

# A posteriori error estimates and adaptive solvers for porous media flows

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# Outline

- 1 Introduction: context, motivation, and goals
- 2 Steady linear Darcy flow
  - Discretization
  - A posteriori error estimate
  - Numerical experiments
- 3 Adaptivity: mesh, polynomial degree, linear solvers, nonlinear solvers
  - Mesh and polynomial degree
  - Linear and nonlinear solvers
  - Error in a quantity of interest
- 4 Unsteady multi-phase multi-compositional Darcy flow
- 5 Conclusions

# Context

## Multi-phase, multi-compositional porous media flows

- **unsteady nonlinear** degenerate **systems** of PDEs
- possibly algebraic inequality constraints (phase appearance/disappearance)

General polygonal/polyhedral meshes, arbitrary scheme

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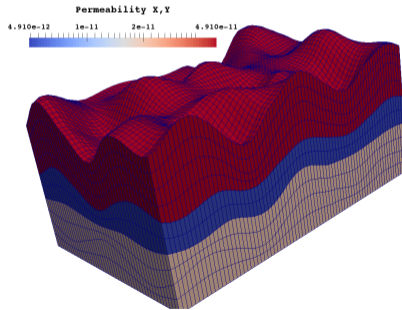
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# Example: steady nonlinear Darcy flow $\nabla \cdot (-\underline{\mathbf{K}}(\nabla p)\nabla p) = f$

## Discretization: system of nonlinear algebraic eqs

Find  $\mathbf{P} \in \mathbb{R}^N$  such that

$$\underbrace{\mathcal{U}}_{\text{nonlin. op.}}(\mathbf{P}) = \mathbf{F}$$

## Linearization: system of linear algebraic eqs

Find  $\mathbf{P}^k \in \mathbb{R}^N$  such that

$$\underbrace{\mathbf{U}^{k-1}}_{\text{matrix}} \mathbf{P}^k = \mathbf{F}^{k-1}$$

## Algebraic solver:

On step  $i$ , one has  $\mathbf{P}^{k,i} \in \mathbb{R}^N$  such that

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## Common situation

- **too costly** if  $i, k \rightarrow \infty$

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*mass balance lost*

- *linearization stopping crit.*

*$\|\mathbf{P}^k - \mathbf{P}^{k-1}\|_\infty$  small,*

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*$\|\mathbf{R}^{k,i}\|_2 / \|\mathbf{R}^{k,0}\|_2$  small:*

*comparing apples and oranges*

- *no control of the overall error between the obtained numerical approximation  $\mathbf{P}^{k,i}$  and the exact solution  $p$*

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# Goals

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- guaranteed **a posteriori** error **estimate**

$$\|\mathbf{u}|_{I_n} - \mathbf{u}_h^{n,k,i}\| \leq \eta_{\text{sp}}^{n,k,i} + \eta_{\text{tm}}^{n,k,i} + \eta_{\text{lin}}^{n,k,i} + \eta_{\text{alg}}^{n,k,i}$$

- valid at each step: time  $n$ , linearization  $k$ , linear solver  $i$
- distinguishing different error components, all estimators with the same (flux) physical units
- easy to code, fast to evaluate, cosy to use in practice
- full adaptivity (stopping criteria for linear and nonlinear solvers, mesh  $hp$  refinement, time step adjustment)

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# Linear Darcy flow

## Steady linear Darcy flow

$$\begin{aligned} -\nabla \cdot (\underline{\mathbf{K}} \nabla p) &= f && \text{in } \Omega, \\ p &= 0 && \text{on } \partial\Omega \end{aligned}$$

- $\Omega \subset \mathbb{R}^d$ ,  $d \geq 1$ , polytope
- $f \in L^2(\Omega)$  source term, pw constant for simplicity
- $\underline{\mathbf{K}} \in [L^\infty(\Omega)]^{d \times d}$  symmetric elliptic diffusion-dispersion tensor (pw constant)

## Unknowns

- $p$  pressure head
- $\mathbf{u} := -\underline{\mathbf{K}} \nabla p$  Darcy velocity (flux)

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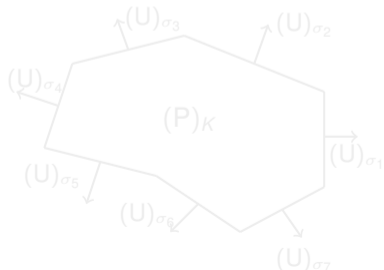


# Locally conservative discretization

## Assumption A (Locally conservative discretization)

- 1 There is one **pressure**  $(P)_K \in \mathbb{R}$  per element  $K \in \mathcal{T}_H$  and one **face normal flux**  $(U)_\sigma \in \mathbb{R}$  per face  $\sigma \in \mathcal{E}_H$ .
- 2 The **flux balance** is satisfied, with  $(F)_K := (f, 1)_K$ :

$$\sum_{\sigma \in \mathcal{E}_K} (U)_\sigma \mathbf{n}_{K,\sigma} \cdot \mathbf{n}_\sigma = (F)_K \quad \forall K \in \mathcal{T}_H.$$



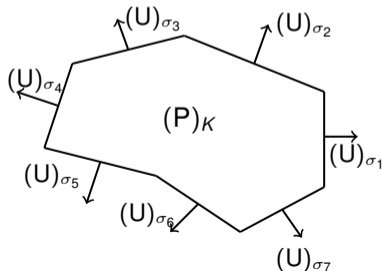
- $(U)_\sigma \approx \langle \mathbf{u} \cdot \mathbf{n}, 1 \rangle_\sigma = \int_\sigma \mathbf{u} \cdot \mathbf{n}$
- any (lowest-order) **locally conservative method**
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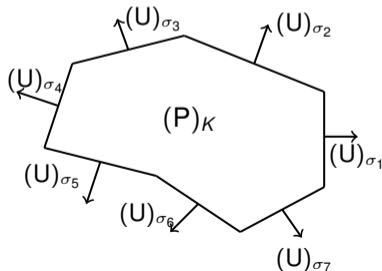
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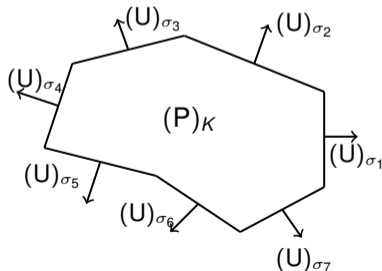
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# A posteriori error estimate

## Theorem (Linear Darcy flow)

Under *Assumption A*, there holds

$$\|\underline{\mathbf{K}}^{-\frac{1}{2}}(\mathbf{u} - \mathbf{u}_h)\| \leq \left\{ \sum_{K \in \mathcal{T}_H} \eta_K^2 \right\}^{\frac{1}{2}},$$

where

$$\begin{aligned} \eta_K^2 := & (\mathbf{U}_K^{\text{ext}})^t \mathbf{A}_K \mathbf{U}_K^{\text{ext}} + \mathbf{S}_K^t \mathbf{S}_K \mathbf{S}_K \\ & + 2(\mathbf{U}_K^{\text{ext}})^t \mathbf{S}_K^{\text{ext}} - 2(\mathbf{F})_K |K|^{-1} \mathbf{1}^t \mathbf{M}_K \mathbf{S}_K. \end{aligned}$$

