

# A quantitative approach for hydrodynamic limits.

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# Hydrodynamic limits

2 possible descriptions of a gas :

- Atomistic description :  $N$  particles in interaction (Newton's laws, etc...)
- Continuum description : (system of) PDE(s) (Navier-Stokes, Euler,...)

Hydrodynamic limit : deriving a continuous model as a scaling limit of discrete models.

In this talk, we shall consider the more simple situation of scaling limits for stochastic models.

We are interested in diffusions of the form

$$dx_t = -\psi'(x_t)dt + \sqrt{2}dB_t.$$

We consider a large number  $N$  of such diffusions, and add a nearest-neighbor interaction, such that

$$dx_i(t) = N^2(\psi'(x_{i+1}) + \psi'(x_{i-1}) - 2\psi'(x_i))dt + \sqrt{2}N(dB_t^{i+1} - dB_t^i)$$

where the  $B^i$  are independent Brownian motions. The additional factor  $N$  corresponds to a scaling in time. The quantity

$$\frac{1}{N} \sum x_i$$

is conserved, and the fluctuations around this mean tend to diminish in time.

## Some assumptions

We can write the dynamic as

$$dX_t = -A\nabla H(X_t)dt + \sqrt{2A}dB_t.$$

The phase state is

$$X_{N,m} := \left\{ x \in \mathbb{R}^N ; \sum x_i = Nm \right\},$$

which we equip with the usual  $\ell^2$  norm. The Hamiltonian  $H$  is given by

$$H(x) := \sum_{i=1}^N \psi(x_i),$$

with

$$\psi(x) = |x|^p + \delta(x), \quad p \geq 2, \quad \|\delta\|_{C^2} < \infty.$$

Finally,  $A$  is the discrete Laplacian

$$A_{i,j} := N^2(2\delta_{i,j} - \delta_{i,j-1} - \delta_{i,j+1}),$$

where  $N^2$  is a scaling in time of the evolution.

This dynamic is a reversible stochastic dynamic on an affine Euclidean subspace  $X$  of  $\mathbb{R}^N$ , with an (unique) invariant probability measure

$$\mu(dx) := \exp(-H(x))dx$$

The law of this evolution is given by the PDE

$$\frac{\partial}{\partial t}(f\mu) = \nabla \cdot (A\nabla f\mu)$$

where  $f$  is the density with respect to  $\mu$ .

We are interested in the behavior of the probability measure  $f\mu$  when the dimension  $N$  is large.

## Notion of convergence

It will be convenient to see our system as a "random function". We associate to each vector  $x \in X_N$  a step function  $\bar{x}$  on the torus, defined by

$$\bar{x}(\theta) := x_i ; \theta \in \left[ \frac{i-1}{N}, \frac{i}{N} \right).$$

We will say a sequence  $\nu_N$  converges to a macroscopic profile  $\rho \in L^2(\mathbb{T})$  if the quantities

$$\frac{1}{N} \sum J(i/N)x_i \approx \int_{\mathbb{T}} J(\theta)\bar{x}(\theta)d\theta$$

converge in probability to

$$\int_{\mathbb{T}} J(\theta)\rho(\theta)d\theta$$

for every smooth test functions  $J$ .

It has been proven by Guo, Papanicolaou and Varadhan that, if the initial data converges to a macroscopic profile, then the dynamics behave deterministically at later times, and the behavior is given by the solution of the PDE

$$\frac{\partial \rho}{\partial t} = \frac{\partial^2}{\partial \theta^2} \varphi'(\rho)$$

where  $\varphi$  is given by

$$\varphi(m) := \sup_{\sigma} \left( \sigma m - \log \int \exp(\sigma x - \psi(x)) dx \right).$$

Useful property :  $\varphi$  is uniformly convex

## A gradient flow interpretation

This dynamic is a gradient flow of the entropy with respect to the entropy  $\text{Ent}_\mu$ , for the Wasserstein distance associated to the Euclidean distance  $\langle A^{-1}\cdot, \cdot \rangle$ ;

The PDE is the gradient flow of  $\rho \rightarrow \int \varphi(\rho) d\theta$  on the space of functions on the torus, for the  $H^{-1}$  norm.



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We can use gradient flow stability arguments to go from one to the other.

The functional point of view allows to embed all the spaces  $X_N$  into a single space, which is the space  $H^{-1}$ , dual of the Sobolev space  $H^1$ . Then we have

$$\frac{1}{N} \langle A^{-1}x, x \rangle \approx \|\bar{x}\|_{H^{-1}}^2.$$

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Moreover,

$$\frac{1}{N} \text{Ent}_\mu(\cdot) \xrightarrow{\Gamma} \int \varphi(\cdot) d\theta - \varphi \left( \int \cdot d\theta \right).$$

These statements allow us to show that, for well-prepared initial data that weakly converge to a deterministic profile  $\rho$ , and such that

$$\frac{1}{N} \text{Ent}_\mu(f_{0,N} \mu_N) \longrightarrow \int \varphi(\rho_0) d\theta - \varphi \left( \int \rho_0 d\theta \right),$$

then, at positive times, the solutions  $f_N(t) \mu_N$  weakly converge to the solution of the PDE.

