

# Introduction to Propagation of Chaos and Mean-Field Systems

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Summer School - Mean-Field Models  
Centre Henri Lebesgue, IRMAR, Rennes  
12th June 2023

*“From the atomistic view to the laws of motion of continua” . . .*

David Hilbert

1. A short historical introduction
2. Mean-field particle systems and propagation of chaos

# The *Stoßzahlansatz* and the early kinetic theory of gas



Clausius



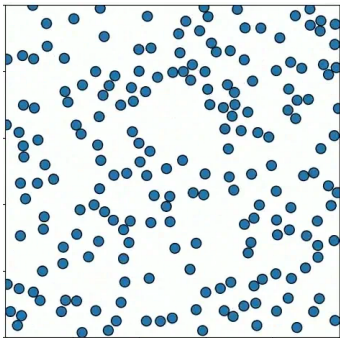
Maxwell



Boltzmann

## The hard-sphere gas

A simple mechanical model?



## The fundamental assumption

**The velocities of two colliding particles are uncorrelated.**

- ▶ The Maxwellian is the equilibrium distribution
- ▶ The entropy increases (H-theorem).
- ▶ The time evolution of the distribution of velocities is given by the Boltzmann equation.

This **cannot** be true for at least two reasons:

1. **The collisions create correlations.**
2. The Boltzmann equation is irreversible.

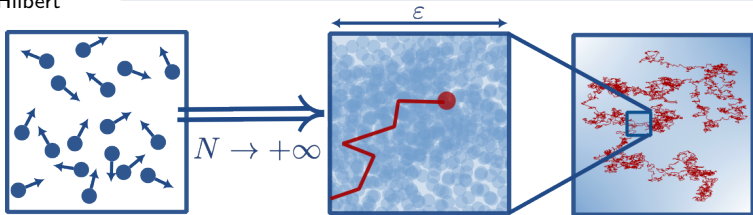
# Toward a rigorous mathematical kinetic theory



David Hilbert

## Hilbert 6th problem (1900)

*Developing mathematically the limiting processes [...] which lead from the atomistic view to the laws of motion of continua.*



### Microscopic scale.

$N$  identical particles in a space  $E$ .

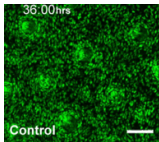
$Nd$ -dimensional dynamical system.

### Mesoscopic scale when $N \rightarrow +\infty$ .

$f_t \in \mathcal{P}(E)$  distribution of a typical particle.

Compute the evolution of statistical quantities

**Goal: extend this framework to other types of particle systems...**



# Collisional and mean-field models



Tatyana and Paul Ehrenfest

## The Conceptual Foundations of the Statistical Approach in Mechanics (1912)

From the *Stoßzahlansatz* to the *molekular Unordnung*: a statistical point of view.

→ The rigorous formulation of Boltzmann's ideas for the hard-sphere gas remains **extremely difficult**: the best available results are only valid in a very **dilute regime** [Grad, 1963] and for **short times** [Lanford, 1975], [Gallagher, Saint-Raymond, Texier, 2014].

## An alternative approach: (stochastic) mean-field models...

→ Point particles in a dense regime with continuous rescaled interactions by  $1/N$ .



Mark Kac

## Foundations of Kinetic Theory (1956)

Probabilistic interpretation of the Boltzmann equation and the mathematical notion of *propagation of chaos*.

## Propagation of chaos for a class of non-linear parabolic equations (1967)

Extension of Kac ideas to diffusion and other stochastic particle models.



Henry P. McKean

*“From the atomistic view to the laws of motion of continua” . . .*

David Hilbert

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# Kac theory: stochastic exchangeable particle systems

## Definition: $N$ -particle system

Given a state space  $E$ , a  $N$ -particle system is a  $E^N$ -valued Markov process  $\mathcal{X}_t^N = (X_t^1, \dots, X_t^N)$ . Its law at time  $t$  is denoted by  $f_t^N \in \mathcal{P}(E^N)$  and is characterized by the (weak-forward) **Kolmogorov equation**:

$$\forall \varphi_N \in C_b(E^N), \quad \frac{d}{dt} \mathbb{E}[\varphi_N(\mathcal{X}_t^N)] \equiv \frac{d}{dt} \langle f_t^N, \varphi_N \rangle = \langle f_t^N, \mathcal{L}_N \varphi_N \rangle,$$

where  $\mathcal{L}_N : C_b(E^N) \rightarrow C_b(E^N)$  is the **Markov generator**.

