

Numerical Methods for the Solution of PDEs

Laboratory with deal.II – www.dealii.org

Manufactured solutions, global refinement, measuring error rates

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<https://luca-heltai.github.io/nmpde>
<https://github.com/luca-heltai/nmpde>



How to measure the Error?

- Method of Manufactured Solutions
 - Take the “ u ” you want as a solution, plug in the equations, get the boundary conditions and the right hand side that force the given “ u ”
 - Integrate (with a fine quadrature formula) the difference between the exact solution and the computed one (`VectorTools::integrate_difference`, or helper classes)
 - Possibly integrate the difference between the gradients of the exact and computed solutions



Error Estimates

Local Estimate:

$$\|u - \Pi u\|_{s, T_m} \lesssim \rho_m^{-s} h_m^{k+1} |u|_{k+1, T_m}$$

Global Estimate (for quasi uniform triangulations):

$$\sum_m \left(\|u - \Pi u\|_{s, T_m} \right) \lesssim h^{k+1-s} |u|_{k+1, \Omega}$$



Error Estimates

Local Estimate:

$$\|u - \Pi u\|_{s,T_m} \lesssim \rho_m^{-s} h_m^{k+1} |u|_{k+1,T_m}$$

If $V_h \subset H^s(\Omega)$ and Triangulation is *quasi-uniform*

$$\|u - \Pi u\|_{s,\Omega} \lesssim h^{k+1-s} |u|_{k+1,\Omega}$$



To Reduce the Error:

- Globally, the error is dominated by *largest* element of the mesh and the $H^{k+1}(\Omega)$ norm of the exact solution
- Reduce the overall size of the mesh h (**global refinement**), when we don't know the $H^{k+1}(\Omega)$ norm of the exact solution
- Reduce the size of the elements where the solution has large $H^{k+1}(\Omega)$ norm, or where we estimate that $H^{k+1}(\Omega)$ norm of the solution would be large (**local refinement**)



Estimate the rate of convergence

- Once you have computed the error, how do we measure if we get the correct *convergence ratio*?
- Consider Poisson Problem. $V := H^1(\Omega)$

$$\| u - u_h \|_1 \lesssim \| u - \Pi u \|_1 \lesssim h^1 |u|_{2,\Omega}$$

$$\| u - \Pi u \|_0 \lesssim h^2 |u|_{2,\Omega}$$

We still need to prove that we can use u_h in the last estimate!



Estimate the rate of convergence

- Compute two successive solutions, on half the size of the mesh (i.e., after one global refinement):

$$\| u - u_{2h} \| \sim \tilde{C}(2h)^p$$

$$\| u - u_h \| \sim \tilde{C}(h)^p$$

$$\frac{\| u - u_{2h} \|}{\| u - u_h \|} \sim 2^p$$

$$p \sim \log_2 \left(\frac{\| u - u_{2h} \|}{\| u - u_h \|} \right)$$



Back to C++

- Today's program:
 - Poisson for general coefficients, boundary data, and rhs
 - Work on successively refined grids
 - Estimate $L^2(\Omega)$ and $H^1(\Omega)$ errors



Poisson problem revisited

Homogeneous Dirichlet case, constant coefficient equal to 1:

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

$$\gamma_\Gamma : H^1(\Omega) \mapsto H^{\frac{1}{2}}(\Gamma) \quad \text{Trace operator}$$

$$V := H_0^1(\Omega) := \{v \mid v \in L^2(\Omega), \nabla v \in L^2(\Omega), \gamma_{\partial\Omega} v = 0\}$$

Weak form: given $f \in V^*$, find $u \in V$ such that

$$(\nabla u, \nabla v) = (f, v) \quad \forall v \in V$$



Poisson problem revisited

Non-homogeneous Dirichlet case, constant coefficient equal to 1:

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

$$V_0 := H_0^1(\Omega) := \{v \mid v \in L^2(\Omega), \nabla v \in L^2(\Omega), \gamma_{\partial\Omega} v = 0\}$$

$$V_g := V_0 + u_D \quad \text{Where } \gamma_{\partial\Omega} u_D = g$$

Weak form: given $f \in V^*$, find $u \in V_g$ such that

$$(\nabla u, \nabla v) = (f, v) \quad \forall v \in V_0$$



Poisson problem revisited

Mixed boundary conditions, non-constant coefficients

$$-\nabla \cdot (a \nabla u) = f \quad \text{in } \Omega$$

$$u = g_D \quad \text{on } \Gamma_D$$

$$n \cdot (a \nabla u) = g_N \quad \text{on } \Gamma_N$$

$$V_{0,\Gamma_D} := H_0^1(\Omega) := \{v \mid v \in L^2(\Omega), \nabla v \in L^2(\Omega), \gamma_{\Gamma_D} v = 0\}$$

$$V_{g_D, \Gamma_D} := V_{0,\Gamma_D} + u_D \quad \text{Where } \gamma_{\Gamma_D} u_D = g_D$$

Weak form: given $f \in V_{0,\Gamma_D}^*$, find $u \in V_{g_D, \Gamma_D}$ such that

$$(a \nabla u, \nabla v) = (f, v) + \int_{\Gamma_N} g_N v \quad \forall v \in V_{0,\Gamma_D}$$



Trial spaces VS test spaces

$$V_{0,\Gamma_D} := H_0^1(\Omega) := \{v \mid v \in L^2(\Omega), \nabla v \in L^2(\Omega), \gamma_{\Gamma_D} v = 0\}$$

$$V_{g_D, \Gamma_D} := V_{0,\Gamma_D} + u_D \quad \text{Where } \gamma_{\Gamma_D} u_D = g_D$$

Weak form: given $f \in V_{0,\Gamma_D}^*$, find $u \in V_{g_D, \Gamma_D}$ such that

$$(a \nabla u, \nabla v) = (f, v) + \int_{\Gamma_N} g_N v \quad \forall v \in V_{0,\Gamma_D}$$

CANNOT apply Lax-Milgram: $V_{0,\Gamma_D} \neq V_{g_D, \Gamma_D}$



Trial spaces VS test spaces

$$V_{0,\Gamma_D} := H_0^1(\Omega) := \{v \mid v \in L^2(\Omega), \nabla v \in L^2(\Omega), \gamma_{\Gamma_D} v = 0\}$$

$$V_{g_D, \Gamma_D} := V_{0,\Gamma_D} + u_D \quad \text{Where } \gamma_{\Gamma_D} u_D = g_D$$

Weak form: given $f \in V_{0,\Gamma_D}^*$, find $u_0 \in V_{0,\Gamma_D}$ such that

$$(a \nabla u_0, \nabla v) = (f, v) + \int_{\Gamma_N} (g_N - n \cdot (a \nabla u_D)) v - (a \nabla u_D, \nabla v) \quad \forall v \in V_{0,\Gamma_D}$$

Write $u = u_0 + u_D$ (now we can apply Lax-Milgram)

u_D is arbitrary, and such that $\gamma_{\Gamma_D} u_D = g_D$



How to implement V_{g_D, Γ_D} , V_{0, Γ_D} ?

- Option 1 (**not implemented in deal.II**):
encode in DoFHandler (n_dofs of $H_{0, \Gamma_D}^1(\Omega)$ < n_dofs of $H^1(\Omega)$)
and in basis functions (i.e., $\gamma_{\Gamma_D} v_i = 0 \quad \forall v_i \in V_h$)
- Option 2 (Penalty methods, Lagrange multipliers):
impose boundary conditions weakly
- Option 3 (Algebraic approach: strong imposition):
post-process Linear systems, solution vectors, and rhs vectors to **set to g_D**
degrees of freedom with support points on Γ_D



Algebraic approach

- Main idea: assemble matrix $\tilde{A}_{ij} := (a \nabla v_j, \nabla v_i)$

and right-hand-side

$$\tilde{F}_i := (f, v_i) + \int_{\Gamma_N} g_N v_i$$

- split dofs

$$u = \begin{pmatrix} u_{\Omega \cup \Gamma_N} \equiv u_O \\ u_C \end{pmatrix} \quad \tilde{F} = \begin{pmatrix} F_O \\ F_C \end{pmatrix}$$

- and matrix

$$\tilde{A} = \begin{pmatrix} A_{OO} & A_{OC} \\ A_{CO} & A_{CC} \end{pmatrix}$$

- where “C” stands for “constrained”



Mimic continuous approach

- compute g_D , using `VectorTools::interpolate_boundary_values`

- eliminate row “C” from \tilde{A} , and set rhs $\tilde{F}_C \mapsto g_D$:

$$\begin{pmatrix} A_{OO} & A_{OC} \\ 0 & I_{CC} \end{pmatrix} \begin{pmatrix} u_O \\ u_D \end{pmatrix} = \begin{pmatrix} \tilde{F}_O \\ g_D \end{pmatrix}$$

- “move” A_{OC} to rhs to restore symmetry in matrix:

$$\begin{pmatrix} A_{OO} & 0 \\ 0 & I_{CC} \end{pmatrix} \begin{pmatrix} u_O \\ u_D \end{pmatrix} = \begin{pmatrix} \tilde{F}_O - A_{OC}g_D \\ g_D \end{pmatrix}$$

