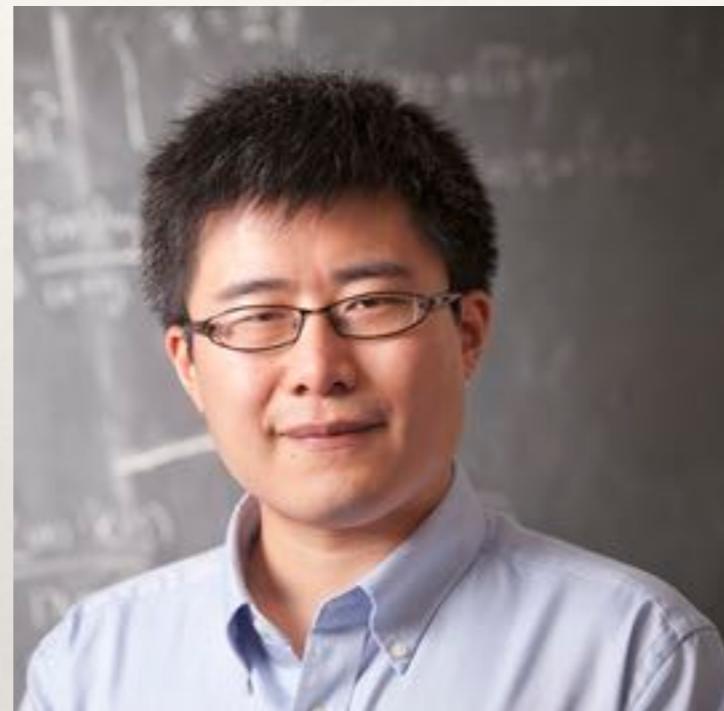

Random Sampling and Efficient Algorithms for Multiscale PDEs

Conference on Fast Direct
Solvers
Nov 9th, Ke Chen

Random Sampling and Efficient Algorithms for Multiscale PDEs.
arXiv preprint arXiv:1807.08848.



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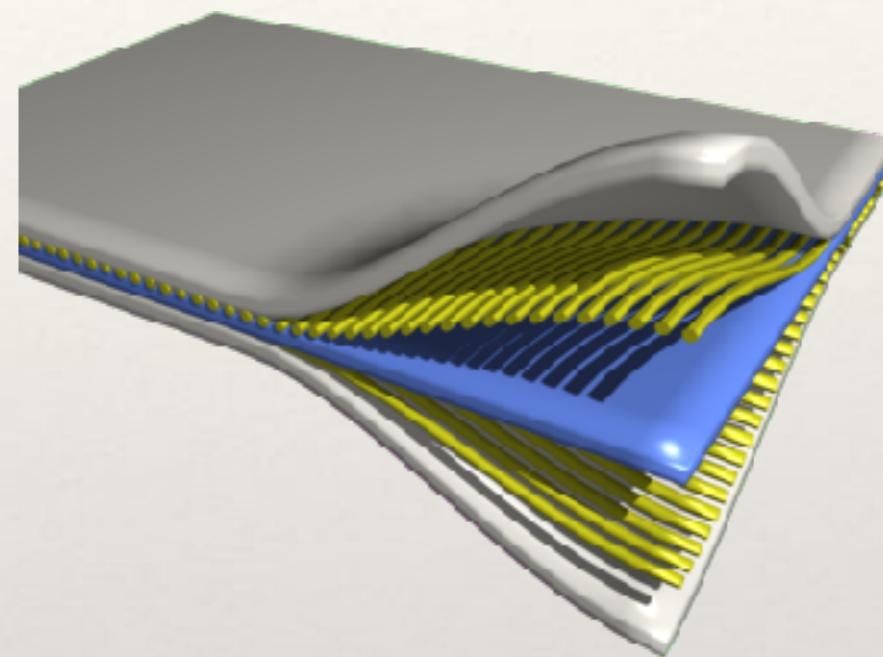
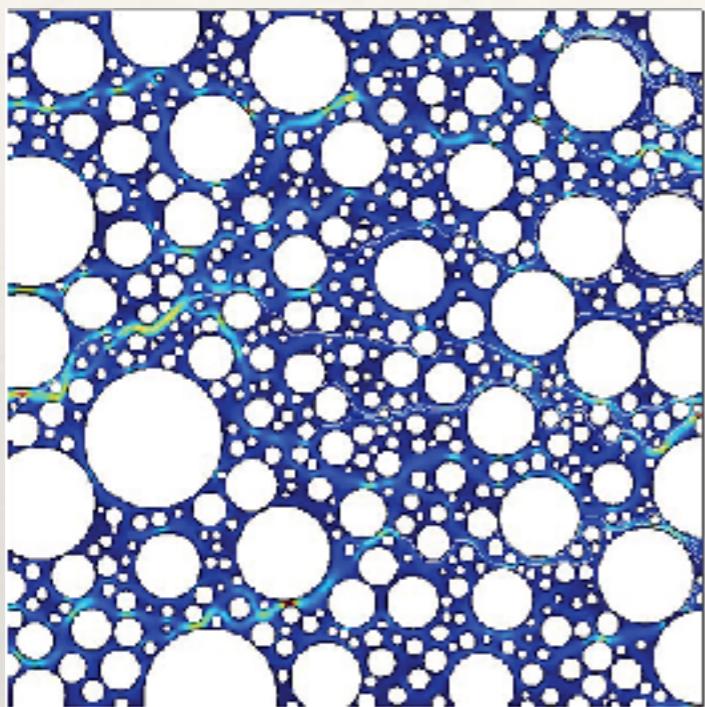


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Multiscale PDEs



Multiscale PDEs

Boundary value problem

$$\begin{cases} \mathcal{L}^\varepsilon u^\varepsilon = 0 \\ \mathcal{B}u^\varepsilon = f \end{cases}$$

Multiscale PDEs

$$\begin{cases} \mathcal{L}^\varepsilon u^\varepsilon = 0 \\ \mathcal{B}u^\varepsilon = f \end{cases}$$

- ❖ Offline: prepare basis functions/Green functions
- ❖ Online: solve with various boundary conditions

