

h-Adaptive FEM for Transport Problems

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- 1 Motivation
- 2 Dynamic mesh adaptation
 - Red-green refinement
 - Mesh re-coarsening
 - Numerical examples
- 3 Goal-oriented error estimation
 - Error splitting
 - Error localization
 - Numerical examples
- 4 Conclusions and outlook

Scalar conservation law

$$\frac{\partial u}{\partial t} + \nabla \cdot \mathbf{f}(u) = 0$$

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Scalar conservation law

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Galerkin FEM

$$M_C \frac{du}{dt} = K u$$

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Scalar conservation law

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Low-order scheme

$$M_L \frac{du}{dt} = Ku + Du = Lu$$

■ Convection-diffusion equation

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Scalar conservation law

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High-resolution scheme

$$M_L \frac{du}{dt} = Lu + \bar{f}(u)$$

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$$\frac{\partial u}{\partial t} + \nabla \cdot (\mathbf{v}u - d\nabla u) = 0$$

High-resolution scheme

$$M_L \frac{du}{dt} = Lu + \bar{f}(u)$$

- Compressible Euler equations

$$\frac{\partial}{\partial t} \begin{pmatrix} \rho \\ \rho \mathbf{v} \\ \rho E \end{pmatrix} + \nabla \cdot \begin{pmatrix} \rho \mathbf{v} \\ \rho \mathbf{v} \otimes \mathbf{v} + pI \\ (\rho E + p)\mathbf{v} \end{pmatrix} = 0$$

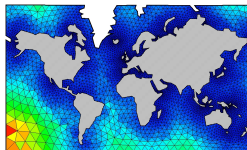
Algebraic flux correction

↔ talks by D. Kuzmin, M. Garris

- p -adaptation between first- and second-order approximations
- h -adaptation improves resolution of flow features (e.g., shocks)

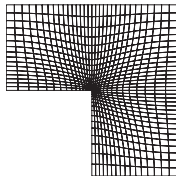
Unstructured meshes

- mesh generation for complex domains
- prevent distorted cells near singular points
- overhead costs due to indirect addressing



Structured grids

- efficient hardware oriented numerics
- orthogonal grids to resolve boundary layers
- unflexible/impractical for complex domains



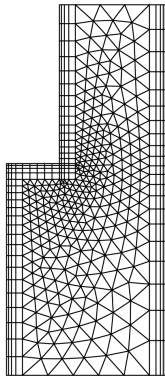
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AFC schemes can handle hybrid meshes

Structured grids

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- orthogonal grids to resolve boundary layers
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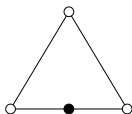


- conforming triangulations based on hybrid initial mesh
- no deterioration of grid quality due to mesh refinement
- mesh re-coarsening 'undoes' subdivision of elements
- adaptive hierarchy of locally nested meshes is generated
- vertices/structure of initial triangulation is preserved
- efficient data structures for dynamic mesh adaptation

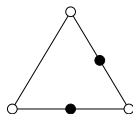
Refinement algorithm in 2D

R.E. Bank, A.H. Sherman, A. Weiser

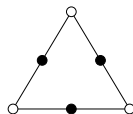
- 1 subdivide marked elements regularly (red refinement)
- 2 eliminate 'hanging nodes' by transition cells (green refinement)



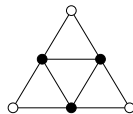
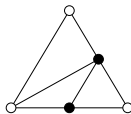
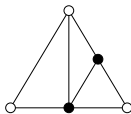
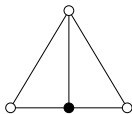
green refinement



