# Quantitative stochastic homogenization 

Jean-Christophe Mourrat with S. Armstrong and T. Kuusi

CNRS - ENS Paris<br>July 27, 2018

## Elliptic equations

We consider

$$
\begin{cases}\partial_{t} u-\nabla \cdot(\mathbf{a} \nabla u)=0 & \text { in } U \\ u=f & \text { on } \partial U\end{cases}
$$

## Elliptic equations

We consider

$$
\begin{cases}-\nabla \cdot(\mathbf{a} \nabla u)=0 & \text { in } U \\ u=f & \text { on } \partial U\end{cases}
$$

## Elliptic equations

We consider

$$
\begin{aligned}
& \begin{cases}-\nabla \cdot(\mathbf{a} \nabla u)=0 & \text { in } U \\
u=f\end{cases} \\
& \text { an } \partial U . \\
& \mathbf{a} \mathbb{R}^{d} \rightarrow \mathbb{R}_{\mathrm{sym}}^{d \times d}
\end{aligned}
$$

## Elliptic equations

We consider

$$
\left.\begin{array}{c}
\left\{\begin{array}{l}
-\nabla \cdot(\mathbf{a} \nabla u)=0 \\
u=f
\end{array} \quad \text { in } U,\right. \\
\text { an } \partial U . \\
\mathbf{a} \mathbb{R}^{d} \rightarrow \mathbb{R}_{\text {sym }}^{d \times d}
\end{array}\right]
$$

## Elliptic equations

We consider

$$
\begin{gathered}
\begin{cases}-\nabla \cdot(\mathbf{a} \nabla u)=0 & \text { in } U \\
u=f & \text { on } \partial U .\end{cases} \\
\mathbf{a}: \mathbb{R}^{d} \rightarrow \mathbb{R}_{\text {sym }}^{d \times d} \\
\text { random }
\end{gathered}, \begin{gathered}
\Lambda^{-1} \leqslant \mathbf{a}(x) \leqslant \Lambda
\end{gathered}
$$

## Elliptic equations

We consider

$$
\left.\begin{array}{c} 
\begin{cases}-\nabla \cdot(\mathbf{a} \nabla u)=0 & \text { in } U, \\
u=f & \text { on } \partial U .\end{cases} \\
\mathbf{a}: \mathbb{R}^{d} \rightarrow \mathbb{R}_{\mathrm{sym}}^{d \times d} \\
\text { random }
\end{array}\right\}
$$

translation-invariant law

## Elliptic equations

We consider

$$
\left.\begin{array}{c} 
\begin{cases}-\nabla \cdot(\mathbf{a} \nabla u)=0 & \text { in } U \\
u=f & \text { on } \partial U .\end{cases} \\
\mathbf{a}: \mathbb{R}^{d} \rightarrow \mathbb{R}_{\mathrm{sym}}^{d \times d} \\
\text { random }
\end{array}\right\}
$$

## translation-invariant law

finite range of dependence

## Coefficients



## Coefficients



## Scaling

$$
\begin{cases}-\nabla \cdot\left(\mathbf{a}\left(\varepsilon^{-1} \cdot\right) \nabla u_{\varepsilon}\right)=0 & \text { in } U \\ u_{\varepsilon}=f & \text { on } \partial U\end{cases}
$$



## Homogenization

$$
\begin{cases}-\nabla \cdot\left(\mathbf{a}\left(\varepsilon^{-1} \cdot\right) \nabla u_{\varepsilon}\right)=0 & \text { in } U \\ u_{\varepsilon}=f & \text { on } \partial U\end{cases}
$$

There exists a matrix $\overline{\mathbf{a}}$ s.t.

$$
\begin{gathered}
u_{\varepsilon} \underset{\varepsilon \rightarrow 0}{L^{2}} \bar{u}, \\
\begin{cases}-\nabla \cdot(\overline{\mathbf{a}} \nabla \bar{u})=0 & \text { in } U, \\
\bar{u}=f & \text { on } \partial U .\end{cases}
\end{gathered}
$$

## Homogenization

$$
\begin{cases}-\nabla \cdot\left(\mathrm{a}\left(\varepsilon^{-1} \cdot\right) \nabla u_{\varepsilon}\right)=0 & \text { in } U \\ u_{\varepsilon}=f & \text { on } \partial U\end{cases}
$$

There exists a matrix $\overline{\mathbf{a}}$ s.t.