Multiscale PDEs

Discretization

$$\begin{cases} \mathcal{L}^\varepsilon u^\varepsilon = 0 \\ \mathcal{B}u^\varepsilon = f \end{cases}$$



$$u^\varepsilon = \int G^\varepsilon(x, y) f(y) dy$$



$$u^\varepsilon \in \{G^*(x, y)\}$$



Green function

$$\begin{bmatrix} \mathcal{L}^\varepsilon \\ \mathcal{B} \end{bmatrix} \cdot \mathbf{U}^\varepsilon = \begin{bmatrix} 0 \\ \mathbf{f} \end{bmatrix}$$



$$\mathbf{U}^\varepsilon = \mathbf{G}^\varepsilon \cdot \mathbf{f}$$



$$\mathbf{U}^\varepsilon \in \text{span}\{\mathbf{G}^\varepsilon\}$$



Green matrix

$$N_x = \mathcal{O}\left(\frac{1}{\varepsilon}\right)$$



Multiscale PDEs

Discretization

$$\mathbf{G}^\varepsilon \in \mathbb{R}^{N_x^d \times N_x^{d-1}}$$

$$N_x = \mathcal{O}\left(\frac{1}{\varepsilon}\right)$$

Multiscale PDEs

Asymptotic limit

$$\begin{cases} \mathcal{L}^* u^* = 0 \\ \mathcal{B} u^* = f \end{cases} \xleftarrow{\mathcal{O}(\epsilon)} \begin{cases} \mathcal{L}^\varepsilon u^\varepsilon = 0 \\ \mathcal{B} u^\varepsilon = f \end{cases}$$

$$u^* \xleftarrow{0 \leftarrow \varepsilon} u^\varepsilon$$

Multiscale PDEs

Example: fluid limit

$$-v \cdot \nabla_x u^\varepsilon + \frac{1}{\varepsilon} S[u^\varepsilon] = 0 \longrightarrow C \nabla_x \cdot \left(\frac{1}{\sigma} \nabla_x u^*(x) \right) = 0$$

$$u^\varepsilon(x, v) \longrightarrow u^*(x)$$

$$S[u] = \sigma(x) \int_V u(x, v') - u(x, v) dv'$$

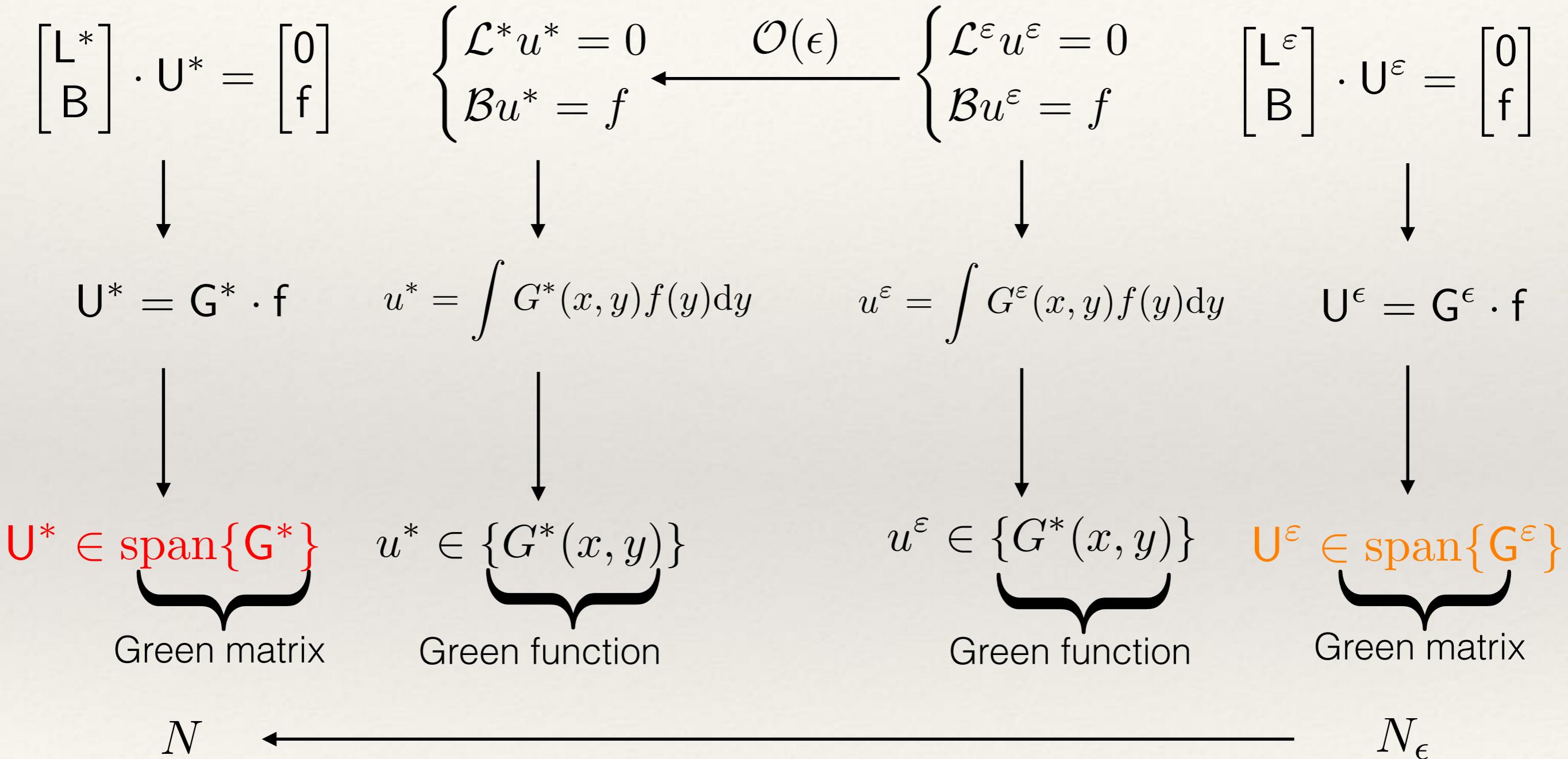
Multiscale PDEs

Example: homogenization

$$\nabla_x \cdot \left(a\left(x, \frac{x}{\varepsilon}\right) \nabla_x u^\varepsilon \right) = 0 \longrightarrow \nabla_x \cdot (a^*(x) \nabla_x u^*) = 0$$

$$u^\varepsilon\left(x, \frac{x}{\varepsilon}\right) \longrightarrow u^*(x)$$

Multiscale PDEs



Random Sampling

Green matrix

$$\begin{cases} \mathcal{L}^\varepsilon u_i^\varepsilon = 0, & \text{in } \Omega \\ u_i^\varepsilon = \delta_i, & \text{on } \partial\Omega \end{cases}$$

$$\mathbf{G}^\varepsilon = [u_1^\varepsilon, \dots, u_{N_\varepsilon}^\varepsilon]$$