- rescale I_{CC} for conditioning:

$$\begin{pmatrix} A_{OO} & 0 \\ 0 & \alpha I_{CC} \end{pmatrix} \begin{pmatrix} u_O \\ u_D \end{pmatrix} = \begin{pmatrix} \tilde{F}_O - A_{OC}g_D \\ \alpha g_D \end{pmatrix}$$

`MatrixTools::apply_boundary_values`

$$\tilde{A} \mapsto \begin{pmatrix} A_{OO} & 0 \\ 0 & \alpha I_{CC} \end{pmatrix} \quad u \mapsto \begin{pmatrix} u_O \\ u_D \end{pmatrix} \quad \tilde{F} \mapsto \begin{pmatrix} \tilde{F}_O - A_{OC}g_D \\ \alpha g_D \end{pmatrix}$$



Special case of AffineConstraints

- General case: constrained dofs are a subset of all dofs $\mathcal{N}_C \subset \mathcal{N}$
- AffineConstraints: $x_i = \sum_{j \in \mathcal{N} \setminus \mathcal{N}_C} C_{ij}x_j + b_i \quad \forall i \in \mathcal{N}_C$
- Algebraic solution can be performed efficiently as a three-step process:
 - Condense
 - Solve
 - Distribute (only needed if $C \neq 0$)

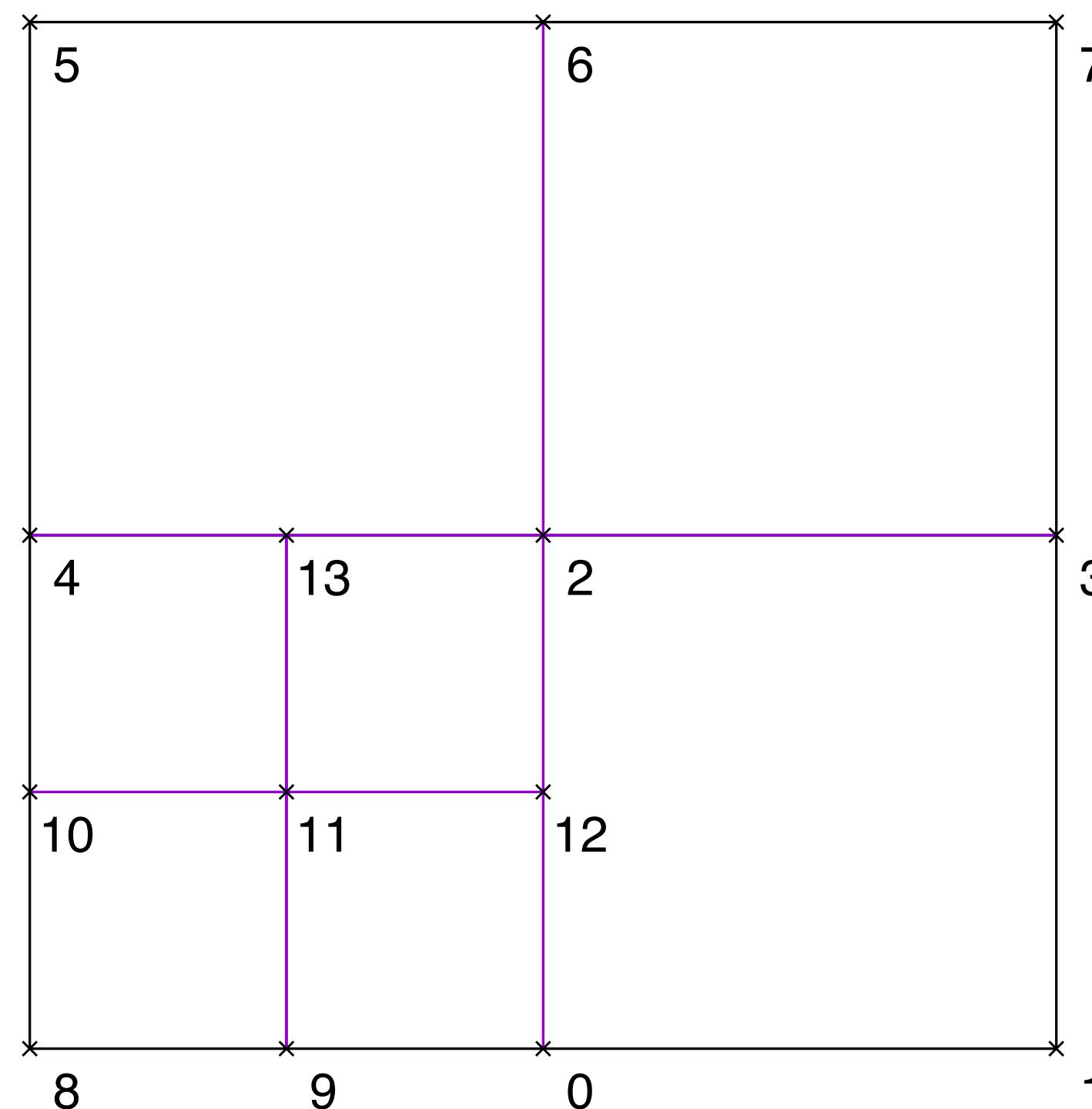


Condense-Solve-Distribute

- Given, $\tilde{A} = \begin{pmatrix} A_{OO} & A_{OC} \\ A_{CO} & A_{CC} \end{pmatrix}$, $\tilde{F} = \begin{pmatrix} F_O \\ F_C \end{pmatrix}$, and constraints $u_C = Cu_O + b$
- Take constraints into accounts in “O”: $A_{OO}u_O + A_{OC}u_C = (A_{OO} + A_{OC}C)u_O + A_{OC}b = F_O$
- Ignore rows “C” in matrix and rhs and solve $Au = F$ where
 - $\tilde{A} = \begin{pmatrix} A_{OO} & A_{OC} \\ A_{CO} & A_{CC} \end{pmatrix} \mapsto A = \begin{pmatrix} A_{OO} + A_{OC}C & 0 \\ 0 & aI_{CC} \end{pmatrix}$
 - $\tilde{F} = \begin{pmatrix} F_O \\ F_C \end{pmatrix} \mapsto F = \begin{pmatrix} F_O - A_{OC}b \\ ab \end{pmatrix}$
- Distribute constraints: $u = \begin{pmatrix} u_O \\ b \end{pmatrix} \mapsto u = \begin{pmatrix} u_O \\ Cu_O + b \end{pmatrix}$