## Comments

- $\mathbf{U}_K^{\text{ext}}, \mathbf{S}_K, \mathbf{S}_K^{\text{ext}}$ : flux and pressure vectors on element  $K$
- $\mathbf{A}_K, \mathbf{S}_K, \mathbf{M}_K$ : mass/stiffness matrices on element  $K$
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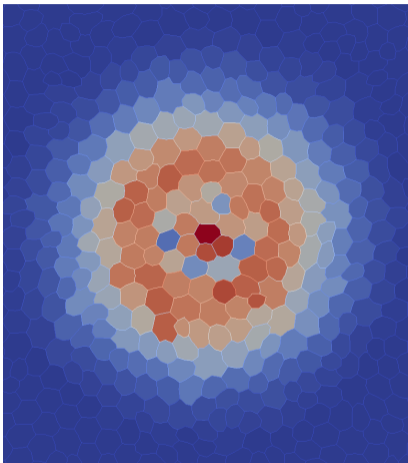
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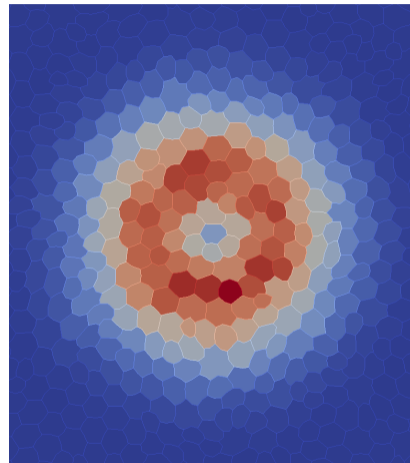
# Outline

- 1 Introduction: context, motivation, and goals
- 2 Steady linear Darcy flow
  - Discretization
  - A posteriori error estimate
  - Numerical experiments
- 3 Adaptivity: mesh, polynomial degree, linear solvers, nonlinear solvers
  - Mesh and polynomial degree
  - Linear and nonlinear solvers
  - Error in a quantity of interest
- 4 Unsteady multi-phase multi-compositional Darcy flow
- 5 Conclusions

# Energy error & simple polygonal estimate



Estimated error distribution



Exact error distribution

M. Vohralík, S. Yousef, Computer Methods in Applied Mechanics and Engineering (2020)

# How large is the overall error?

$h$	$m$	$\eta(p_h)$	rel. error estimate $\frac{\eta(p_h)}{\ \nabla p_h\ }$	$\ \nabla(p - p_h)\ $	rel. error $\frac{\ \nabla(p - p_h)\ }{\ \nabla p\ }$	$\ p - p_h\ $	rel. error $\frac{\ p - p_h\ }{\ p\ }$
$h_0$	1	1.25	28%	1.07	24%	1.17	21%
$\approx h_0/2$							
$\approx h_0/4$							
$\approx h_0/8$							
$\approx h_0/2$							
$\approx h_0/4$							
$\approx h_0/8$							

Figure 10: A posteriori error estimates and adaptive refinement for the multi-phase Darcy problem. The error is measured in the  $H^1$  norm of the pressure gradient. The error is shown for the reference solution  $p$  and the numerical solution  $p_h$  on a sequence of meshes. The error is shown for the reference solution  $p$  and the numerical solution  $p_h$  on a sequence of meshes.

# How large is the overall error? (model pb, known sol.)

$h$	$m$	$\eta(p_h)$	rel. error estimate $\frac{\eta(p_h)}{\ \nabla p_h\ }$	$\ \nabla(p - p_h)\ $	rel. error $\frac{\ \nabla(p - p_h)\ }{\ \nabla p_h\ }$	$\frac{\ p - p_h\ }{\ p\ } = \frac{\ p_h - p\ }{\ p_h\ }$
$h_0$	1	1.25	28%	1.07	24%	1.17
$\approx h_0/2$		$5.07 \times 10^{-1}$				
$\approx h_0/4$		$3.10 \times 10^{-1}$				
$\approx h_0/8$		$1.45 \times 10^{-1}$				
$\approx h_0/2$	2	$4.23 \times 10^{-2}$				
$\approx h_0/4$	3	$2.62 \times 10^{-2}$				
$\approx h_0/8$	4	$2.60 \times 10^{-2}$				

Figure 10: A posteriori error estimates and corresponding error bounds for the numerical solution of the Darcy problem. The error is measured in the  $H^1$  norm.

# How large is the overall error? (model pb, known sol.)

$h$	$m$	$\eta(p_h)$	rel. error estimate $\frac{\eta(p_h)}{\ \nabla p_h\ }$	$\ \nabla(p - p_h)\ $	rel. error $\frac{\ \nabla(p - p_h)\ }{\ \nabla p_h\ }$	$\rho_{\text{rel}} = \frac{\eta(p_h)}{\ \nabla(p - p_h)\ }$
$h_0$	1	1.25	28%	1.07	24%	1.17
$\approx h_0/2$		$5.07 \times 10^{-1}$	14%			
$\approx h_0/4$		$3.10 \times 10^{-1}$	7.0%			
$\approx h_0/8$		$1.45 \times 10^{-1}$	3.5%			
$\approx h_0/2$	2	$4.23 \times 10^{-1}$	14%			
$\approx h_0/4$	3	$2.62 \times 10^{-1}$	7.0%			
$\approx h_0/8$	4	$2.60 \times 10^{-1}$	7.0%			

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 J. Voutilainen, A. Ahti, M. Vohralík, J. T. T. Tang, M. M. Tang, M. M. Tang

# How large is the overall error? (model pb, known sol.)

$h$	$m$	$\eta(p_h)$	rel. error estimate $\frac{\eta(p_h)}{\ \nabla p_h\ }$	$\ \nabla(p - p_h)\ $	rel. error $\frac{\ \nabla(p - p_h)\ }{\ \nabla p_h\ }$	$\rho_{\text{eff}} = \frac{\eta(p_h)}{\ \nabla(p - p_h)\ }$
$h_0$	1	1.25	28%	1.07	24%	1.17
$\approx h_0/2$		$6.07 \times 10^{-1}$	14%	$5.56 \times 10^{-1}$	13%	
$\approx h_0/4$		$3.10 \times 10^{-1}$	7.0%	$2.92 \times 10^{-1}$	6.8%	
$\approx h_0/8$		$1.45 \times 10^{-1}$	3.5%	$1.39 \times 10^{-1}$	3.4%	
$\approx h_0/2$	2	$4.23 \times 10^{-1}$	14%	$4.07 \times 10^{-1}$	13%	
$\approx h_0/4$	3	$2.62 \times 10^{-1}$	7.0%	$2.60 \times 10^{-1}$	6.8%	
$\approx h_0/8$	4	$2.60 \times 10^{-1}$	3.5%	$2.58 \times 10^{-1}$	3.4%	

Figure 10: A posteriori error estimates bounding the overall error. The overall error is bounded by the error estimator  $\eta(p_h)$  and the error estimator  $\|\nabla p_h\|$ .