Random Sampling

Singular value decomposition

$$G^\varepsilon =$$



$$G =$$



Random Sampling

Randomized SVD

Thm. Let A be a n by n matrix and target rank $k \geq 2$. Define

$$Y = AR$$

where R is a matrix of size $n \times (k + p)$ with entries randomly drawn i.i.d. normal distribution, where p is an oversampling parameter. If A is approximately rank k , then with high probability,

$$\|A - P_Y(A)\| \ll \sigma_1$$

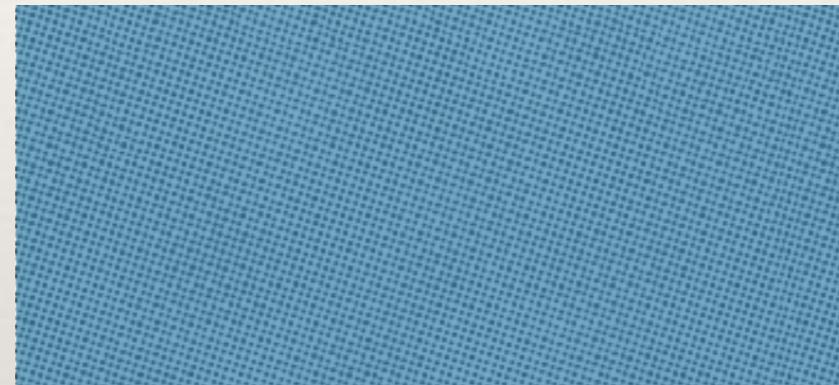
Random Sampling

Randomized SVD

$$\text{span}\{G\} \approx \text{span}\{G^\varepsilon R\}$$



\approx



Random Sampling

Green matrix

$$\begin{cases} \mathcal{L}^\varepsilon u_i^\varepsilon = 0, & \text{in } \Omega \\ u_i^\varepsilon = \delta_i, & \text{on } \partial\Omega \end{cases}$$
$$G^\varepsilon = [u_1^\varepsilon, \dots, u_{N_\varepsilon}^\varepsilon]$$

$$\begin{cases} \mathcal{L}^\varepsilon w_i = 0, & \text{in } \Omega \\ w_i = r_i, & \text{on } \partial\Omega \end{cases}$$
$$G = [w_1, \dots, w_{k+p}]$$

Algorithm

- ❖ Offline Stage
 - ❖ Domain decomposition
 - ❖ Prepare basis using random sampling
- ❖ Online Stage
 - ❖ Use continuity across local domains and global boundary condition

$$\begin{cases} \mathcal{L}^\varepsilon u^\varepsilon = 0 \\ \mathcal{B}u^\varepsilon = f \end{cases}$$

Algorithm

Domain decomposition

$$\Omega = \bigcup_{m=1}^M \Omega_m$$

$$u = \sum_{m=1}^M u_m \approx \sum_{m=1}^M \mathbf{G}_m c_m$$

Algorithm

Offline: random basis

$$\begin{cases} \mathcal{L}^\varepsilon w_i^m = 0, & \text{in } \Omega_m \\ w_i^m = r_i^m, & \text{on } \partial\Omega_m \end{cases}$$

$$\mathbf{G}_m = [w_1^m, \dots, w_{k_m}^m]$$

Online: solve for c_m

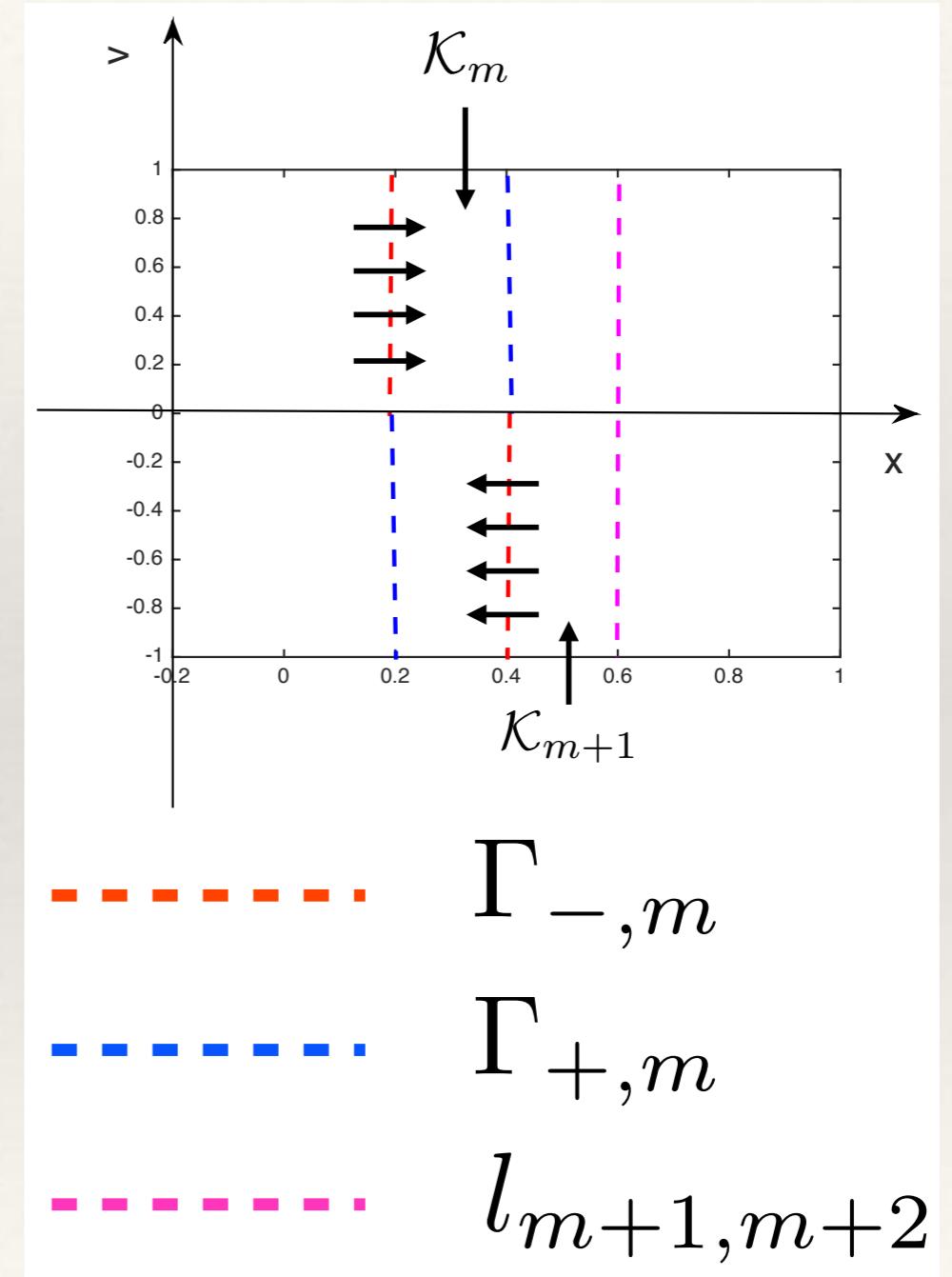
$$\begin{aligned} \mathcal{B}u &= f && \text{on } \partial\Omega \\ u_m &= u_{m+1} && \text{on } \Omega_m \cap \Omega_{m+1} \end{aligned}$$

