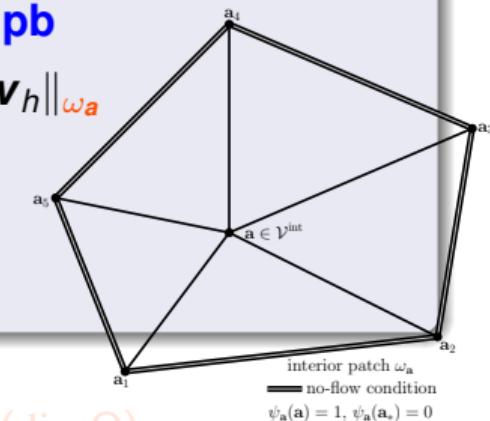
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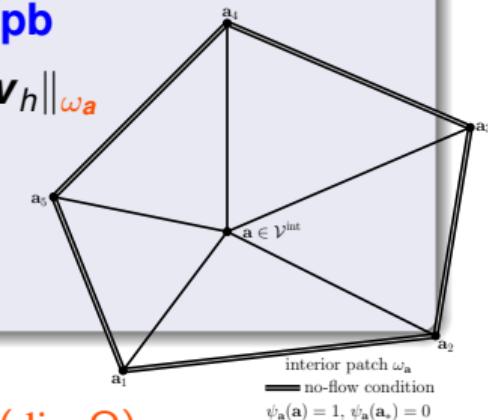
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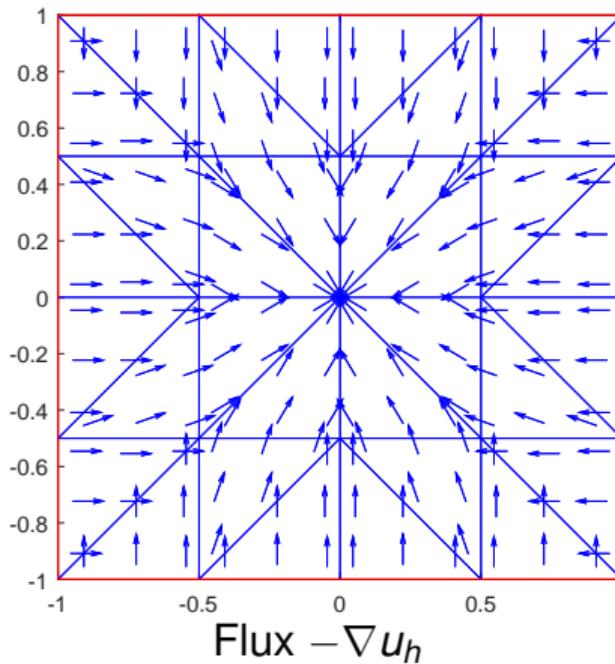
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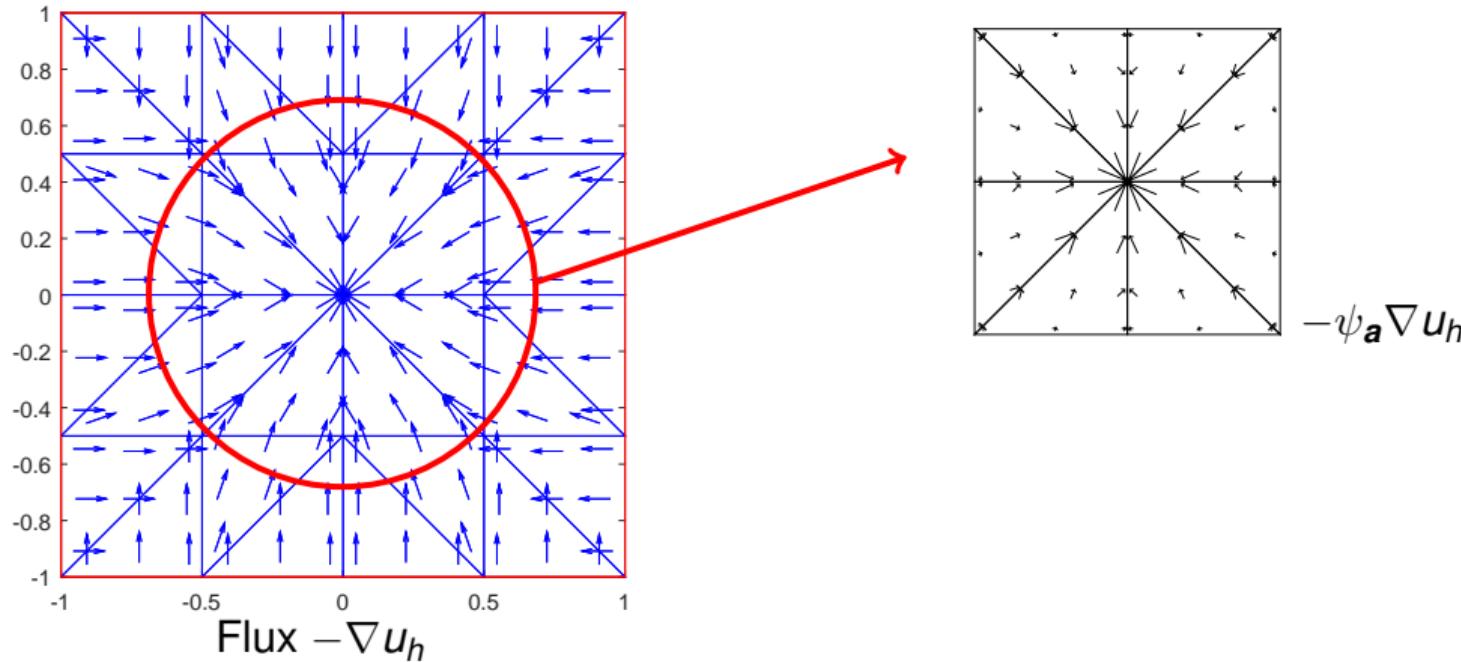


Equilibrated flux reconstruction



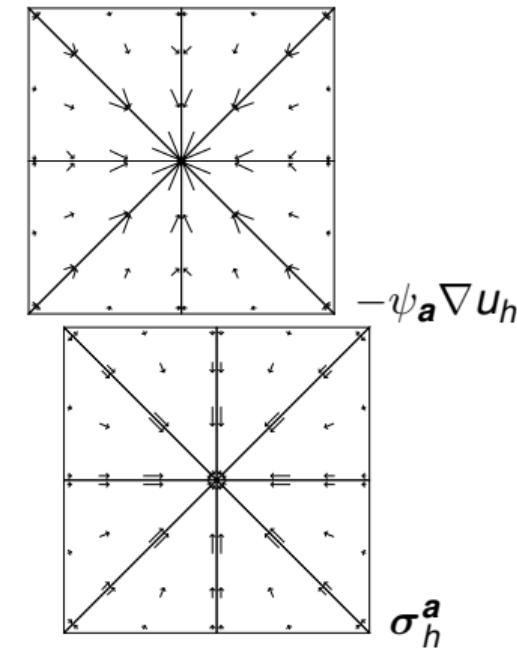
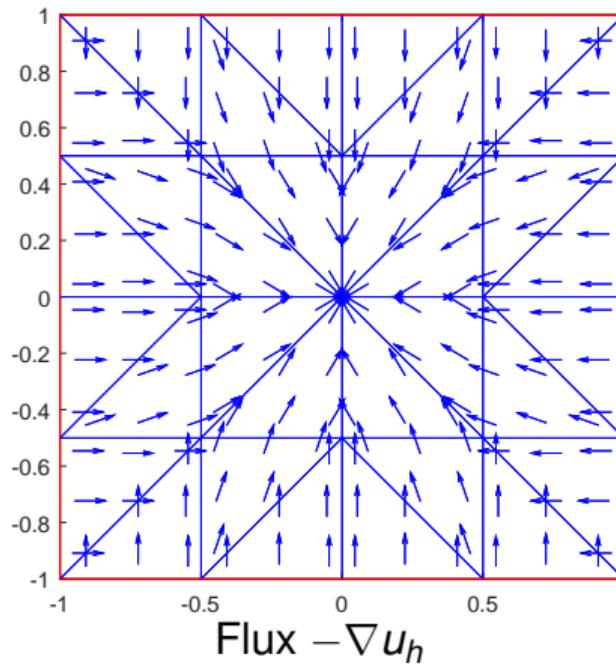
$$\underbrace{-\nabla u_h \in \mathcal{RT}_{p-1}(\mathcal{T}_h), f \in L^2(\Omega)}_{(f, \psi_a)_{\omega_a} - (\nabla u_h, \nabla \psi_a)_{\omega_a} = 0 \quad \forall a \in \mathcal{V}_h^{\text{int}}}$$

