
Adaptive Source Term Iteration

– A Stable Formulation for Radiative Transfer –

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IGPM, RWTH Aachen

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(mono-energetic) Radiative Transfer Problem

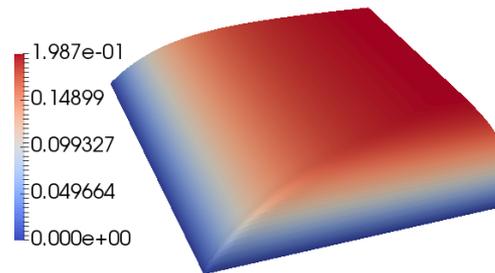
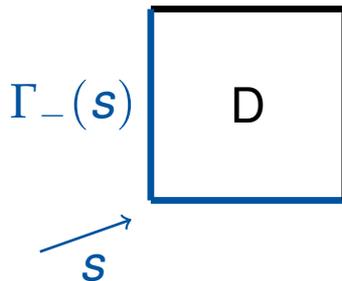
We are looking for a particle density $u \in L_2(D \times S)$ satisfying

$$\begin{aligned} (\mathcal{T}_S - \mathcal{K}_S)u(x, s) &= f(x, s) && \text{in } D \times S \\ u &= g && \text{on } \Gamma_- \end{aligned}$$

with

$$\mathcal{T}_S u(x, s) := s \cdot \nabla u(x, s) + \sigma(x, s)u(x, s)$$

$$\mathcal{K}_S u(x, s) := \int_S k(x, s', s)u(x, s') ds'$$



(mono-energetic) Radiative Transfer Problem

Obstructions

- high dimensional ($n = 2, 3$ dimensional space + $n - 1$ dimensional transport direction)
- global scattering kernel
- reliable error estimates?
 - a priori error estimates often require unrealistic regularity assumptions on the solution
 - a posteriori estimates
 - ▶ error control of the solution
 - ▶ adaptive grid refinement

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$$u_0 = 0$$

$$u_{n+1} = \mathcal{T}_S^{-1}(\mathcal{K}_S u_n + f), \quad n = 0, 1, 2, \dots$$

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- In the iterations:
 - Accuracy in solution of transport problems is dynamically increased across iterations
→ Need for tight error bounds to avoid adding unnecessary numerical effort \rightsquigarrow DPG [Broersen et al., 2017]
 - Repeated application of \mathcal{K}_S with increased accuracy \rightsquigarrow Compression techniques.

The Henyey–Greenstein Kernel

We explain how to approximate

$$\mathcal{K}v(x, s) = \int_{\mathcal{S}} k(s, s') v(x, s') \, ds'$$

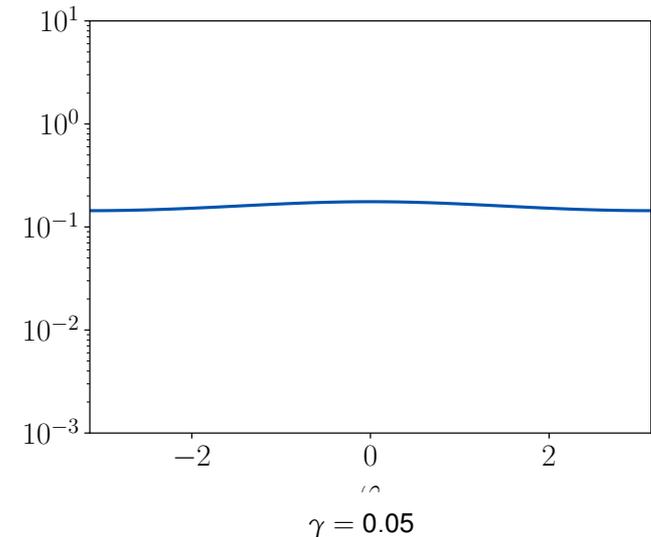
with the model kernel of Henyey and Greenstein [1941]

$$k(s, s') = k(\underbrace{s \cdot s'}_{=\cos \theta}) := \frac{1}{2\pi} \frac{1 - \gamma^2}{1 + \gamma^2 - 2\gamma s \cdot s'}$$

where $\gamma \in (-1, 1)$.

The example illustrates the following issue:

- A **naive** approximation of $\mathcal{K}v$ with quadratures entails a **quadratic cost** in the number of directions.
- One can diminish this cost by exploiting **sparsity**.
- We illustrate how to achieve this depending on γ .