Numerical Results

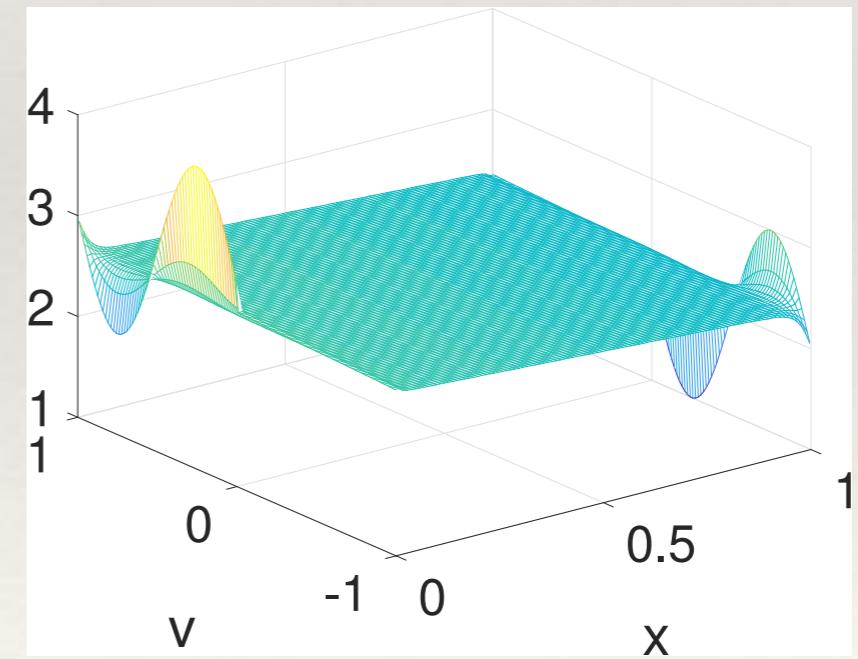
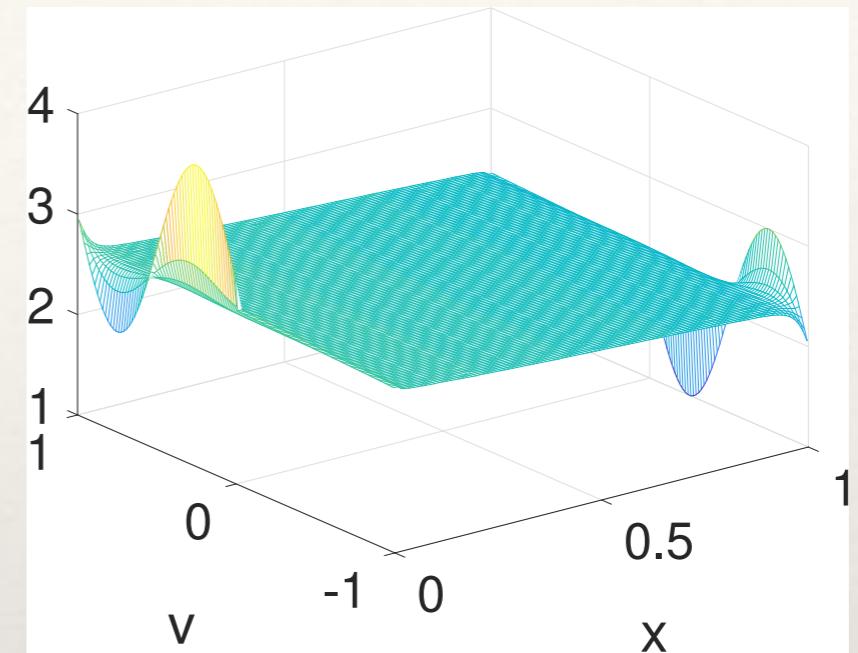
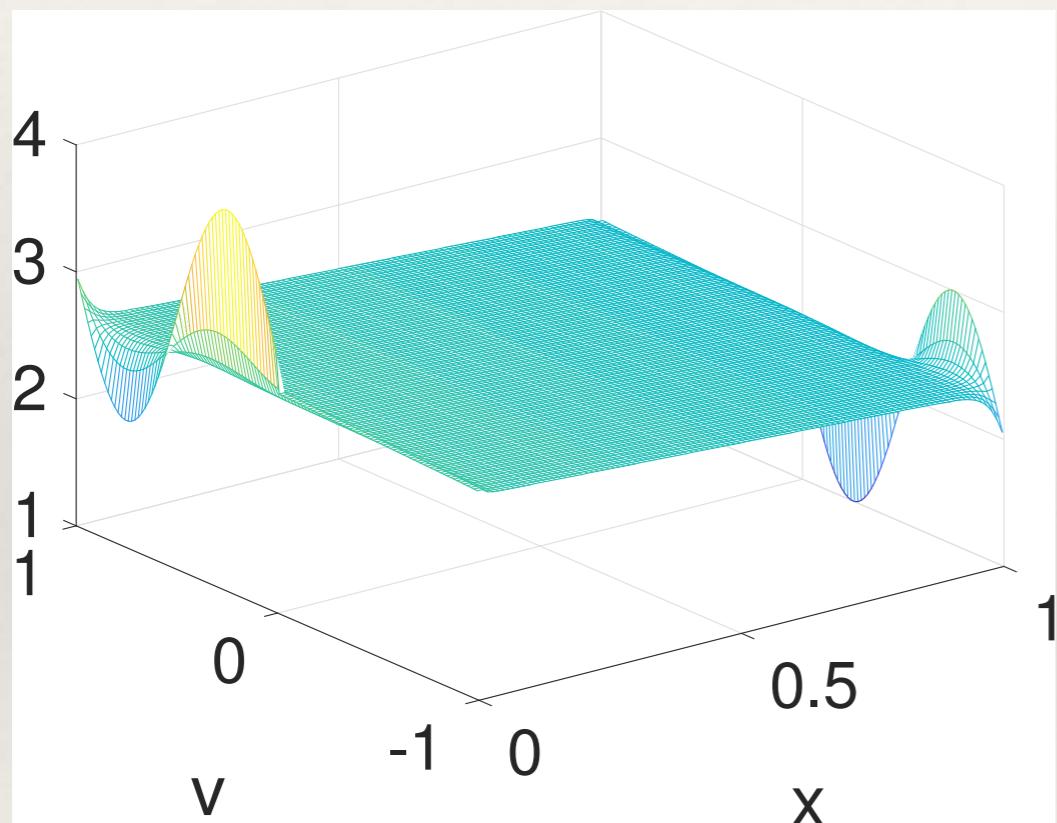
$$-v \cdot \nabla_x u^\varepsilon + \frac{1}{\varepsilon} S[u^\varepsilon] = 0$$

$$S[u] = \int_{-1}^1 k(x, v, v') u(x, v') dv' - \int_{-1}^1 k(x, v', v) u(x, v) dv$$