## Assumption: Indistinguishability

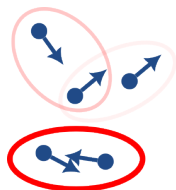
The process is symmetric:  $\forall \pi \in \mathfrak{S}_N, (X_t^{\pi(1)}, \dots, X_t^{\pi(N)}) \sim (X_t^1, \dots, X_t^N)$ . The  $N$ -particle system can thus be represented by its **empirical measure**

$$\mu_{\mathcal{X}_t^N} := \frac{1}{N} \sum_{i=1}^N \delta_{X_t^i} \in \mathcal{P}(E).$$

This is a **random measure** whose law is denoted by  $F_t^N \in \mathcal{P}(\mathcal{P}(E))$ .

# Kac collision process

## Kac model



“Rare stochastic collisions”

A mean-field stochastic collision process

Consider a stochastic Poisson process on each pair of particles with “collision” rate  $\lambda(Z_t^i, Z_t^j)/N$ .

E.g. : Hard-sphere gas  $\lambda(x, y) = \delta_{|x-y|=2R}$ .

**Collision event at time  $t$** , post-collisional states:

$$Z_{t+}^i, Z_{t+}^j \sim \Gamma^{(2)}(Z_t^i, Z_t^j, dz, dz^*)$$

*Note:*  $\Gamma^{(2)}(z_1, z_2, dz'_1, dz'_2) = \Gamma^{(2)}(z_2, z_1, dz'_2, dz'_1)$ .

**Two-particle Markov generator:** for  $\varphi_2 \in C_b(E^2)$ ,

$$L^{(2)}\varphi_2(z_1, z_2) = \lambda(z_1, z_2) \int_{E^2} \left\{ \varphi_2(z'_1, z'_2) - \varphi_2(z_1, z_2) \right\} \Gamma^{(2)}(z_1, z_2, dz'_1, dz'_2).$$

**$N$ -particle Markov generator:** for  $\varphi_N \in C_b(E^N)$ ,

$$\mathcal{L}_N \varphi_N = \frac{1}{N} \sum_{i < j} L^{(2)} \diamond_{ij} \varphi_N.$$

$$L^{(2)} \diamond_{ij} \varphi_N(z_1, \dots, z_N) := L^{(2)}[(u_i, u_j) \mapsto \varphi_N(z_1, \dots, u_i, \dots, u_j, \dots, z_N)](z_i, z_j).$$

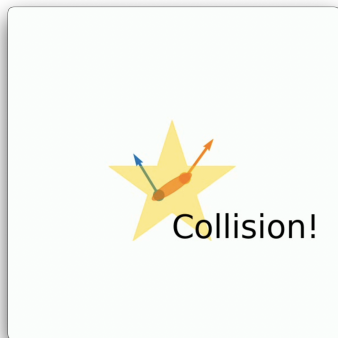


## Kac model: example

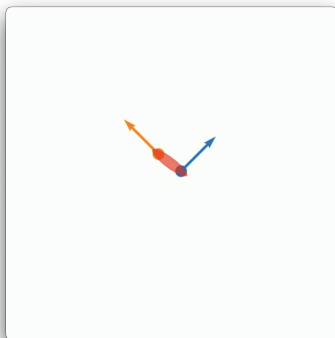
The random collision time  $T$  between two particles depends on the distance:

$$\mathbb{P}(T \geq t) = e^{-\int_0^t \lambda(|X_s^1 - X_s^2|) ds}$$

with  $r \mapsto \lambda(r)$  non-increasing and new velocities are sampled randomly.



Collision (likely)

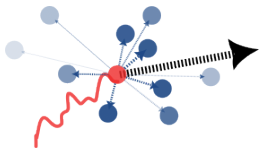


No collision (rare but possible)

**Other applications:** social sciences, games, opinion dynamics, economics. . .

# McKean-Vlasov diffusion model

## McKean-Vlasov model



*“Small deterministic binary forces plus individual noise”*

A mean-field diffusion process

Each particle  $i$  feels a small force of size  $1/N$  from each of the other particles:

$$dX_t^i = F \star \mu_{\mathcal{X}_t^N}(X_t^i)dt + \sigma dB_t^i.$$

where  $F \star \mu(x) := \int_E F(y - x)\mu(dy)$ .

