

Tensor Approximations for Elliptic PDEs with Jumping Coefficients

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Tensor Methods in Multi-Dimensional Boundary-Value and
Spectral problems
MPI MiS Leipzig, May 3-5, 2010

Introduction

Main problem

Diffusion equation

$$\begin{cases} -\nabla(a(\mathbf{x})\nabla u(\mathbf{x})) = f(\mathbf{x}) & \text{in } \Omega \subset \mathbb{R}^d \\ \alpha u(\mathbf{x})|_{\partial\Omega} + \beta \frac{\partial u}{\partial \mathbf{n}}|_{\partial\Omega} = g(\partial\Omega), \end{cases} \quad (1)$$

where $a > 0$, $\alpha^2 + \beta^2 \neq 0$.

Examples

- Flow models: heat conductivity, liquid, gas flows.
- Electrostatics.
- Financial math.

Solution methods - GFEM

Galerkin method (“weak”, generalized formulation) ($g \equiv 0$, $\beta = 0$)

- Find u : $(a\nabla u, \nabla \phi)_{L_2(\Omega)} = (f, \phi)_{L_2(\Omega)}$.
- u and ϕ are assumed to belong to some function class in H^1 .

Discrete form - FEM

- suppose $u = \sum_i u_i \phi_i(\mathbf{x})$, $\phi_i \in H^1$.
- find matrix $\Gamma = [(a\nabla \phi_i, \nabla \phi_j)]$,
- right-part vector $F = (F_1, \dots, F_N)^T$, $F_i = (f, \phi_i)$.
- Solve $\Gamma \mathbf{u} = F$, where $\mathbf{u} = (u_1, \dots, u_N)^T$.

GFEM

Computational difficulties

- Curse of dimensionality:
 d dimensions, n grid points in each variable. Then $N = n^d$.
- Ill conditioned matrices:
 $\text{cond}(\Gamma) \sim 10^8 - 10^9$.

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Approaches

- Use of data compression tensor technics.
- Use of preconditioners, special solvers.

Continuous formulation

Simple problem

$$\begin{cases} -\nabla(a\nabla u) = f & \text{in } \Omega = [0, 1]^d \\ u|_{\partial\Omega} = 0. \end{cases}$$

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Auxiliary Poisson equation

$$\begin{cases} -\Delta v = f & \text{in } \Omega = [0, 1]^d \\ v|_{\partial\Omega} = 0. \end{cases}$$

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"Motivating" equation

Suppose v is known. Then

$$-\nabla(a\nabla u) = -\Delta v.$$

This formulation brings good stuff

Discrete formulation

Galerkin formulation

- Consider $u_h = \sum_{\mathbf{i}} u_{\mathbf{i}} \phi_{\mathbf{i}}(\mathbf{x})$, $v_h = \sum_{\mathbf{i}} v_{\mathbf{i}} \phi_{\mathbf{i}}(\mathbf{x})$, $\{\phi_{\mathbf{i}}\} \in H^1(\Omega)$.
- We are to solve $(a \nabla u_h, \nabla \phi_{\mathbf{j}}) = (\nabla v_h, \nabla \phi_{\mathbf{j}})$.

Where are tensors?

- Suppose $\phi_{\mathbf{i}}(\mathbf{x}) = \varphi_{i_1}(x_1) \cdots \varphi_{i_d}(x_d)$.
- Then

$$\Delta_h = [(\nabla \phi_{\mathbf{i}}, \nabla \phi_{\mathbf{j}})] = G \otimes H \otimes \cdots \otimes H + \cdots + H \otimes \cdots \otimes H \otimes G,$$

$$G = [(\nabla \varphi_i, \nabla \varphi_j)] - \text{1D stiffness}, \quad H = [(\varphi_i, \varphi_j)] - \text{mass matrix}.$$

Discrete formulation

Why tensors?

- By imposing separability properties on a and f , we can also get separability for v and u .
- Hence we get $O(nd)$ rather than $O(n^d)$ complexity.

Requirements

Suppose the following conditions:

- We have $(a \nabla u_h, \nabla \phi_j) = (\nabla v_h, \nabla \phi_j)$.
- $\phi_i(\mathbf{x}) = \varphi_{i_1}(x_1) \cdots \varphi_{i_d}(x_d)$, $i_q = 1, \dots, n$, $q = 1..d$,
 $\text{supp}(\varphi_i) \in [x_{i-1}, x_{i+1}]$.