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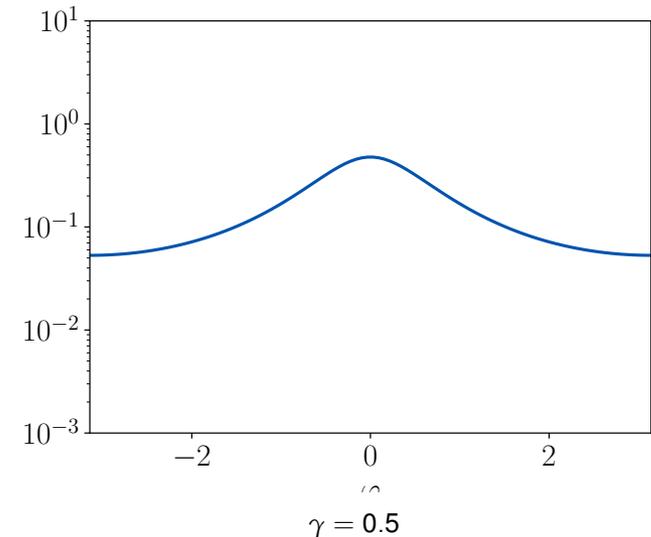
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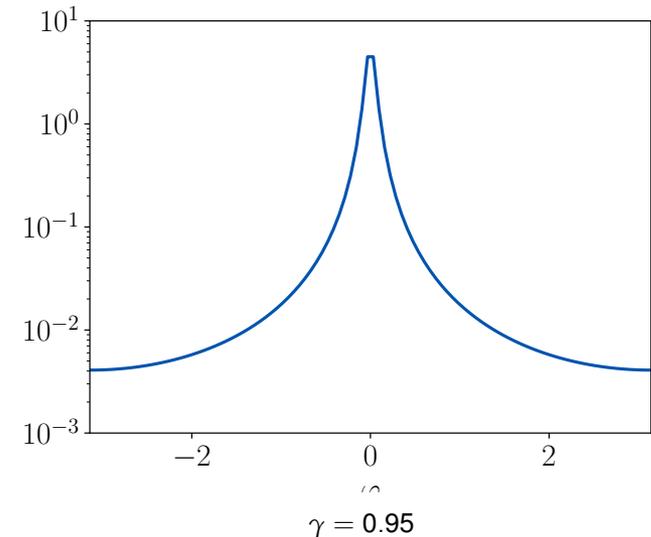
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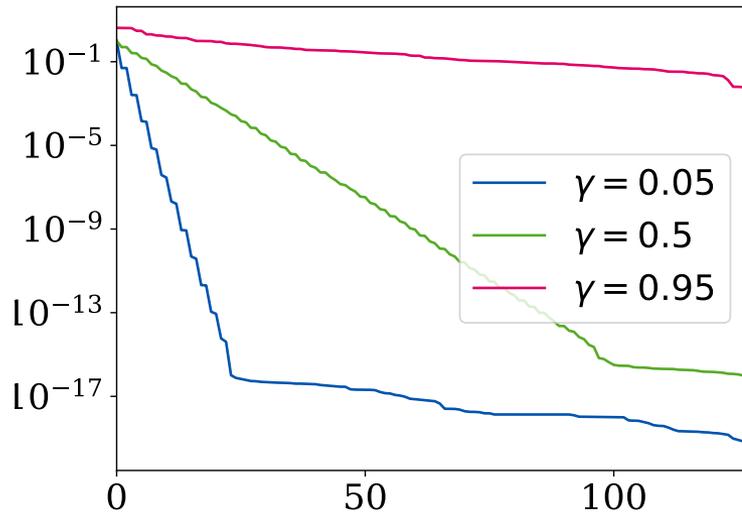
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Low-Rank Approximation of the Henyey–Greenstein Kernel