# How large is the overall error? (model pb, known sol.)

$h$	$m$	$\eta(p_h)$	rel. error estimate $\frac{\eta(p_h)}{\ \nabla p_h\ }$	$\ \nabla(p - p_h)\ $	rel. error $\frac{\ \nabla(p - p_h)\ }{\ \nabla p_h\ }$	$\rho_{\text{eff}} = \frac{\eta(p_h)}{\ \nabla(p - p_h)\ }$
$h_0$	1	1.25	28%	1.07	24%	1.17
$\approx h_0/2$		$6.07 \times 10^{-1}$	14%	$5.56 \times 10^{-1}$	13%	1.29
$\approx h_0/4$		$3.10 \times 10^{-1}$	7.0%	$2.92 \times 10^{-1}$	6.6%	1.39
$\approx h_0/8$		$1.45 \times 10^{-1}$	3.5%	$1.39 \times 10^{-1}$	3.1%	1.49
$\approx h_0/2$	2	$4.23 \times 10^{-2}$	1.5%	$4.07 \times 10^{-2}$	$9.2 \times 10^{-1}\%$	1.59
$\approx h_0/4$	3	$2.62 \times 10^{-2}$	0.9%	$2.60 \times 10^{-2}$	$5.9 \times 10^{-1}\%$	1.69
$\approx h_0/8$	4	$2.60 \times 10^{-2}$	0.9%	$2.58 \times 10^{-2}$	$5.8 \times 10^{-1}\%$	1.79

Figure 10: A posteriori error estimates (assuming  $\rho_{\text{eff}} = 1.7$ ) for the model problem. The error is measured in the  $H^1$  norm.



# How large is the overall error? (model pb, known sol.)

$h$	$m$	$\eta(p_h)$	rel. error estimate $\frac{\eta(p_h)}{\ \nabla p_h\ }$	$\ \nabla(p - p_h)\ $	rel. error $\frac{\ \nabla(p - p_h)\ }{\ \nabla p_h\ }$	$j^{eff} = \frac{\eta(p_h)}{\ \nabla(p - p_h)\ }$
$h_0$	1	1.25	28%	1.07	24%	1.17
$\approx h_0/2$		$6.07 \times 10^{-1}$	14%	$5.56 \times 10^{-1}$	13%	1.09
$\approx h_0/4$		$3.10 \times 10^{-1}$	7.0%	$2.92 \times 10^{-1}$	6.6%	1.06
$\approx h_0/8$		$1.45 \times 10^{-1}$	3.3%	$1.39 \times 10^{-1}$	3.1%	1.04
$\approx h_0/2$	2	$4.23 \times 10^{-1}$	9.5%	$4.07 \times 10^{-1}$	$9.2 \times 10^{-1}$ %	1.04
$\approx h_0/4$	3	$2.62 \times 10^{-1}$	5.9%	$2.60 \times 10^{-1}$	$5.9 \times 10^{-1}$ %	1.01
$\approx h_0/8$	4	$2.60 \times 10^{-1}$	5.9%	$2.58 \times 10^{-1}$	$5.8 \times 10^{-1}$ %	1.01

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Mathematics of Adaptive Simulation (MAS) – A Posteriori Error Estimates and Adaptive Solvers

# How large is the overall error? (model pb, known sol.)

$h$	$m$	$\eta(p_h)$	rel. error estimate $\frac{\eta(p_h)}{\ \nabla p_h\ }$	$\ \nabla(p - p_h)\ $	rel. error $\frac{\ \nabla(p - p_h)\ }{\ \nabla p_h\ }$	$j^{\text{eff}} = \frac{\eta(p_h)}{\ \nabla(p - p_h)\ }$
$h_0$	1	1.25	28%	1.07	24%	1.17
$\approx h_0/2$		$6.07 \times 10^{-1}$	14%	$5.56 \times 10^{-1}$	13%	1.09
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$\approx h_0/4$	3	$2.62 \times 10^{-2}$	$5.9 \times 10^{-1}\%$	$2.60 \times 10^{-2}$	$5.9 \times 10^{-1}\%$	1.01
$\approx h_0/8$	4	$2.60 \times 10^{-2}$	$5.9 \times 10^{-1}\%$	$2.58 \times 10^{-2}$	$5.8 \times 10^{-1}\%$	1.01

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# How large is the overall error? (model pb, known sol.)

$h$	$m$	$\eta(p_h)$	rel. error estimate $\frac{\eta(p_h)}{\ \nabla p_h\ }$	$\ \nabla(p - p_h)\ $	rel. error $\frac{\ \nabla(p - p_h)\ }{\ \nabla p_h\ }$	$j^{\text{eff}} = \frac{\eta(p_h)}{\ \nabla(p - p_h)\ }$
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$\approx h_0/4$	3	$2.62 \times 10^{-2}$	$5.9 \times 10^{-2}\%$	$2.60 \times 10^{-2}$	$5.9 \times 10^{-2}\%$	1.01
$\approx h_0/8$	4	$2.60 \times 10^{-2}$	$5.9 \times 10^{-2}\%$	$2.58 \times 10^{-2}$	$5.8 \times 10^{-2}\%$	1.01

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$\approx h_0/4$	3	$2.62 \times 10^{-4}$	$5.9 \times 10^{-3}\%$	$2.60 \times 10^{-4}$	$5.9 \times 10^{-3}\%$	1.01
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A. Ern, M. Vohralík, SIAM Journal on Numerical Analysis (2014)

V. Doležal, A. Ern, M. Vohralík, SIAM Journal on Scientific Computing (2014)

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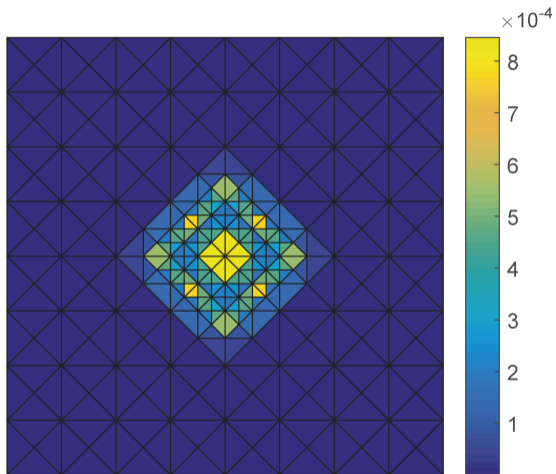
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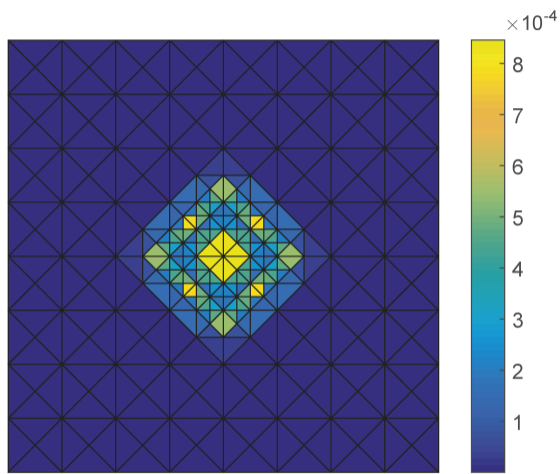
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# Where (in space) is the error localized?