blue refinement



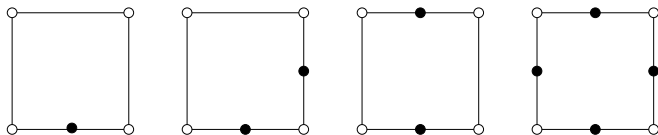
red refinement



Refinement algorithm in 2D

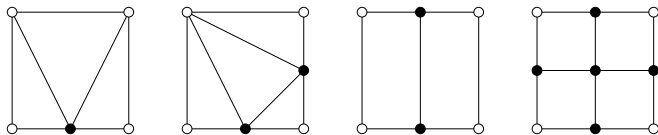
R.E. Bank, A.H. Sherman, A. Weiser

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admissible types of green refinement

red refinement



Triangulation $\mathcal{T}_m(\mathcal{E}_m, \mathcal{V}_m)$, $m = 0, 1, 2, \dots$ consists of

$$\mathcal{E}_m = \{\Omega_k : k = 1, \dots, N_E\} \quad \text{and} \quad \mathcal{V}_m = \{v_i : i = 1, \dots, N_V\}$$

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- nodal **generation function** $g : \mathcal{V}_m \rightarrow \mathbb{N}_0$ is defined recursively

$$g(v_i) := \begin{cases} 0 & \text{if } v_i \in \mathcal{V}_0 \\ \max_{v_j \in \Gamma_{kl}} g(v_j) + 1 & \text{if } v_i \in \Gamma_{kl} := \bar{\Omega}_k \cap \bar{\Omega}_l \\ \max_{v_j \in \partial\Omega_k} g(v_j) + 1 & \text{if } v_i \in \Omega_k \setminus \partial\Omega_k \end{cases}$$

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- represents number of subdivisions \Rightarrow prescribe maximum depth
- characterizes elements and their relation to neighboring cells

Coarsening algorithms (classical approach)

- 1 identify (patches of) elements which can be coarsened
- 2 delete elements/vertices and re-triangulate subdomain

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Re-coarsening algorithms (vertex-based approach)

- 1 'lock' **vertices** step-by-step which must not be removed
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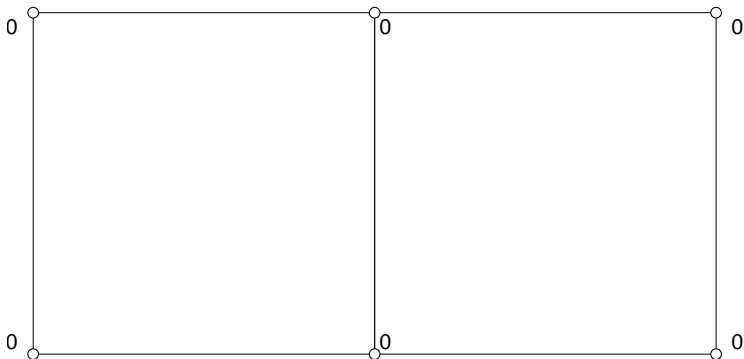
Result: Vertex v_i is locked if $d(v_i) \leq 0$; otherwise it can be deleted.

Re-coarsening algorithms (vertex-based approach)

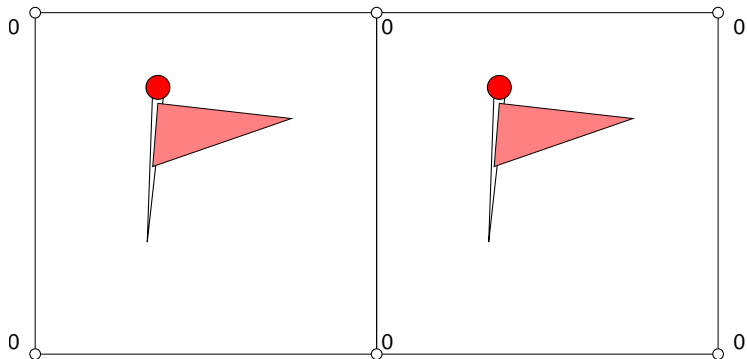
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 - 3 vertices are locked to preclude the creation of blue elements

Result: Vertex v_i is locked if $d(v_i) \leq 0$; otherwise it can be deleted.
All vertices of the initial mesh are locked by construction!