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We wish for two improvements :

- Weaken the assumption on the initial data ;
- Obtain explicit quantitative rates of convergence.

Theorem (Grunewald, Otto, Villani, Westdickenberg, 2009, F.-Menz 2013)

If  $\int_{X_N} f_0 \log f_0 d\mu_N \leq CN$  and

$$\int_X \|\bar{x} - \rho_0\|_{H^{-1}}^2 f_{0,N}(x) \mu_N(dx) \longrightarrow 0,$$

then there is a nice step-function approximation  $\eta(t)$  of the solution of the PDE, with mesh size  $N^{-1/2}$ , such that for any  $T > 0$ ,

$$\sup_{t \in [0, T]} \frac{1}{N} W_{2, A^{-1}}(f(t)\mu, \delta_{\eta(t)})^2 \longrightarrow 0$$

with quantitative bounds of order  $N^{-1/2}$ .

## Method of proof

We introduce a macroscopic profile  $y = P_x$ , by separating the spins into  $\sqrt{N}$  boxes of  $\sqrt{N}$  neighboring spins, and taking the average on each box.

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For  $N$  large enough,  $\bar{H}$  is uniformly convex  
→ functional inequalities in positive curvature (Log-Sobolev, Talagrand,...)

We consider a time-dependent macroscopic profile  $\eta(t)$ , given by the ODE

$$\frac{d\eta}{dt} = -\bar{A}\nabla\bar{H}(\eta)$$

with  $\bar{A}$  a well-chosen symmetric matrix.

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When computing  $\frac{d}{dt} W_{2,A^{-1}}(f(t)\mu, \delta_{\eta(t)})^2$ , we can separate the expression we obtain into a macroscopic component and a fluctuations component.

The macroscopic component can be handled using functional inequalities, and the fluctuation component doesn't contribute too much to

$$\|\bar{x} - \eta\|_{H^{-1}}^2.$$

## Local Gibbs behavior

### Theorem (F., 2013)

For any time  $t > 0$ , we have

$$\frac{1}{N} \text{Ent}_{\mu_N}(f_N(t)\mu_N) \longrightarrow \int_{\mathbb{T}} \varphi(\rho(t)) d\theta - \varphi\left(\int \rho(t) d\theta\right)$$

with quantitative bounds of order  $\frac{\log N}{N^{1/4}}$ .

This result means that, even though we didn't assume the initial data was well-prepared, we have convergence of the free energy at any positive time.

## Sketch of proof

There exists a sequence of measures of the form

$\tilde{\mu}(dx) = \frac{1}{Z} \exp(\lambda(t) \cdot Px) \mu(dx)$  which converge to  $\rho(t)$ , and are well-prepared.

Since the associated macroscopic measures are log-concave, we can use the HWI inequality at macroscopic level :

$$\text{Ent}_{\tilde{\mu}}(\bar{f}\bar{\mu}) \leq W_2(\bar{f}\bar{\mu}, \tilde{\mu}) \sqrt{I_{\tilde{\mu}}(\bar{f}\bar{\mu})}.$$

We have  $\frac{1}{N} W_2(\bar{f}\bar{\mu}, \tilde{\mu})^2 \leq \frac{C}{\sqrt{N}}$ , and bounds of order  $N$  on the (time-integrated) relative Fisher information.

Convergence of  $\frac{1}{N} \text{Ent}_{\mu_N}(f_N(t)\mu_N)$  can then be deduced.

## Non-reversible dynamics

The method can be extended to cover non-reversible dynamics of the form

$$dX_t = -A\nabla H(X_t)dt + J\nabla H(X_t)dt + \sqrt{2A}dB_t$$

where  $J$  is an antisymmetric matrix such that  $-J^2 \leq cA$ .

In the case where  $J$  is a discrete derivation, we obtain the scaling limit

$$\frac{\partial \rho}{\partial t} = \frac{\partial^2}{\partial \theta^2} \varphi'(\rho) + \frac{\partial}{\partial \theta} \varphi'(\rho).$$

(Joint work with M.H. Duong)

## Two open problems

Two main questions remain :

- How can we extend the method to cover genuinely Riemannian situations? We are interested in dynamics of the form

$$dX_t = -A(X_t)\nabla H(X_t)dt - \operatorname{div}(A)(X_t)dt + \sqrt{2A(X_t)}dB_t,$$

which are gradient flows of the entropy for the Riemannian metric with tensor  $A^{-1}(x)$ . These can lead to hydrodynamic limits of the form

$$\frac{\partial \rho}{\partial t} = \frac{\partial}{\partial \theta} \left( a(\rho) \frac{\partial}{\partial \theta} \varphi'(\rho) \right)$$

with a coefficient  $a(m)$  that depends on both  $A(x)$  and  $\psi$ ;

- Is there a similar method that works for discrete dynamics, such as interacting particle systems?