Estimated error distribution  $\eta_K(p_h)$



Exact error distribution  $\|\nabla(p - p_h)\|_K$

# Adaptive mesh refinement (linear problem with exact solvers)

## Adaptive mesh refinement

- Dörfler marking: subset  $\mathcal{M}_\ell$  containing  $\theta$ -fraction of the estimated error

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

**Convergence** on a sequence of adaptively refined meshes

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

**Optimal error decay rate wrt degrees of freedom**

- $\|\nabla(p - p_\ell)\| \lesssim |\text{DoF}_\ell|^{-m/d}$  (replaces  $h^m$ )
- 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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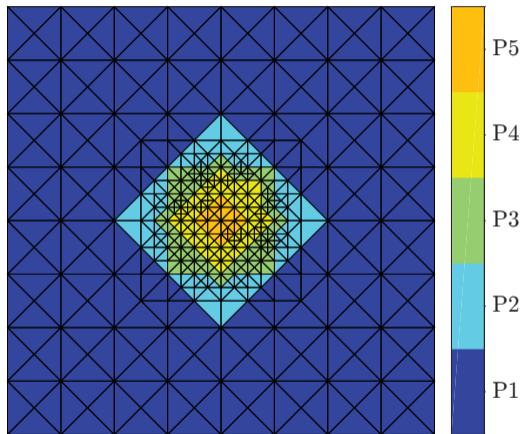
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## Optimal error decay rate wrt degrees of freedom

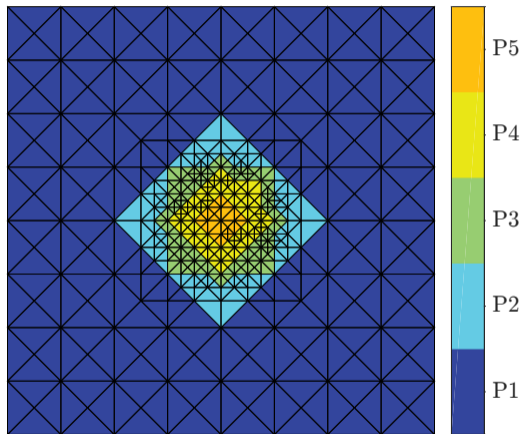
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# Can we decrease the error efficiently? *hp* adaptivity, (**smooth** solution)

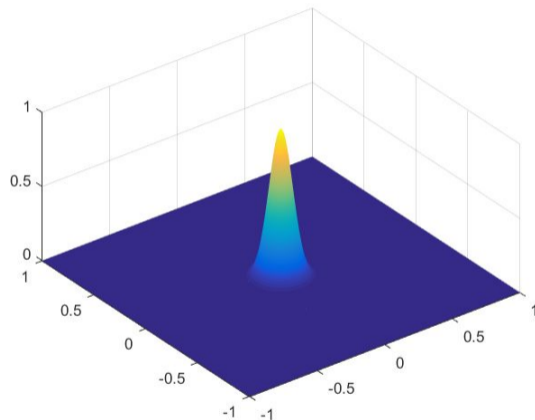


Mesh  $\mathcal{T}_\ell$  and pol. degrees  $m_K$

# Can we decrease the error efficiently? *hp* adaptivity, (smooth solution)



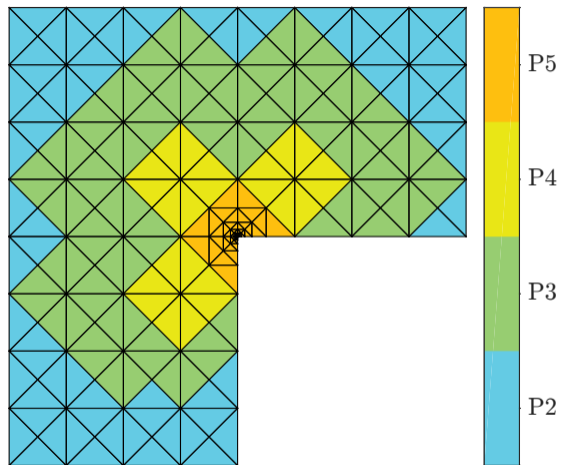
Mesh  $\mathcal{T}_\ell$  and pol. degrees  $m_K$



Exact solution

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

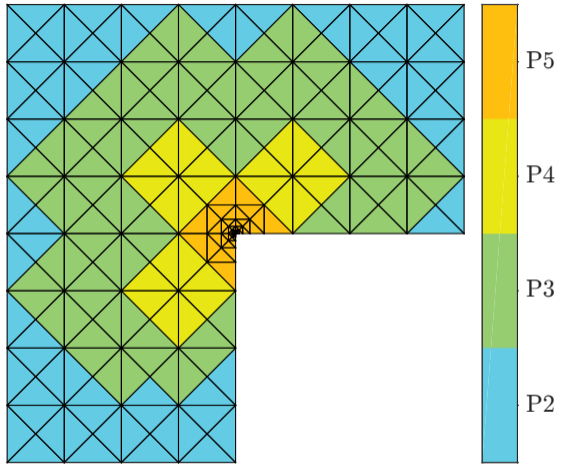
# Can we decrease the error efficiently? *hp* adaptivity, (**singular** solution)



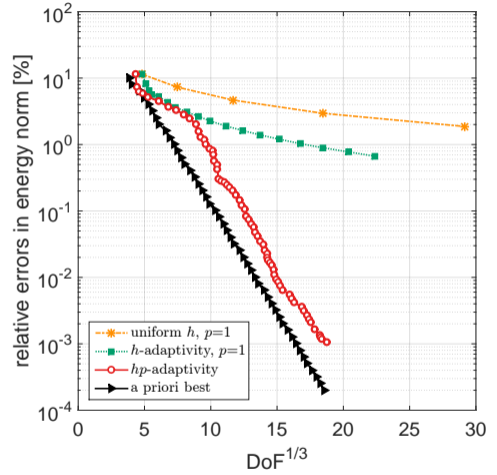
Mesh  $\mathcal{T}_\ell$  and polynomial degrees  $m_K$



# Can we decrease the error efficiently? *hp* adaptivity, (singular solution)



Mesh  $\mathcal{T}_\ell$  and polynomial degrees  $m_K$



Relative error as a function of DoF

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

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# Balancing error components (nonlinear problem with inexact solvers)

## Fully adaptive algorithm (adaptive inexact Newton method)

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

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

- balancing error components: work where needed

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

$$\eta_{\ell,\text{alg}}^{k,i} \leq \gamma_{\text{alg}} \eta_{\ell,\text{disc}}^{k,i} \quad \text{stopping criterion nonlinear solver}$$