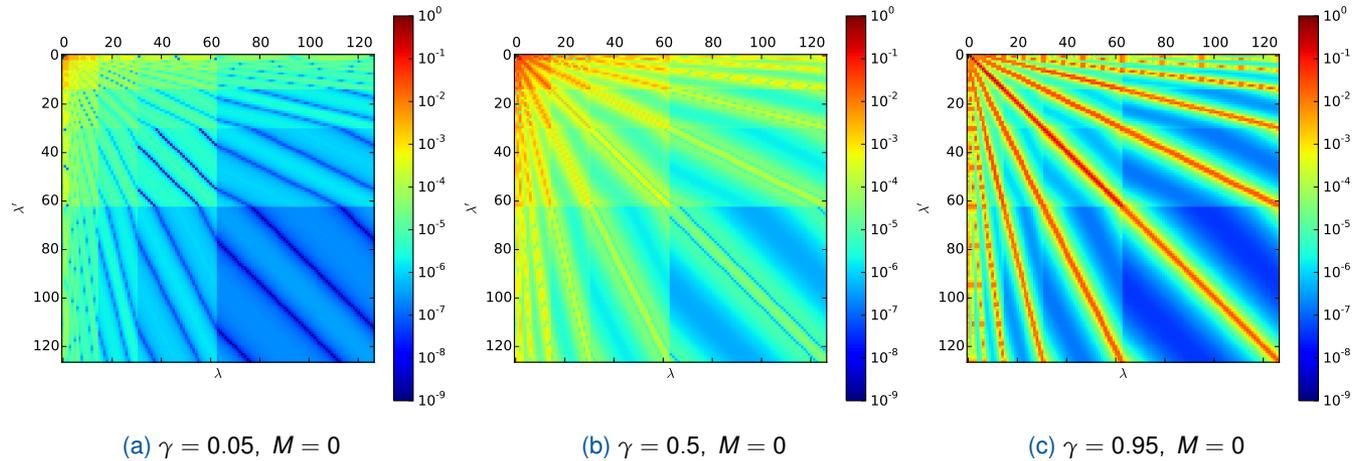


Singular values of Henyey–Greenstein kernel.

$$K \approx U \Sigma V^T$$

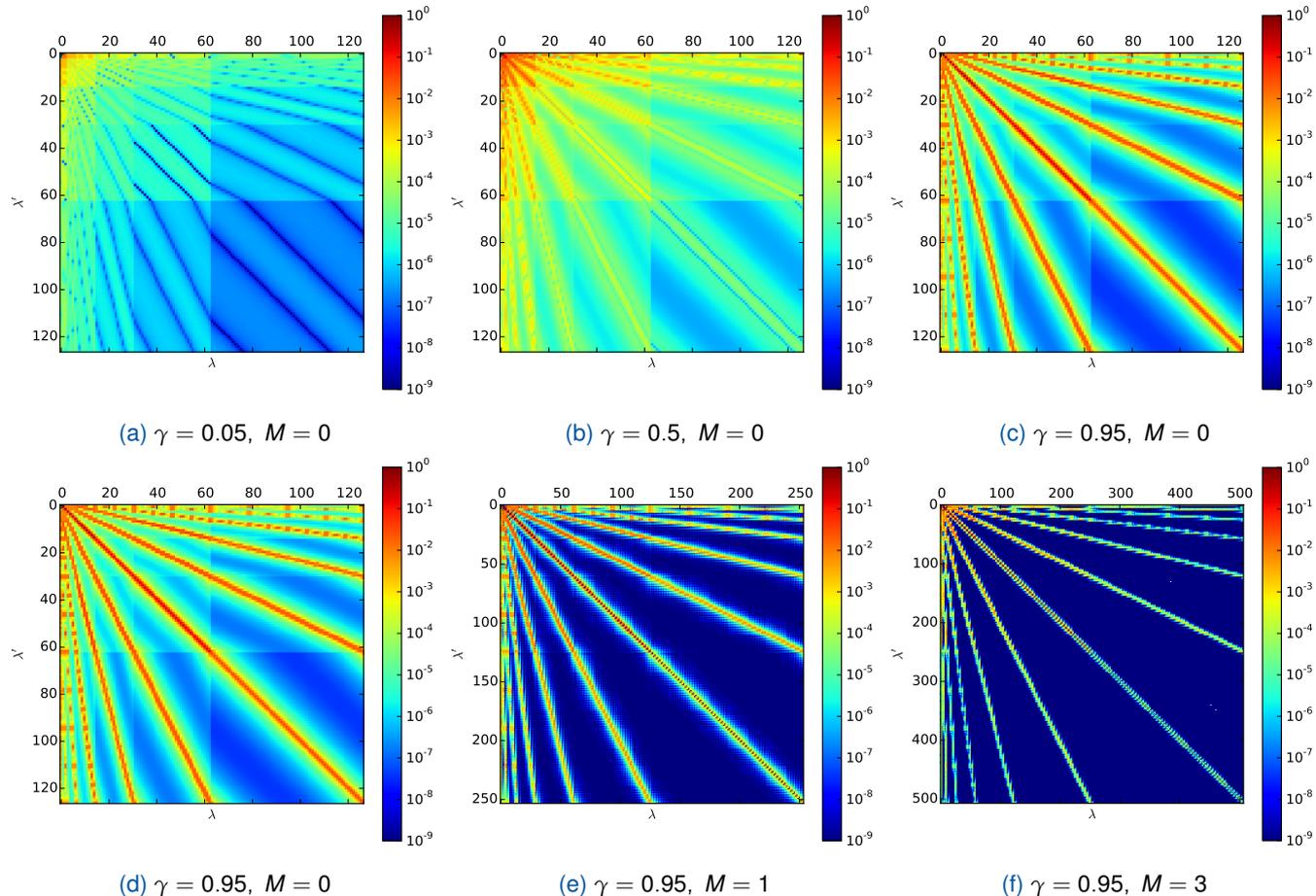
Low-rank approximation,
accurate for small γ .