**One-particle Markov generator:** for  $\varphi \in C_b(E)$ ,  $\mu \in \mathcal{P}(E)$ ,

$$L_\mu \varphi(x) := F \star \mu(x) \cdot \nabla \varphi + \frac{1}{2} \sigma^2 \Delta \varphi$$

**$N$ -particle Markov generator:** for  $\varphi_N \in C_b(E^N)$ ,  $\mathbf{x}^N = (x^1, \dots, x^N)$ ,

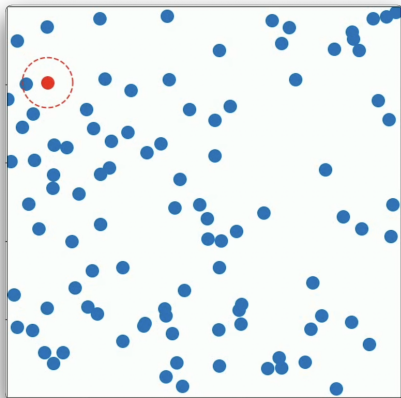
$$\mathcal{L}_N \varphi_N(\mathbf{x}^N) = \sum_{i=1}^N L_{\mu_{\mathbf{x}^N}} \diamond_i \varphi_N(\mathbf{x}^N),$$

with  $L_\mu \diamond_i \varphi_N(x^1, \dots, x^N) := L_\mu[u_i \mapsto \varphi_N(x^1, \dots, u_i, \dots, x^N)](x^i)$ .

# McKean-Vlasov model: example

Self-propulsion and short-range repulsion:

$$\frac{dX_t^i}{dt} = V_t^i, \quad \frac{dV_t^i}{dt} = (1 - |V_t^i|^2)V_t^i - \frac{1}{N} \sum_{j=1}^N \nabla_{x^i} e^{-|X_t^j - X_t^i|/R}.$$



## Definition: Kac chaos at a fixed time $t$

The  $N$ -particle distribution  $f_t^N$  is  $f_t$ -**chaotic** for a given distribution  $f_t \in \mathcal{P}(E)$  when for any  $s \in \mathbb{N}$ , the  $s$ -th marginal  $f_t^{s,N} \in \mathcal{P}(E^s)$  of  $f_t^N \in \mathcal{P}(E^N)$  satisfies

$$f_t^{s,N} \xrightarrow{N \rightarrow +\infty} f_t^{\otimes s} \text{ weakly in } \mathcal{P}(E^s).$$

→ “When  $N$  is large, any group of  $s$  particles is close to be independent.”

## Definition: Propagation of chaos

It means:  $f_0^N$  is  $f_0$ -chaotic **implies**  $f_t^N$  is  $f_t$ -chaotic for  $t \geq 0$ .

From now on,  $f_0^N = f_0^{\otimes N}$  (the particles are initially i.i.d.).

## Lemma

The two following assertions are **equivalent** to Kac chaos.

- (i) Kac chaos for the marginal  $s = 2$ , i.e.  $f_t^{2,N} \rightarrow f_t^{\otimes 2}$  weakly in  $\mathcal{P}(E)$ .
- (ii) The empirical measure process converges in law towards the deterministic measure  $f_t$ , i.e.  $\forall \Phi \in C_b(\mathcal{P}(E)), \quad \mathbb{E}[\Phi(\mu_{\mathcal{X}_t^N})] \rightarrow \Phi(f_t)$ .

# The two building block theorems of Kac and McKean.

1. Kac theorem: Markov generator and series expansion
2. McKean theorem: empirical measure, stochastic paths, coupling
3. Variations and alternative points of view

**Recall:**  $\mathcal{L}_N \varphi_N = \frac{1}{N} \sum_{i < j} L^{(2)} \diamond_{ij} \varphi_N$  and  $L^{(2)}$  is a two-particle jump operator.

## Cut-off assumption

The operator  $L^{(2)}$  is **bounded** in  $L^\infty$ . E.g. the collision rate  $\lambda \equiv 1$  is **constant**.