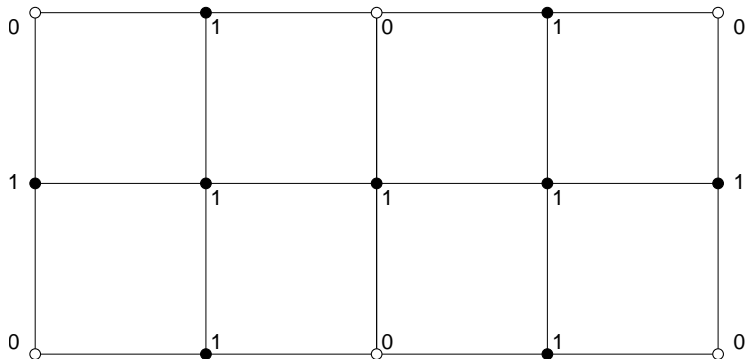
Refinement algorithm: initial mesh



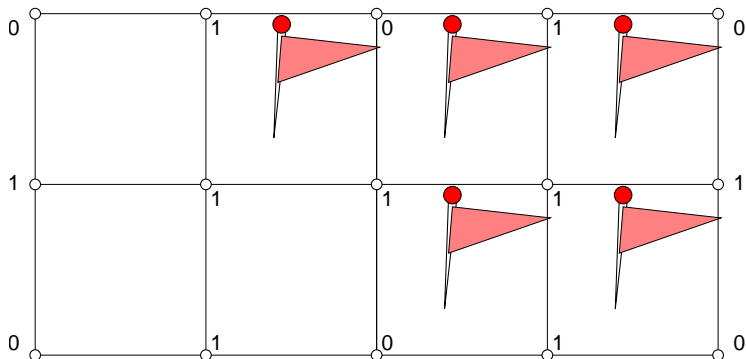
Refinement algorithm: mark elements for **regular refinement**



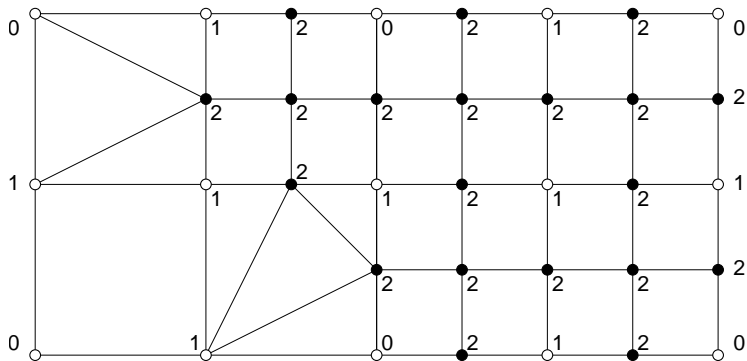
Refinement algorithm: perform regular refinement



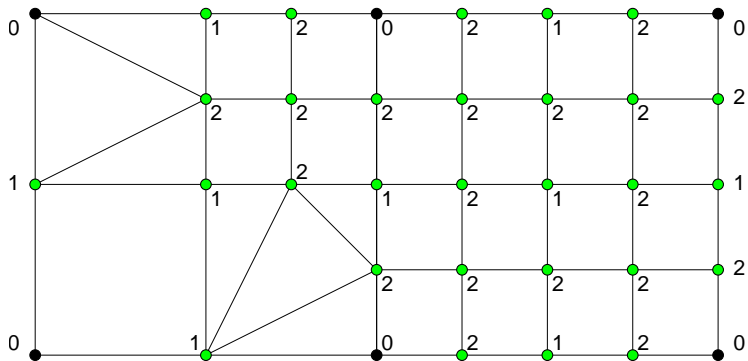
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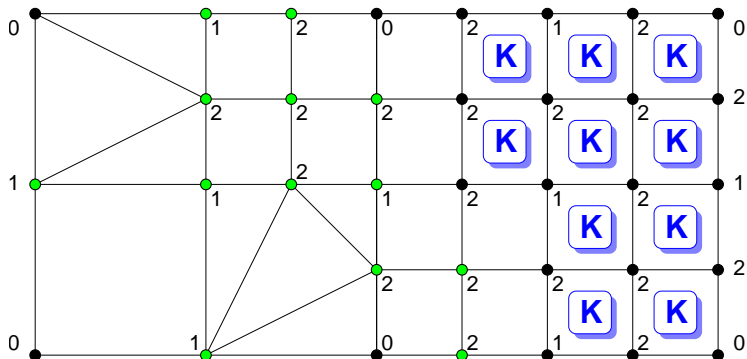
Refinement algorithm: perform regular refinement + transition cells