Wavelet Approximation of the Henyey–Greenstein Kernel



When $\gamma \rightarrow 1$, the matrix $(k_{\lambda,\lambda'})_{\lambda,\lambda'}$ becomes quasi-sparse and we can apply compression techniques to efficiently apply the kernel.

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Solving the Transport Part

In our ideal iteration, we need to solve transport problems of the type

$$\mathcal{T}_s u = s \cdot \nabla u + \sigma u = f.$$

To obtain reliable a posteriori error estimates, we solve this equation using a Discontinuous Petrov–Galerkin method.

Stable Variational Formulations

Given a variational formulation:

Find $u \in \mathcal{U}$ such that

$$b(u, v) = \ell(v) \quad \text{for all } v \in \mathcal{V}$$

for Hilbert spaces $(\mathcal{U}, \|\cdot\|_{\mathcal{U}})$, $(\mathcal{V}, \|\cdot\|_{\mathcal{V}})$, continuous bilinear form $b : \mathcal{U} \times \mathcal{V} \rightarrow \mathbb{R}$ and $\ell \in \mathcal{V}'$.

Goal: Stability

[see e. g. Demkowicz and Gopalakrishnan, 2015; Barrett and Morton, 1984; Ern and Guermond, 2004]

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- Discrete approximation yields a best approximation (up to a constant)

$$\|u - u_h\|_{\mathcal{U}} \leq \kappa_{\mathcal{U}, \mathcal{V}'}(\mathcal{B}_h) \inf_{w_h \in \mathcal{U}_h} \|u - w_h\|_{\mathcal{U}} .$$

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- Residual-based error bound

$$\|u - u_h\|_{\mathcal{U}} \simeq \|b(u_h, \cdot) - \ell\|_{\mathcal{V}'} .$$

[see e. g. Demkowicz and Gopalakrishnan, 2015; Barrett and Morton, 1984; Ern and Guermond, 2004]

Stable Variational Formulations

- For elliptic problems we can set $\mathcal{V} = \mathcal{U}$. Then coercivity

$$b(u, u) \geq c_B \|u\|_{\mathcal{U}}^2 \quad \forall u \in \mathcal{U}$$

gives us stability (Lax–Milgram / Céa lemma).

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$$\inf_{u \in \mathcal{U}} \sup_{v \in \mathcal{V}} \frac{b(u, v)}{\|u\|_{\mathcal{U}} \|v\|_{\mathcal{V}}} \geq c_B > 0.$$

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This needs to be checked for the finite dimensional discretization, as it does not automatically carry over from the infinite dimensional setting!

[see e. g. Demkowicz and Gopalakrishnan, 2015; Barrett and Morton, 1984; Ern and Guermond, 2004]

Choose \mathcal{U}_h to Ensure Good Approximation Properties, Choose \mathcal{V}_h to Ensure Stability

How to choose \mathcal{V}_h for given \mathcal{U}_h ?

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$$\|\cdot\|_{\mathcal{V},opt} := \sup_{u \in \mathcal{U}} \frac{b(u, v)}{\|u\|_{\mathcal{U}}}$$

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$$\langle T(u_h), v \rangle_{\mathcal{V},opt} = b(u_h, v), \quad \forall v \in \mathcal{V}$$

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- This yields

- residual based error bound

$$\|u_h - u\|_{\mathcal{U}} = \|b(u_h, \cdot) - \ell\|_{\mathcal{V}',opt}$$

- best approximation property

$$\|u - u_h\|_{\mathcal{U}} = \inf_{w_h \in \mathcal{U}_h} \|u - w_h\|_{\mathcal{U}}$$

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Computation of the Optimal Test Space

We have to compute \mathcal{V}_h by solving

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We can compute an approximation for \mathcal{V}_h by solving

$$\langle \hat{T}(u_h), v \rangle_{\mathcal{V}, K} = b_K(u_h, v), \quad \forall v \in \hat{\mathcal{V}}|_K,$$

where K is a single cell and $\langle \cdot, \cdot \rangle_{\mathcal{V}, K}$ and $b_K(\cdot, \cdot)$ denote restrictions to K .

[see e. g. Demkowicz and Gopalakrishnan, 2015; Broersen et al., 2017]

A Stable DPG Formulation of Linear Transport

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Ultra-weak formulation with $u \in L_2(\mathbf{D})$.