Equilibrated flux reconstruction



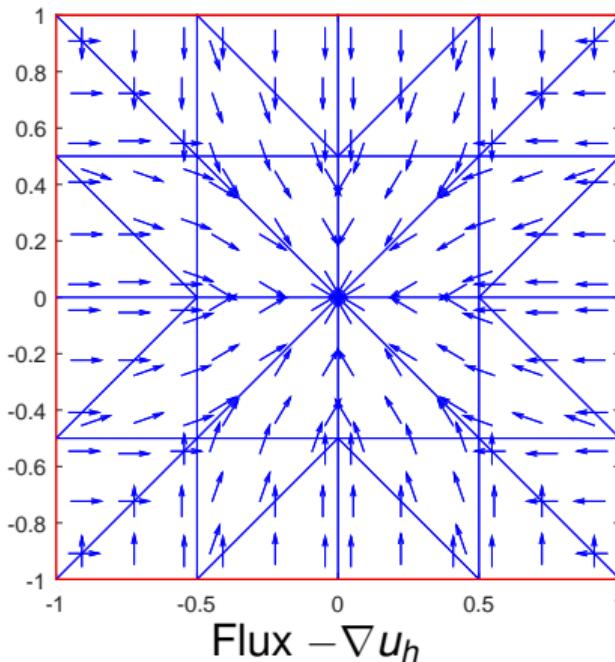
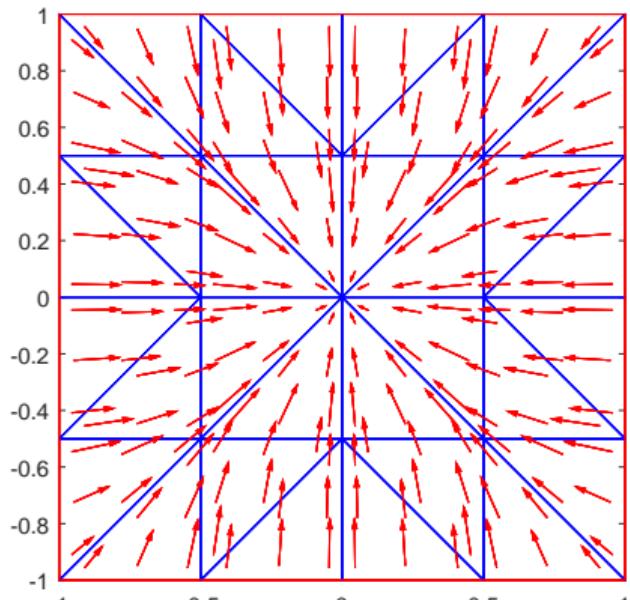
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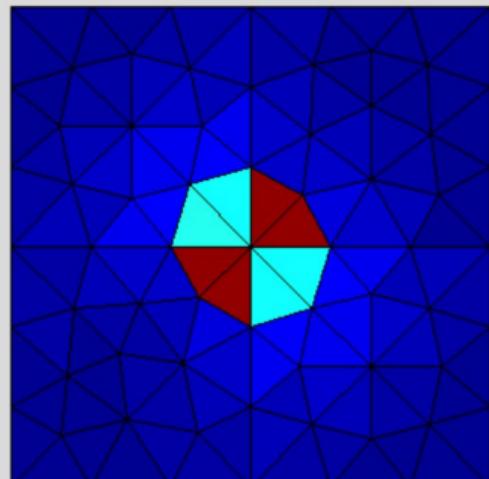
Flux $-\nabla u_h$ Equilibrated flux reconstruction σ_h

$$\underbrace{-\nabla u_h \in \mathcal{RT}_{p-1}(\mathcal{T}_h), f \in L^2(\Omega)}_{(f, \psi_a)_{\omega_a} - (\nabla u_h, \nabla \psi_a)_{\omega_a} = 0 \ \forall a \in \mathcal{V}_h^{\text{int}}} \rightarrow \sigma_h \in \mathcal{RT}_p(\mathcal{T}_h) \cap \mathbf{H}(\text{div}, \Omega), \nabla \cdot \sigma_h = \Pi_p f$$

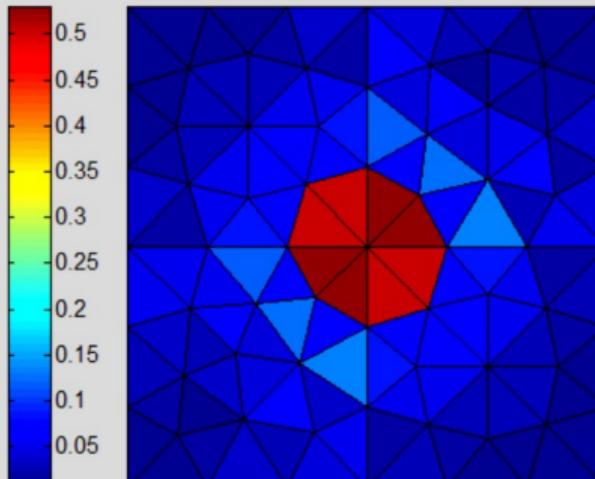
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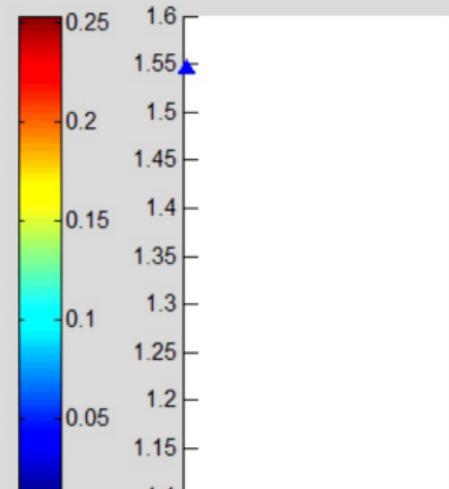
Can we decrease the error efficiently? (adaptive mesh refinement)



Estimated error



Actual error

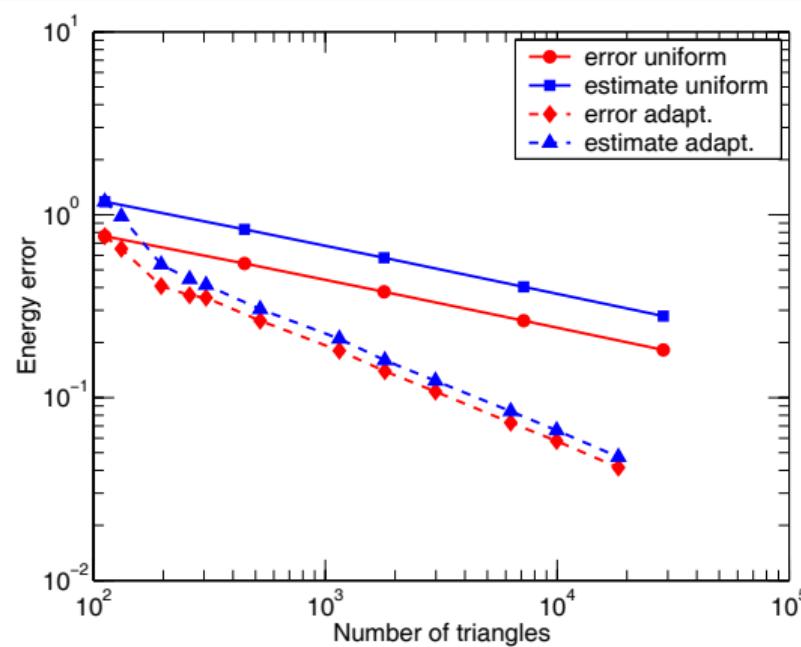


Effectivity index

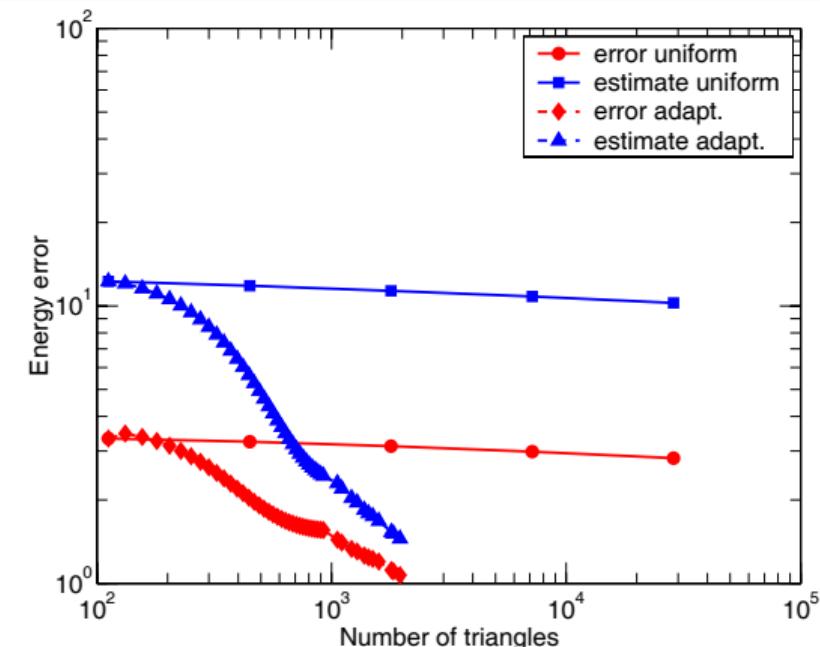
M. Vohralík, SIAM Journal on Numerical Analysis (2007)



Estimated and actual error against the number of elements in uniformly/adaptively refined meshes (singular solutions)