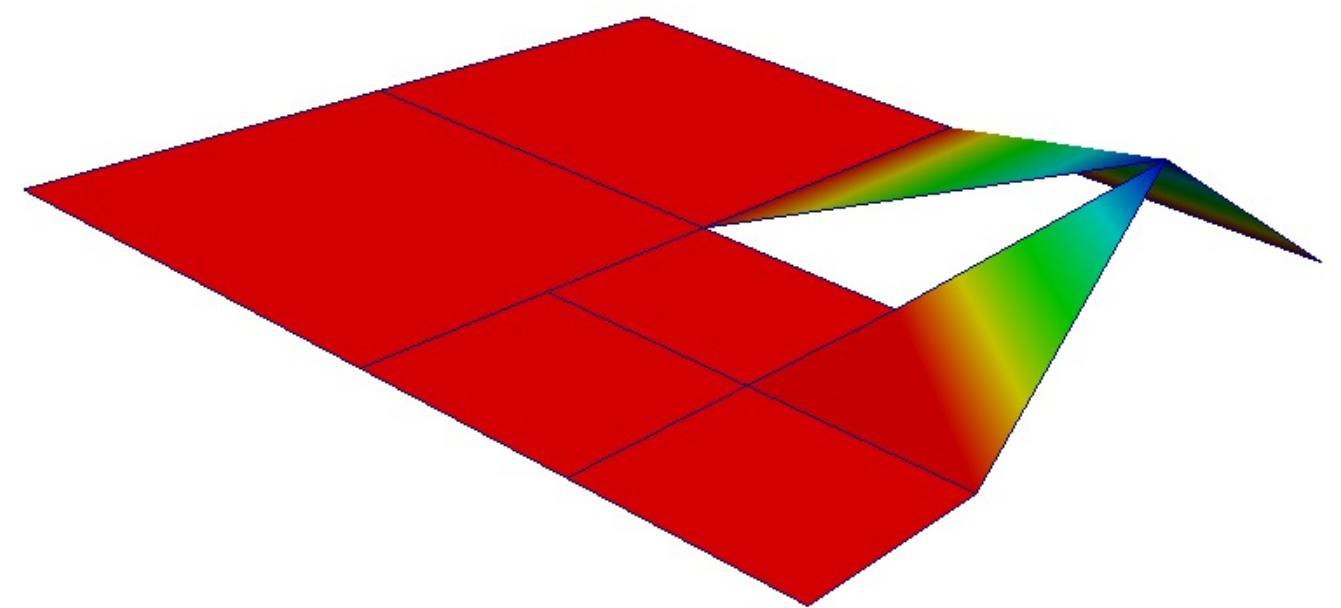


Hanging nodes

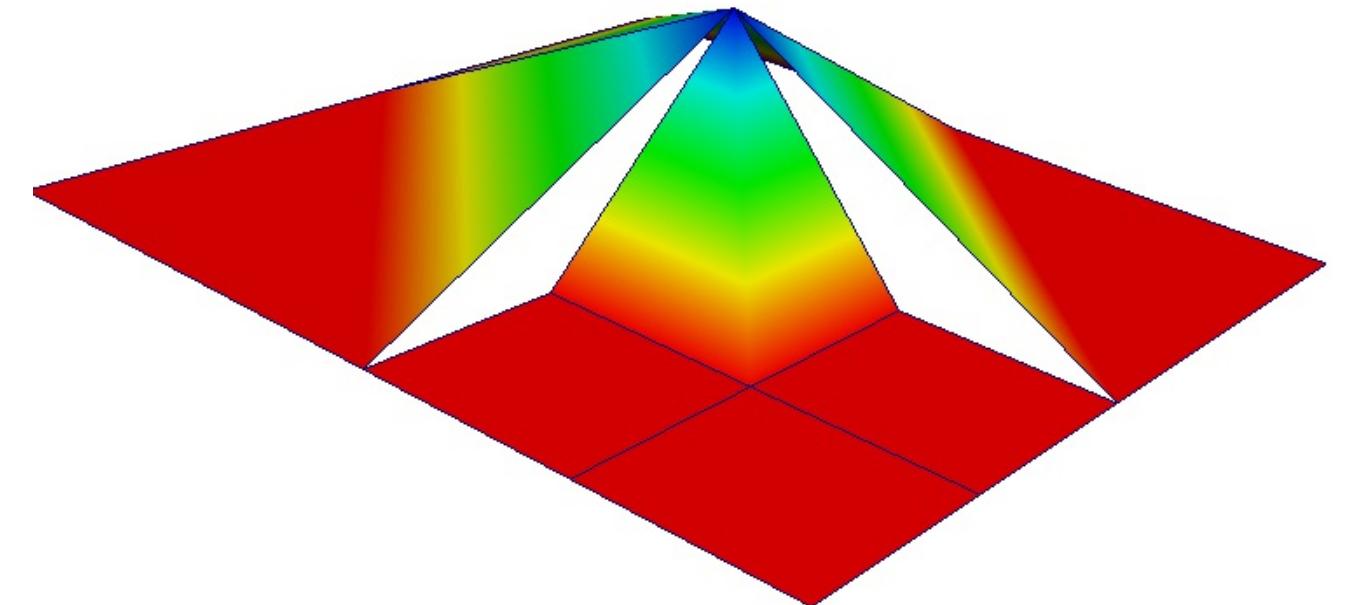


Discontinuous FE space!
Not a subspace of H^1
Bilinear forms would
require special treatment
as gradients are not
defined everywhere

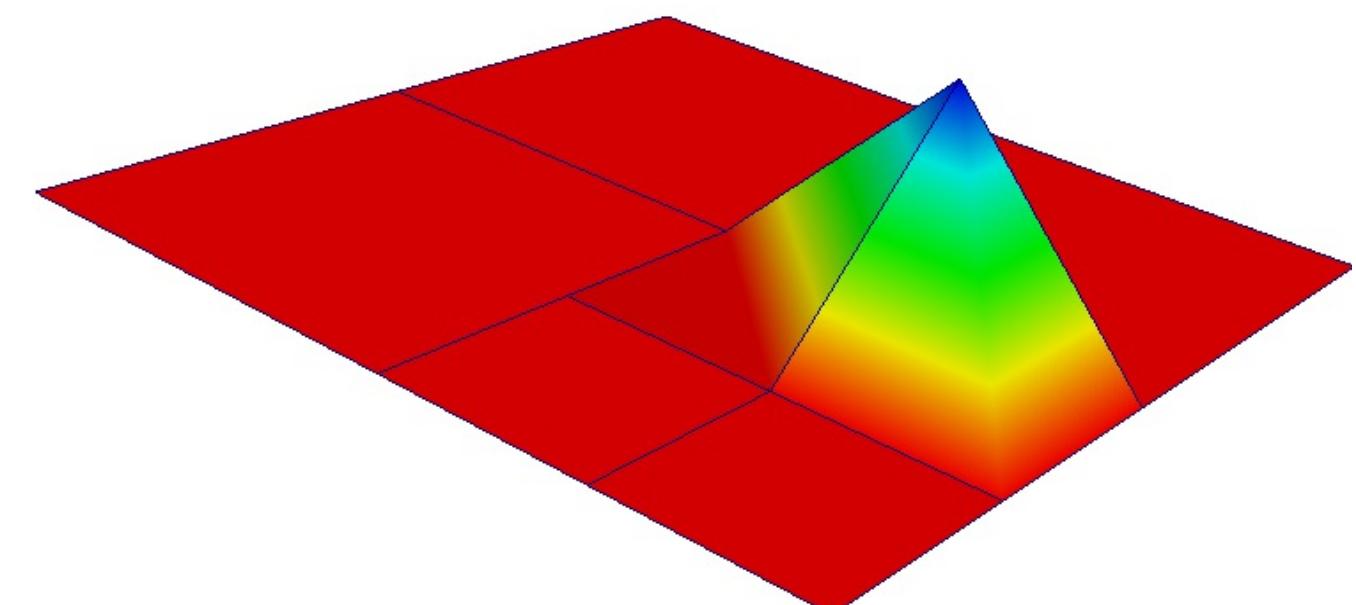
$N_0(\mathbf{x}) :$



$N_2(\mathbf{x}) :$



$N_{12}(\mathbf{x}) :$



Solution: introduce constraints to require continuity!



Use standard (possibly globally discontinuous) shape functions,
but require continuity of their linear combination

Hanging nodes

$$\mathcal{S}^h = \left\{ u^h = \sum_i u_i N_i(\mathbf{x}) : u^h(\mathbf{x}) \in C^0 \right\}$$