$$
\begin{gathered}
u_{\varepsilon} \xrightarrow[\varepsilon \rightarrow 0]{L^{2}} \bar{u}, \\
\begin{cases}-\nabla \cdot(\overline{\mathbf{a}} \nabla \bar{u})=0 & \text { in } U, \\
\bar{u}=f & \text { on } \partial U .\end{cases} \\
\nabla u_{\varepsilon} \rightharpoonup \nabla \bar{u}, \quad \mathbf{a}\left(\varepsilon^{-1} \cdot\right) \nabla u_{\varepsilon} \rightharpoonup \overline{\mathbf{a}} \nabla \bar{u} .
\end{gathered}
$$

## Law of large numbers

A law of large numbers...

## Law of large numbers

A law of large numbers... But

$$
\overline{\mathbf{a}} \neq \mathbb{E}[\mathbf{a}] \quad!
$$

## Law of large numbers

A law of large numbers. . . But

$$
\overline{\mathbf{a}} \neq \mathbb{E}[\mathbf{a}] \quad!
$$



## Numerical approximations

Very interesting result from a computational point of view.

## Numerical approximations

Very interesting result from a computational point of view.

- Computation of $\overline{\mathbf{a}}$ and then of $\bar{u}$.


## Numerical approximations

Very interesting result from a computational point of view.

- Computation of $\bar{a}$ and then of $\bar{u}$.
- Higher-order approximations; approximations in law; CLT.


## Numerical approximations

Very interesting result from a computational point of view.

- Computation of $\overline{\mathbf{a}}$ and then of $\bar{u}$.
- Higher-order approximations; approximations in law; CLT.
- Efficient algorithms for exact computation at fixed $\varepsilon$.


## Numerical approximations

Very interesting result from a computational point of view.

- Computation of $\overline{\mathbf{a}}$ and then of $\bar{u}$.
- Higher-order approximations; approximations in law; CLT.
- Efficient algorithms for exact computation at fixed $\varepsilon$.

Goal: estimate rates of convergence.

## Approach

## Difficulty:

## Approach

## Difficulty: solutions are non-local, non-linear functions of the coefficient field.

## Approach

Difficulty: solutions are non-local, non-linear functions of the coefficient field.

- 1st approach (Gloria, Neukamm, Otto, ...): "non-linear" concentration inequalities (cf. also Naddaf-Spencer).


## Approach

Difficulty: solutions are non-local, non-linear functions of the coefficient field.

- 1st approach (Gloria, Neukamm, Otto, ...): "non-linear" concentration inequalities (cf. also Naddaf-Spencer).
- 2nd approach (Armstrong, Kuusi, M., Smart, ...): renormalization, focus on energy quantities.


## Motivations

## Motivations

- Prove stronger results


## Motivations

- Prove stronger results
- Renormalization: very inspiring, broad and powerful idea, with still a lot of potential as a mathematical technique


## Motivations

- Prove stronger results
- Renormalization: very inspiring, broad and powerful idea, with still a lot of potential as a mathematical technique
- Develop tools that will hopefully shed light on variety of other problems: other equations, Gibbs measures, interacting particle systems, etc.


## Motivations

- Prove stronger results
- Renormalization: very inspiring, broad and powerful idea, with still a lot of potential as a mathematical technique
- Develop tools that will hopefully shed light on variety of other problems: other equations, Gibbs measures, interacting particle systems, etc.
- Suggests new numerical algorithms


## Problem reduction



## Problem reduction



## Problem reduction

For $p \in \mathbb{R}^{d}$, write a-harmonic function with slope $p$ as

$$
x \mapsto p \cdot x+\phi_{p}(x)
$$

that is,

$$
-\nabla \cdot \mathbf{a}\left(p+\nabla \phi_{p}\right)=0
$$

## Problem reduction

For $p \in \mathbb{R}^{d}$, write a-harmonic function with slope $p$ as

$$
x \mapsto p \cdot x+\phi_{p}(x)
$$

that is,

$$
\begin{gathered}
-\nabla \cdot \mathbf{a}\left(p+\nabla \phi_{p}\right)=0 \\
\left|\phi_{p}(x)\right| \ll|x| ?
\end{gathered}
$$

## Problem reduction

For $p \in \mathbb{R}^{d}$, write a-harmonic function with slope $p$ as

$$
x \mapsto p \cdot x+\phi_{p}(x)
$$

that is,

$$
\begin{gathered}
-\nabla \cdot \mathbf{a}\left(p+\nabla \phi_{p}\right)=0 \\
\left|\phi_{p}(x)\right| \ll|x| ?
\end{gathered}
$$

Quantify
Spat. av. $\nabla \phi_{p} \rightarrow 0$
Spat. av. $\mathbf{a}\left(p+\nabla \phi_{p}\right) \rightarrow \overline{\mathbf{a}} p$.