$H^{1.54}$ singularity



$H^{1.13}$ singularity

Adaptive mesh refinement

Adaptive mesh refinement

↪ Talk by Dirk Praetorius

Adaptive mesh refinement

Adaptive mesh refinement \hookrightarrow Talk by Dirk Praetorius

$$\sum_{K \in \mathcal{T}_\ell} \eta_K(u_\ell)^2 = \eta(u_\ell)^2$$

Adaptive mesh refinement

Adaptive mesh refinement \hookrightarrow Talk by Dirk Praetorius

- Dörfler marking: subset \mathcal{M}_ℓ containing θ -fraction of the estimates

$$\sum_{K \in \mathcal{M}_\ell} \eta_K(u_\ell)^2 \geq \theta^2 \sum_{K \in \mathcal{T}_\ell} \eta_K(u_\ell)^2 = \theta^2 \eta(u_\ell)^2$$

Adaptive mesh refinement

Adaptive mesh refinement → Talk by Dirk Praetorius

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Convergence on a sequence of adaptively refined meshes

- $\|\nabla(u - u_\ell)\| \rightarrow 0$
- some mesh elements may not be refined at all: $h \searrow 0$
- Babuška & Miller (1987), Dörfler (1996)

Adaptive mesh refinement

Adaptive mesh refinement \hookrightarrow Talk by Dirk Praetorius

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Optimal error decay rate wrt degrees of freedom

- $\|\nabla(u - u_\ell)\| \lesssim |\text{DoF}_\ell|^{-p/d}$ (replaces h^p)
- same for smooth & singular solutions: higher order only pay off for sm. sol.
- decays to zero as fast as on a best-possible sequence of meshes
- Morin, Nochetto, Siebert (2000), Stevenson (2005, 2007), Cascón, Kreuzer, Nochetto, Siebert (2008), Canuto, Nochetto, Stevenson, Verani (2017)

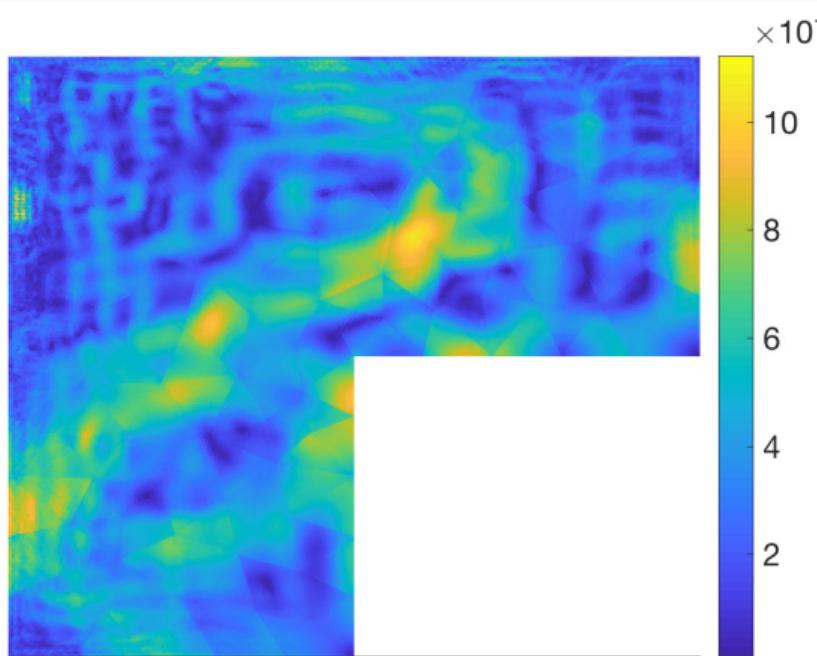
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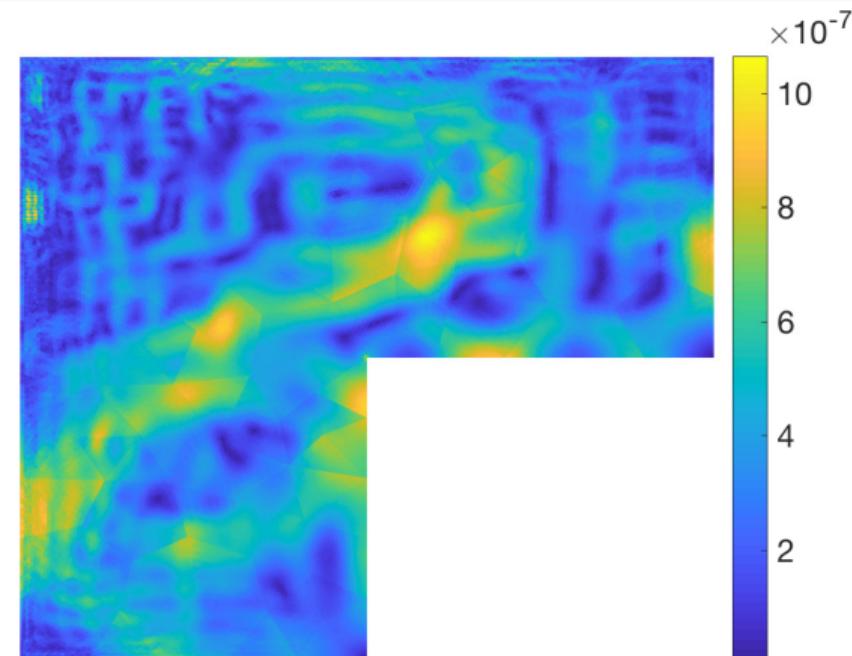
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Including algebraic error: $\mathbb{A}_\ell \mathbf{U}_\ell^i \neq \mathbf{F}_\ell$



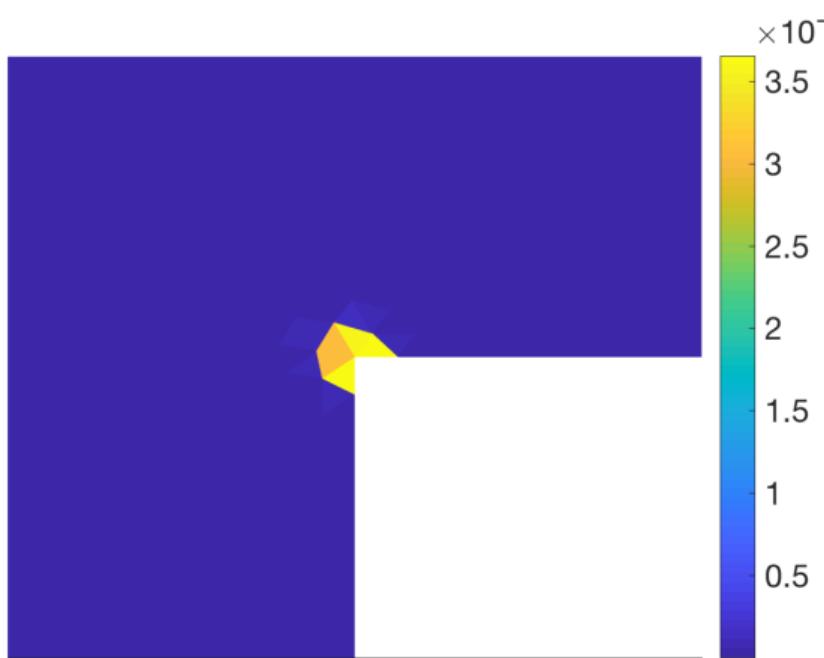
Estimated algebraic errors $\eta_{\text{alg}, \kappa}(u_\ell^i)$



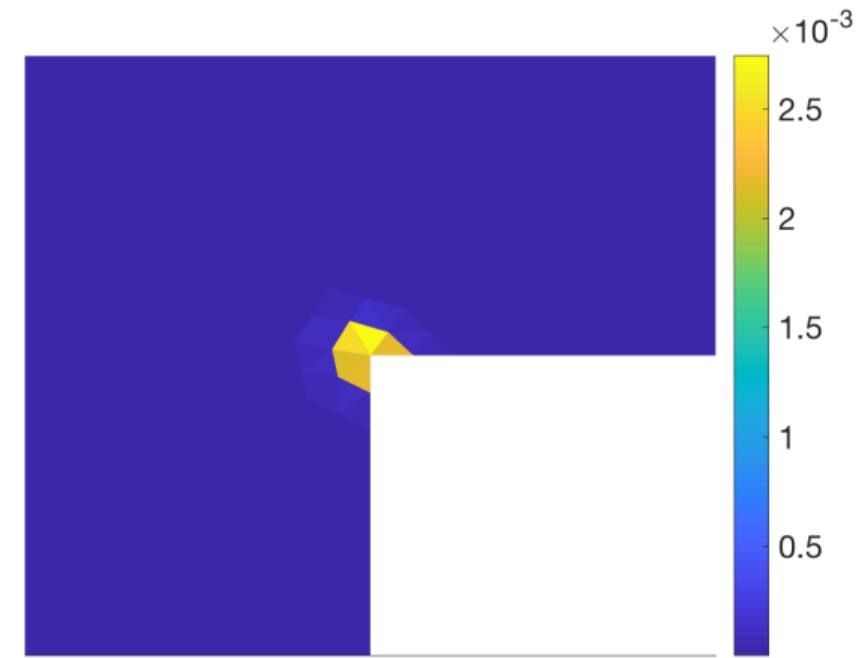
Exact algebraic errors $\|\nabla(u_\ell - u_\ell^i)\|_\kappa$

J. Papež, U. Rüde, M. Vohralík, B. Wohlmuth, Computer Methods in Applied Mechanics and Engineering (2020)

Including algebraic error: $\mathbb{A}_\ell \mathbf{U}_\ell^i \neq \mathbf{F}_\ell$