Note, that we encounter

We can make the function
continuous by making it

$$u_{12} = \frac{1}{2}u_0 + \frac{1}{2}u_2$$

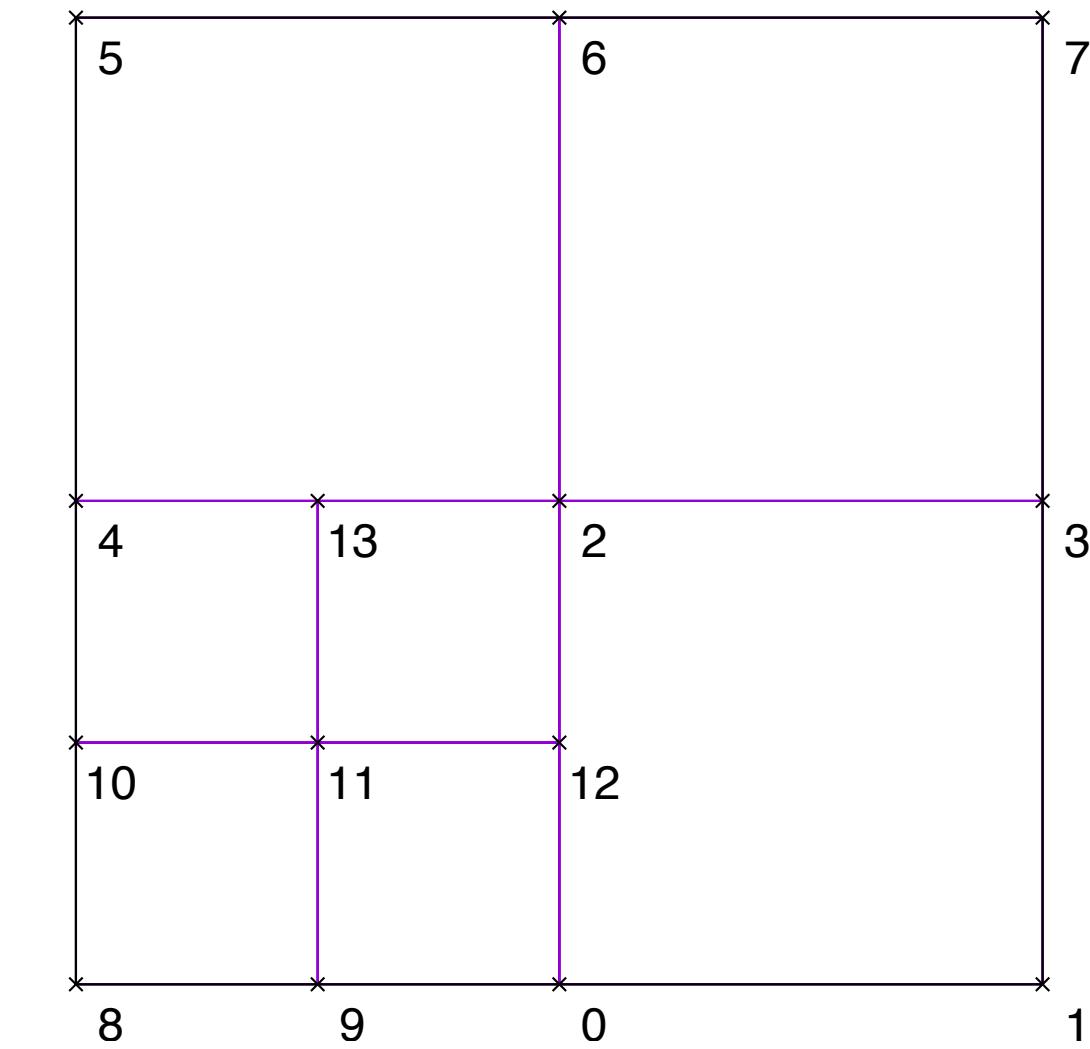
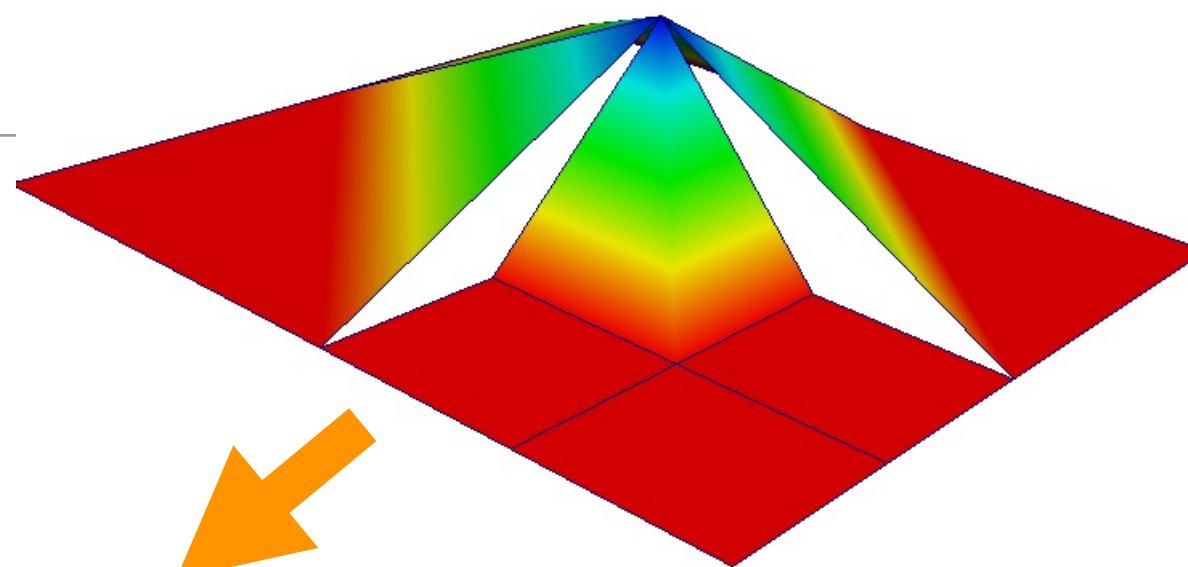
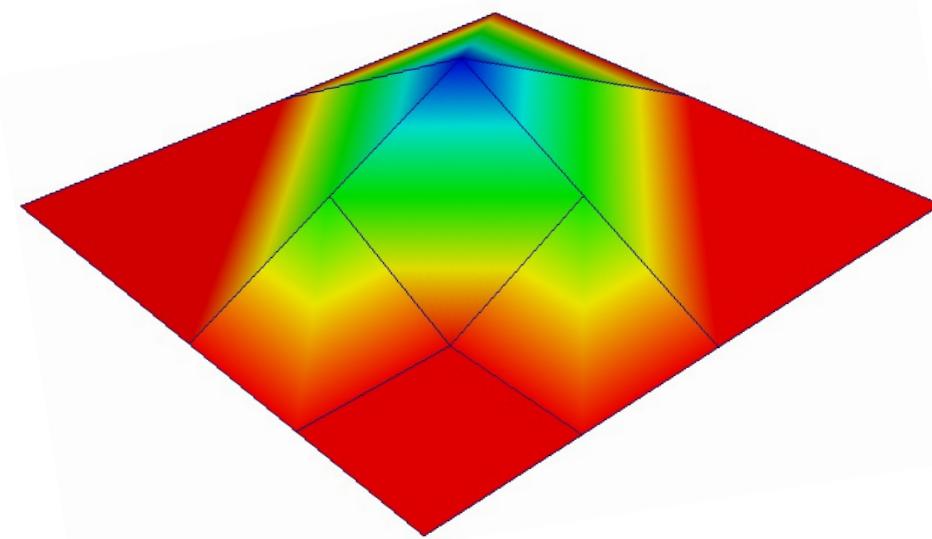
$$u_{13} = \frac{1}{2}u_2 + \frac{1}{2}u_4$$

The general

$$u_i = \sum_{j \in \mathcal{N}} c_{ij} u_j + b_i \quad \forall i \in \mathcal{N}_C$$

define a subset
of all DoFs to

$$\mathcal{N}_C \subset \mathcal{N}$$

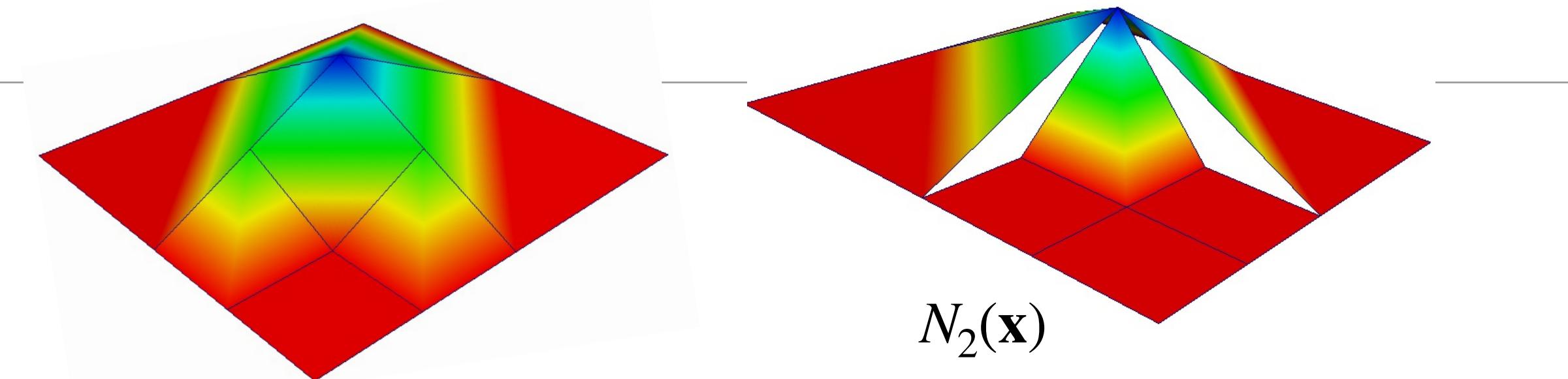


similar constraints arise from boundary
conditions (normal/tangential
component) or hp-adaptive FE



Condensed shape functions

The alternative viewpoint is to construct a set of conforming shape functions:

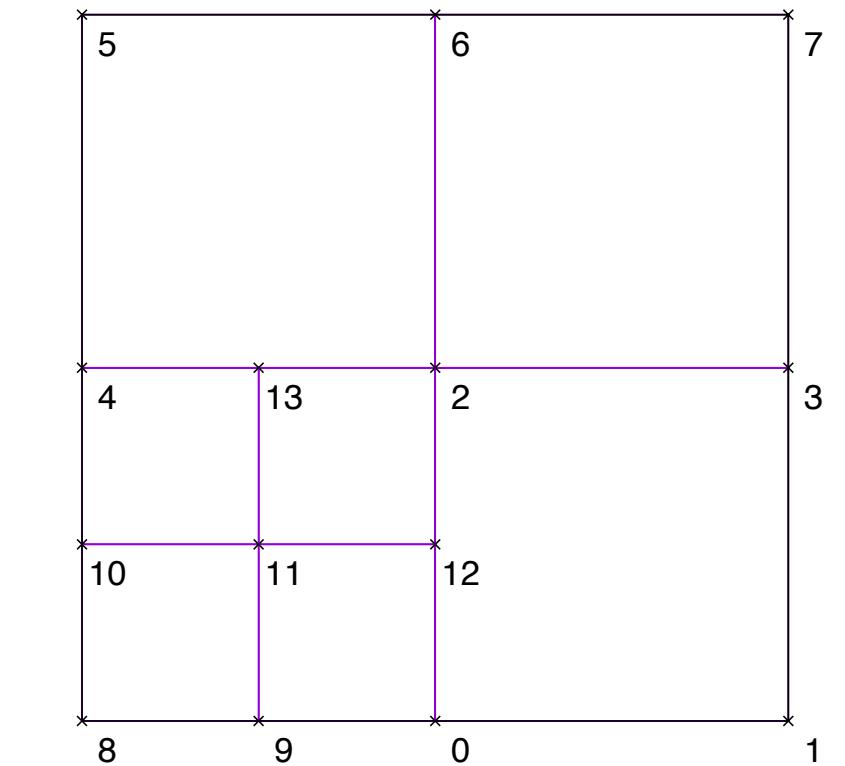


$$\tilde{N}_2 := N_2 + \frac{1}{2}N_{13} + \frac{1}{2}N_{12}$$

$$\mathcal{S}^h = \{u^h = \sum_{i \in \mathcal{N} \setminus \mathcal{N}_c} u_i \tilde{N}_i(\mathbf{x})\}$$

$$[\mathbf{K}]_{ij} = \begin{cases} a(\tilde{N}_i, \tilde{N}_j) & \text{if } i \in \mathcal{N} \setminus \mathcal{N}_c \text{ and } j \in \mathcal{N} \setminus \mathcal{N}_c \\ 1 & \text{if } i \equiv j \text{ and } j \in \mathcal{N}_c \\ 0 & \text{otherwise} \end{cases}$$

$$[\mathbf{F}]_i = \begin{cases} (f, \tilde{N}_i) & \text{if } i \in \mathcal{N} \setminus \mathcal{N}_c \\ 0 & \text{otherwise} \end{cases}$$