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

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

Convergence, optimal error decay rate wrt DoFs

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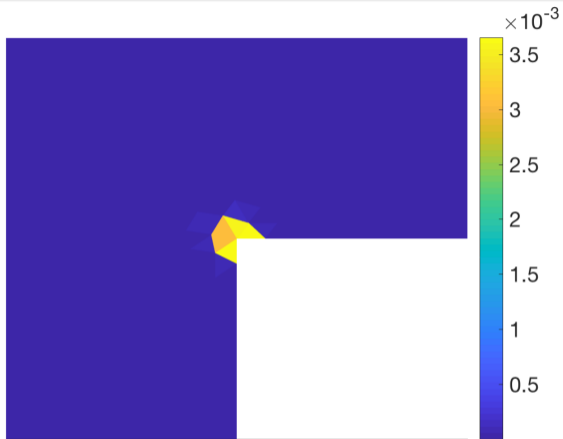
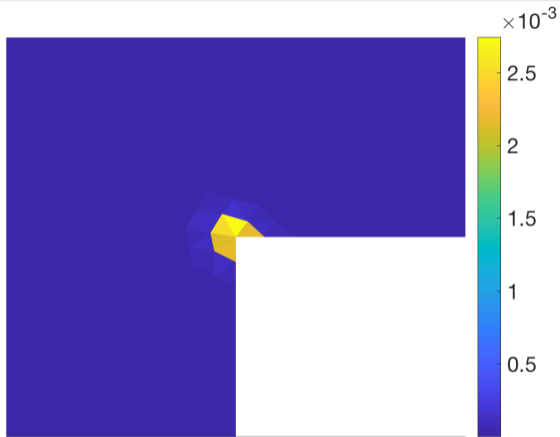
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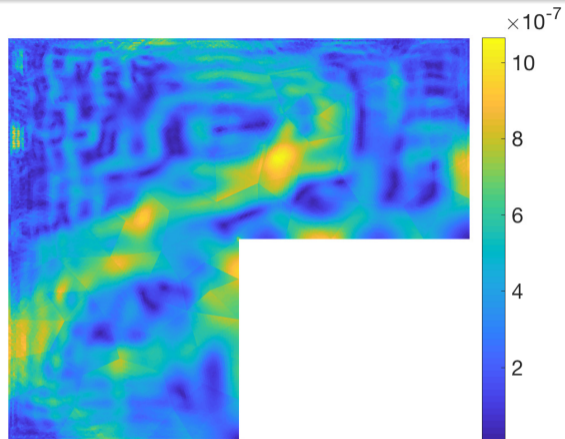
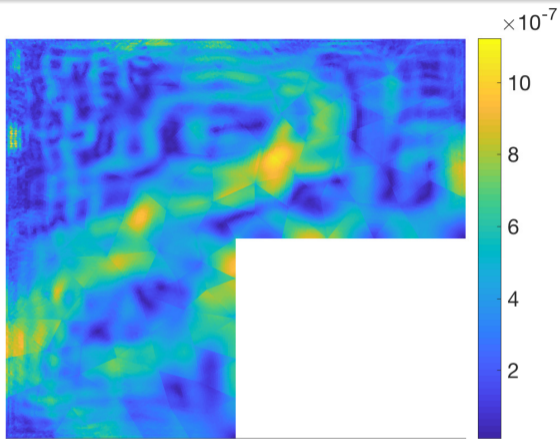
## Optimal error decay rate wrt overall computational cost

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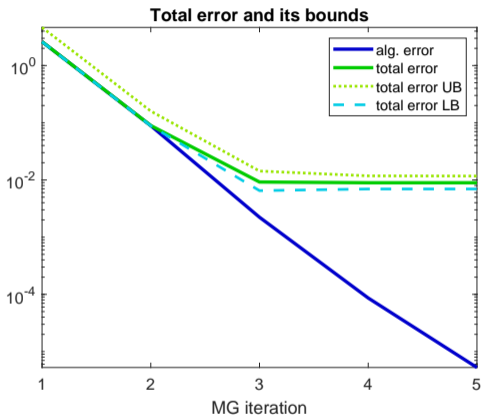
Including **algebraic** error:  $\mathbb{U}_\ell \mathbb{P}_\ell^i \neq \mathbb{F}_\ell$

Including **algebraic** error:  $\mathbb{U}_\ell \mathbf{P}_\ell^i \neq \mathbb{F}_\ell$ Estimated total errors  $\eta_K(p_\ell^i)$ Exact total errors  $\|\nabla(p - p_\ell^i)\|_K$ 

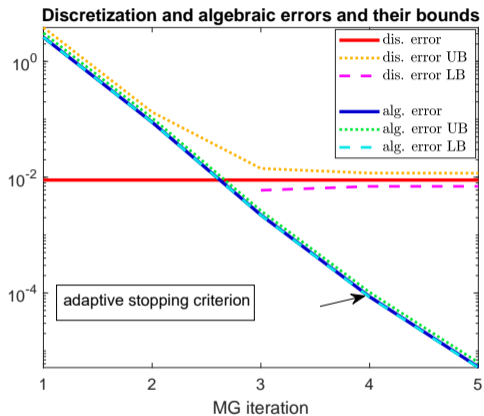
J. Papež, U. Růde, M. Vohralík, B. Wohlmuth (2020)

Including algebraic error:  $\mathbb{U}_l \mathbf{P}_l^i \neq \mathbf{F}_l$ 

J. Papež, U. Růde, M. Vohralík, B. Wohlmuth (2020)

Including algebraic error:  $U_l P_l^i \neq F_l$ 

Total error



Error components and adaptive st. crit.

J. Papež, U. Råde, M. Vohralík, B. Wohlmuth (2020)

Nonlinear pb  $-\nabla \cdot \boldsymbol{\sigma}(\nabla p) = f$ : including linearization and algebraic

error:  $U_h(P_r^{k-1}) \neq F_h, U_r^{k-1} P_r^{k-1} \neq F_r^{k-1}$

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

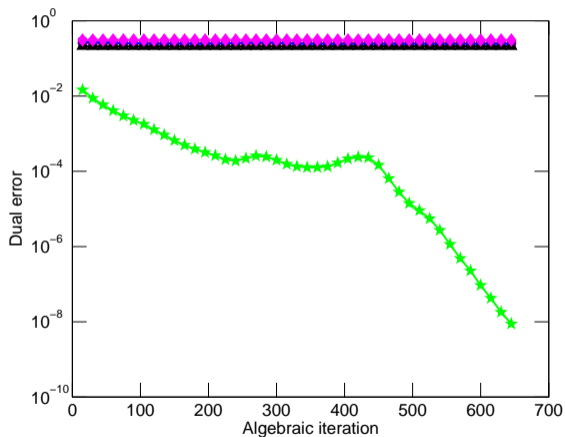
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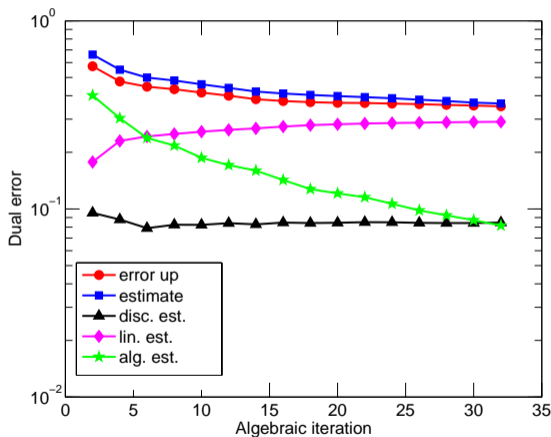


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Newton

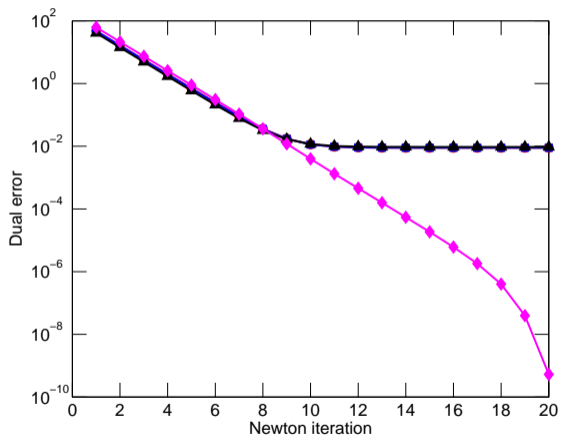


adaptive inexact Newton

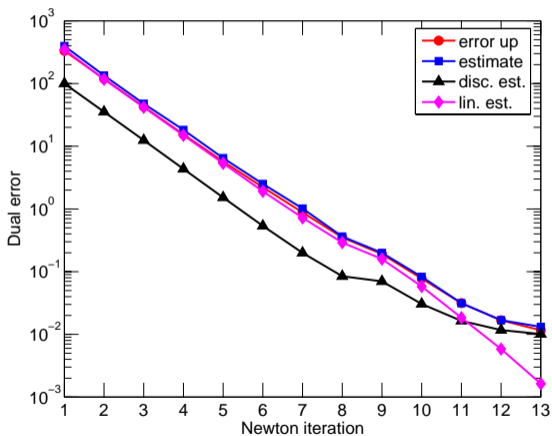
A. Ern, M. Vohralík, SIAM Journal on Scientific Computing (2013)