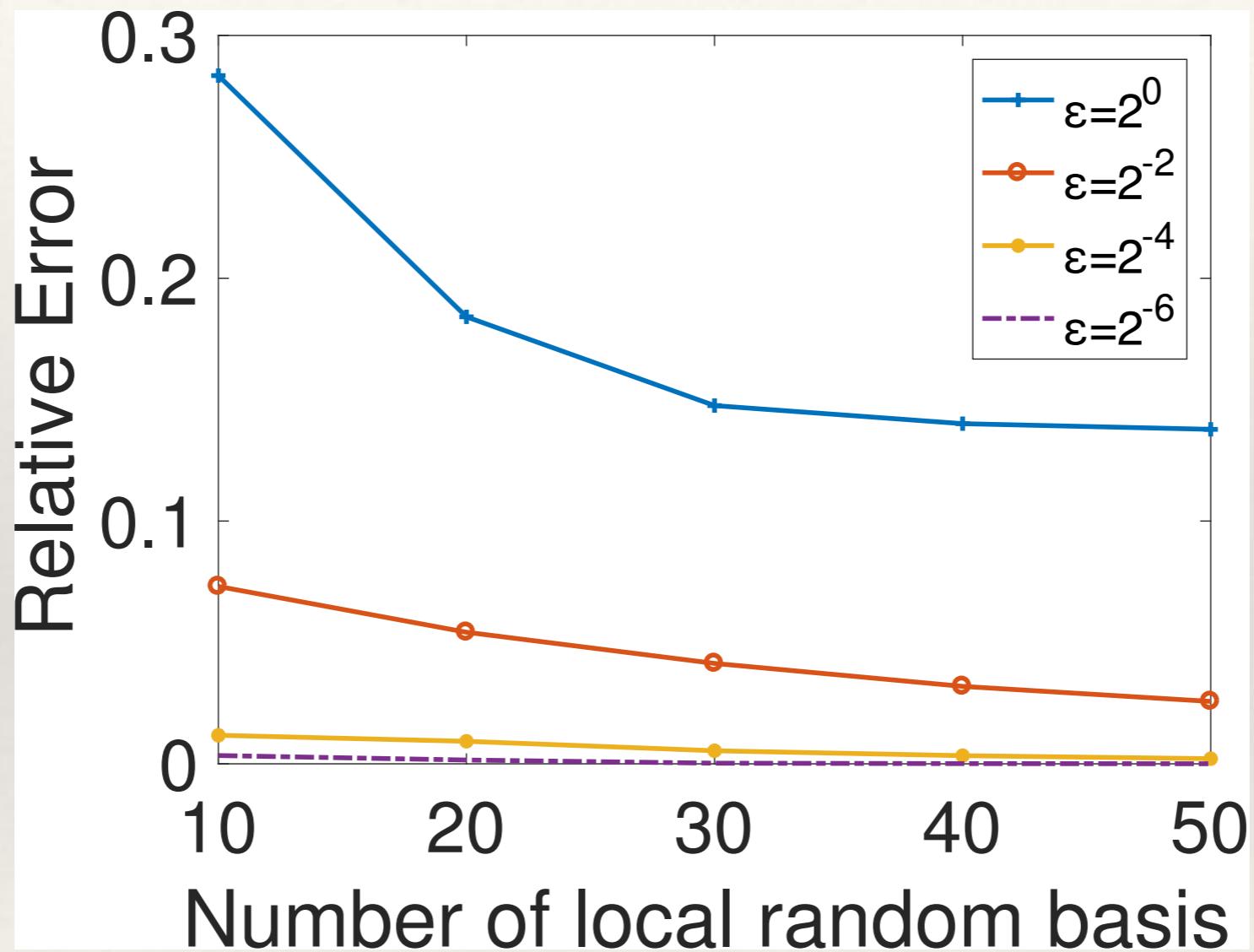
$$k(x, v, v') = \frac{1}{2} \frac{1 - g^2}{1 + g^2 + 2g(v \cdot v')}$$



Numerical Results



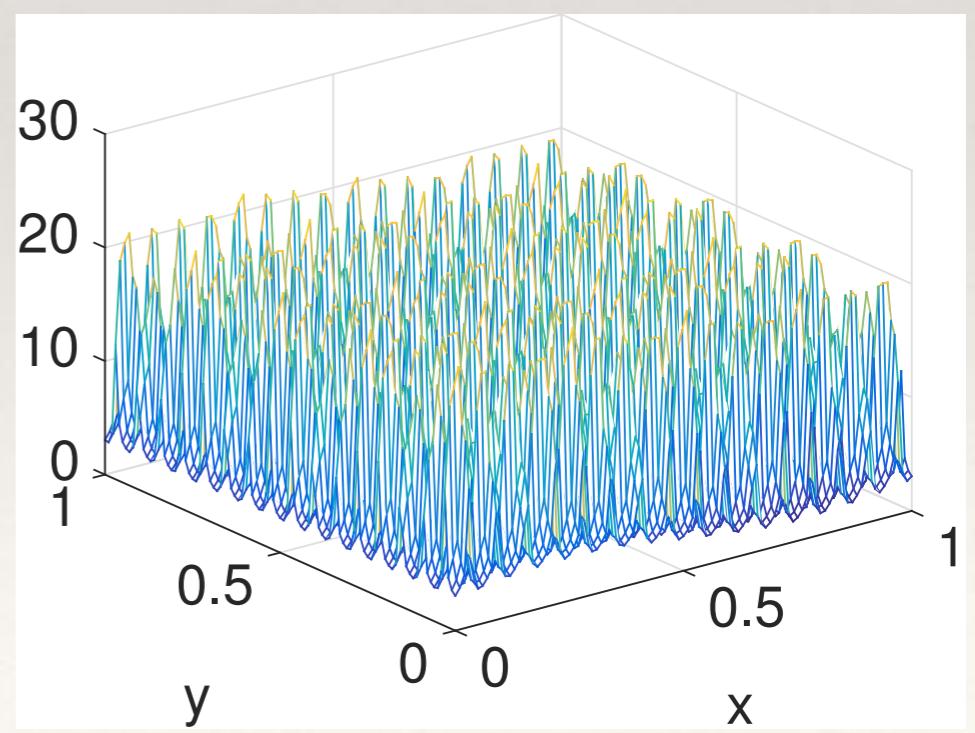
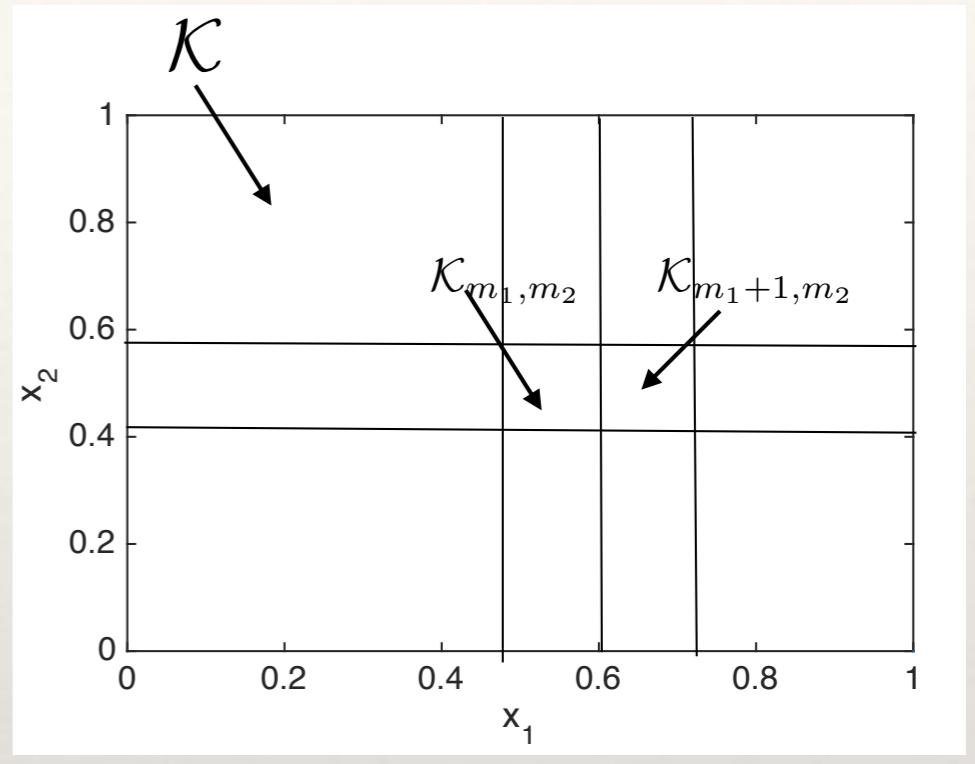
Numerical Results