**Consequence:**  $\mathcal{L}_N$  is bounded in  $L^\infty$  and for  $\varphi_s \equiv \varphi_s \otimes 1^{N-s} \in C_b(E^s) \subset C_b(E^N)$

$$\langle f_t^{s,N}, \varphi_s \rangle = \langle f_0^N, e^{t\mathcal{L}_N} \varphi_s \rangle = \sum_{k=0}^{+\infty} \frac{t^k}{k!} \langle f_0^N, \mathcal{L}_N^k \varphi_s \rangle.$$

→ Take the limit  $N \rightarrow +\infty$  of each term **uniformly in  $t$** .

## Main observation for $k = 1$

$$\langle f_0^N, \mathcal{L}_N \varphi_s \rangle = \frac{s}{N} \langle f_0^{s,N}, \mathcal{L}_s \varphi_s \rangle + \frac{N-s}{N} \langle f_0^{s+1,N}, \mathbf{D} \varphi_s \rangle,$$

where the operator  $\mathbf{D} : C_b(E^s) \rightarrow C_b(E^{s+1})$  is defined by:

$$\mathbf{D} \varphi_s = \sum_{i=1}^s L^{(2)} \diamond_{i,s+1} (\varphi_s \otimes 1).$$

**Note:** hierarchy structure or “recollision tree” [Graham, Méléard, *Ann. Prob.* 25, 1997]

## The main lemma

For  $k > 1$ , the same structure holds and under the initial chaos assumption  $f_0^s = f_0^{\otimes s}$ ,

$$\langle f_0^N, \mathcal{L}_N^k \varphi_s \rangle \xrightarrow{N \rightarrow +\infty} \langle f_0^{\otimes(s+k)}, \mathbf{D}^k \varphi_s \rangle.$$

Moreover the series converges absolutely uniformly in  $N$  on  $(0, t_0)$ .

Consequently, this **defines** a limit distribution  $f_t^{s,\infty} \in \mathcal{P}(E^s)$  by:

$$\langle f_t^{s,N}, \varphi_s \rangle = \sum_{k=0}^{+\infty} \frac{t^k}{k!} \langle f_0^N, \mathcal{L}_N^k \varphi_s \rangle \xrightarrow{N \rightarrow +\infty} \sum_{k=0}^{+\infty} \frac{t^k}{k!} \langle f_0^{\otimes(s+k)}, \mathbf{D}^k \varphi_s \rangle =: \langle f_t^{s,\infty}, \varphi_s \rangle.$$

It remains to prove that  $f_t^{s,\infty} = f_t^{\otimes s}$  where  $f_t = f_t^{1,\infty} \dots$

This follows from Leibniz formula and the following observation (due to McKean)

$$\mathbf{D}(\varphi_{s_1} \otimes \varphi_{s_2}) = \mathbf{D}\varphi_{s_1} \otimes \varphi_{s_2} + \varphi_{s_1} \otimes \mathbf{D}\varphi_{s_2}.$$

$$\begin{aligned} \langle f_t^{s_1+s_2,\infty}, \varphi_{s_1} \otimes \varphi_{s_2} \rangle &= \sum_{k=0}^{+\infty} \frac{t^k}{k!} \sum_{\ell=0}^k \binom{k}{\ell} \langle f_0^{\otimes(s_1+s_2+k)}, \mathbf{D}^\ell \varphi_{s_1} \otimes \mathbf{D}^{k-\ell} \varphi_{s_2} \rangle \\ &= \langle f_t^{s_1,\infty}, \varphi_{s_1} \rangle \langle f_t^{s_2,\infty}, \varphi_{s_2} \rangle. \end{aligned}$$

Computing  $\frac{d}{dt}\langle f_t, \varphi \rangle = \sum_{k=0}^{+\infty} \frac{t^k}{k!} \langle f_0^{\otimes(s+2)}, \mathbf{D}^k[\mathbf{D}\varphi] \rangle = \langle f_t^{2,\infty}, \mathbf{D}\varphi \rangle$  leads to:

## Theorem: The Kac-Boltzmann equation

For any  $s \leq N$ ,  $f_t^{s,N} \rightarrow f_t^{\otimes s}$  and the limit law  $f_t$  satisfies for all  $\varphi \in C_b(E)$ ,

$$\frac{d}{dt}\langle f_t, \varphi \rangle = \langle f_t^{\otimes 2}, \mathbf{D}\varphi \rangle.$$