## Gradual homogenization

$$
\begin{aligned}
& \text { If } \quad 1-\delta \leqslant \mathbf{a}(x) \leqslant 1+\delta, \\
& \text { then } \quad|\overline{\mathbf{a}}-\mathbb{E}[\mathbf{a}]| \leqslant C \delta^{2} .
\end{aligned}
$$

## Gradual homogenization

$$
\begin{aligned}
& \text { If } \quad 1-\delta \leqslant \mathbf{a}(x) \leqslant 1+\delta, \\
& \text { then } \quad|\overline{\mathbf{a}}-\mathbb{E}[\mathbf{a}]| \leqslant C \delta^{2} .
\end{aligned}
$$

Gradual homogenization $\quad \mathbf{a}(x) \leadsto \mathbf{a}_{r}(x) \leadsto \overline{\mathbf{a}}$

## Gradual homogenization

$$
\begin{aligned}
& \text { If } \quad 1-\delta \leqslant \mathbf{a}(x) \leqslant 1+\delta, \\
& \text { then } \quad|\overline{\mathbf{a}}-\mathbb{E}[\mathbf{a}]| \leqslant C \delta^{2} .
\end{aligned}
$$

Gradual homogenization $\quad \mathbf{a}(x) \leadsto \mathbf{a}_{r}(x) \leadsto \overline{\mathbf{a}}$

Linearization for $r \gg 1$.

## Energies

Dal Maso, Modica 1986:

$$
\nu(U, p):=\inf _{v \in \ell_{p}+H_{0}^{1}(U)} \frac{1}{2} f_{U} \nabla v \cdot \mathbf{a} \nabla v .
$$

## Energies

Dal Maso, Modica 1986:

$$
\nu(U, p):=\inf _{v \in \ell_{p}+H_{0}^{1}(U)} \frac{1}{2} f_{U} \nabla v \cdot \mathbf{a} \nabla v .
$$

$U \mapsto \nu(U, p)$ is sub-additive.

## Energies

Dal Maso, Modica 1986:

$$
\nu(U, p):=\inf _{v \in \ell_{p}+H_{0}^{1}(U)} \frac{1}{2} f_{U} \nabla v \cdot \mathbf{a} \nabla v
$$

$U \mapsto \nu(U, p)$ is sub-additive.

$$
\nu(U, p)=: \frac{1}{2} p \cdot \mathbf{a}(U) p .
$$

## Energies

Dal Maso, Modica 1986:

$$
\nu(U, p):=\inf _{v \in \ell_{p}+H_{0}^{1}(U)} \frac{1}{2} f_{U} \nabla v \cdot \mathbf{a} \nabla v .
$$

$U \mapsto \nu(U, p)$ is sub-additive.

$$
\begin{aligned}
& \nu(U, p)=: \frac{1}{2} p \cdot \mathbf{a}(U) p . \\
& \nu(\square, p) \xrightarrow[|\square| \rightarrow \infty]{\text { a.s. }} \frac{1}{2} p \cdot \overline{\mathbf{a}} p .
\end{aligned}
$$

## Coarse-grained coefficients

$$
v_{p}:=\text { minimizer for } \nu(U, p)
$$

## Coarse-grained coefficients

$$
v_{p}:=\text { minimizer for } \nu(U, p)
$$

$$
f_{U} \nabla v_{p}=p
$$

## Coarse-grained coefficients

$$
v_{p}:=\text { minimizer for } \nu(U, p)
$$

$$
\begin{gathered}
f_{U} \nabla v_{p}=p \\
q \cdot \mathbf{a}(U) p=f_{U} \nabla v_{q} \cdot \mathbf{a} \nabla v_{p}
\end{gathered}
$$