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Broken test space with broken norm

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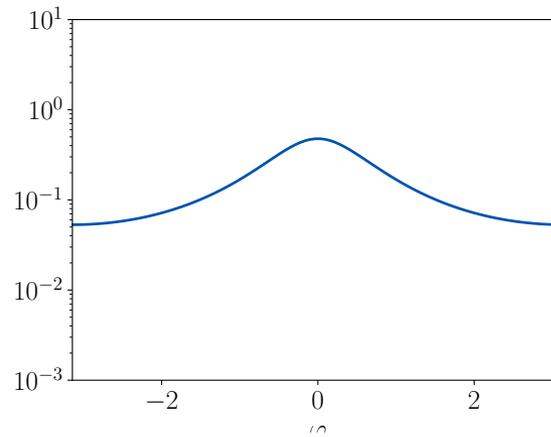
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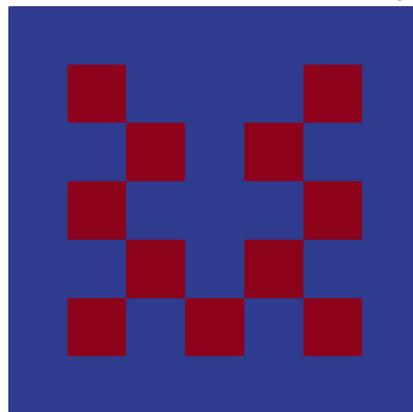
$$\|v\|_{H(\mathbf{s}; \mathbf{D}_h)} = \left(\sum_{T \in \mathbf{D}_h} \|v\|_{H(\mathbf{s}; K)}^2 \right)^{1/2}.$$

Broersen et al. [2017]: Fullfills requirements of Banach–Nečas–Babuška.

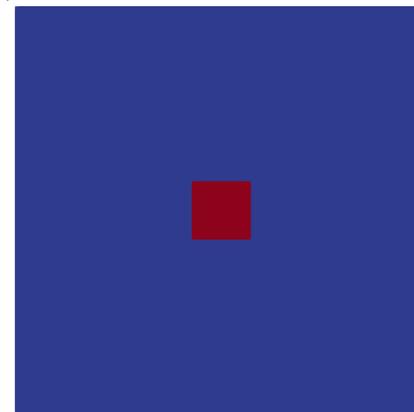
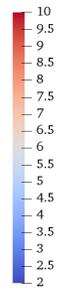
Checkerboard Example



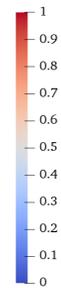
Henyey–Greenstein scattering with $\gamma = 0.5$



absorption coefficient σ



source term f



Data of the checkerboard benchmark problem

Checkerboard Example

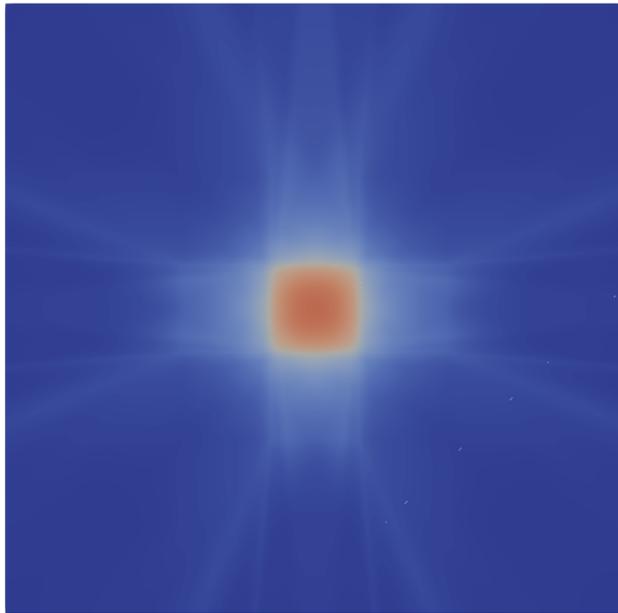
To reach target accuracy η in a step of the Source Term Iteration, we have some freedom in distributing the discretization errors:

- $\kappa_1\eta$: accuracy for kernel application
- $\kappa_2\eta$: accuracy for evaluation of source term f
- $\kappa_3\eta$: accuracy for transport solver