Estimated total errors $\eta_K(\mathbf{u}_\ell^i)$

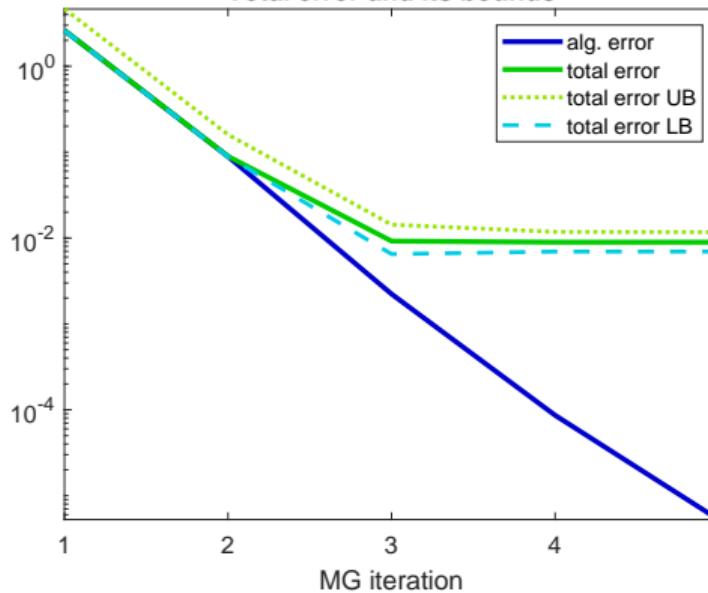


Exact total errors $\|\nabla(\mathbf{u} - \mathbf{u}_\ell^i)\|_K$

J. Papež, U. Rüde, M. Vohralík, B. Wohlmuth, Computer Methods in Applied Mechanics and Engineering (2020)

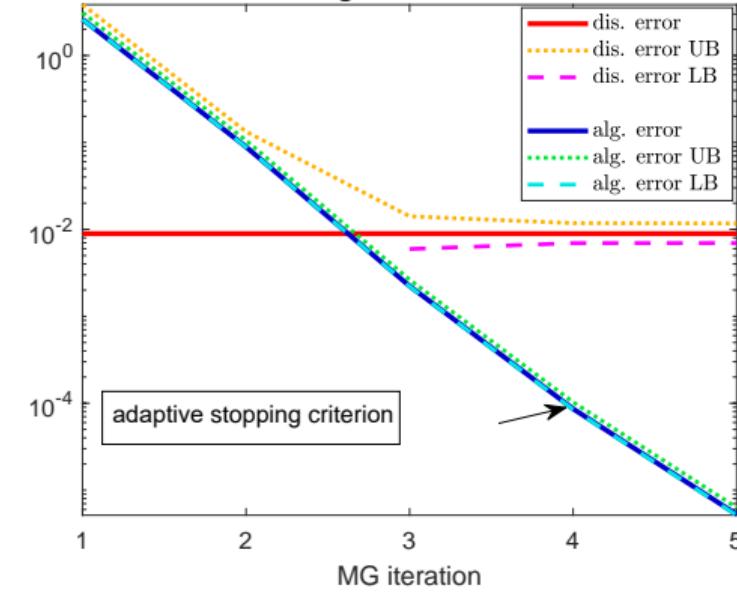
Including algebraic error: $\mathbb{A}_\ell \mathbf{U}_\ell^i \neq \mathbf{F}_\ell$

Total error and its bounds



Total error

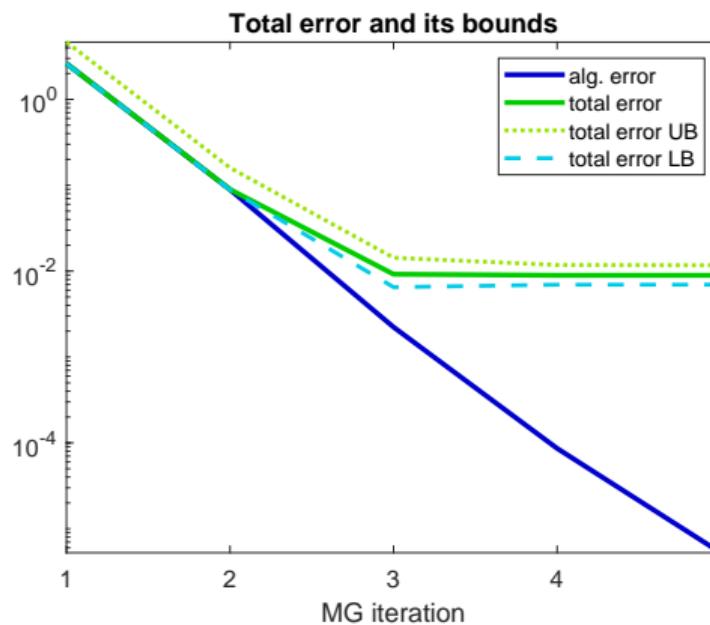
Discretization and algebraic errors and their bounds



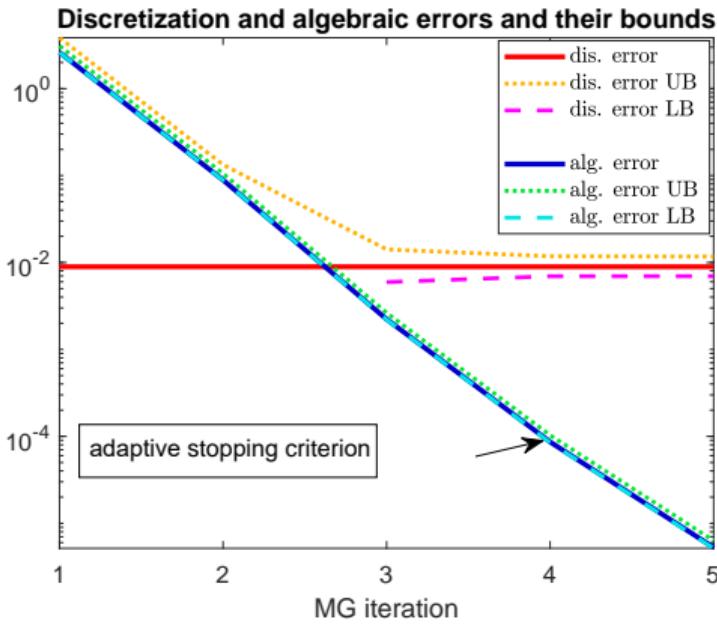
Error components and adaptive st. crit.

J. Papež, U. Rüde, M. Vohralík, B. Wohlmuth, Computer Methods in Applied Mechanics and Engineering (2020)

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J. Papež, U. Rüde, M. Vohralík, B. Wohlmuth, Computer Methods in Applied Mechanics and Engineering (2020)

→ Talk by Ani Miraçi 

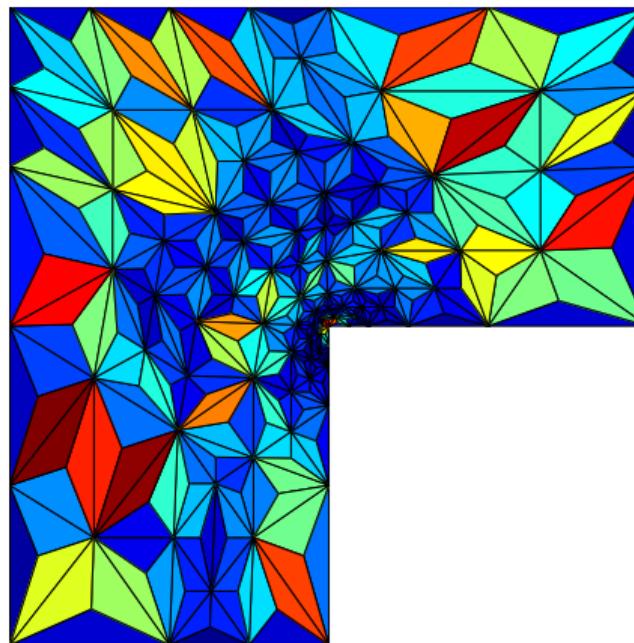
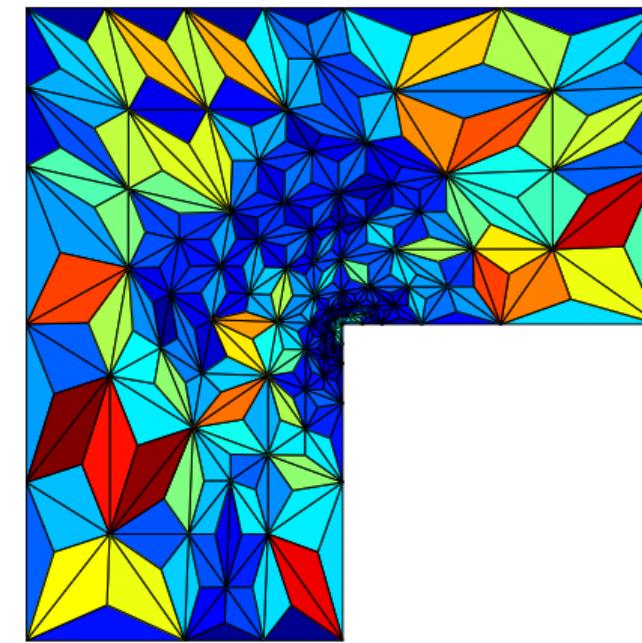
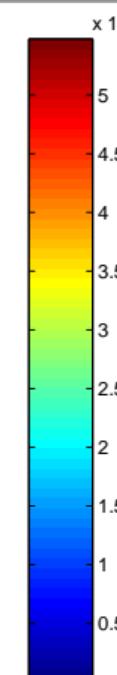