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- $v_i \approx v_{r,i} = \sum_{k=1}^{r_v} v_{k,i_1}^{(1)} \cdots v_{k,i_d}^{(d)}$, $\|v - v_r\| \leq \varepsilon_v$

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- $\frac{1}{a_i} \approx \frac{1}{a_{r,i}} = \sum_{l=1}^{r_{1/a}} \frac{1}{a_{l,i_1}^{(1)}} \cdots \frac{1}{a_{l,i_d}^{(d)}}$, $\|\frac{1}{a} - \frac{1}{a_r}\| \leq \varepsilon_a$

Requirements

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- $\frac{1}{a_i} \approx \frac{1}{a_{r,i}} = \sum_{l=1}^{r_{1/a}} \frac{1}{a_{l,i_d}^{(1)}} \cdots \frac{1}{a_{l,i_1}^{(d)}}$, $\|\frac{1}{a} - \frac{1}{a_r}\| \leq \varepsilon_a$
- $a_{l,i}^{(q)} > 0$, $q = 1, \dots, d$, $l = 1, \dots, r_{1/a}$, $i = 1, \dots, n$

Result

Then we get:

- $u_{\mathbf{i}} \approx u_{r,\mathbf{i}} = \sum_{k=1}^{r_u} u_{k,i_1}^{(1)} \cdots u_{k,i_d}^{(d)}, \quad \|u - u_r\| \leq \varepsilon_u.$

Result

Then we get:

- $u_{\mathbf{i}} \approx u_{r,\mathbf{i}} = \sum_{k=1}^{r_u} u_{k,i_1}^{(1)} \cdots u_{k,i_d}^{(d)}, \|u - u_r\| \leq \varepsilon_u.$
- $\varepsilon_u = O(\varepsilon_v) + O(\varepsilon_a) + O(h^\alpha), h = 1/(n+1), \alpha = 1, 2.$
- $r_u = r_{1/a} r_v.$

Result

Then we get:

- $u_i \approx u_{r,i} = \sum_{k=1}^{r_u} u_{k,i_1}^{(1)} \cdots u_{k,i_d}^{(d)}, \|u - u_r\| \leq \varepsilon_u.$
- $\varepsilon_u = O(\varepsilon_v) + O(\varepsilon_a) + O(h^\alpha), h = 1/(n+1), \alpha = 1, 2.$
- $r_u = r_{1/a} r_v.$
- Factors $u^{(q)}$ can be computed independently from the systems with tridiagonal matrices:

$$a_{i-1} u_{i-1} + \frac{a_{i-1} + a_i}{2} F_1(v_r) u_i + a_i u_{i+1} = \frac{1}{a_i} F_0(v_r)$$

Black-box preconditioner

Left preconditioning

- We are to solve $Ax = f \leftarrow$ **hard**.
- Apply a non singular matrix B : $BAx = Bf$.
- Solve $(BA)x = (Bf)$.

Black-box MatVec approach

- Iterative solvers exploit just Ax operation.
- Obtaining BA and $(BA)x$ can be difficult.
- One may apply black-box procedure for $Ax \rightarrow y$ and $By \rightarrow z$ on each iteration (faster).

Black-box preconditioner

Application to diffusion problem

- Suppose $Au = f$ - diffusion problem with separability properties.
- We have an algorithm which gives $\tilde{u} \approx u = A^{-1}f$:
 - Compute $v = \Delta^{-1}f$ (using FFT, quadratures - fast).
 - Apply sweep-based algorithm: $\tilde{u} = S[1/a](v)$.
- Now we have $By \rightarrow z$ operation: $z = S[1/a](\Delta^{-1}y)$.
- FFT, quadrature solver, sweep solver - fast methods, complexity $O(n)$, $O(n \log n)$.

As A is sparse, we have
complexity of one iteration of $O(n)$, or $O(n \log n)$.

Numerical results

- We test complexity $S[1/a](v)$ on v in canonical format with rank r_v , $\text{rank}(1/a) = r_{1/a}$, grid size n .