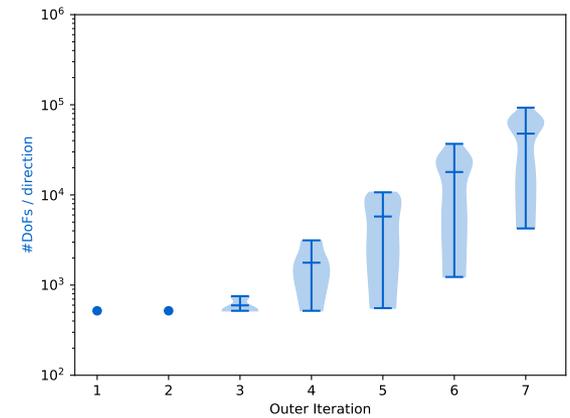
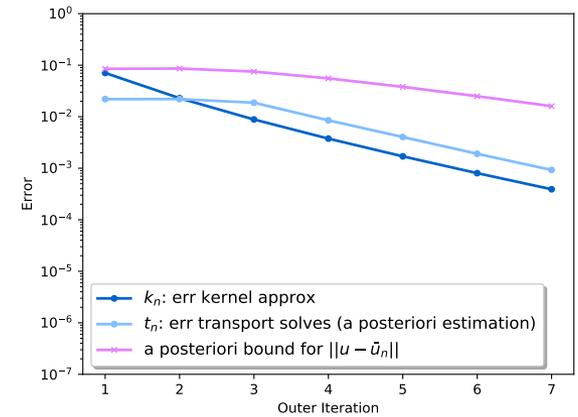
To guarantee convergence, the following restriction holds:

$$C_{\mathcal{T}}\kappa_1 + C_{\mathcal{T}}\kappa_2 + 2\kappa_3 \leq 1.$$

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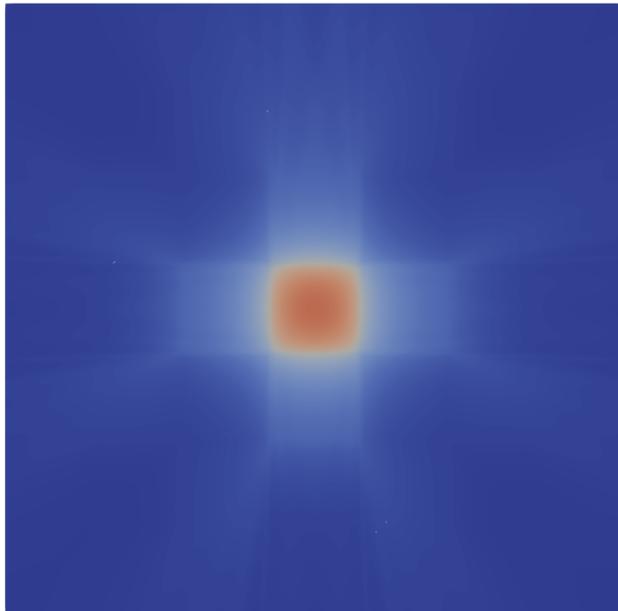


integrated solution

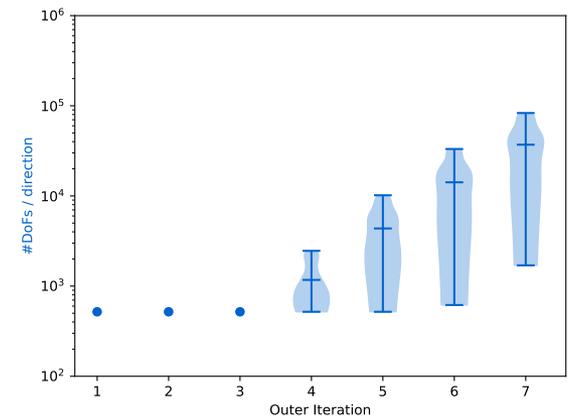
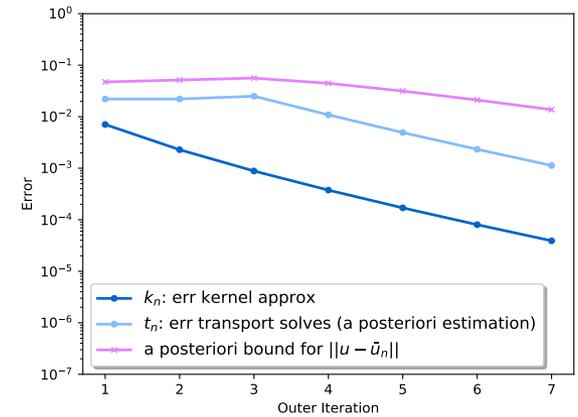
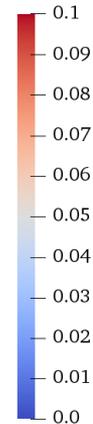


$$\kappa_1 = \theta / C_T, \kappa_2 = 0, \kappa_3 = (1 - \theta) / 2, \theta = 0.2$$