The beauty of the approach is that we can assemble local matrix and RHS as

$$\forall i \in \mathcal{N} \setminus \mathcal{N}_c : \quad [\mathbf{F}]_i = (f, \tilde{N}_i) = (f, N_i + \sum_{j \in \mathcal{N}_c} c_{ji} N_j) = (f, N_i) + \sum_{j \in \mathcal{N}_c} c_{ji} (f, N_j) = [\tilde{\mathbf{F}}]_i + \sum_{j \in \mathcal{N}_c} c_{ji} [\tilde{\mathbf{F}}]_j$$



Using constraints:

- The beauty of the FEM is that we do exactly the same thing on every cell
- In other words: assembly on cells with hanging nodes should work exactly as on cells without



Approach 1:

$$\widetilde{\mathcal{S}}^h = \{u^h = \sum_i u_i N_i(x)\}$$

this is not a continuous space, but we may still use it as an intermediate step for matrices!

$$\mathcal{S}^h = \{u^h = \sum_i u_i N_i(x) : u^h(x) \in C^0\}$$

Step 1: Build matrix/rhs $\widetilde{\mathbf{K}}, \widetilde{\mathbf{F}}$ with all DoFs as if there were no constraints.

Step 2: Modify $\widetilde{\mathbf{K}}, \widetilde{\mathbf{F}}$ to get \mathbf{K}, \mathbf{F}

i.e. eliminate the rows and columns of the matrix that correspond to constrained degrees of freedom

Step 3: Solve $\mathbf{K} \cdot \mathbf{u} = \mathbf{F}$

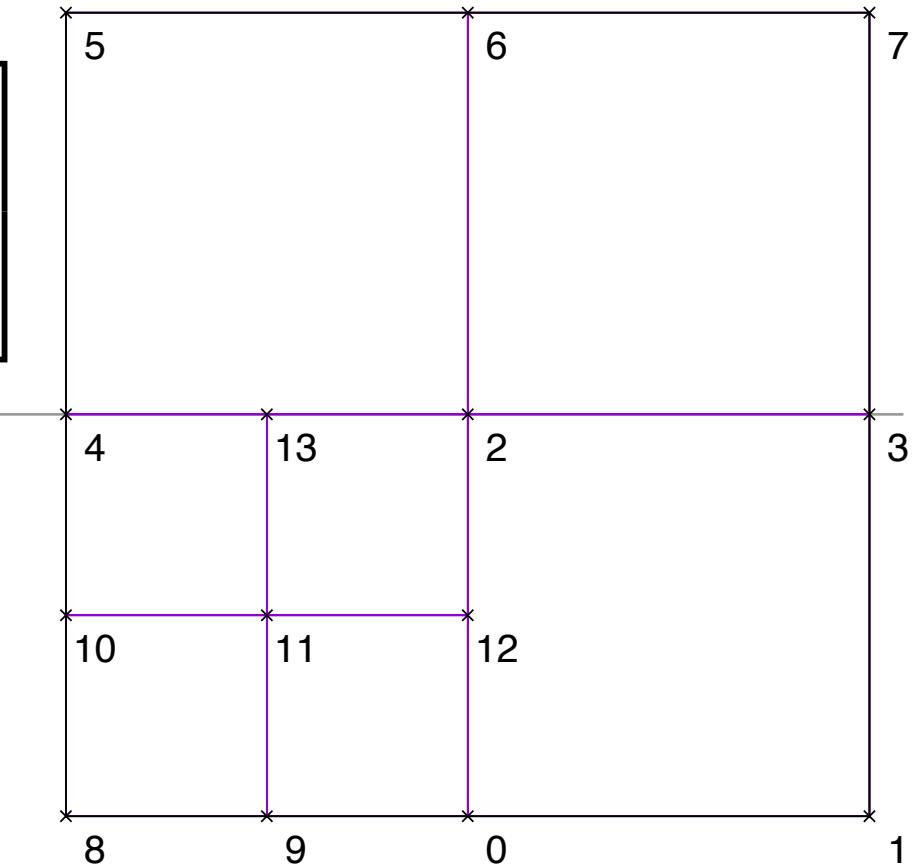
Step 4: Fill in the constrained components of \mathbf{u} to use \mathcal{S}^h for evaluation of the field.

Disadvantages: (i) bottleneck for 3d or higher order/hp FEM; (ii) hard to implement in parallel where a



Approach 1 (example).

$$\begin{bmatrix} u_{12} \\ u_{13} \end{bmatrix} = \begin{bmatrix} 0.5 & 0.5 & 0 \\ 0 & 0.5 & 0.5 \end{bmatrix} \begin{bmatrix} u_0 \\ u_2 \\ u_4 \end{bmatrix}$$



```

=====
Number of active cells: 7
Number of degrees of freedom: 14
===== constraints =====
 12 0: 0.5
 12 2: 0.5
 13 2: 0.5
 13 4: 0.5
===== un-condensed =====
===== matrix =====
 1.333e+00 -1.667e-01 -1.667e-01 -3.333e-01 0.000e+00 -1.667e-01 -3.333e-01 -1.667e-01
-1.667e-01 6.667e-01 -3.333e-01 -1.667e-01 0.000e+00 0.000e+00 -3.333e-01 -1.667e-01 -1.667e-01
-1.667e-01 -3.333e-01 2.667e+00 -3.333e-01 -1.667e-01 -3.333e-01 -3.333e-01 -1.667e-01
-3.333e-01 -1.667e-01 -3.333e-01 1.333e+00 -3.333e-01 -1.667e-01 -1.667e-01 -1.667e-01
 0.000e+00 -1.667e-01 1.333e+00 -1.667e-01 -3.333e-01 -3.333e-01 -1.667e-01 -1.667e-01
-3.333e-01 -1.667e-01 -1.667e-01 6.667e-01 -1.667e-01 -1.667e-01 -1.667e-01 -1.667e-01
-3.333e-01 -3.333e-01 -3.333e-01 -3.333e-01 -1.667e-01 1.333e+00 -1.667e-01
-3.333e-01 -1.667e-01 -1.667e-01 -1.667e-01 -1.667e-01 -1.667e-01 6.667e-01
-1.667e-01 0.000e+00 0.000e+00 -1.667e-01 -1.667e-01 -1.667e-01 -1.667e-01 -3.333e-01
-3.333e-01 -3.333e-01 -3.333e-01 -3.333e-01 -3.333e-01 -3.333e-01 -3.333e-01 -3.333e-01
-1.667e-01 -1.667e-01 -1.667e-01 -1.667e-01 -1.667e-01 -1.667e-01 -1.667e-01 -1.667e-01
-1.667e-01 -1.667e-01 -1.667e-01 -1.667e-01 -1.667e-01 -1.667e-01 -1.667e-01 -1.667e-01
===== condensed =====
===== matrix =====
 1.500e+00 -1.667e-01 -8.333e-02 -3.333e-01 -8.333e-02 -3.333e-01 -5.000e-01 0.000e+00
-1.667e-01 6.667e-01 -3.333e-01 -1.667e-01 0.000e+00 0.000e+00 0.000e+00 0.000e+00
-8.333e-02 -3.333e-01 2.833e+00 -3.333e-01 -8.333e-02 -3.333e-01 -3.333e-01 -3.333e-01
-3.333e-01 -1.667e-01 -3.333e-01 1.333e+00 -3.333e-01 -1.667e-01 0.000e+00 0.000e+00
-8.333e-02 -8.333e-02 1.500e+00 -1.667e-01 -3.333e-01 -3.333e-01 -3.333e-01 -3.333e-01
-3.333e-01 -3.333e-01 -1.667e-01 6.667e-01 -1.667e-01 -1.667e-01 -1.667e-01 -1.667e-01
-3.333e-01 -3.333e-01 -3.333e-01 -3.333e-01 -1.667e-01 1.333e+00 -1.667e-01
-3.333e-01 -1.667e-01 -1.667e-01 -1.667e-01 -1.667e-01 -1.667e-01 6.667e-01
-3.333e-01 -1.667e-01 -1.667e-01 -1.667e-01 -1.667e-01 -1.667e-01 -1.667e-01 -1.667e-01
-1.667e-01 -1.667e-01 -1.667e-01 -1.667e-01 -1.667e-01 -1.667e-01 -1.667e-01 -1.667e-01
-1.667e-01 -1.667e-01 -1.667e-01 -1.667e-01 -1.667e-01 -1.667e-01 -1.667e-01 -1.667e-01
-5.000e-01 -6.667e-01 -5.000e-01 0.000e+00 0.000e+00 0.000e+00 1.333e+00 0.000e+00
 0.000e+00 0.000e+00 0.000e+00 0.000e+00 0.000e+00 0.000e+00 0.000e+00 1.333e+00
 0.000e+00 0.000e+00 0.000e+00 0.000e+00 0.000e+00 0.000e+00 0.000e+00 0.000e+00

```



Approach 2:

$$\widetilde{\mathcal{S}}^h = \{u^h = \sum_i u_i N_i(x)\}$$

$$\mathcal{S}^h = \{u^h = \sum_i u_i N_i(x) : u^h(x) \in C^0\}$$

Step 1: Build local matrix/rhs $\widetilde{\mathbf{K}}_K, \widetilde{\mathbf{F}}_K$ with all DoFs as if there were no constraints.