Nonlinear pb $-\nabla \cdot \sigma(\nabla u) = f$: including linearization and algebraic error: $\mathcal{A}_\ell(\mathbf{U}_\ell^{k,r}) \neq \mathbf{F}_\ell$, $\mathbf{A}_\ell^{k-1} \mathbf{U}_\ell^{k,r} \neq \mathbf{F}_\ell^{k-1}$

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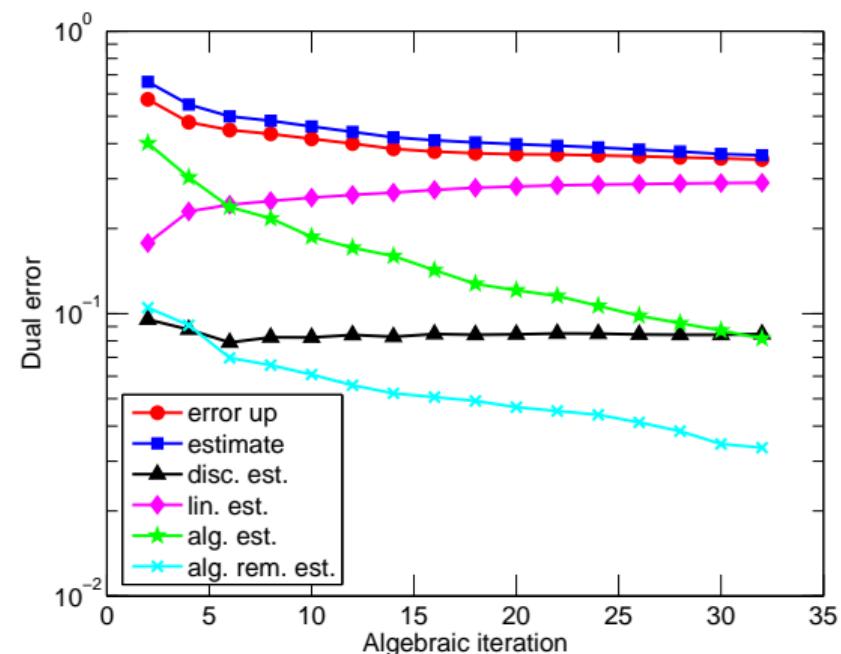
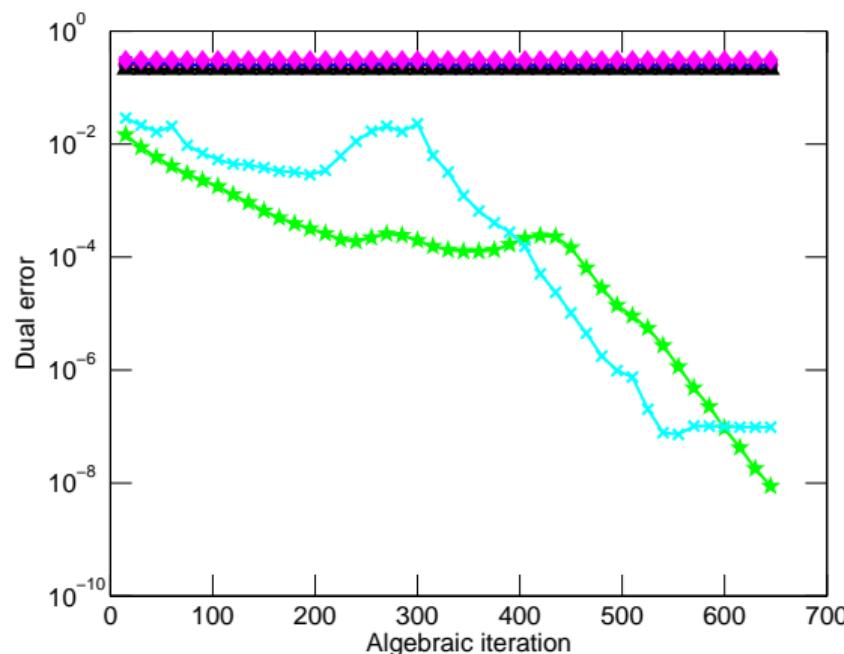
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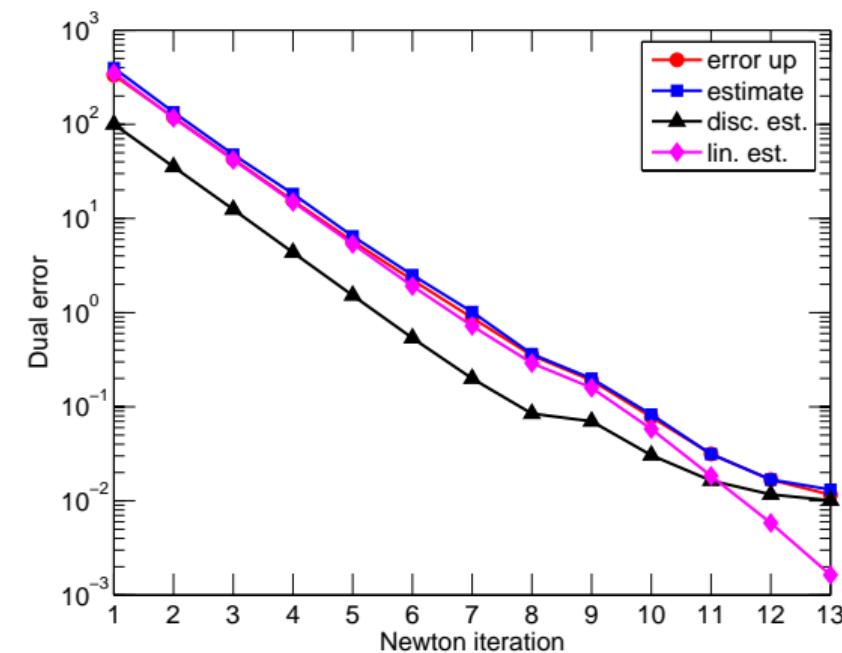
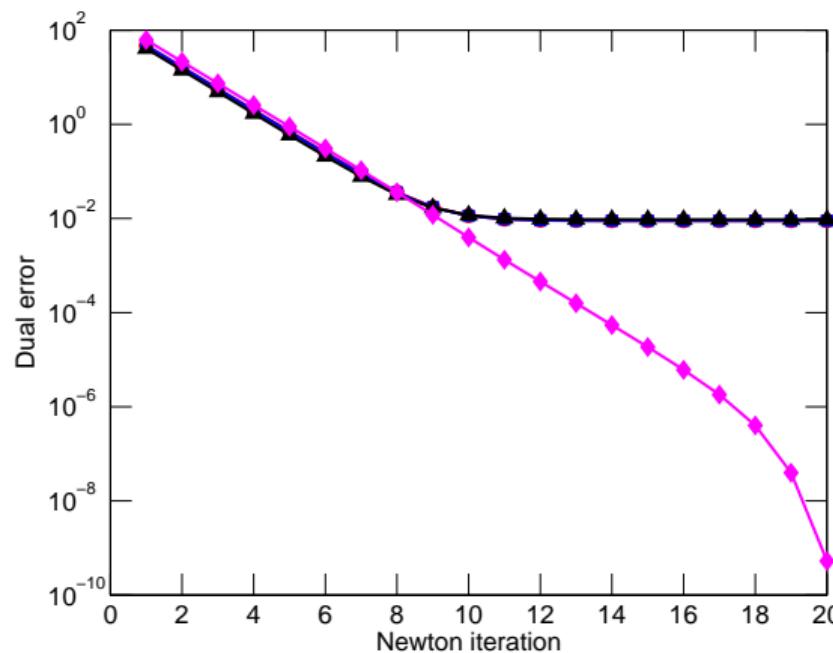
Estimated errors $\eta_K(u_\ell^{k,i})$ Exact errors $\|\sigma(\nabla u) - \sigma(\nabla u_\ell^{k,i})\|_{q,K}$ 

A. Ern, M. Vohralík, SIAM Journal on Scientific Computing (2013)

Nonlinear pb $-\nabla \cdot \sigma(\nabla u) = f$: including linearization and algebraic error: $\mathcal{A}_\ell(U_\ell^{k,i}) \neq F_\ell$, $\mathbb{A}_\ell^{k-1}U_\ell^{k,i} \neq F_\ell^{k-1}$



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Solver adaptivity (nonlinear problem, inexact solvers)

Fully adaptive algorithm (adaptive inexact Newton method)

- total error estimate on mesh \mathcal{T}_ℓ , linearization step k , algebraic solver step i

$$\underbrace{\|u - u_\ell^{k,i}\|_*}_{\text{total error}} \leq \underbrace{\eta_{\ell,\text{disc}}^{k,i}}_{\text{discretization estimate}} + \underbrace{\eta_{\ell,\text{lin}}^{k,i}}_{\text{linearization estimate}} + \underbrace{\eta_{\ell,\text{alg}}^{k,i}}_{\text{algebraic estimate}}$$