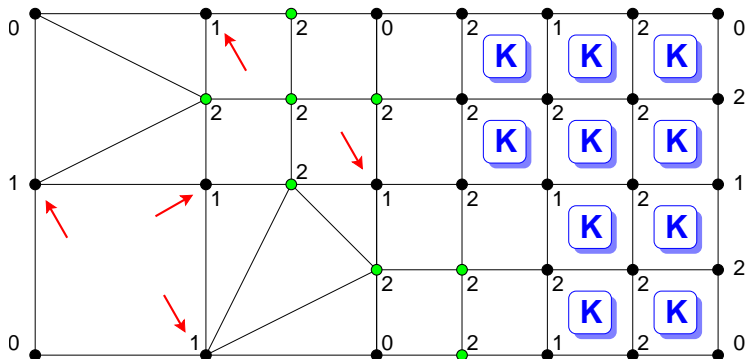
Re-coarsening algorithm: vertices from initial mesh are locked



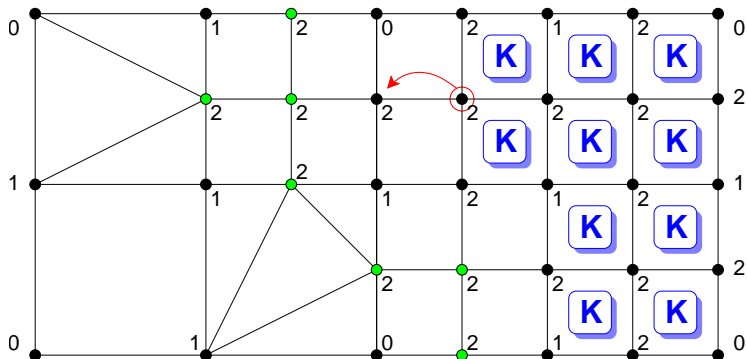
Re-coarsening algorithm: keep cells and lock connected vertices



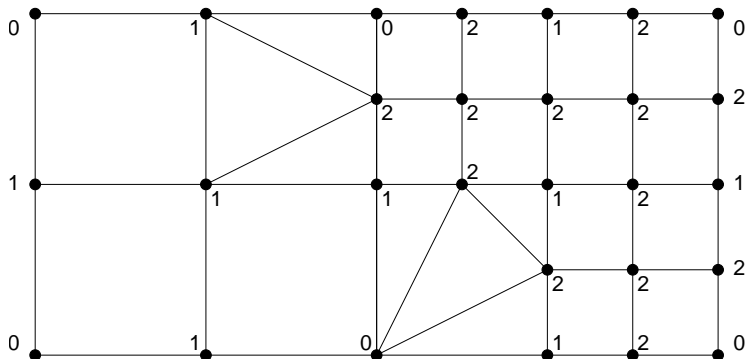
Re-coarsening algorithm: lock vertices if there are younger neighbors