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Newton

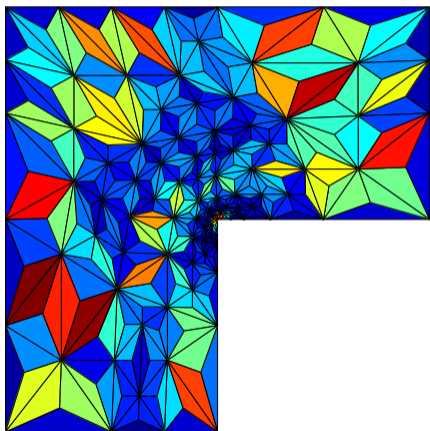


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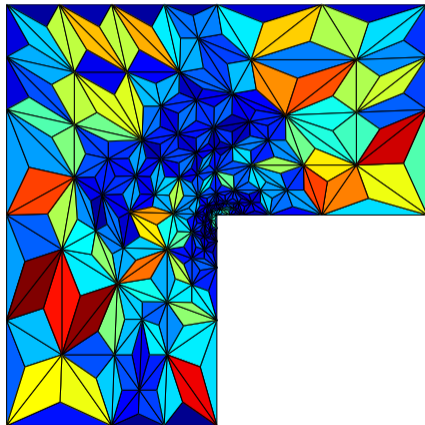
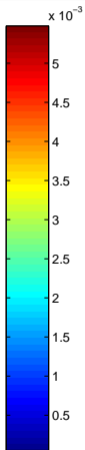
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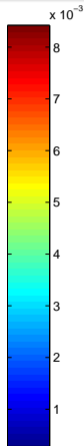
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Estimated errors  $\eta_{\mathcal{K}}(p_l^{k,i})$

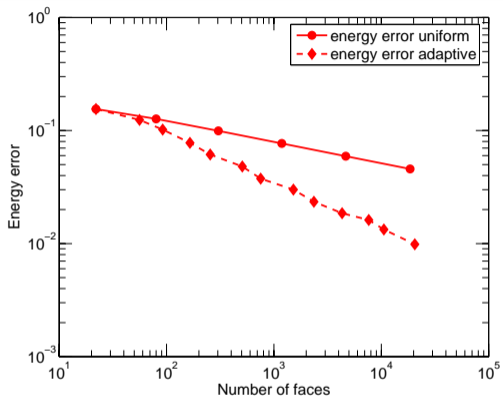


Exact errors  $\|\sigma(\nabla p) - \sigma(\nabla p_l^{k,i})\|_{q,\mathcal{K}}$



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

# Convergence and optimal decay rate wrt DoFs & computational cost



Optimal decay rate wrt DoFs

classical

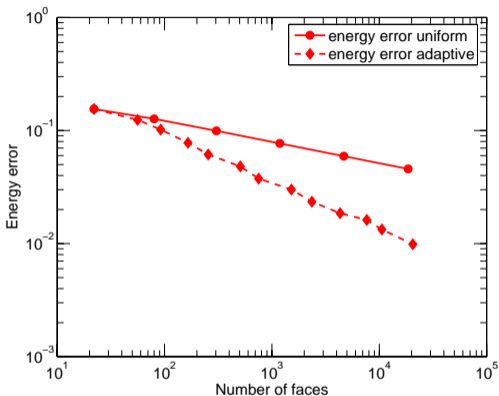
total alg. solver iterations	10890
relative error estimate	4.6%

adaptive

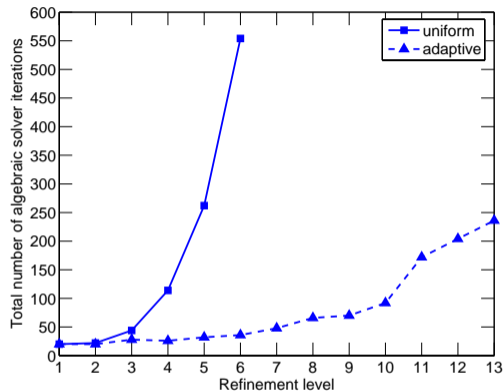
total alg. solver iterations	242
relative error estimate	1.1%

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

# Convergence and optimal decay rate wrt DoFs & computational cost



Optimal decay rate wrt DoFs

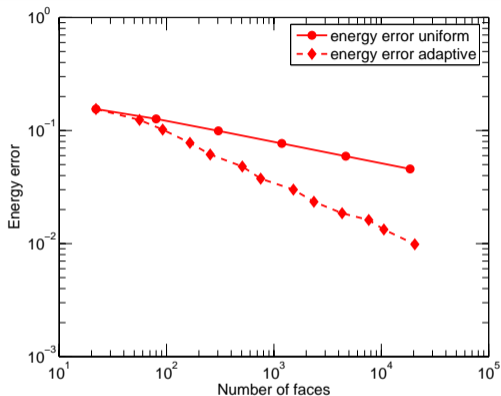


Optimal computational cost

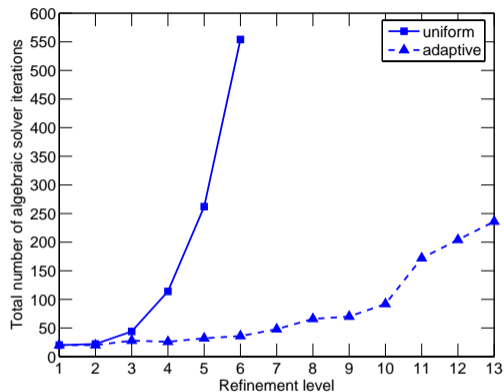
classical	total alg. solver iterations	10890
	relative error estimate	4.6%

adaptive	total alg. solver iterations	242
	relative error estimate	1.1%

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Optimal decay rate wrt DoFs



Optimal computational cost

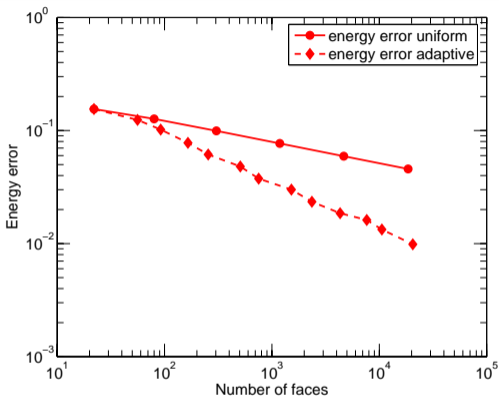
**classical**

total alg. solver iterations	<b>10890</b>
relative error estimate	<b>4.6%</b>

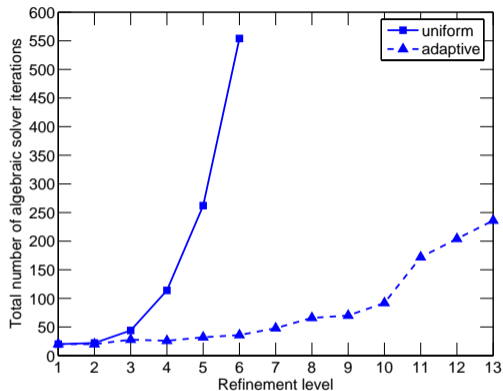
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Optimal decay rate wrt DoFs