Step 2: Apply constraints during assembly operation (local-to-global) $\mathbf{K}_K, \mathbf{F}_K$

Step 3: Solve $\mathbf{K} \cdot \mathbf{u} = \mathbf{F}$

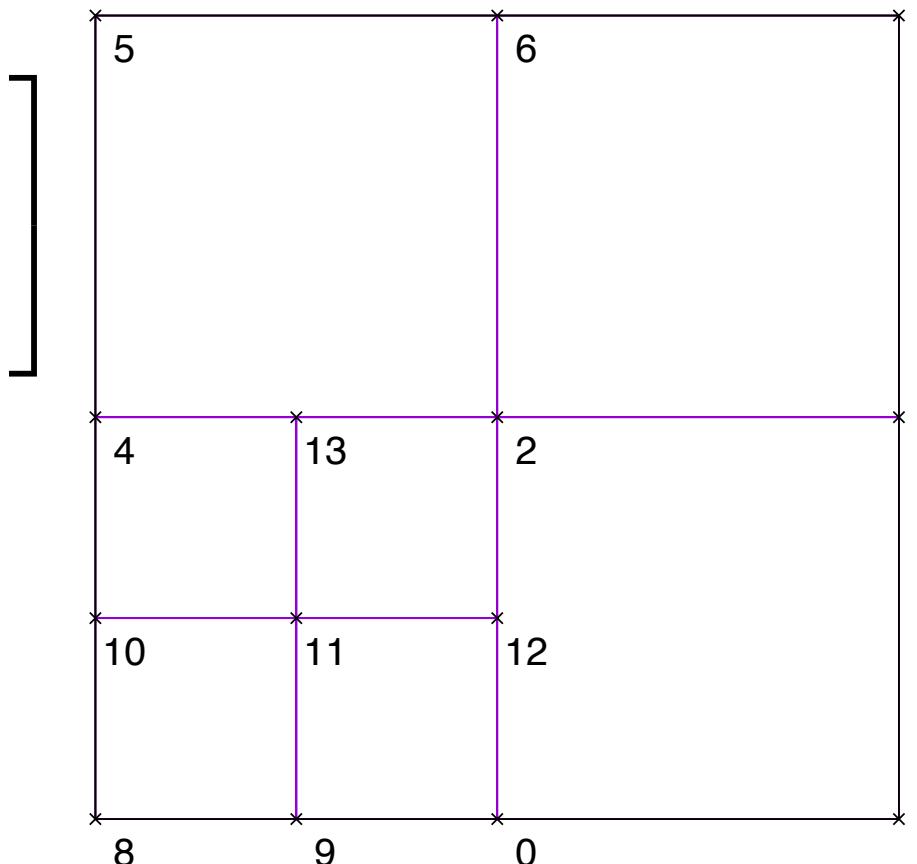
Step 4: Fill in the constrained components of \mathbf{u} to use $\widetilde{\mathcal{S}}^h$ for evaluation of the field.



Approach 2 (example):