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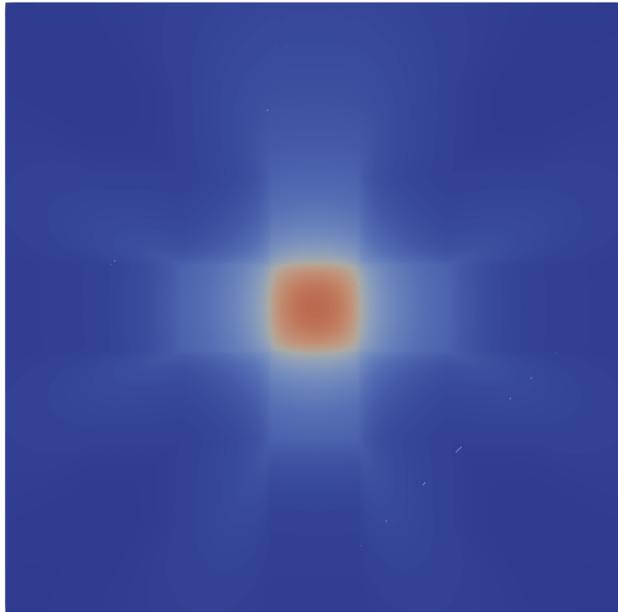


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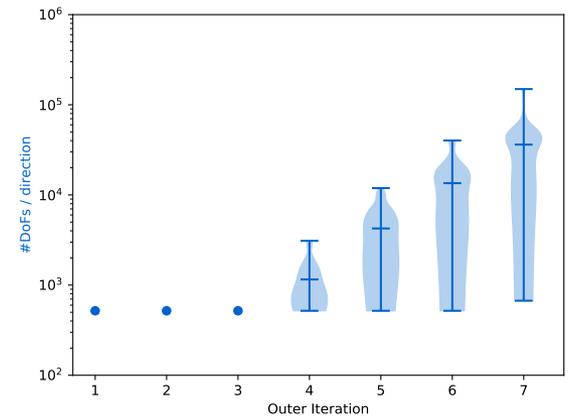
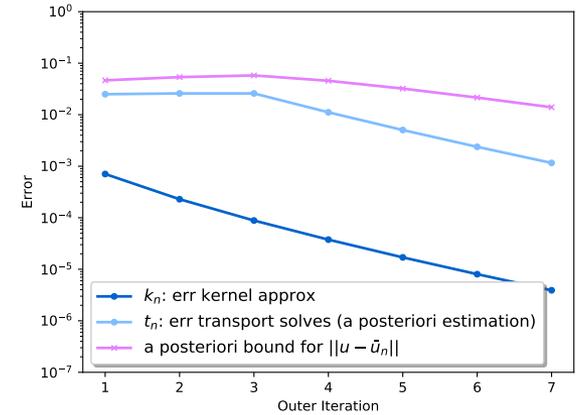


$$\kappa_1 = \theta / C_T, \kappa_2 = 0, \kappa_3 = (1 - \theta) / 2, \theta = 0.02$$