Re-coarsening algorithm: lock vertices to preclude blue elements

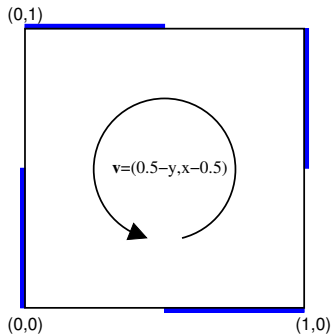


Re-coarsening algorithm: remove vertices and update elements



FEM-FCT scheme, Crank-Nicolson time-stepping, $\Delta t = 10^{-3}$

$$\frac{\partial u}{\partial t} + \nabla \cdot (\mathbf{v}u) = 0 \quad \text{in } (0,1)^2 \times (0,T] \quad u = 0 \quad \text{on } \Gamma_D$$



domain and velocity

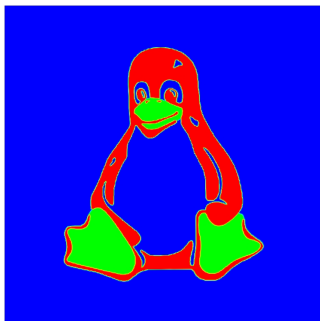
- dynamic mesh adaptation
 - every 5 time steps
 - protective layers
- approximate $\nabla u \approx \mathbf{g}(\nabla u_h)$

$$\|\nabla u - \nabla u_h\|_{\Omega}^2 \approx \sum_k \eta_k$$

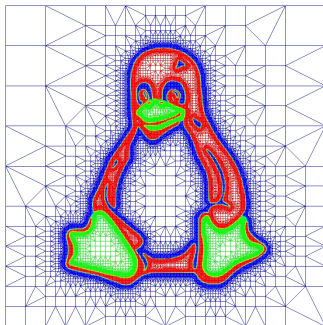
$$\text{where } \eta_k = \|\mathbf{g} - \nabla u_h\|_{\Omega_k}^2$$

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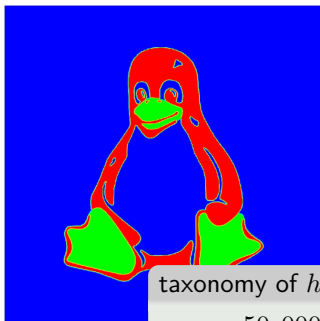
initial/exact solution



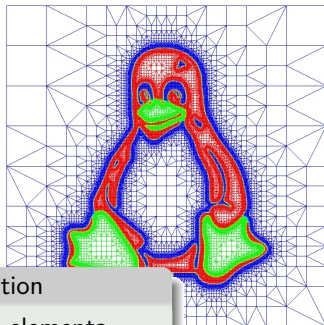
$1/512 \leq h \leq 1/8$

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initial/exact



taxonomy of h -adaptation

$\sim 50,000 P_1/Q_1$ elements

vs.

>1 million Q_1 elements

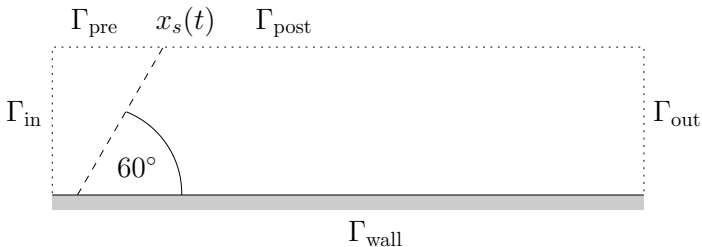
$\leq 1/8$

- Initial conditions: left and right states for a Mach 10 shock

$$\begin{bmatrix} \rho_{\text{pre}} \\ u_{\text{pre}} \\ v_{\text{pre}} \\ p_{\text{pre}} \end{bmatrix} = \begin{bmatrix} 8.0 \\ 8.25 \cos(30^\circ) \\ -8.25 \sin(30^\circ) \\ 116.5 \end{bmatrix} \quad \begin{bmatrix} \rho_{\text{post}} \\ u_{\text{post}} \\ v_{\text{post}} \\ p_{\text{post}} \end{bmatrix} = \begin{bmatrix} 1.4 \\ 0.0 \\ 0.0 \\ 1.0 \end{bmatrix}$$