- balancing error components: work where needed

$$\eta_{\ell,\text{alg}}^{k,i} \leq \gamma_{\text{alg}} \eta_{\ell,\text{lin}}^{k,i} \quad \text{stopping criterion linear solver.}$$

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$$\eta_{\ell,\text{disc}}^{k,i} \leq \eta_{\ell,\text{disc},M_i}^{k,i} \quad \text{adaptive mesh refinement}$$

- link – inexact Newton method: Bank & Rose (1982), Hackbusch & Reusken (1989), Deuflhard (1991), Eisenstat & Walker (1994)

Convergence, optimal error decay rate wrt DoFs

- Gantner, Haberl, Praetorius, & Stiftner (2018), Heid & Wihler (2019)

Optimal error decay rate wrt overall computational cost

- Haberl, Praetorius, Schimanko, & Vohralík (2021) → Talk by Dörfler

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Outline

- 1 Introduction: numerical approximation of partial differential equations
- 2 Laplace equation: error control and mesh adaptivity
 - A posteriori error estimates: error control
 - Potential reconstruction
 - Flux reconstruction
 - A posteriori error estimates: mesh adaptivity
- 3 Nonlinear Laplace equation: error control and solver adaptivity
 - A posteriori error estimates: error control
 - A posteriori error estimates: solver adaptivity
- 4 Reaction–diffusion equation: robustness wrt parameters
- 5 Heat equation: robustness wrt final time and space–time localization
- 6 Eigenvalue problems
- 7 Conclusions

The reaction–diffusion equation: $f \in L^2(\Omega)$, $\varepsilon > 0$, $\kappa \geq 0$ parameters

Find $u : \Omega \rightarrow \mathbb{R}$ such that ($\varepsilon \ll \kappa$ **singular perturbation**)

$$\begin{aligned} -\varepsilon^2 \Delta u + \kappa^2 u &= f \quad \text{in } \Omega, \\ u &= 0 \quad \text{on } \partial\Omega \end{aligned}$$

Guaranteed error upper bound (reliability) ($u_h \in \mathcal{P}_p(\mathcal{T}_h) \cap H_0^1(\Omega)$, $p \geq 1$, FEs)

$$\underbrace{\|u - u_h\|}_{\text{unknown error}} \quad \underbrace{\eta(u_h)}_{\text{computable estimator}}$$

error lower bound (efficiency, $f \in \mathcal{P}_{p-1}(\mathcal{T}_h)$)

$$\eta(u_h) \leq C_{\text{eff}} \|u - u_h\|$$

- C_{eff} a generic constant independent of Ω , u , u_h , h ,

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Equilibrated flux and potential reconstructions

Definition (Flux σ_h and potential ϕ_h)

For each vertex $a \in \mathcal{V}$, let

$$(\sigma_h^a, \phi_h^a) := \arg \min_{(v_h, q_h) \in \mathcal{RT}_p(\mathcal{T}^a) \times \mathcal{P}_p(\mathcal{T}^a)} \|v_h\|_{\omega_a}^2 + \|\kappa[\Pi_h(\psi_a u_h) - q_h]\|_{\omega_a}^2$$

$$J_{\Omega_h}^a(v_h, q_h) := \eta_a^2 \|e\psi_a \nabla u_h + \varepsilon^{-1} v_h\|_{\omega_a}^2 + \|\kappa[\Pi_h(\psi_a u_h) - q_h]\|_{\omega_a}^2$$

Comments

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$$J_{\omega_a}^{\theta}(\psi_a, q_h) := w_a^2 \| \kappa \psi_a \nabla u_h + \kappa^{-1} v_h \|_{\omega_a}^2 + \| \kappa [\Pi_h(\psi_a u_h) - q_h] \|_{\omega_a}^2$$

with the weight $w_a := \min \left\{ 1, C_* \sqrt{\frac{1}{\kappa h \omega_a}} \right\}$. Combine

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Comments

- **local discrete** constrained minimization problems
- choose the locally **best-possible** estimators
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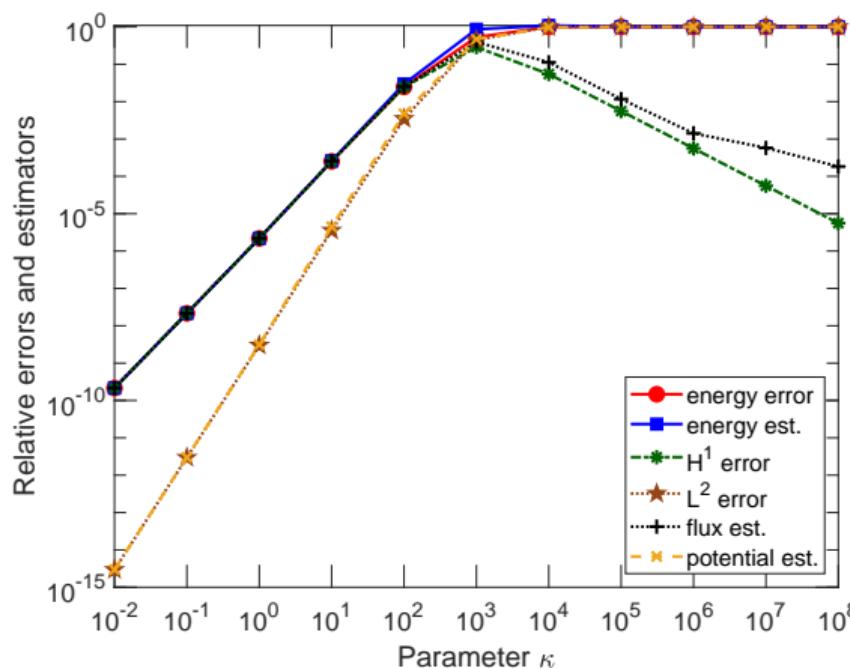
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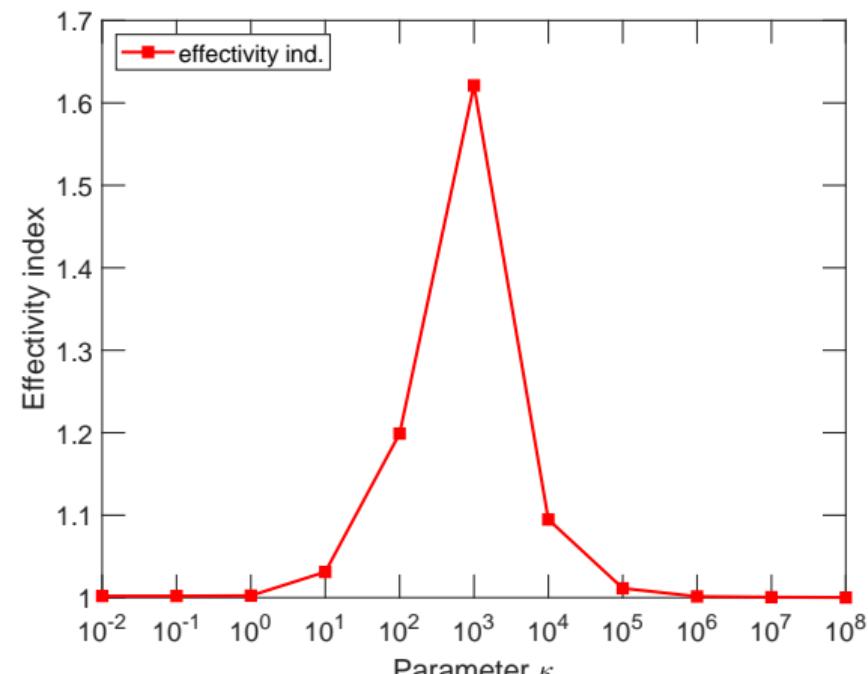
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Boundary layer, solution $u(x, y) = e^{-\frac{\kappa}{\varepsilon}x} + e^{-\frac{\kappa}{\varepsilon}y}$, $p = 2$