Checkerboard Example

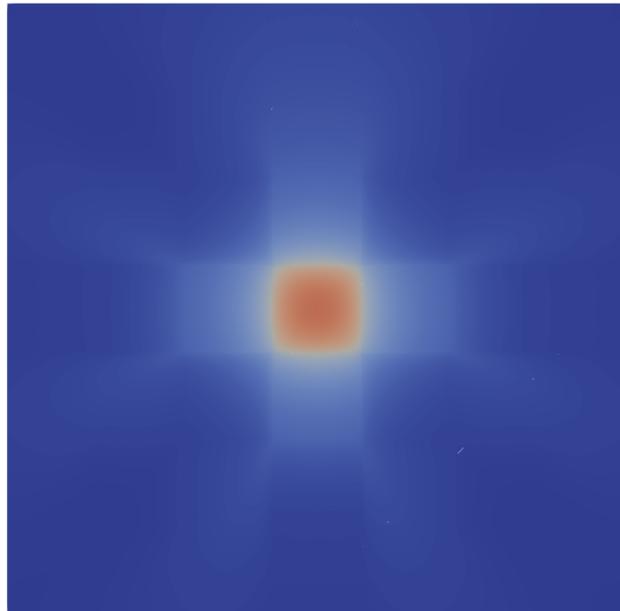


integrated solution

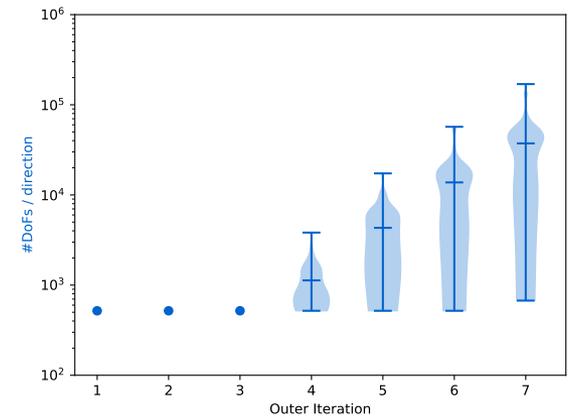
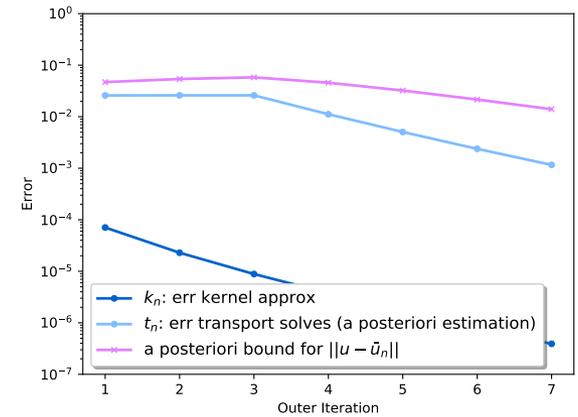
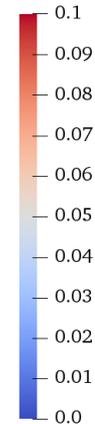


$$\kappa_1 = \theta / C_T, \kappa_2 = 0, \kappa_3 = (1 - \theta) / 2, \theta = 0.002$$

Checkerboard Example

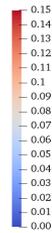
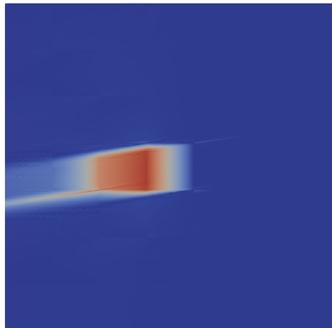


integrated solution

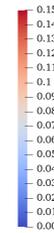
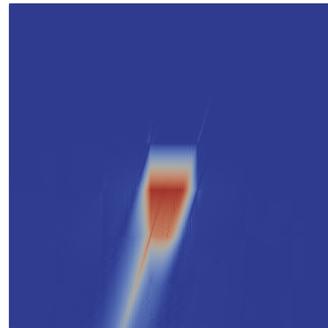


$$\kappa_1 = \theta / C_T, \kappa_2 = 0, \kappa_3 = (1 - \theta) / 2, \theta = 0.0002$$

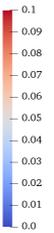
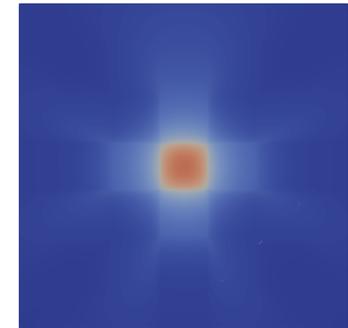
Checkerboard Example



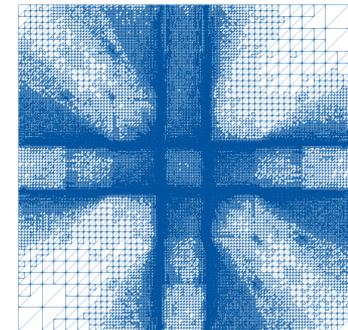
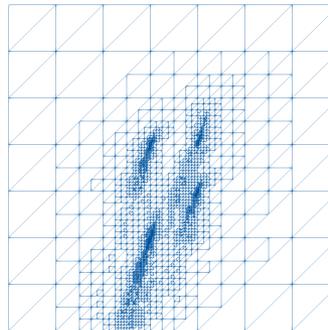
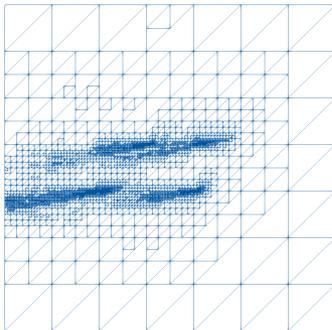
directional solution



directional solution



integrated solution



Grids for two different transport solutions and the integrated solution.

A Generic Library for DPG: dune-dpg

Joint work with Angela Klewinghaus and Olga Mula [Gruber et al., 2017], based upon the Dune finite element library [Blatt et al., 2016] (<https://dune-project.org/>).

- Suitable for different types of problems, e. g.
 - radiative transport (O. Mula, F. Gruber)
 - convection–diffusion (A. Klewinghaus)
 - optimal control problems with transport constraints (A. Klewinghaus)
 - porous media (V. König)
- a posteriori estimation
- capable of adaptive h refinement
- free software (GPL 2 with runtime-exception)
available at <https://gitlab.dune-project.org/felix.gruber/dune-dpg>

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