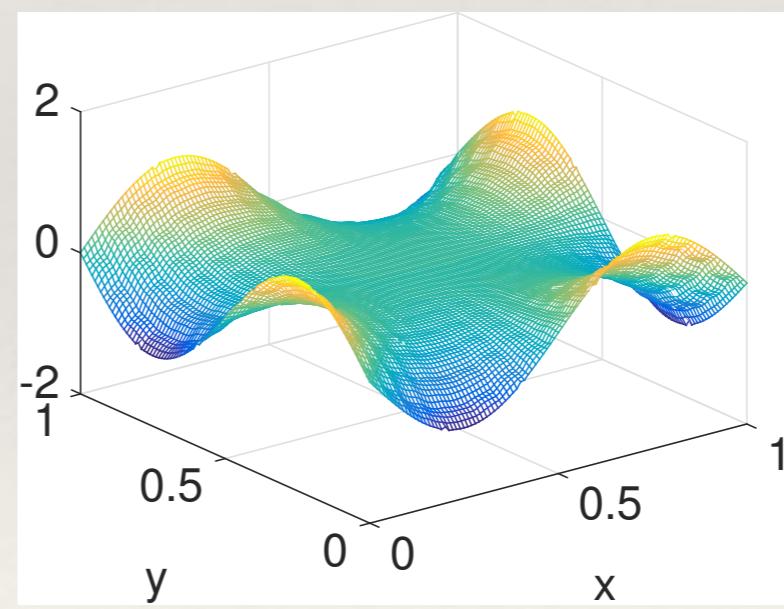
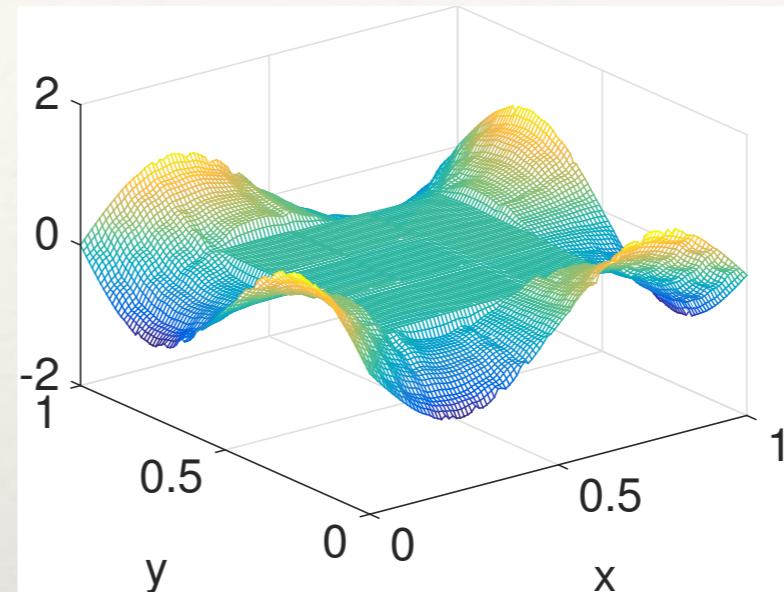
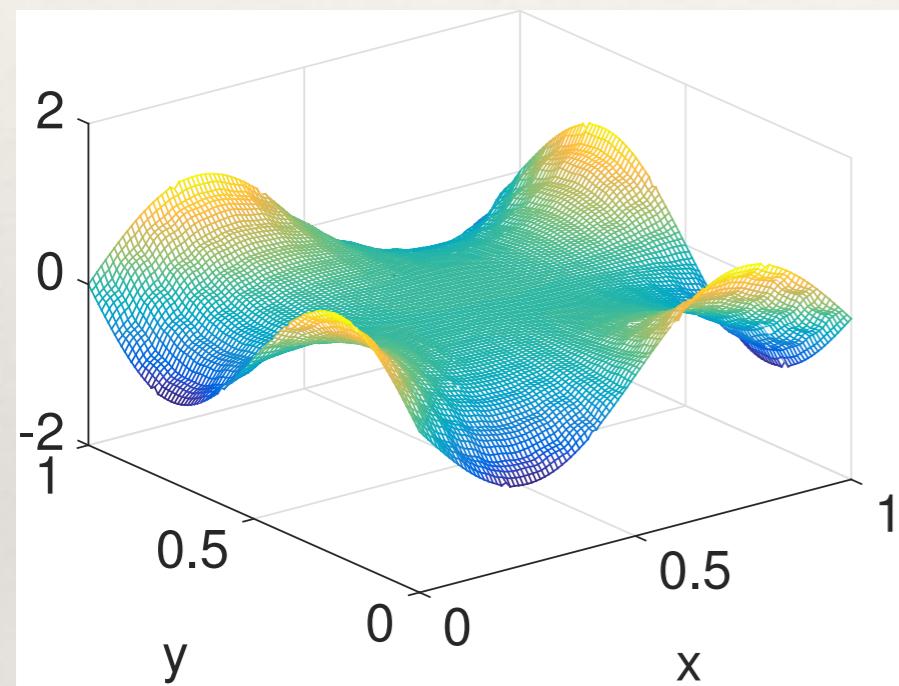
Numerical Results

$$\nabla_x \cdot \left(a(x, \frac{x}{\varepsilon}) \nabla_x u^\varepsilon \right) = 0$$