Optimal computational cost

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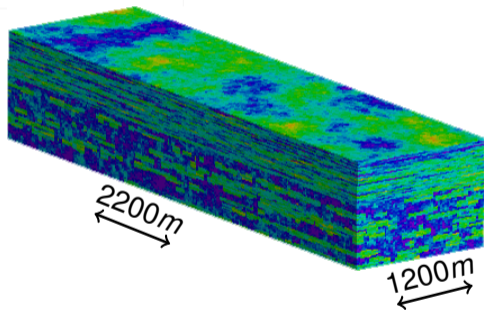
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Can we certify error in a practical case  $-\nabla \cdot (\mathbf{K} \nabla p) = f$ : outflow error

$\int_{\Gamma_{\text{out}}} \mathbf{K} \nabla p \cdot \mathbf{n}$  (goal functional)

no of unknowns	825	3300	13200
rel. error est.	46%	34%	24%



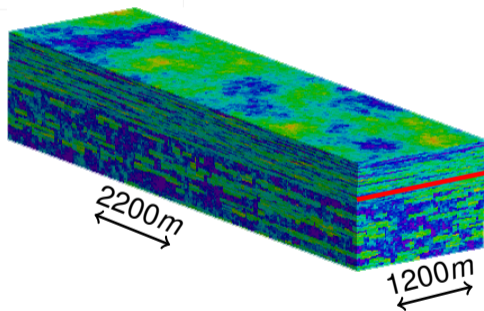
Underground reservoir,  
10th SPE test case

© 2013-2014, Martin Vohralík, Institute for Mathematics and its Applications (IMA)

Can we certify error in a practical case  $-\nabla \cdot (\mathbf{K} \nabla p) = f$ : outflow error

$$\left| \int_{y=2200} \mathbf{K} \nabla (p - p_\ell) \cdot \mathbf{n} \right| \text{ (goal functional)}$$

no of unknowns	825	3300	13200
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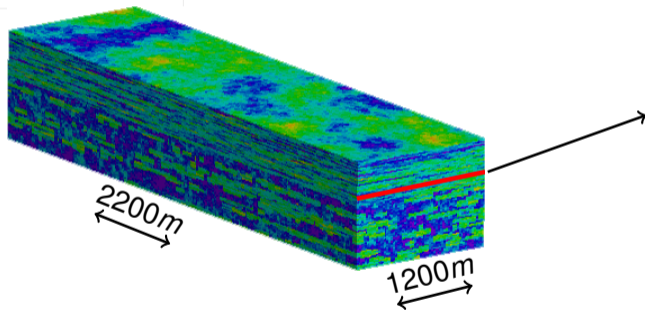
Underground reservoir,  
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G. Mallik, M. Vohralik, S. Yousef, *Journal of Computational and Applied Mathematics* (2018)

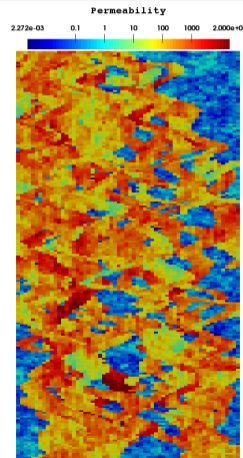
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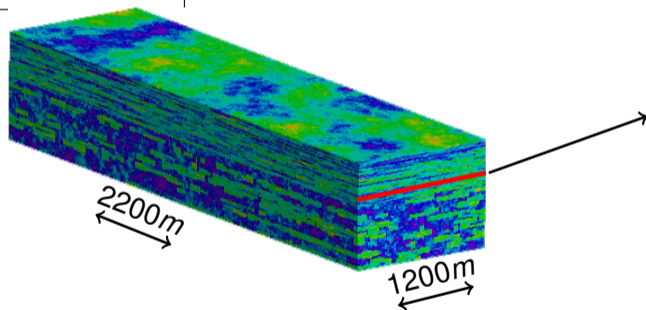
Layer permeability

G. Mallik, M. Vohralik, S. Yousef, Journal of Computational and Applied Mathematics (2018)

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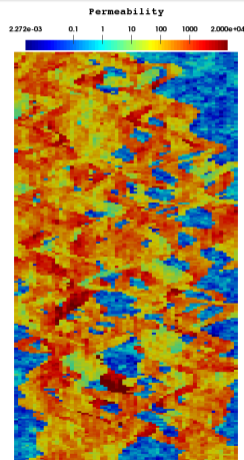
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Layer permeability

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# Two-phase flow

## Incompressible two-phase flow in porous media

Find  *saturations*  $s_\alpha$  and  *pressures*  $p_\alpha$ ,  $\alpha \in \{g, w\}$ , such that

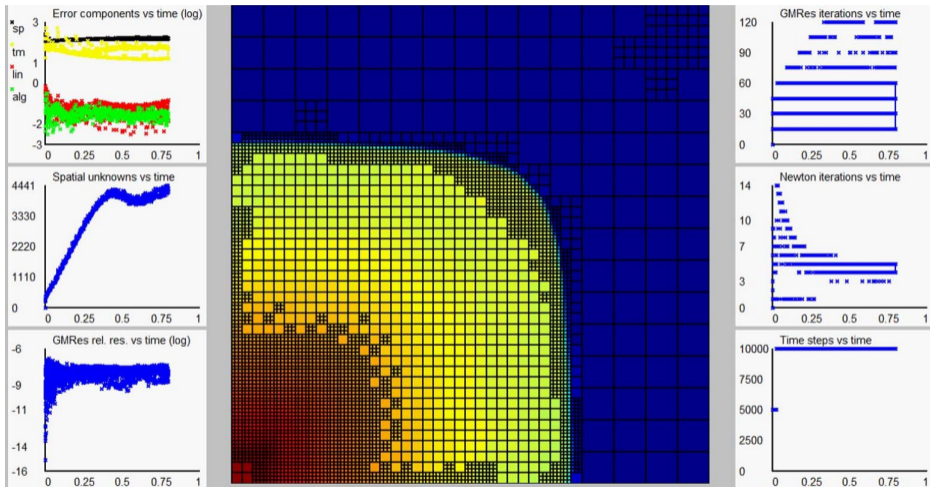
$$\partial_t(\phi \mathbf{s}_\alpha) - \nabla \cdot \left( \frac{k_{r,\alpha}(\mathbf{s}_w)}{\mu_\alpha} \mathbf{K}(\nabla p_\alpha + \rho_\alpha \mathbf{g} \nabla z) \right) = \mathbf{q}_\alpha, \quad \alpha \in \{g, w\},$$

$$\mathbf{s}_g + \mathbf{s}_w = \mathbf{1},$$

$$p_g - p_w = p_c(\mathbf{s}_w)$$

- **unsteady**, **nonlinear**, and **degenerate** problem
- coupled **system** of PDEs & **algebraic constraints**
- **sharp** evolving **fronts**