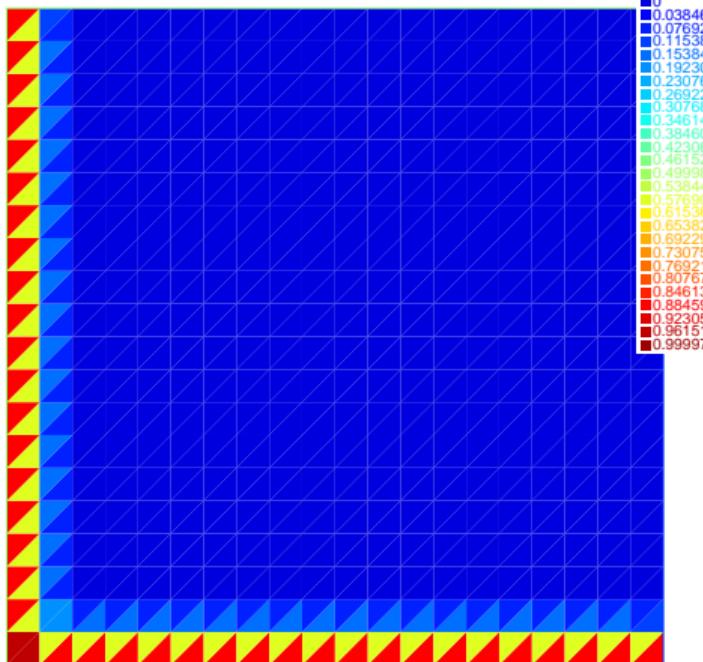


Relative energy errors and estimates

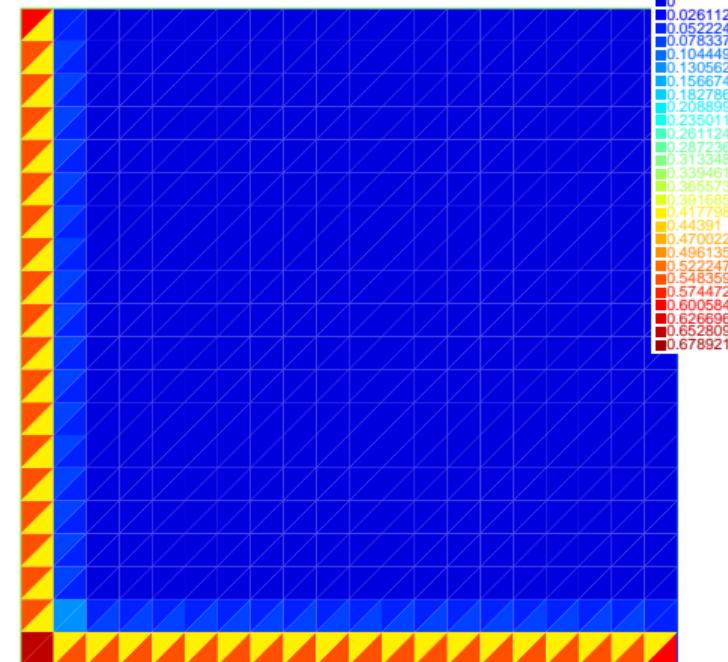
Effectivity indices $\eta(u_h)/\|u - u_h\|$

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estimators

Estimated error distribution $\eta_K(u_h)$

energy errors

Exact error distribution $\|u - u_h\|_K$

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The heat equation ($f \in L^2(0, T; L^2(\Omega))$, $u_0 \in L^2(\Omega)$)

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$$X := L^2(0, T; H_0^1(\Omega)), \|v\|_X^2 := \int_0^T \|\nabla v\|^2 dt,$$

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Y norm error is the dual X norm of the residual + initial condition error

$$\|u - u_{h\tau}\|_Y^2 = \sup_{v \in X, \|v\|_X=1} \left[\int_0^T (f, v) - \langle \partial_t u_{h\tau}, v \rangle - (\nabla u_{h\tau}, \nabla v) dt \right]^2 + \|u_0 - u_{h\tau}(0)\|^2$$

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Guaranteed error upper bound (reliability) ($u_{h\tau}$ FE in space, DG in time approx.)

$$\underbrace{\|u - u_{h\tau}\|}_{\text{unknown error}} \leq \underbrace{\eta(u_{h\tau})}_{\text{computable estimator}}$$

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For each time-step interval I_n and for each vertex $\mathbf{a} \in \mathcal{V}^n$, let

$$\sigma_{h\tau}^{\mathbf{a},n} := \arg \min_{\mathbf{v}_h \in \mathbf{V}_{h\tau}^{\mathbf{a},n}} \int_{I_n} \|\mathbf{v}_h + \psi_{\mathbf{a}} \nabla \mathbf{u}_{h\tau}\|_{\omega_{\mathbf{a}}}^2 dt.$$

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- satisfies $\sigma_{h\tau} \in L^2(0, T; \mathbf{H}(\text{div}, \Omega))$ with $\nabla \cdot \sigma_{h\tau} = f - \partial_t \mathcal{I} \mathbf{u}_{h\tau}$
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Eigenvalue problems

→ Talks by Tomáš Vejchodský and Philip Lederer

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- full **adaptivity**: space mesh, time step, linear solver, nonlinear solver, polynomial degree
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Thank you for your attention!

Outline

- Motivation
- Polynomial-degree (p) adaptivity

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- deterministic, steady problem, PDE known, data known, implementation OK

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probably **numerical simulations done with insufficient precision,**



Reliability study and simulation of the progressive collapse of
Roissy Charles de Gaulle Airport

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CDG Terminal 2E collapse in 2004 (opened in 2003)



- no earthquake, flooding, tsunami, heavy rain, extreme temperature
- deterministic, steady problem, PDE known, data known, implementation OK

probably **numerical simulations done with insufficient precision**,
I believe **without error control**

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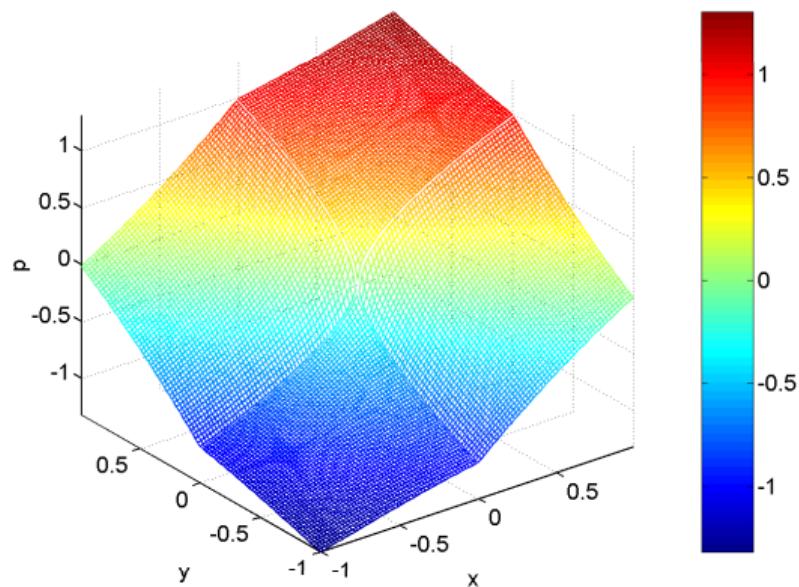
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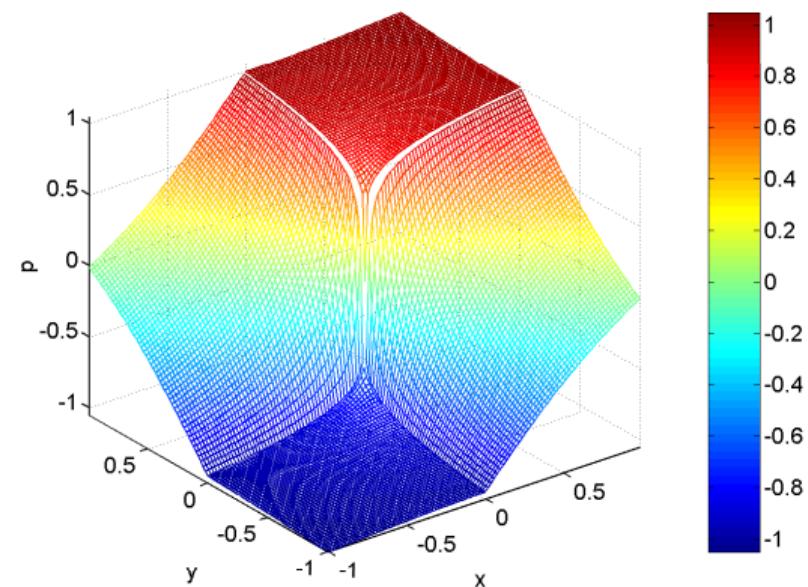
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Singular solutions