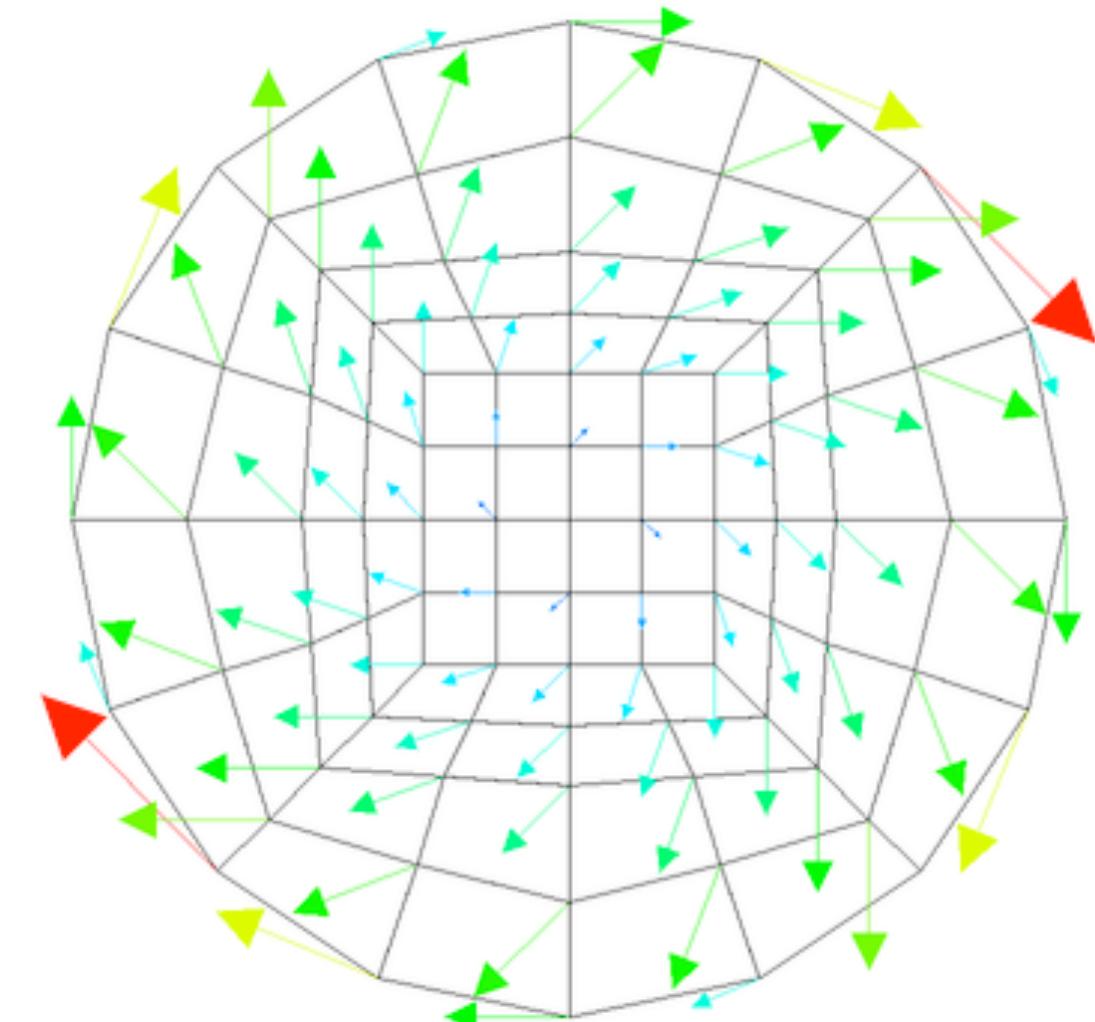
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 -8.333e-02 -3.333e-01 2.833e+00 -3.333e-01 -8.333e-02 -3.333e-01 -3.333e-01 -3.333e-01
 -3.333e-01 -1.667e-01 -3.333e-01 1.333e+00
 -8.333e-02 -8.333e-02 1.500e+00 -1.667e-01 -3.333e-01
 -3.333e-01 -1.667e-01 6.667e-01 -1.667e-01
 -3.333e-01 -3.333e-01 -3.333e-01 -1.667e-01 1.333e+00 -1.667e-01
 -3.333e-01 -1.667e-01 -1.667e-01 6.667e-01
 -3.333e-01 -1.667e-01
 -3.333e-01 -1.667e-01
 -5.000e-01 -6.667e-01 -5.000e-01
 0.000e+00 0.000e+00
 0.000e+00 0.000e+00
 -3.333e-01 -1.667e-01 -1.667e-01 -3.333e-01
 -1.667e-01 1.333e+00 -3.333e-01 -3.333e-01 0.000e+00
 -1.667e-01 -3.333e-01 1.333e+00 -3.333e-01 0.000e+00
 -3.333e-01 -3.333e-01 -3.333e-01 2.667e+00 0.000e+00 0.000e+00
 0.000e+00 0.000e+00 1.333e+00 0.000e+00
 0.000e+00 0.000e+00 0.000e+00 1.333e+00
```



Applying constraints: the `AffineConstraints` class

- This class is used for
 - Hanging nodes
 - Dirichlet and periodic constraints
 - Other constraints
- Linear constraints of the form $u_C = Cu_O + b$



Applying constraints: the AffineConstraints class

- System setup
 - Hanging node constraints created using
`DoFTools::make_hanging_node_constraints()`
 - Will also use for boundary values from now on:
`VectorTools::interpolate_boundary_values(..., constraints);`
 - Need different SparsityPattern creator
`DoFTools::make_sparsity_pattern(..., constraints, ...)`
 - Can remove constraints from linear system
`DoFTools::make_sparsity_pattern(..., constraints,
/ *keep_constrained_dofs = */ false)`
 - Sort, rearrange, optimise constraints
`constraints.close()`



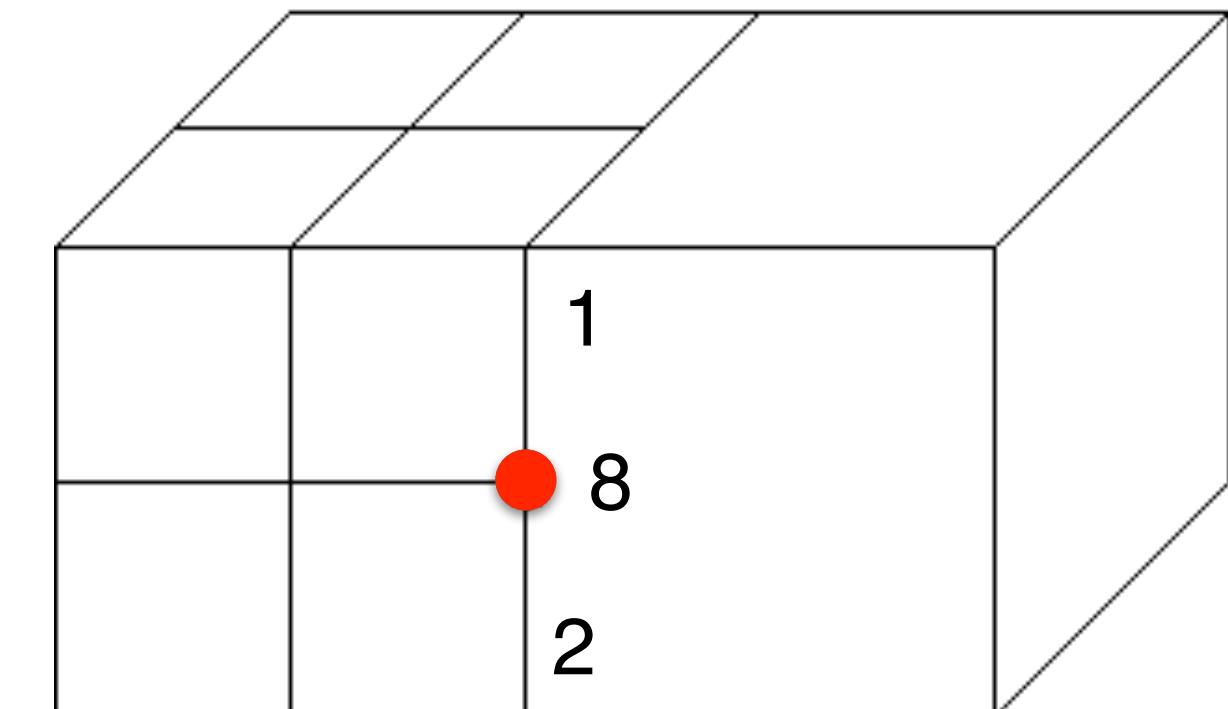
Applying constraints: the AffineConstraints class

- Assembly
 - Assemble local matrix and vector as normal
 - Eliminate while transferring to global matrix:
`constraints.distribute_local_to_global (`
 `cell_matrix, cell_rhs,`
 `local_dof_indices,`
 `system_matrix, system_rhs);`
 - Solve and then set all constraint values correctly:
`ConstraintMatrix::distribute(...)`



Applying constraints: Conflicts

- When writing into a `AffineConstraints`, existing constraints are not overwritten.
- Can merge constraints together:
`constraints.merge (other_constraints,
MergeConflictBehavior::left_object_wins);`
- Which is right? $u_8 = \bar{u}$ or
$$u_8 = \frac{1}{2} [u_1 + u_2]$$
- Careful on loops: $u_1 = u_2 ; u_2 = u_3 ; u_3 = u_1$



Numerical Methods for the Solution of PDEs

Laboratory with deal.II – www.dealii.org

Numerical Solution of PDEs using the Finite Element Method

Luca Heltai <luca.heltai@unipi.it>

<https://luca-heltai.github.io/nmpde>
<https://github.com/luca-heltai/nmpde>

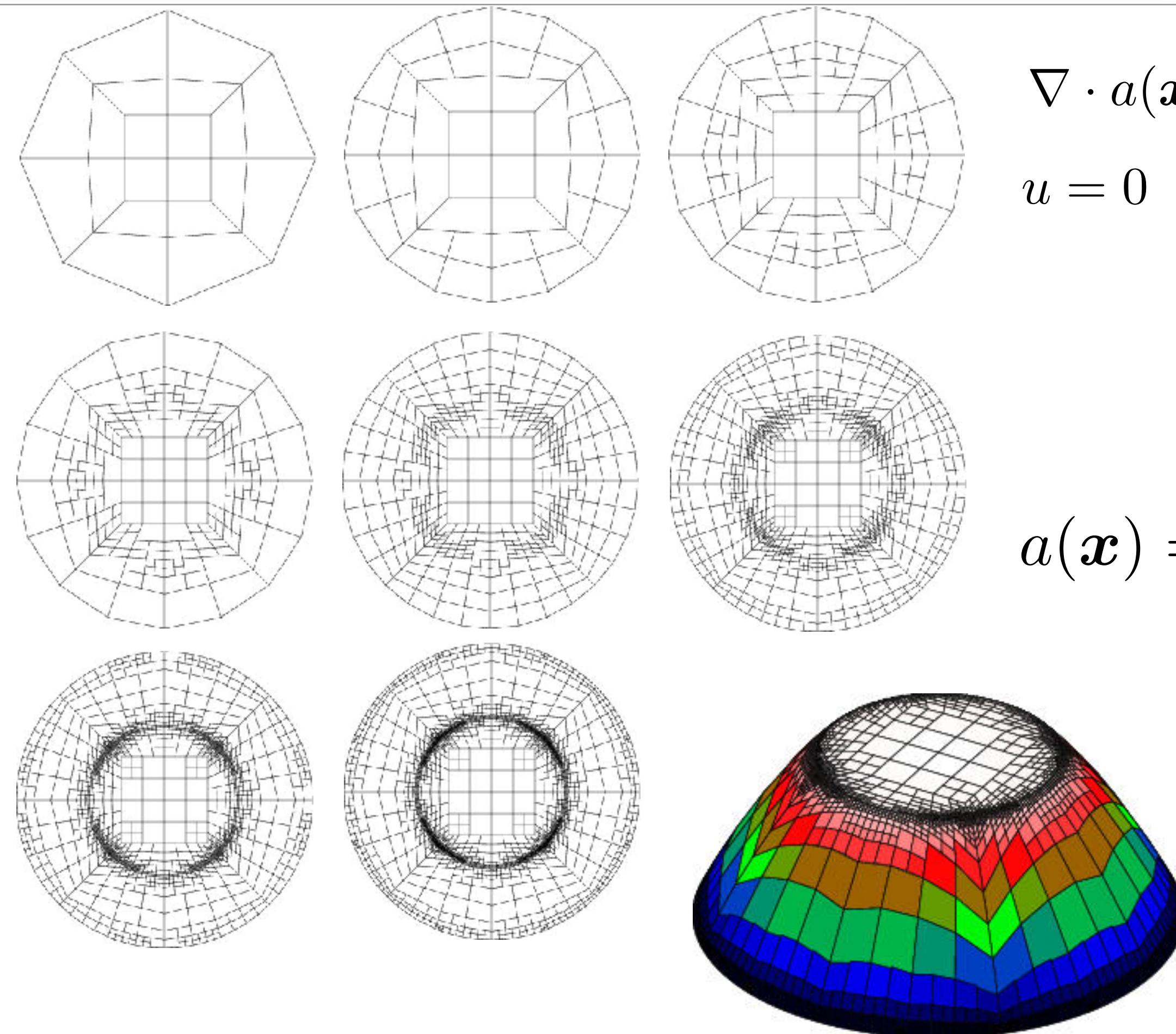
A posteriori error estimates and adaptive me...



Adaptive mesh refinement

- Typical steps to perform adaptivity
 - Solve (non-)linear system
 - Estimate error
 - Mark cells
 - Refine/coarsen
 - Interpolate original solution to new mesh

Need an error indicator
on each cell without
knowing the exact
solution. η_K



$$\begin{aligned}\nabla \cdot a(\mathbf{x}) \nabla u(\mathbf{x}) &= 1 && \text{in } \Omega \\ u &= 0 && \text{on } \partial\Omega\end{aligned}$$

$$a(\mathbf{x}) = \begin{cases} 20 & \text{if } |\mathbf{x}| < 0.5 \\ 1 & \text{otherwise} \end{cases}$$



Adaptive mesh refinement