Table: CPU time versus n , $r_v = 59$, $r_{1/a} = 1$, $d = 2$.

n	CPU Time, sec
32	0.069945
64	0.139432
128	0.275668
256	0.515547
512	1.005040
1024	1.987609

Numerical results

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Table: CPU time versus $r_u = r_{1/a}r_v$, $d = 2$, $n = 256$

r_u	CPU Time, sec
8	0.081331
16	0.147973
32	0.283700
64	0.562467

Numerical results

- We test complexity $S[1/a](v)$ on v in canonical format with rank r_v , $\text{rank}(1/a) = r_{1/a}$, grid size n .

Table: CPU time versus d , $r_u = 16$, $n = 256$

d	CPU Time, sec
2	0.147973
4	0.522492
8	3.120825
16	23.232763

The complexity is of $O(d^3)$ (due to $F_1(v_r)$, $F_0(v_r)$).
Application on full vector $N = n^d$ is of $O(N)$.

Gradient equation

- Recall $(a\nabla u, \nabla \phi) = (\nabla v, \nabla \phi) \Rightarrow (a\nabla u - \nabla v, \nabla \phi) = 0$, $\phi \in H^1$.
- Require $\nabla u = \frac{1}{a} \nabla v$ in the least squares sense:

$$\|\nabla u - \frac{1}{a} \nabla v\|^2 \rightarrow \min.$$
- Then $\Delta u - \nabla \frac{1}{a} \nabla v = 0$.
- If $v = \Delta^{-1} f$, then $u = \Delta^{-1} (\nabla \frac{1}{a} \nabla) \Delta^{-1} f$.

Gradient equation

- Suppose $\Gamma[a]u = f$ is a diffusion problem with coefficient a ,
 $\Gamma[a]u = \nabla(a\nabla u)$.
- Then $\Gamma[1/a] = \nabla(\frac{1}{a}\nabla)$.
- We have the following preconditioner: $\Delta^{-1}\Gamma[1/a]\Delta^{-1}$

$$\Delta^{-1} \Gamma[1/a] \Delta^{-1} \approx \Gamma[a]^{-1}?$$

- Hypothesis: $\Delta^{-1} \Gamma[1/a] \Delta^{-1} \Gamma[a] = I + R$.
- In 1D: $\text{rank } R = 1$ (in functional view: $\dim R = 1$) (proved).
- In higher dimension: R has low-rank approximation (in functional view: R is a compact operator) (hypothesis).

LS functional vs Black-box discrete

LS

- (+) Simple explicit operator form.
- (+) Symmetric matrix.
- (\pm) Convergence depends on jumping of the coefficient.
- (-) Requires 2 Laplace inversions (4(3) FFTs).
- (-) $\|\Gamma[a]^{-1} - \Delta^{-1}\Gamma[1/a]\Delta^{-1}\| = O(1)$.
- (-) In tensor form, has the rank $\text{rank}(1/a)\text{rank}(\Delta^{-1})^2$.

LS functional vs Black-box discrete

Black-box

- (+) Requires 1 Laplace inversion + $d \cdot \text{rank}$ sweeps.
- (+) Intrinsic tensor structure with ranks $\text{rank}(1/a) \text{rank}(\Delta^{-1})$.
- (+) $\|\Gamma[a]^{-1} - S(\Delta^{-1})\| = O(h^\alpha)$.
- (\pm) Convergence depends on rank of $1/a$.
- (-) Non-symmetric matrix.
- (-) Requires positive tensor approximation for $1/a$.
- (-) Complicated formulation.

Common properties

- We are solving diffusion problem via GMRES with one of mentioned preconditioners.
- Initial guess is taken as zero in all cases.
- For integration in Galerkin matrix assembly, the rectangle quadrature formula is used.
- No restarts are made in GMRES.
- For both preconditioners, the low-rank positive diffusion is used.