Recall,

$$\langle f_t^{\otimes 2}, \mathbf{D}\varphi \rangle = \int_{E^3} \{\varphi(z'_1) - \varphi(z_1)\} \Gamma^{(2)}(z_1, z_2, dz'_1, E) f_t(dz_1) f_t(dz_2).$$

→ The equation is written in **weak form**, the strong form  $\partial_t f_t = Q(f_t, f_t)$  can (sometimes) be obtained by computing the dual operator

$$\mathbf{D}^* : \mathcal{P}(E^2) \rightarrow \mathcal{P}(E).$$

→ In the final equation only the marginal  $\Gamma^{(2)}(z_1, z_2, dz'_1, E)$  appears which means that **the details of the interaction mechanism is lost in the limit**: different Kac processes can have the same mean-field limit.



# The two building block theorems of Kac and McKean.

1. Kac theorem: Markov generator and series expansion
2. McKean theorem: empirical measure, stochastic paths, coupling
3. Variations and alternative points of view

# First step: guess the limit

**Recall:**  $\mathcal{L}_N \varphi_N(\mathbf{x}^N) = \sum_{i=1}^N L_{\mu_{\mathbf{x}^N}} \diamond_i \varphi_N(\mathbf{x}^N)$  where  $L_{\mu}$  is a one-particle operator.

$$\begin{aligned} \frac{d}{dt} \langle f_t^{1,N}, \varphi \rangle &= \int_E L_{\mu_{\mathbf{x}^N}} \varphi(x^1) f_t^N(d\mathbf{x}^N) = \int_E \left( \frac{1}{N} \sum_{i=1}^N L_{\mu_{\mathbf{x}^N}} \varphi(x^i) \right) f_t^N(d\mathbf{x}^N) \\ &= \int_E \langle \mu_{\mathbf{x}^N}, L_{\mu_{\mathbf{x}^N}} \varphi \rangle f_t^N(d\mathbf{x}^N) = \int_{\mathcal{P}(E)} \langle \mu, L_{\mu} \varphi \rangle F_t^N(d\mu). \end{aligned}$$

If  $\mu_{\mathcal{X}_t^N} \rightarrow f_t$  then  $f_t^{1,N} = \mathbb{E} \mu_{\mathcal{X}_t^N} \rightarrow f_t$  and  $f_t$  satisfies the **nonlinear equation**

$$\frac{d}{dt} \langle f_t, \varphi \rangle = \langle f_t, L_{f_t} \varphi \rangle \quad \text{i.e.} \quad \partial_t f_t = L_{f_t}^* f_t.$$

## Fokker-Planck equation

Drift  $b(x, \mu) = F \star \mu(x)$  and diffusion matrix  $\sigma(x, \mu)$ ,

$$L_{\mu} \varphi(x) = b(x, \mu) \cdot \nabla \varphi + \frac{1}{2} \sum_{i,j=1}^d \sigma_{ij} \sigma_{ij}^T(x, \mu) \partial_{x^i} \partial_{x^j} \varphi.$$

$$\partial_t f_t = -\nabla_x \cdot (b(x, f_t) f_t) + \frac{1}{2} \sum_{i,j=1}^d \partial_{x^i} \partial_{x^j} \{ \sigma_{ij} \sigma_{ij}^T(x, f_t) f_t \}.$$

# Wasserstein distance between marginals and coupling

## Definition: Wasserstein distance

Let  $\mathcal{P}_2(\mathbb{R}^d)$  be the set of probability measures with bounded second moment. Then for  $\mu, \nu \in \mathcal{P}_2(\mathbb{R}^d)$ ,

$$W_2^2(\mu, \nu) := \inf_{X \sim \mu, Y \sim \nu} \mathbb{E}|X - Y|^2$$

defines a distance on  $\mathcal{P}_2(\mathbb{R}^d)$  which **metrizes** the weak convergence.

