1 Background

Learning aggregation for 3D anisotropic diffusion on a structured grid

$$-\nabla \cdot (\mathbf{D}\nabla u) = 0, \tag{1}$$

$$\boldsymbol{D} := \boldsymbol{R}^T \begin{bmatrix} \varepsilon_x & & \\ & \varepsilon_y & \\ & & 1 \end{bmatrix} \boldsymbol{R}, \tag{2}$$

$$\boldsymbol{R} := \begin{bmatrix} \cos \theta_z & -\sin \theta_z & 0\\ \sin \theta_z & \cos \theta_z & 0\\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \cos \theta_y & 0 & \sin \theta_y\\ 0 & 1 & 0\\ -\sin \theta_y & 0 & \cos \theta_y \end{bmatrix}. \tag{3}$$

For now, this is on the specific problem for $N_x = N_y = N_z = 12$ (number of elements in each dimension), $\theta_z = 1.11\pi$, $\theta_y = 0.58\pi$, $\varepsilon_x = 0.001$, $\varepsilon_y = 1000.0$.

This was discretized in Firedrake [2] using piecewise linear tetrahedral finite elements with homogeneous Dirichlet boundary conditions. Afterwards, the degrees-of-freedom corresponding to the Dirichlet boundary were removed from the system. Overall, there are $11 \times 11 \times 11 = 1331$ degrees of freedom total.

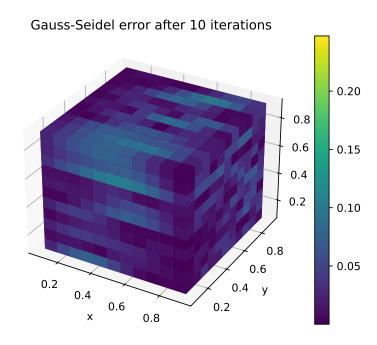


Figure 1: Error behavior on the problem with a random initial guess, solving Ax = 0 with Gauss-Seidel iterations. The direction and strength of anisotropy are visible by looking at in which areas the error is geometrically smooth.

References

[1] L. N. OLSON AND J. B. SCHRODER, *Pyamg: Algebraic multigrid solvers in python v4.0.* https://github.com/pyamg/pyamg, 2018. Release 4.0.

Lloyd Aggregation, conv=0.8447

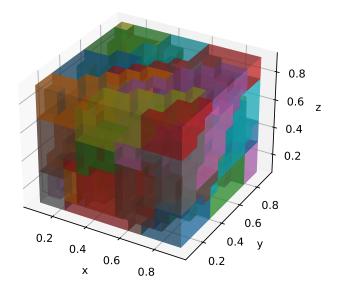


Figure 2: Aggregate selection when using PyAMG's (regular) Lloyd aggregation [1].

Generation 23, ML AMG, conv=0.8279

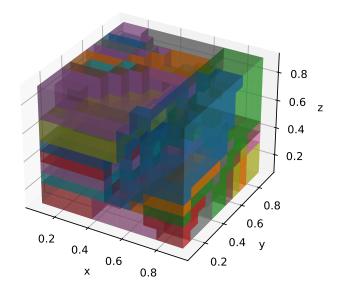


Figure 3: Aggregate selection from the ML method. This is trained on the specific problem being shown.

[2] F. RATHGEBER, D. A. HAM, L. MITCHELL, M. LANGE, F. LUPORINI, A. T. T. MCRAE, G. BERCEA, G. R. MARKALL, AND P. H. J. KELLY, Firedrake: automating the finite element method by composing abstractions, CoRR, abs/1501.01809 (2015).