Dependence on n

Smooth coefficient: $1/a = (x + 1) \cdot e^y + 2 \cos(x + y)$

Table: Number of iterations to $\|Au - f\|/\|f\| < 10^{-8}$, and
CPU time of one iteration.

n	Black-box	time, s	LS	time,s
32	5	0.0024	3	0.002261
64	5	0.0079	3	0.005482
128	5	0.0293	3	0.02683
256	5	0.1065	3	0.093763
512	5	0.5008	3	0.513589

Dependence on n

Smooth coefficient: $1/a = (x+1) \cdot e^y + 2 \cos(x+y)$

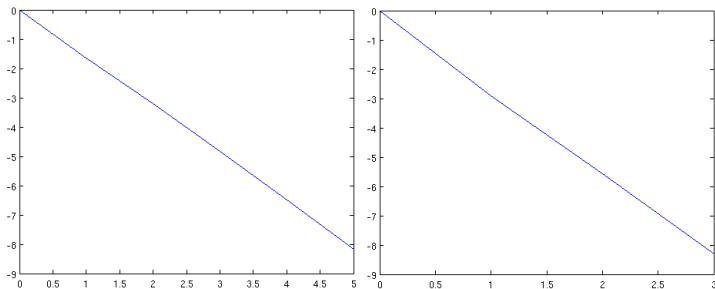


Figure: Convergence history for Black-box (left) and LS (right):

$\log \frac{\|Au-f\|}{\|f\|}$ vs number of iteration.

Dependence on n

Jumping coefficient: $1/a$ of rank 3, values from 2 to 1400.

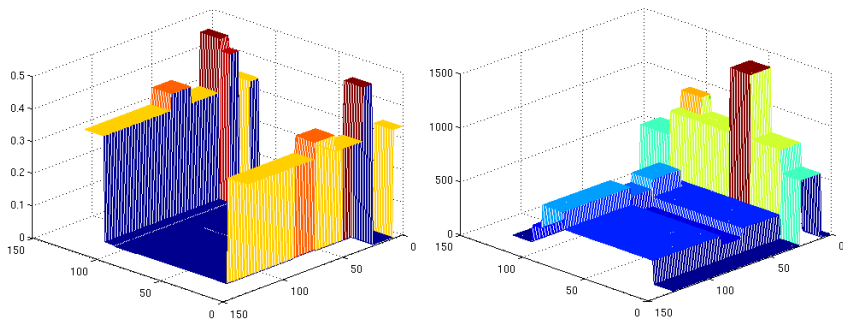


Figure: Diffusion coefficient a (left) and $1/a$ (right)

Dependence on n

Jumping coefficient: $1/a$ of rank 3, values from 2 to 1400.

Table: Number of iterations to $\|Au - f\|/\|f\| < 10^{-8}$, and
CPU time of one iteration.

n	Black-box	time, s	LS	time, s
32	17	0.0022	45	0.002394
64	18	0.0063	51	0.005692
128	18	0.0259	53	0.023622
256	18	0.0999	54	0.098719
512	18	0.5275	55	0.512126

Dependence on n

Jumping coefficient: $1/a$ of rank 3, values from 2 to 1400.

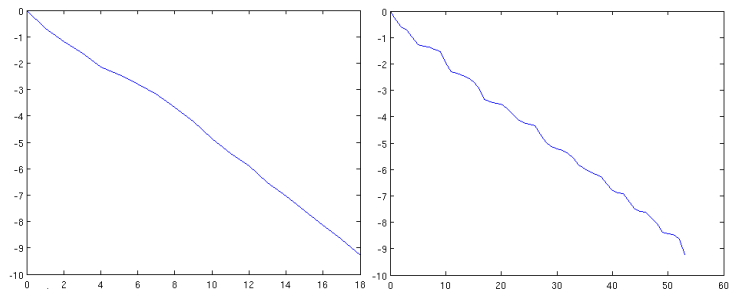


Figure: Convergence history for Black-box (left) and LS (right):

$\log \frac{\|Au-f\|}{\|f\|}$ vs number of iteration.