- Boundary conditions: separation point $x_s(t) = \frac{1}{6} + \frac{1+20t}{\sqrt{3}}$

$$\Gamma_{\text{pre}} = \{x < x_s(t), y = 1\}, \quad \Gamma_{\text{post}} = \{x \geq x_s(t), y = 1\}$$



$$\begin{cases} \nabla \cdot (\mathbf{v}u - d\nabla u) = f & \text{in } \Omega \\ u = b & \text{on } \Gamma \end{cases}$$

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Primal problem: find $u \in H_b^1(\Omega)$
 $a(w, u) = (w, f) \quad \forall w \in H_0^1(\Omega)$

$$\begin{aligned} \blacksquare \quad a(w, u) &= \int_{\Omega} w \nabla \cdot (\mathbf{v}u) \, d\mathbf{x} \\ &\quad + \int_{\Omega} \nabla w \cdot (d\nabla u) \, d\mathbf{x} \end{aligned}$$

Dual problem: find $z \in H_0^1(\Omega)$
 $a(z, w) = j(w) \quad \forall w \in H_0^1(\Omega)$

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Error representation: $u \approx \bar{u} = \sum_j \bar{u}_j \varphi_j$

$$j(u - \bar{u}) = (z, f) - a(z, \bar{u}) = \rho(z, \bar{u})$$

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$$j(u - \bar{u}) = (z, f) - a(z, \bar{u}) = \rho(z - \bar{z}, \bar{u}) + \rho(\bar{z}, \bar{u})$$

$$\begin{cases} \nabla \cdot (\mathbf{v}u - d\nabla u) = f & \text{in } \Omega \\ u = b & \text{on } \Gamma \end{cases}$$

$$\begin{aligned} a(w, u) &= \int_{\Omega} w \nabla \cdot (\mathbf{v}u) \, dx \\ &\quad + \int_{\Omega} \nabla w \cdot (d\nabla u) \, dx \end{aligned}$$

Primal problem: find $u \in H_b^1(\Omega)$
 $a(w, u) = (w, f) \quad \forall w \in H_0^1(\Omega)$

Dual problem: find $z \in H_0^1(\Omega)$
 $a(z, w) = j(w) \quad \forall w \in H_0^1(\Omega)$

Error representation: $u \approx \bar{u} = \sum_j \bar{u}_j \varphi_j, \quad z \approx \bar{z} = \sum_i \bar{z}_i \varphi_i$

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Galerkin orthogonality error
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Dual weighted residual error
needs to be estimated

Galerkin orthogonality error
can be computed

- Approximate dual solution $z \approx \hat{z} = \sum_i \bar{z}_i \psi_i$

$$\rho(\hat{z} - \bar{z}, \bar{u}) = \int_{\Omega} (\hat{z} - \bar{z})(f - \nabla \cdot (\mathbf{v}\bar{u})) \, d\mathbf{x} - d \int_{\Omega} \nabla(\hat{z} - \bar{z}) \cdot \nabla \bar{u} \, d\mathbf{x}$$

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$$0 = \int_{\Omega} (\hat{z} - \bar{z}) \nabla \cdot \mathbf{g}(\bar{u}) \, d\mathbf{x} + \int_{\Omega} \nabla(\hat{z} - \bar{z}) \cdot \mathbf{g}(\bar{u}) \, d\mathbf{x}$$

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Computable DWR error

$$\begin{aligned} \rho(\hat{z} - \bar{z}, \bar{u}) &= \int_{\Omega} (\hat{z} - \bar{z})(f - \nabla \cdot (\mathbf{v}\bar{u} - d\mathbf{g}(\bar{u}))) \, dx && \text{residual error} \\ &+ d \int_{\Omega} \nabla(\hat{z} - \bar{z}) \cdot (\mathbf{g}(\bar{u}) - \nabla \bar{u}) \, dx && \text{diffusive flux error} \end{aligned}$$