## Coarse-grained coefficients

$$
v_{p}:=\text { minimizer for } \nu(U, p)
$$

$$
\begin{gathered}
f_{U} \nabla v_{p}=p \\
q \cdot \mathbf{a}(U) p=f_{U} \nabla v_{q} \cdot \mathbf{a} \nabla v_{p} \\
\mathbf{a}(U) p=f_{U} \mathbf{a} \nabla v_{p}
\end{gathered}
$$

## Strategy

## Strategy

- Get a small rate of convergence: $\exists \alpha>0$ s.t.

$$
\left|\nu(\square, p)-\frac{1}{2} p \cdot \overline{\mathbf{a}} p\right| \lesssim|\square|^{-\alpha} .
$$

## Strategy

- Get a small rate of convergence: $\exists \alpha>0$ s.t.

$$
\left|\nu(\square, p)-\frac{1}{2} p \cdot \overline{\mathbf{a}} p\right| \lesssim|\square|^{-\alpha} .
$$

- Coarse-grained coefficients vary by $\pm|\square|^{-\alpha}$, so

$$
\left|\nu(\square, p)-2^{-d} \sum_{z} \nu\left(z+\square^{\prime}, p\right)\right| \lesssim|\square|^{-2 \alpha} .
$$

## Strategy

- Get a small rate of convergence: $\exists \alpha>0$ s.t.

$$
\left|\nu(\square, p)-\frac{1}{2} p \cdot \overline{\mathbf{a}} p\right| \lesssim|\square|^{-\alpha} .
$$

- Coarse-grained coefficients vary by $\pm \mid \underline{\mid-\alpha}$, so

$$
\left|\nu(\square, p)-2^{-d} \sum_{z} \nu\left(z+\square^{\prime}, p\right)\right| \lesssim|\square|^{-2 \alpha} .
$$

- Control of fluctuations

$$
|\nu(\square, p)-\mathbb{E}[\nu(\square, p)]|<|\square|^{-(2 \alpha) \wedge \frac{1}{2}} .
$$

## Strategy

- Get a small rate of convergence: $\exists \alpha>0$ s.t.

$$
\left|\nu(\square, p)-\frac{1}{2} p \cdot \overline{\mathbf{a}} p\right| \lesssim|\square|^{-\alpha} .
$$

- Coarse-grained coefficients vary by $\pm \mid \underline{\mid-\alpha}$, so

$$
\left|\nu(\square, p)-2^{-d} \sum_{z} \nu\left(z+\square^{\prime}, p\right)\right| \lesssim|\square|^{-2 \alpha} \text {. }
$$

- Control of fluctuations

$$
|\nu(\square, p)-\mathbb{E}[\nu(\square, p)]| \lesssim|\square|^{-(2 \alpha) \wedge \frac{1}{2}} .
$$

- $\Longrightarrow$ Exponent improvement $\alpha \rightarrow(2 \alpha) \wedge \frac{1}{2}$.


## Corrector estimates

For $\left.\square_{r}:=\right]-\frac{r}{2} ; \frac{r}{2}\left[^{d}\right.$,

$$
\mathbf{a}\left(x+\square_{r}\right) \simeq \overline{\mathbf{a}}+W_{r}(x), \quad \text { where } \quad W_{r}(x) \simeq \mathcal{N}\left(0, r^{-d}\right)
$$

## Corrector estimates

For $\left.\square_{r}:=\right]-\frac{r}{2} ; \frac{r}{2}\left[{ }^{d}\right.$,

$$
\mathbf{a}\left(x+\square_{r}\right) \simeq \overline{\mathbf{a}}+W_{r}(x), \quad \text { where } \quad W_{r}(x) \simeq \mathcal{N}\left(0, r^{-d}\right)
$$

Recall that $-\nabla \cdot \mathbf{a}\left(p+\nabla \phi_{p}\right)=0$. For

$$
\phi_{p, r}:=\phi_{p} \star \frac{\mathbf{1}_{\square_{r}}}{\left|\square_{r}\right|},
$$

## Corrector estimates

For $\left.\square_{r}:=\right]-\frac{r}{2} ; \frac{r}{2}\left[{ }^{d}\right.$,

$$
\mathbf{a}\left(x+\square_{r}\right) \simeq \overline{\mathbf{a}}+W_{r}(x), \quad \text { where } \quad W_{r}(x) \simeq \mathcal{N}\left(0, r^{-d}\right)
$$