Dependence on jumps and ranks

Rank-2 checkerboard: $1/a = \text{chk}(x) \cdot 1 + 1 \cdot \text{chk}(y)$, where

$$\text{chk}(x) = \begin{cases} 1, [x \cdot 16] \text{ is odd,} \\ \alpha, [x \cdot 16] \text{ is even.} \end{cases}$$

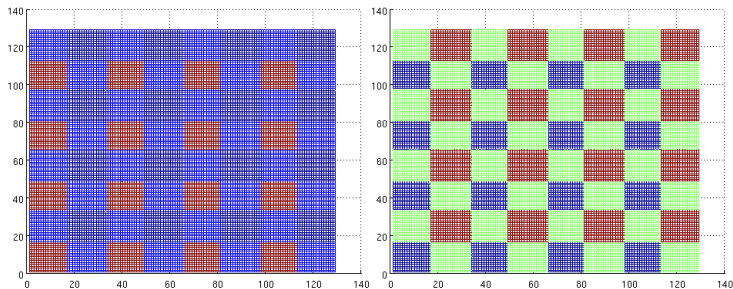


Figure: Diffusion coefficient a (left) and $1/a$ (right)

Dependence on jumps and ranks

Rank-2 checkerboard: dependency on α , $n = 128$.

Table: Number of iterations to $\|Au - f\|/\|f\| < 10^{-8}$.

α	Black-box	LS
0.01	14	14
0.1	10	8
10	11	9
100	19	17
1000	23	24

CPU time of one iteration: Black-box - 0.0207 s, LS - 0.024795 s.

Dependence on jumps and ranks

Rank-2 checkerboard: $\alpha = 1000$.

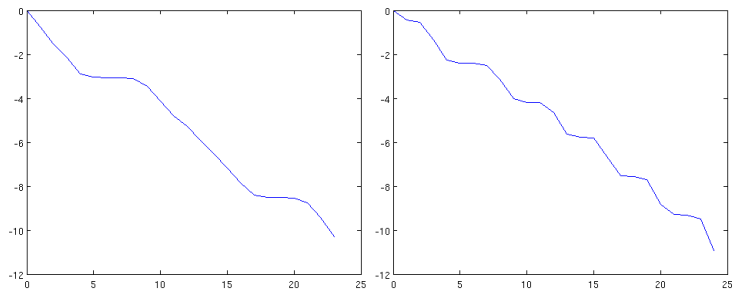


Figure: Convergence history for Black-box (left) and LS (right):

$\log \frac{\|Au - f\|}{\|f\|}$ vs number of iteration.

Dependence on jumps and ranks

3 test functions:

- $1/a_1 = \text{if1}(x) \cdot \text{if2}(y)$ (rank = 1),
- $1/a_2 = \text{if1}(x) \cdot \text{if2}(y) + (x+1) \cdot e^y$ (rank = 2),
- $1/a_3 = \text{if1}(x) \cdot \text{if2}(y) + (x+1) \cdot e^y + \text{chk}(x) \cdot 1 + 1 \cdot \text{chk}(y)$ (rank = 4),

where

$$\text{if1}(x) = \begin{cases} 0.1, & x \in [0, 0.25], \\ 1, & x \in (0.25, 1]; \end{cases} \quad \text{if2}(x) = \begin{cases} 1, & x \in [0, 0.75], \\ 7, & x \in [0.75, 1], \end{cases}$$

$\text{chk}(x)$ parameter $\alpha = 10$.

Dependence on jumps and ranks

3 test functions:

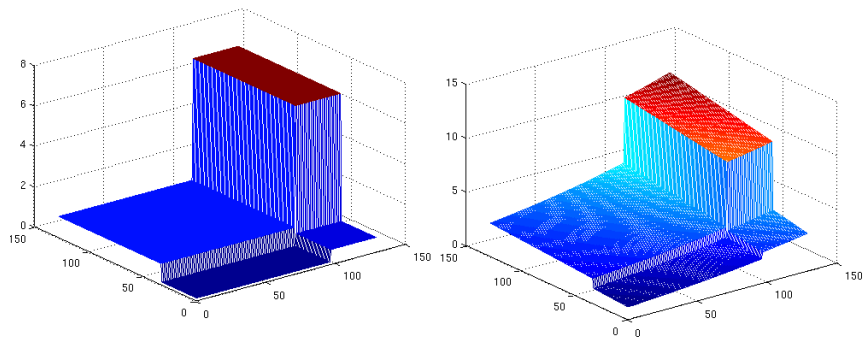


Figure: Reciprocal coefficients $1/a_1$ (left) and $1/a_2$ (right)

Dependence on jumps and ranks

3 test functions: dependency on rank, $n = 128$.