Goal-oriented estimate $j(u - \bar{u}) \approx \rho(w, \bar{u}) + \rho(\bar{z}, \bar{u}), \quad w = \hat{z} - \bar{z}$

$$|\rho(w, \bar{u})| \leq \Phi = \sum_i \Phi_i, \quad |\rho(\bar{z}, \bar{u})| \leq \Psi = \sum_i \Psi_i$$

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$$\Psi_i = \left| \int_{\Omega} \bar{z}_i \{ \varphi_i (f - \nabla \cdot (\mathbf{v}\bar{u})) - \nabla \varphi_i \cdot (d\nabla \bar{u}) \} dx \right|$$

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$$\Phi_i = \int_{\Omega} |w_i (f - \nabla \cdot (\mathbf{v}\bar{u} - d\mathbf{g}(\bar{u}))| dx + d \int_{\Omega} |\nabla w_i \cdot (\mathbf{g}(\bar{u}) - \nabla \bar{u})| dx$$

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$$w_i = \bar{z}_i (\psi_i - \varphi_i) \quad (\text{Schmich \& Vexler, 2008})$$

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Alternative: $w_i = \varphi_i(\hat{z} - \bar{z}), \quad \sum_i \varphi_i \equiv 1$

Conversion to element contributions

$$|j(u - \bar{u})| \leq \Phi + \Psi =: \eta, \quad \eta = \sum_k \eta_k = \sum_i \Phi_i + \Psi_i$$

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- Element contribution $\eta_k = \int_{\Omega_k} \xi \, d\mathbf{x}, \quad \forall \Omega_k \subset \Omega$

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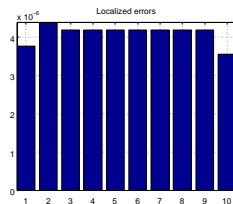
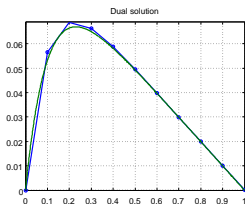
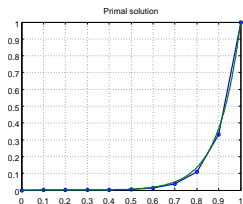
- Continuous error function $\xi = \sum_i \xi_i \varphi_i, \quad \xi_i = \frac{\Phi_i + \Psi_i}{\int_{\Omega} \varphi_i \, d\mathbf{x}}$
- Element contribution $\eta_k = \int_{\Omega_k} \xi \, d\mathbf{x}, \quad \forall \Omega_k \subset \Omega$
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Conversion to element contributions

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- Element contribution $\eta_k = \int_{\Omega_k} \xi \, d\mathbf{x}, \quad \forall \Omega_k \subset \Omega$
- **Relative** effectivity index $I_{\text{rel}} = \left| \frac{\eta - |j(u - \bar{u})|}{j(u)} \right|$

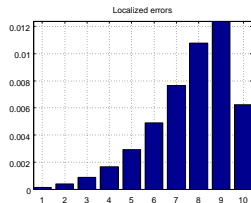
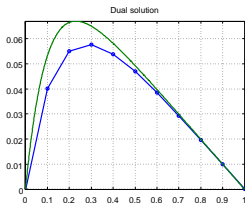
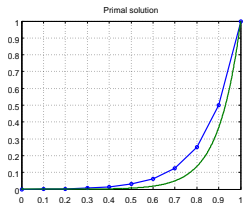
$$\text{Pe} \frac{du}{dt} - \frac{d^2u}{dx^2} = 0, \quad u(0) = 0, \quad u(1) = 1, \quad j(u) = \int_0^1 u \, dx$$