Recall that $-\nabla \cdot \mathbf{a}\left(p+\nabla \phi_{p}\right)=0$. For

$$
\phi_{p, r}:=\phi_{p} \star \frac{\mathbf{1}_{\square_{r}}}{\left|\square_{r}\right|},
$$

we expect

$$
-\nabla \cdot\left(\overline{\mathbf{a}}+W_{r}(x)\right)\left(p+\nabla \phi_{p, r}\right) \simeq 0 .
$$

## Corrector estimates

$$
-\nabla \cdot\left(\overline{\mathbf{a}}+W_{r}\right)\left(p+\nabla \phi_{p, r}\right) \simeq 0 .
$$

## Corrector estimates

$$
\begin{gathered}
-\nabla \cdot\left(\overline{\mathbf{a}}+W_{r}\right)\left(p+\nabla \phi_{p, r}\right) \simeq 0 . \\
-\nabla \cdot\left(\overline{\mathbf{a}}+W_{r}\right) \nabla \phi_{p, r} \simeq \nabla \cdot\left(W_{r} p\right) .
\end{gathered}
$$

## Corrector estimates

$$
\begin{gathered}
-\nabla \cdot\left(\overline{\mathbf{a}}+W_{r}\right)\left(p+\nabla \phi_{p, r}\right) \simeq 0 . \\
-\nabla \cdot\left(\overline{\mathbf{a}}+W_{r}\right) \nabla \phi_{p, r} \simeq \nabla \cdot\left(W_{r} p\right) . \\
\Longrightarrow\left|\nabla \phi_{p, r}\right| \lesssim r^{-\frac{d}{2}} .
\end{gathered}
$$

## Corrector estimates

$$
\begin{gathered}
-\nabla \cdot\left(\overline{\mathbf{a}}+W_{r}\right)\left(p+\nabla \phi_{p, r}\right) \simeq 0 . \\
-\nabla \cdot\left(\overline{\mathbf{a}}+W_{r}\right) \nabla \phi_{p, r} \simeq \nabla \cdot\left(W_{r} p\right) . \\
\Longrightarrow\left|\nabla \phi_{p, r}\right| \lesssim r^{-\frac{d}{2}} . \\
-\nabla \cdot \overline{\mathbf{a}} \nabla \phi_{p, r} \simeq \nabla \cdot\left(W_{r} p\right) .
\end{gathered}
$$

## Corrector estimates

$$
\begin{gathered}
-\nabla \cdot\left(\overline{\mathbf{a}}+W_{r}\right)\left(p+\nabla \phi_{p, r}\right) \simeq 0 . \\
-\nabla \cdot\left(\overline{\mathbf{a}}+W_{r}\right) \nabla \phi_{p, r} \simeq \nabla \cdot\left(W_{r} p\right) . \\
\Longrightarrow\left|\nabla \phi_{p, r}\right| \lesssim r^{-\frac{d}{2}} \\
-\nabla \cdot \overline{\mathbf{a}} \nabla \phi_{p, r} \simeq \nabla \cdot\left(W_{r} p\right) . \\
\Longrightarrow \quad r^{\frac{d}{2}}\left(\nabla \phi_{p}\right)(r \cdot) \xrightarrow[r \rightarrow \infty]{\operatorname{law}} \nabla(G F F) .
\end{gathered}
$$

## Correctors



## Correctors



## GFF $-\nabla \cdot \overline{\mathbf{a}} \nabla \Phi=\nabla \cdot W$



## GFF $-\nabla \cdot \overline{\mathbf{a}} \nabla \Phi=\nabla \cdot W$



## Perspectives and dreams

- Optimal error estimates, next-order information, new numerical algorithms


## Perspectives and dreams

- Optimal error estimates, next-order information, new numerical algorithms
- Expand the reach of rigorous renormalization techniques


## Perspectives and dreams

- Optimal error estimates, next-order information, new numerical algorithms
- Expand the reach of rigorous renormalization techniques
- New tools to attack other models, e.g. other equations, gradient Gibbs measures, interacting particle systems, ...


## Perspectives and dreams

- Optimal error estimates, next-order information, new numerical algorithms
- Expand the reach of rigorous renormalization techniques
- New tools to attack other models, e.g. other equations, gradient Gibbs measures, interacting particle systems, ...


## Perspectives and dreams

- Optimal error estimates, next-order information, new numerical algorithms
- Expand the reach of rigorous renormalization techniques
- New tools to attack other models, e.g. other equations, gradient Gibbs measures, interacting particle systems, ...
- Check out our book!


## Thank you!