In particular let  $\bar{X}_t^i \sim f_t$ ,  $i \in \{1, \dots, N\}$  be  $N$  i.i.d. random variables, then

$$W_2^2(f_t^{s,N}, f_t^{\otimes s}) \leq \sum_{i=1}^s \mathbb{E}|X_t^i - \bar{X}_t^i|^2 = s \mathbb{E}|X_t^1 - \bar{X}_t^1|^2$$

Everything boils down to proving that

$$\mathbb{E}|X_t^1 - \bar{X}_t^1|^2 \xrightarrow{N \rightarrow +\infty} 0 \dots$$

... for some  $X_t^1, \bar{X}_t^1 \sim f_t^{1,N}$ ,  $f_t$  that can be **constructed as one wishes**.

→ Such random variables are called a **coupling**.

*Note:*  $\mathbb{E}W_2^2(\mu_{\mathcal{X}_t^N}, f_t) \rightarrow 0$  also implies  $F_t^N \rightarrow \delta_{f_t}$ .

# McKean Theorem in the bounded Lipschitz case

Consider the McKean-Vlasov model with an **arbitrary** drift  $b : \mathbb{R}^d \times \mathcal{P}(\mathbb{R}^d) \rightarrow \mathbb{R}^d$ ,

$$dX_t^i = b(X_t^i, \mu_{\mathcal{X}_t^N})dt + \sqrt{2}dB_t^i.$$

Introduce the **synchronous coupling** with  $N$  independent **nonlinear processes**

$$d\bar{X}_t^i = b(\bar{X}_t^i, f_t)dt + \sqrt{2}dB_t^i, \quad \bar{X}_0^i = X_0^i.$$

where  $f_t = \text{Law}(\bar{X}_t^i)$  satisfies the nonlinear Fokker-Planck equation:

$$\partial_t f_t = -\nabla_x \cdot (b(x, f_t)f_t) + \Delta_x f_t.$$

## Theorem (well-posedness)

Let  $b$  be **bounded and Lipschitz** for the  $W_2$  distance:

$$|b(x, \mu) - b(y, \nu)| \leq C(|x - y| + W_2(\mu, \nu)).$$

Then for any  $T > 0$ , the nonlinear Fokker-Planck equation is well-posed in  $C([0, T], \mathcal{P}_2(\mathbb{R}^d))$  and the associated SDE has a unique strong solution.

## Theorem (McKean)

$$\forall T > 0, \quad \lim_{N \rightarrow +\infty} \mathbb{E} \left[ \sup_{t \leq T} |X_t^i - \bar{X}_t^i|^2 \right] = 0.$$

# McKean Theorem: proof (1/2) [Sznitman, *St Flour*, 1989]

By construction and the BDG inequality (... or Itô lemma), for  $i \in \{1, \dots, N\}$ ,

$$\begin{aligned}\mathbb{E}\left[\sup_{t \leq T} |X_t^i - \bar{X}_t^i|^2\right] &\leq 2T \int_0^T \mathbb{E}\left|b(X_t^i, \mu_{\mathcal{X}_t^N}) - b(\bar{X}_t^i, f_t)\right|^2 dt \\ &\leq 4T \int_0^T \mathbb{E}\left|b(X_t^i, \mu_{\mathcal{X}_t^N}) - b(\bar{X}_t^i, \mu_{\bar{\mathcal{X}}_t^N})\right|^2 + \mathbb{E}\left|b(\bar{X}_t^i, \mu_{\bar{\mathcal{X}}_t^N}) - b(\bar{X}_t^i, f_t)\right|^2 dt\end{aligned}$$

where  $\mu_{\bar{\mathcal{X}}_t^N} = \frac{1}{N} \sum_{i=1}^N \delta_{\bar{X}_t^i}$ . Then,

- $$\begin{aligned}\mathbb{E}\left|b(X_t^i, \mu_{\mathcal{X}_t^N}) - b(\bar{X}_t^i, \mu_{\bar{\mathcal{X}}_t^N})\right|^2 &\leq C\left(\mathbb{E}|X_t^i - \bar{X}_t^i|^2 + \mathbb{E}W_2^2(\mu_{\mathcal{X}_t^N}, \mu_{\bar{\mathcal{X}}_t^N})\right) \\ &\leq C\left(\mathbb{E}|X_t^i - \bar{X}_t^i|^2 + \frac{1}{N} \sum_{j=1}^N \mathbb{E}|X_t^j - \bar{X}_t^j|^2\right) \leq 2C \mathbb{E}|X_t^i - \bar{X}_t^i|^2.\end{aligned}$$
- $$\mathbb{E}\left|b(\bar{X}_t^i, \mu_{\bar{\mathcal{X}}_t^N}) - b(\bar{X}_t^i, f_t)\right|^2 \leq C \mathbb{E}W_2^2(\mu_{\bar{\mathcal{X}}_t^N}, f_t).$$