Discretization: central difference scheme, $h = 1/10$

Pe	$ j(u - \bar{u}) $	Φ	Ψ	η	I_{rel}
1	7.67e-04	7.80e-04	4.09e-16	7.80e-04	3.05e-05
10	2.84e-05	4.10e-05	3.56e-18	4.10e-05	1.25e-04
100	—	—	—	—	—

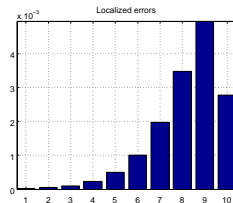
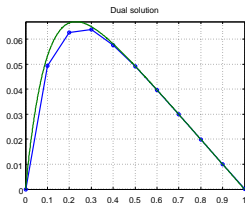
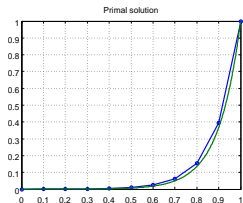
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Discretization: upwind difference scheme, $h = 1/10$

Pe	$ j(u - \bar{u}) $	Φ	Ψ	η	I_{rel}
1	4.52e-03	7.38e-04	3.58e-03	4.32e-03	4.79e-04
10	4.91e-02	3.06e-04	4.76e-02	4.79e-02	1.21e-02
100	5.00e-02	1.59e-09	5.00e-02	5.00e-02	1.21e-08

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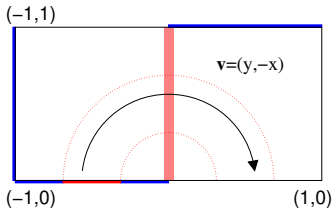
Discretization: TVD scheme, MC limiter, $h = 1/10$

Pe	$ j(u - \bar{u}) $	Φ	Ψ	η	I_{rel}
1	1.03e-03	7.74e-04	2.60e-04	1.03e-03	1.34e-05
10	1.51e-02	9.12e-05	1.50e-02	1.51e-02	3.81e-05
100	4.51e-02	4.23e-09	4.51e-02	4.51e-02	1.97e-07

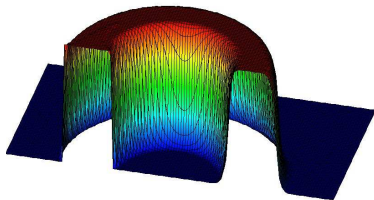
Circular convection $\nabla \cdot (\mathbf{v}u) = 0$ in $\Omega = (-1, 1) \times (0, 1)$

$$u(x, y) = \begin{cases} 1, & 0.35 \leq r \leq 0.65 \\ 0, & \text{otherwise} \end{cases} \quad r(x, y) = \sqrt{x^2 + y^2}$$

Target functional $j(u) = \int_{\omega} u \, d\mathbf{x}$, $\omega = (-0.1, 0.1) \times (0, 1)$



domain and velocity

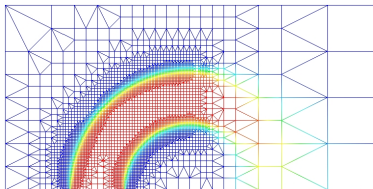


FEM-TVD, $h = 1/64$

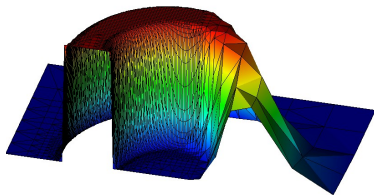
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Goal-oriented mesh adaptation



$$j(u - \bar{u}) \approx \rho(z_h, \bar{u})$$

- dynamic h -adaptation for unsteady flow problems
 - red-green strategy yields an adaptive mesh hierarchy
 - re-coarsening is based on the *vertex locking* algorithm
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- implementation of mesh adaptation procedure in 3D
 - goal-oriented error estimation for unsteady flow problems
 - extension to the compressible Navier-Stokes equations