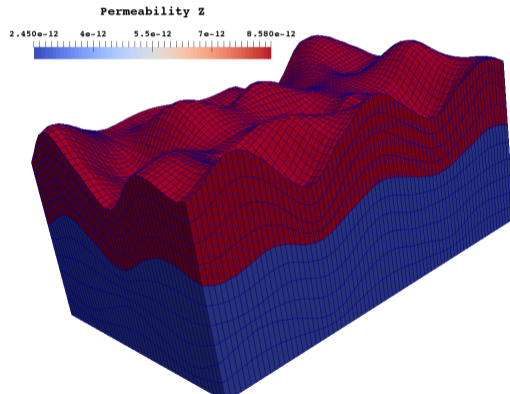
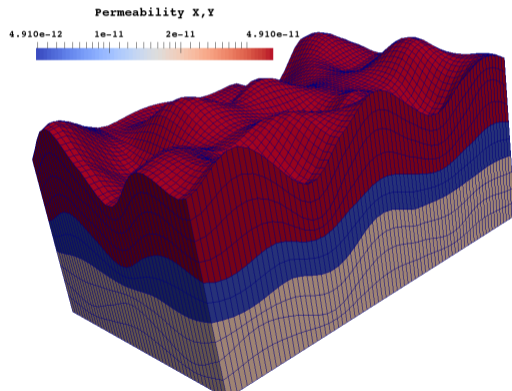
# Space/time/nonlinear solver/linear solver adaptivity



## Fully adaptive computation

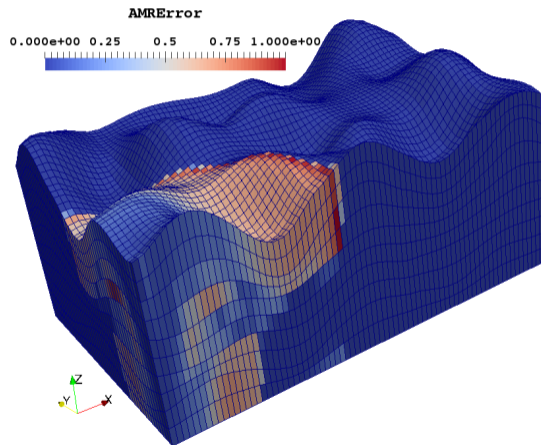
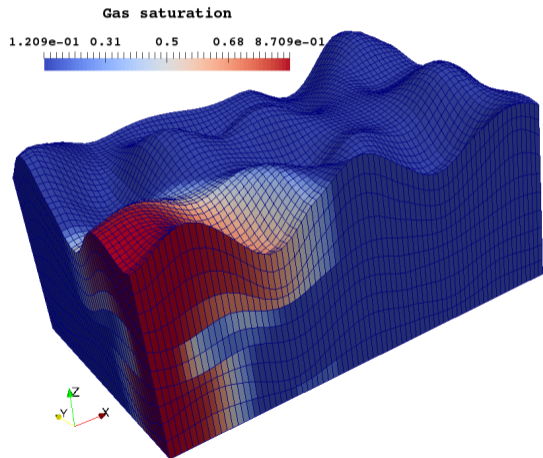
M. Vohralík, M.-F. Wheeler, Computational Geosciences (2013)

# 3 phases, 3 components (black-oil) problem: permeability

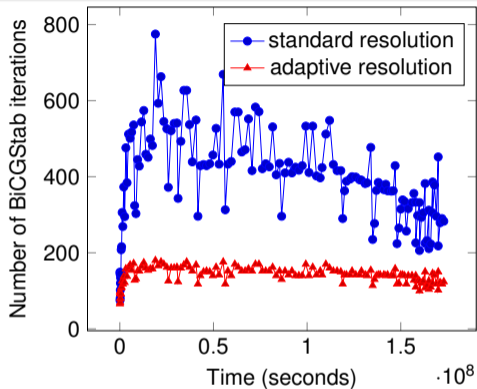
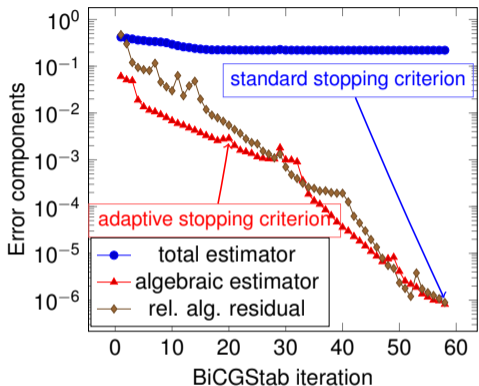




# 3 phases, 3 components (black-oil) problem: gas saturation and a posteriori estimate

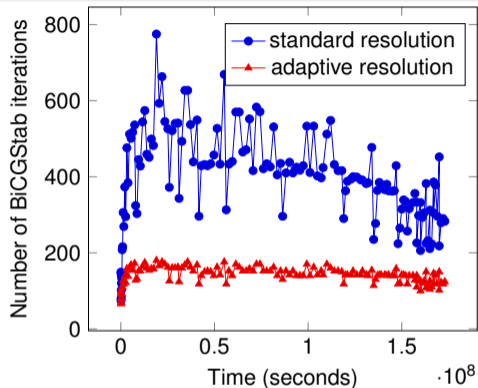
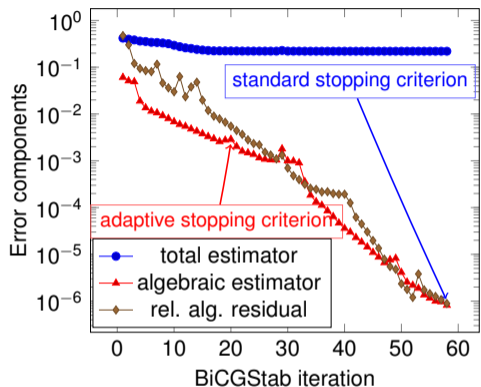


## 3 phases, 3 components (black-oil): alg. solver &amp; mesh adaptivity



	Linear solver steps	Resolution time	AMR time	Estimators evaluation	Gain factor
Standard resolution	66386	1023s	-	-	-
Adaptive resolution	20184	201s	42s	26s	3.8

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# Outline

- 1 Introduction: context, motivation, and goals
- 2 Steady linear Darcy flow
  - Discretization
  - A posteriori error estimate
  - Numerical experiments
- 3 Adaptivity: mesh, polynomial degree, linear solvers, nonlinear solvers
  - Mesh and polynomial degree
  - Linear and nonlinear solvers
  - Error in a quantity of interest
- 4 Unsteady multi-phase multi-compositional Darcy flow
- 5 Conclusions

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- a posteriori estimates: **error control**, **unified framework** for different schemes, **robustness** with respect problem parameters and approximation polynomial degree, **fast evaluation** of the estimators, **polygonal/polyhedral meshes**
- **full adaptivity**: linear solver, nonlinear solver, time step, space mesh ( $hp$ )
- intrinsically leads to **mass balance recovery** in any situation

## Ongoing work

- convergence and optimality proofs
- application to challenging porous media problems

Thank you for your attention!

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