In conclusion,

$$\mathbb{E}\left[\sup_{t \leq T} |X_t^i - \bar{X}_t^i|^2\right] \leq C_1 \int_0^T \mathbb{E}W_2^2(\mu_{\bar{\mathcal{X}}_t^N}, f_t) dt + C_2 \int_0^T \mathbb{E}|X_t^i - \bar{X}_t^i|^2 dt.$$

By Gronwall lemma,

$$\mathbb{E} \left[ \sup_{t \leq T} |X_t^i - \bar{X}_t^i|^2 \right] \leq C_1 e^{C_2 T} \int_0^T \mathbb{E} W_2^2(\mu_{\bar{\mathcal{X}}_t^N}, f_t) dt.$$

- By the strong **Law of Large Numbers**, for some constant  $M_2 > 0$ ,

$$\mu_{\bar{\mathcal{X}}_t^N} \rightarrow f_t \text{ a.s., } \mathbb{E} W_2^2(\mu_{\bar{\mathcal{X}}_t^N}, f_t) \leq M_2 \text{ and } \mathbb{E} W_2^2(\mu_{\bar{\mathcal{X}}_t^N}, f_t) \rightarrow 0.$$

[Carmona, *Lectures on BSDEs [...]*, SIAM, 2015]

- If  $f_0$  has sufficiently **high-order moments**,

$$\mathbb{E} W_2^2(\mu_{\bar{\mathcal{X}}_t^N}, f_t) = \begin{cases} \mathcal{O}(N^{-2/d}) & \text{if } d > 4 \\ \mathcal{O}(N^{-1/2}) & \text{if } d < 4 \\ \mathcal{O}(N^{-1/2} \log(1 + N)) & \text{if } d = 4 \end{cases} .$$

[Fournier, Guillin, *Prob. Th. Rel. Fi.* 162, 2015]

- If  $b(x, \mu) = F \star \mu(x)$  (or a function of  $F \star \mu(x)$ ) with  $F$  bounded Lipschitz,

$$\mathbb{E} \left| b(\bar{X}_t^i, \mu_{\bar{\mathcal{X}}_t^N}) - b(\bar{X}_t^i, f_t) \right|^2 \leq \frac{C}{N}.$$

[Sznitman, *St Flour*, 1989], [McKean, 1967]

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## Variation 1: McKean by McKean (1967)

Synchronous coupling between a  $N$ -particle system and a  $M > N$  particle system:

$$\begin{aligned}dX_t^{i,N} &= F \star \mu_{\mathcal{X}_t^N}(X_t^{i,N})dt + \sigma dB_t^i, & X_0^{i,N} &= X_0^i, \\dX_t^{i,M} &= F \star \mu_{\mathcal{X}_t^M}(X_t^{i,M})dt + \sigma dB_t^i, & X_0^{i,M} &= X_0^i.\end{aligned}$$

1. By the same (slightly simpler) computations:  $\mathbb{E} \sup_{t \leq T} |X_t^{i,N} - X_t^{i,M}|^2 \rightarrow 0$  when  $N, M \rightarrow +\infty$ .
2. For any  $i$ , the process  $(X_t^{i,N})_t$  is **Cauchy** in  $L^2(\Omega, C([0, T], \mathbb{R}^d))$  and thus there are limit points  $(\bar{X}_t^i)_t$  which are identically distributed.
3. By construction

$$\bar{X}_t^i \in \sigma(X_0^1, (B_t^1)_t, X_0^2, (B_t^2)_t, \dots).$$

However, by **exchangeability** and by **Hewitt-Savage 0-1 law**,

$$\bar{X}_t^i \in \sigma(X_0^i, (B_t^i)_t),$$

and these processes are thus **independent**.