Error estimate for Q1/P1 elements applied to Laplace problem:

$$\|u - u^h\|_{H^1} \equiv \|e\|_{H^1} \leq C h_{max} \|u\|_{H^2}$$

this error depends on the largest element size and the global norm of the solution.

To reduce error (increase accuracy) one can refine the mesh size.

more precisely...

$$\|e\|_{H^1}^2 \leq C^2 \sum_K h_K^2 |u|_{H^2(K)}^2$$

Thus one needs to make mesh finer where the local H^2 semi-norm is large.

But apart from some special cases we don't know the exact solution u !

Thus we need to create meshes iteratively (adaptively).

Optimal strategy is to equilibrate the error $e_K := C h_K |u|_{H^2(K)}$

$$\begin{aligned}\|u\|_{H^2(K)}^2 &:= \int_K u^2 + |\nabla u|^2 + |\nabla^2 u|^2 \\ |u|_{H^2(K)}^2 &:= \int_K |\nabla^2 u|^2\end{aligned}$$

That is, we want to choose

$$h_K \sim \frac{1}{|u|_{H^2(K)}}$$



a-posteriori error estimation

$$\|e\|_{H^1(\Omega)}^2 \leq C \sum_K e_K^2$$

$$e_K = h_K \|\nabla^2 u\|_K$$

cell-wise error indicators

(**wrong**) idea:

$$e_K \approx h_K \|\nabla^2 u^h\|_K$$

will not work as linear elements have zero second derivatives within the element and first derivatives have jumps on the interfaces

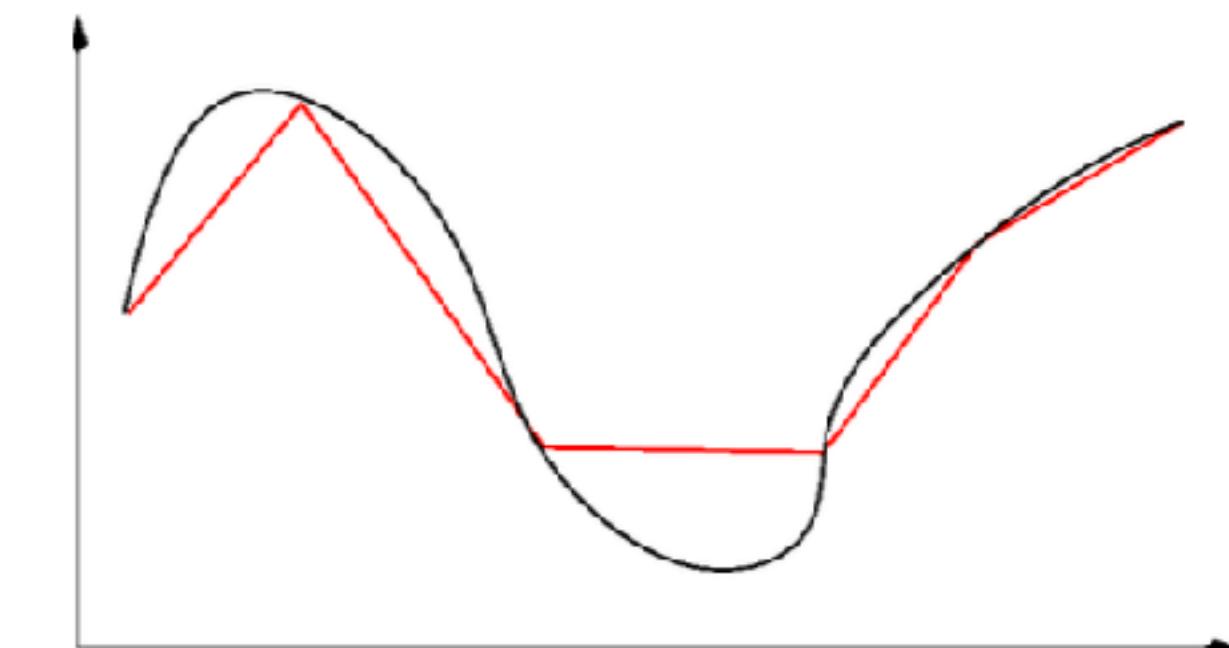
a better idea (in 1D) to approximate second derivatives at interface i:

$$\nabla^2 u \approx \frac{\nabla u^h(x^+) - \nabla u^h(x^-)}{h} =: \llbracket \nabla u^h \rrbracket_i$$

can generalize to:

$$\|\nabla^2 u\|_K^2 \approx \sum_{i \in \partial K} \frac{\llbracket \nabla u^h \rrbracket_i^2}{h}$$

use jump in gradient as an indicator
of the second derivative at vertices



a-posteriori error estimation

As a result, the simplest and most widely used Kelly error **indicator** in 2D/3D follows:

$$e_K^2 = h_K^2 \|\nabla^2 u\|_K^2 \approx h_K \int_{\partial K} |[\![\nabla u \cdot n]\!]|^2 ds =: \eta_K^2$$

For the Laplace equation, **Kelly, de Gago, Zienkiewicz, Babushka (1983)** proved that

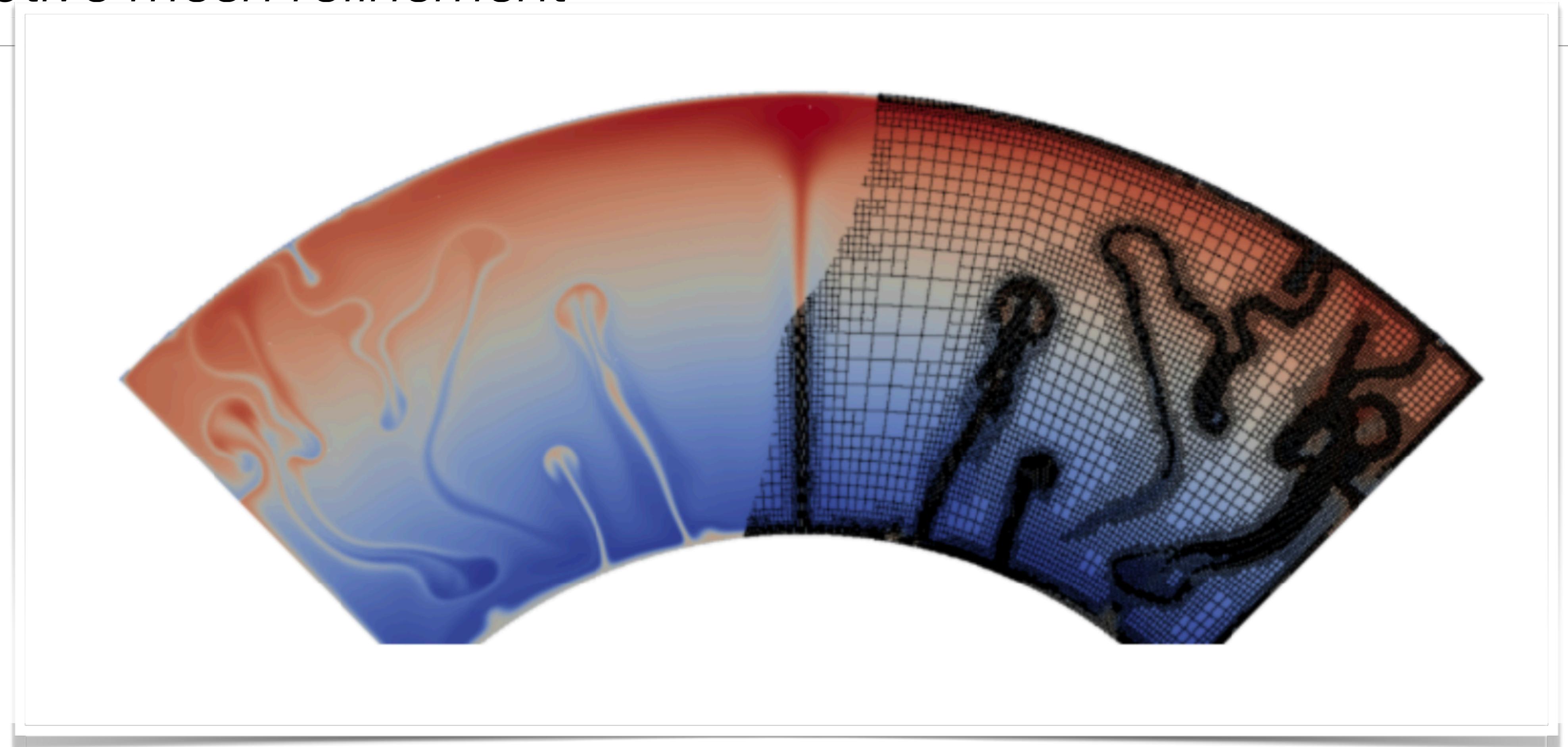
$$\|\nabla [u - u^h]\|^2 \leq C \sum_K \eta_K^2 \quad \text{a-posteriori error estimator} \quad (*)$$

Note I:

“**estimator**” is always a proven upper bound of error (*), whereas “**indicator**” is our best guess of error per cell which may not be an upper bound in the sense (*), but may still work well for considered equations and/or FE space.



Adaptive mesh refinement



Refine where things are happening!
UNIVERSITÀ DI PISA



Basic AFEM algorithm

- SOLVE-ESTIMATE-MARK-REFINE
 - On the current mesh, solve the problem
 - Estimate the error per cell (Exact, Kelly, Residual, etc.)
 - Mark cells according to given criterion (estimator is greater than a tolerance, or fraction of cells with largest error, or ...)
 - Refine the marked cells
- Repeat until tolerance met, or max number of cycles



deal.II classes

- Error estimate is problem dependent:
 - Approximate gradient jumps: `KellyErrorEstimator` class
 - Approximate local norm of gradient: `DerivativeApproximation` class
 - ... or something else
- Cell marking strategy:
 - `GridRefinement::refine_and_coarsen_fixed_number(...)`
 - `GridRefinement::refine_and_coarsen_fixed_fraction(...)`
 - `GridRefinement::refine_and_coarsen_optimize(...)`
- Refine/coarsen grid: `triangulation.execute_coarsening_and_refinement()`
- Transferring the solution: `SolutionTransfer` class (discussed later)