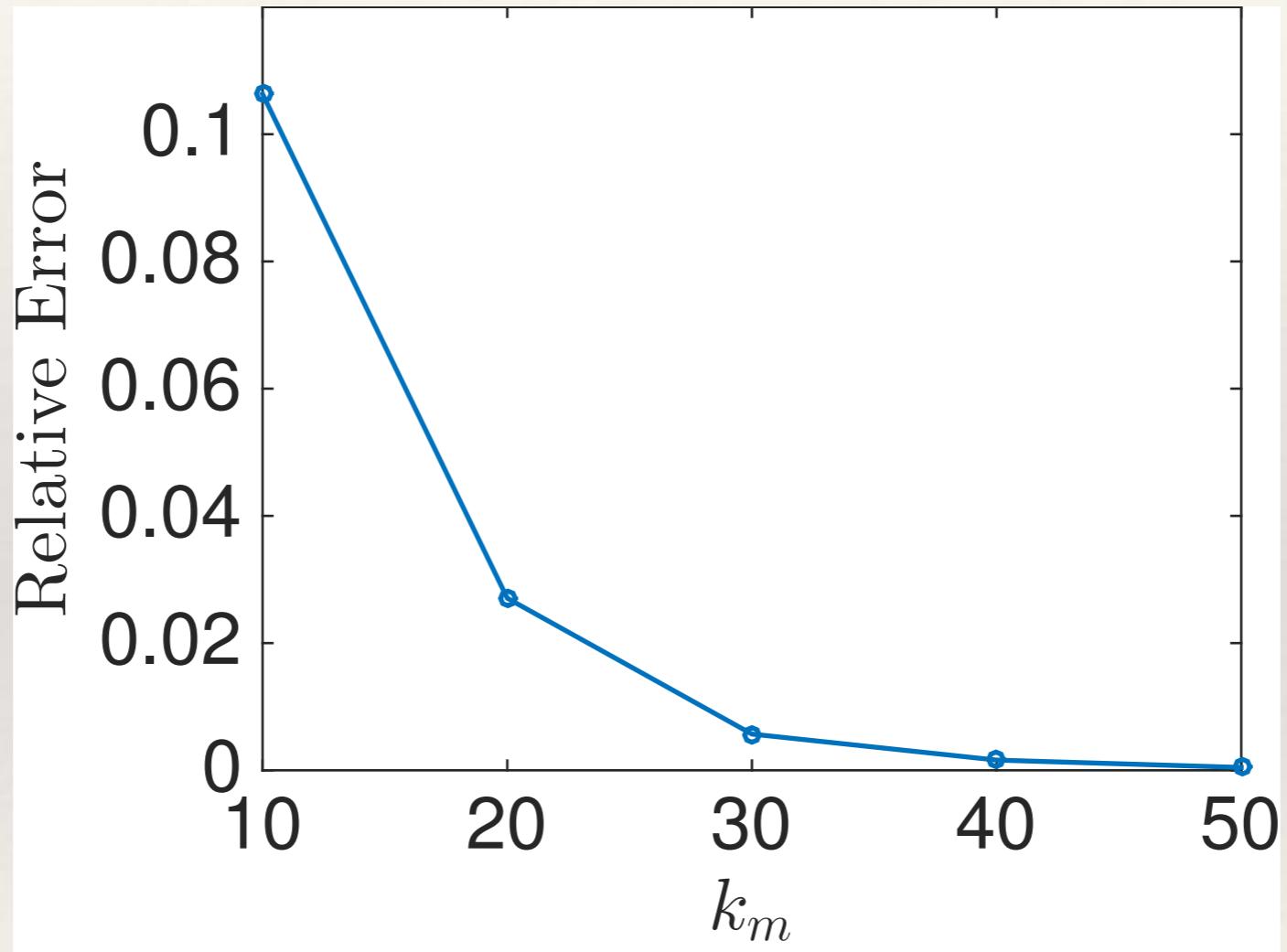
$$a(x, \frac{x}{\varepsilon}) = 2 + \sin(2\pi x_1) \cos(2\pi x_2) + \frac{2 + 1.8 \sin(\frac{2\pi x_1}{\varepsilon})}{2 + 1.8 \cos(\frac{2\pi x_2}{\varepsilon})} + \frac{2 + \sin(\frac{2\pi x_2}{\varepsilon})}{2 + 1.8 \cos(\frac{2\pi x_1}{\varepsilon})}$$