$H^{1.54}$ singularity

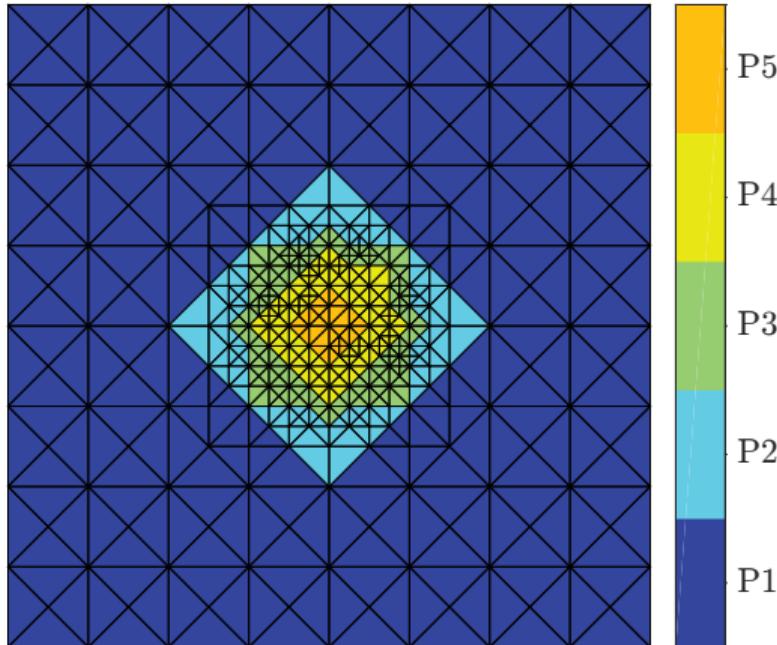


$H^{1.13}$ singularity

Outline

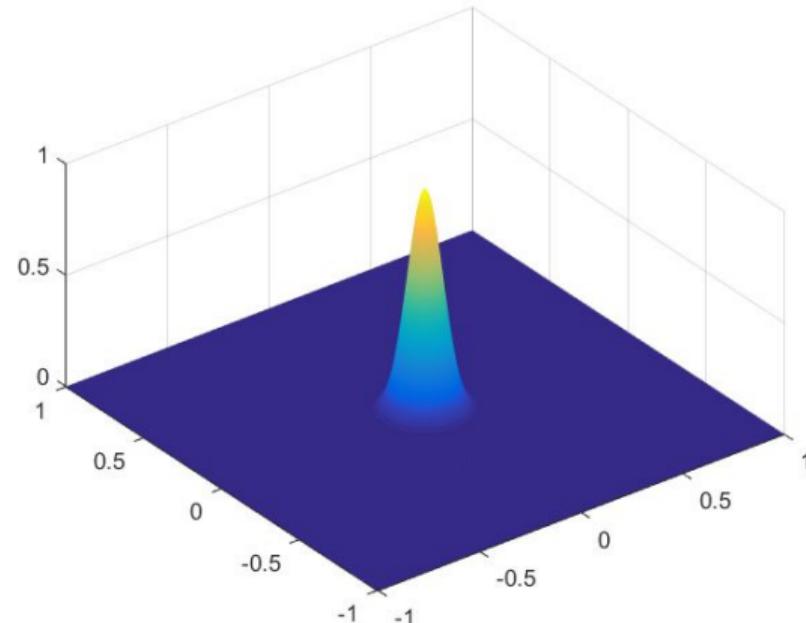
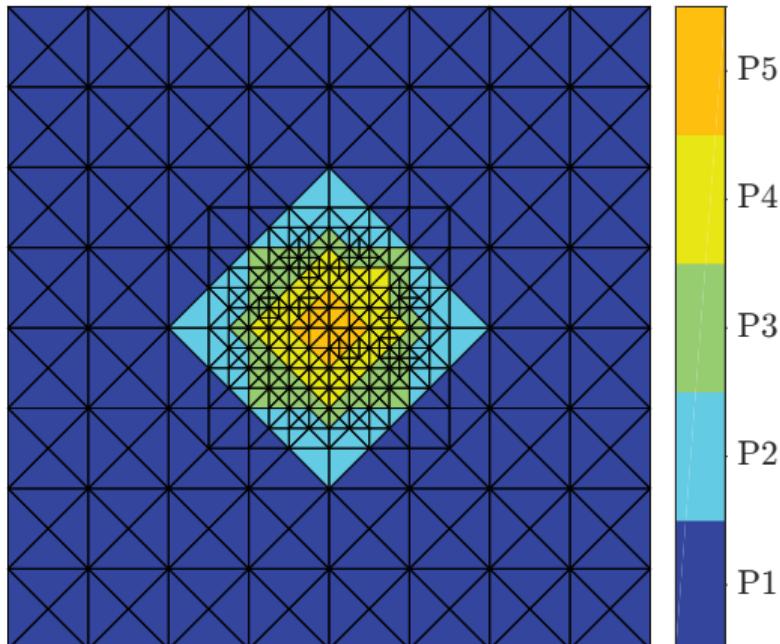
- Motivation
- Polynomial-degree (p) adaptivity

Best-possible error decrease: ***hp*** adaptivity, (**smooth** solution)



Mesh \mathcal{T}_ℓ and pol. degrees p_K

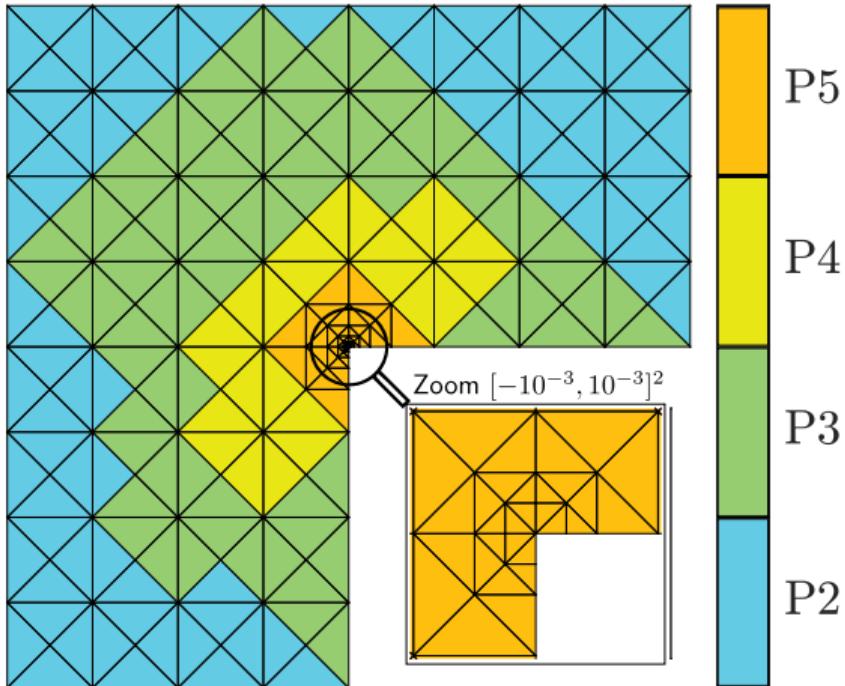
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Mesh \mathcal{T}_ℓ and pol. degrees p_K

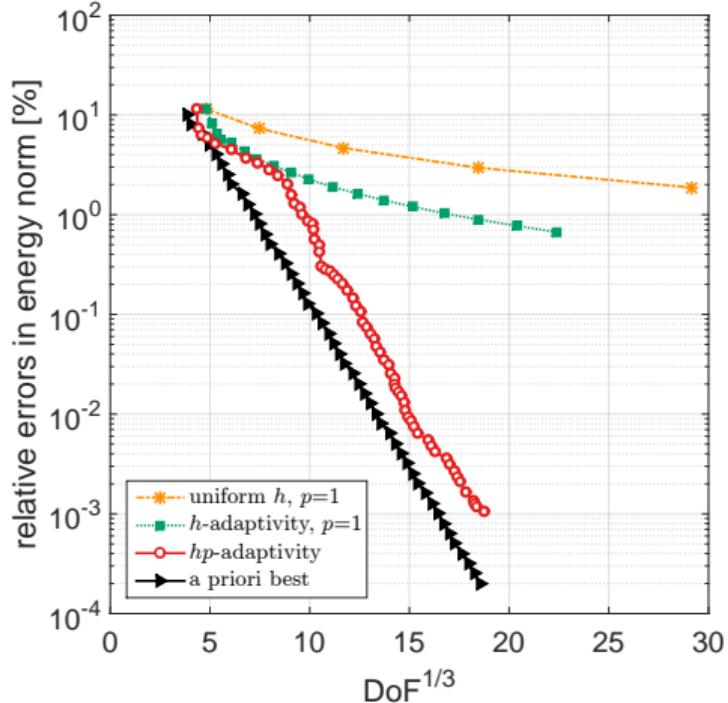
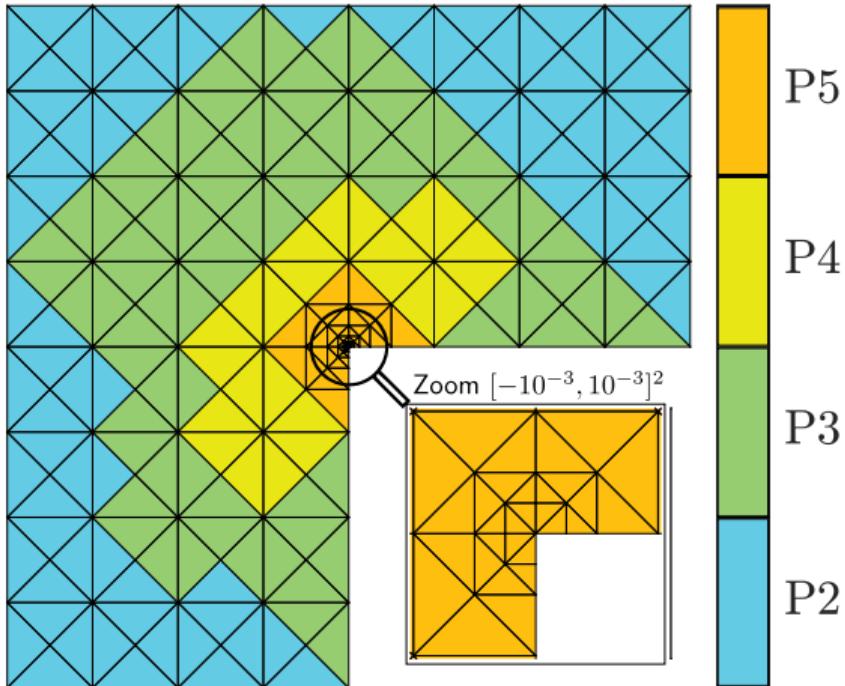
Exact solution

Best-possible error decrease: *hp* adaptivity, (singular) solution



Mesh \mathcal{T}_ℓ and polynomial degrees p_K

Best-possible error decrease: *hp* adaptivity, (singular) solution



Mesh \mathcal{T}_ℓ and polynomial degrees p_K

Relative error as a function of DoF