Table: Number of iterations to $\|Au - f\|/\|f\| < 10^{-8}$, and
CPU time of one iteration.

coefficient	Black-box	time, s	LS	time, s
a_1 (rank = 1, $\frac{\max}{\min} = 70$)	6	0.017	12	0.023088
a_2 (rank = 2, $\frac{\max}{\min} = 11.3$)	8	0.022	6	0.024139
a_3 (rank = 4, $\frac{\max}{\min} = 10.4$)	13	0.029	8	0.022821

Dependence on jumps and ranks

3 test functions: $a = a_1$.

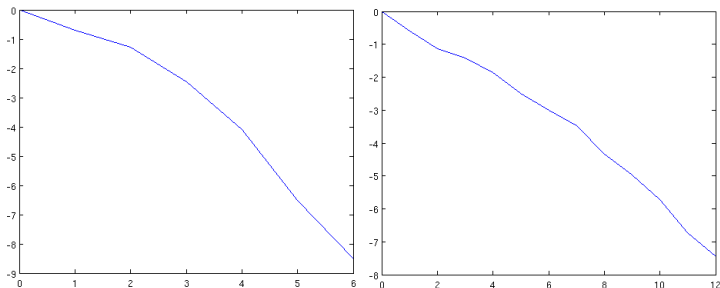


Figure: Convergence history for Black-box (left) and LS (right):

$\log \frac{\|Au-f\|}{\|f\|}$ vs number of iteration.

3D Dirichlet sample problems

$$f = 1. \quad n = 64.$$

- $1/a_1 = \text{if1}(x) \cdot \text{if2}(y) \cdot \text{if3}(z),$

$$\text{if3}(x) = \begin{cases} 10, & x \in [0.125, 0.25], \\ 1, & \text{otherwise}; \end{cases}$$

- $1/a_2 = \text{if1}(x) \cdot \text{if2}(y) \cdot \text{if3}(z) + (x+1) \cdot e^y \cdot \frac{1}{1+10z};$

- $1/a_3 = \text{chk}(x) + \text{chk}(y) + \text{chk}(z), \quad \alpha = 10^{-3}.$

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Table: Number of iterations to $\|Au - f\|/\|f\| < 10^{-8}$, and
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coefficient	Black-box	time, s	LS	time, s
a_1	12	0.5478	24	0.758098
a_2	12	0.7107	17	0.746054
a_3	21	0.8062	23	0.744929

3D Neumann problems

$$f = \cos(\pi x) \cos(\pi y) \cos(\pi z). \quad n = 64.$$

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- $1/a_3 = \text{chk}(x) + \text{chk}(y) + \text{chk}(z), \quad \alpha = 10^{-3}.$

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Table: Number of iterations to $\|Au - f\|/\|f\| < 10^{-8}$, and
CPU time of one iteration.

coefficient	Black-box	time, s	LS	time, s
a_1	13	0.6168	27	0.841716
a_2	25	0.7268	30	0.830226
a_3	15	0.8690	18	0.835752

Sample problem

Sample problem from the Society of Petroleum Engineers benchmark. $n = 512$, $\max(a) = 1000$, $\min(a) = 1$.

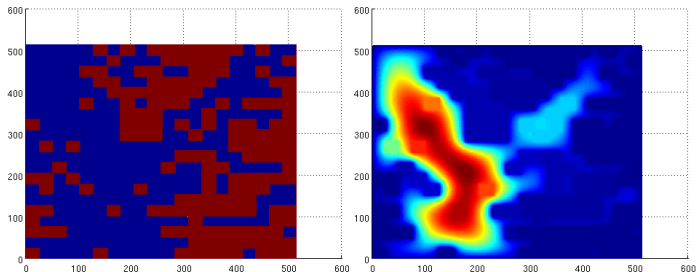


Figure: Diffusion coefficient a (left) and solution u (right)

LS preconditioner: 29 iterations, time of one iteration 0.526171 s.

- Proposed and compared two preconditioners for diffusion problem.
- Preconditioners can be applied in canonical tensor format, or full format, with complexity $O(n)$ and $O(N)$, correspondingly.
- For each coefficient can be chosen an optimal algorithm.

Future plans:

- Application to other PDEs (convection/reaction, etc; arbitrary domains).
- Further improvements of algorithms.

Thank you for your attention.