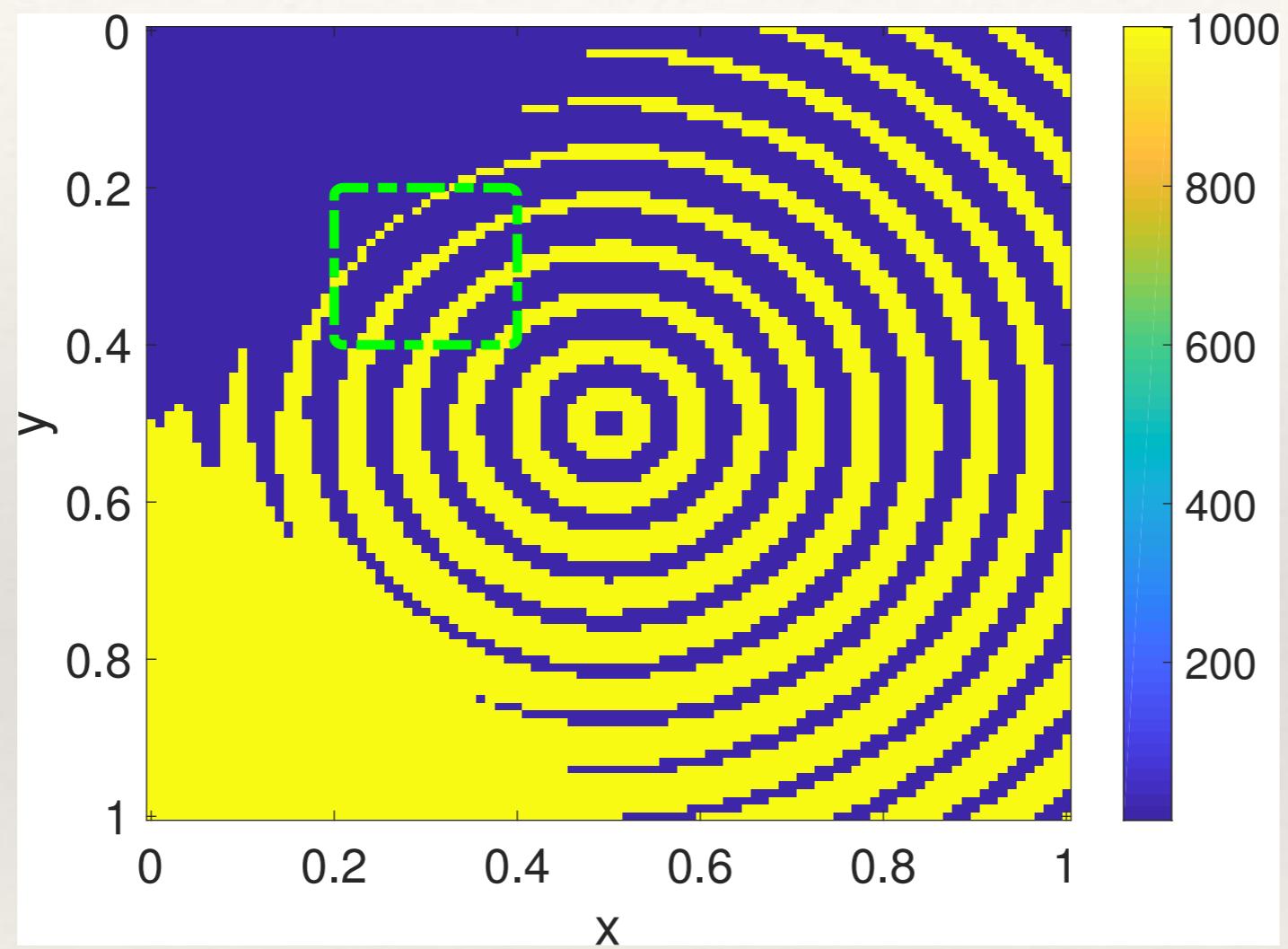
Numerical Results



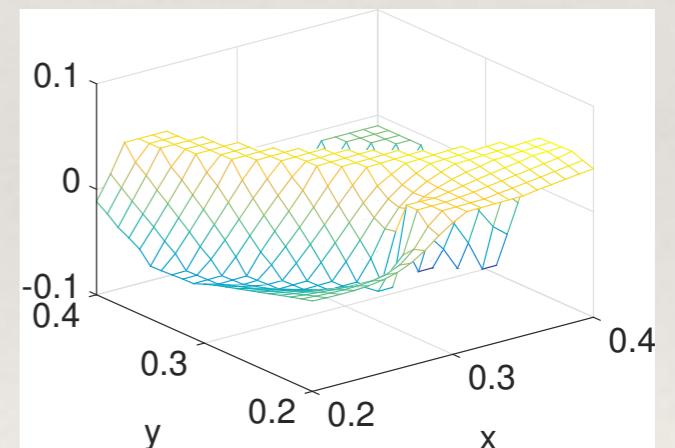
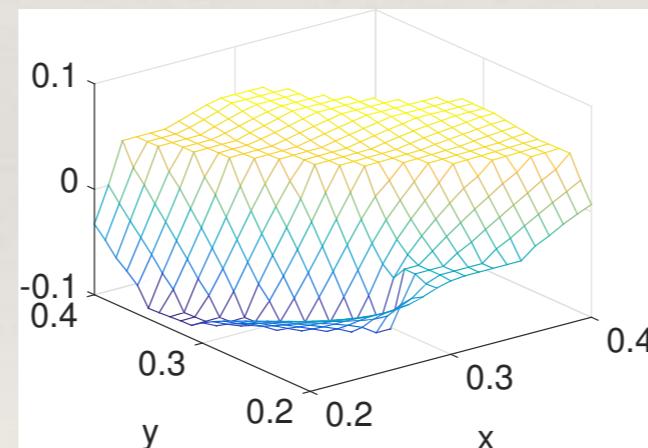
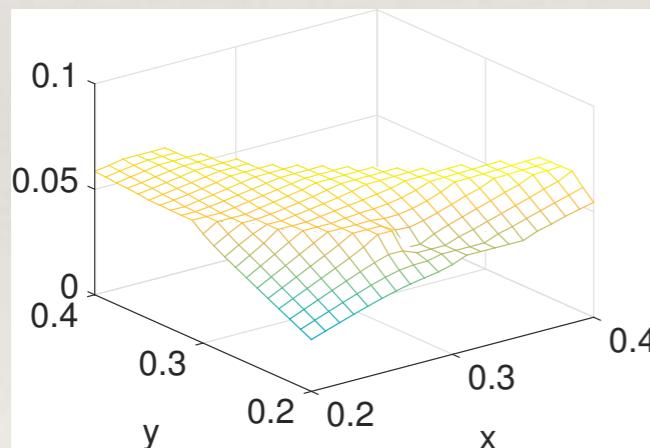
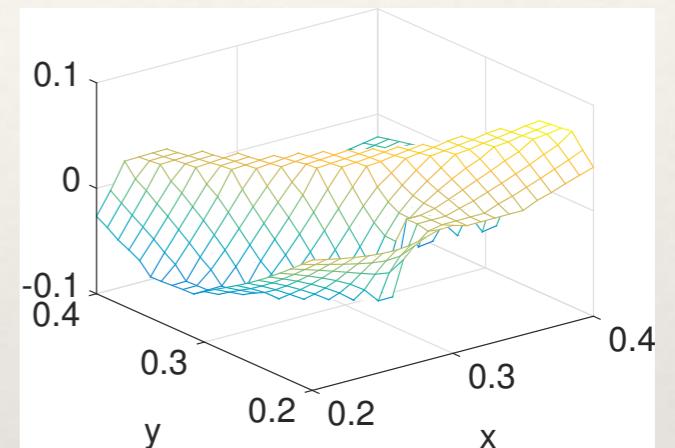
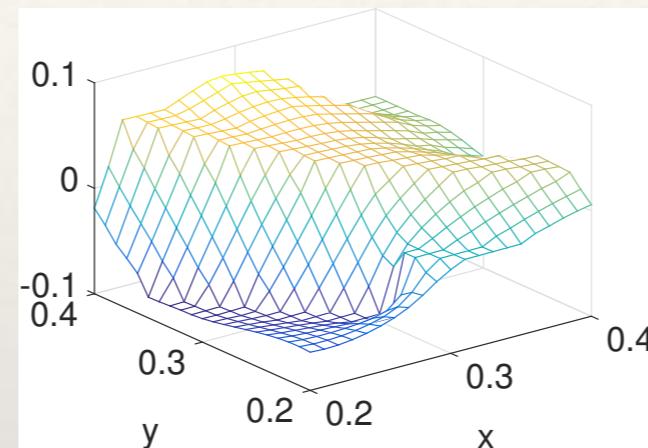
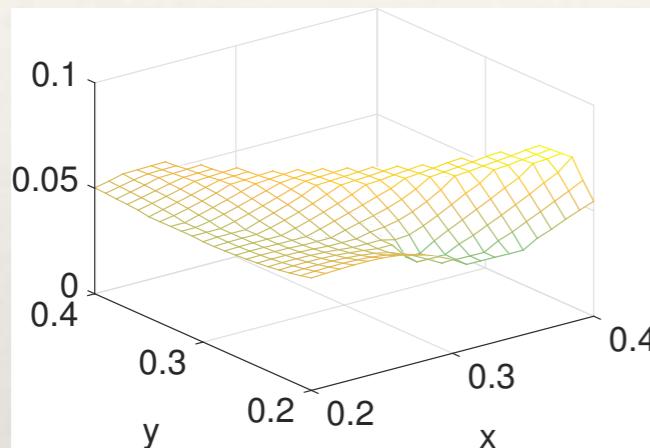
Numerical Results



Numerical Results



Numerical Results



Thanks !