4. Check that the process  $(\bar{X}_t^i)_t$  solves the nonlinear SDE.



# Extension: Mean-field jump processes

## The generator of mean-field jump processes

$$L_\mu \varphi(x) = a \cdot \nabla \varphi(x) + \lambda(x, \mu) \int_E \{\varphi(y) - \varphi(x)\} P_\mu(x, dy),$$

where

- $a : E \rightarrow E$  deterministic flow  $\dot{X}_t = a(X_t)$ ,
- $\lambda(x, \mu)$  (non-homogeneous) jump frequency,
- $P_\mu(x, dy)$  law of the post-jump state.

**Example (Run-and-tumble motion).**  $E = \mathbb{R}^d \times \mathbb{R}^d$  with  $Z_t^i = (X_t^i, V_t^i)$  and

- $a(x, v) = (v, 0)$  (free transport),
- $\lambda(x, \mu) \equiv 1$  constant,
- $P_\mu((x, v), dx', dv') = \delta_x(dx') \otimes \mathcal{M}_{\mu, x}(v') dv'$  with the Maxwellian,

$$\mathcal{M}_{\mu, x}(v) = \frac{1}{(2\pi T)^{d/2}} \exp\left(-\frac{|v - u|^2}{2T}\right),$$

where  $(\rho, u, T)$  are defined by  $(\rho, \rho u, \rho|u|^2 + \rho T) := \int_{\mathbb{R}^d} (1, v, |v|^2) K \star \mu(x, dv)$ .

→ **Mean-field limit:**  $\partial_t f_t + v \cdot \nabla_x f_t = \rho_{f_t}(x) \mathcal{M}_{f_t, x}(v) - f_t$ . (BGK equation)

[Buttà, Hauray, Pulvirenti, *ARMA* 240, 2021], [D., *EJP* 25, 2020]. . .

# SDE representation of mean-field jump and Kac processes

Assume that  $P_\mu(x, dy)$  is **parametrized** by **fixed** parameter probability space  $(\Theta, \nu(d\theta))$  and a given function  $\psi : E \times \mathcal{P}(E) \times \Theta \rightarrow E$  such that

$$\int_E \varphi(y) P_\mu(x, dy) = \int_\Theta \varphi(\psi(x, \mu, \theta)) \nu(d\theta).$$

$$X_t^i = X_0^i + \int_0^t \int_0^{+\infty} \int_\Theta \left\{ \psi\left(X_{s-}^i, \mu_{X_{s-}^N}, \theta\right) - X_{s-}^i \right\} \mathbf{1}_{(0, \lambda(X_{s-}^i, \mu_{X_{s-}^N}))}(u) \mathcal{N}^i(ds, du, d\theta)$$

where  $\mathcal{N}^i(ds, du, d\theta)$  are  $N$  independent Poisson random measures with intensity  $ds \otimes du \otimes \nu(d\theta)$  on  $[0, +\infty) \times [0, +\infty) \times \Theta$ .

$L^1$  framework: [Graham, *Ann. Inst. H. Poincaré* 28, 1992], [Graham, *Sto. Pr. App.* 40, 1992], [Andreis, Dai Pra, Fischer, *Sto. Ana. Appl.* 36, 2018]

**Boltzmann-Kac equation...** (with constant collision rate)

New state function  $\psi$ , collision partner  $\alpha$ , collision type  $\sigma$ , and non-independent  $\mathcal{N}^i$

$$Z_t^i = Z_0^i + \int_0^t \int_\Theta \int_{\{0,1\}} \int_{\{1, \dots, N\}} \left\{ \psi_\sigma(Z_{s-}^i, Z_{s-}^\alpha, \theta) - Z_{s-}^i \right\} \mathcal{N}^i(ds, d\theta, d\sigma, d\alpha).$$

[Tanaka, *Z. Wahr. verw. Geb.* 46, 1978], [Murata, *Hiroshima Math. J.* 7, 1977], [Cortez, Fontbona, *Ann. App. Pro.* 26, 2016], [Cortez, Fontbona, *Comm. Math. Phys.* 357, 2018], [Fournier, Mischler, *Ann. Pro.* 44, 2016]

# Pathwise point of view on $I = (0, T)$

- **Pointwise** propagation of chaos holds towards a flow of measures  $(f_t)_t \in C(I, \mathcal{P}(E))$  when the law  $f_t^N \in \mathcal{P}(E^N)$  of  $\mathcal{X}_t^N$  is  $f_t$ -chaotic for every time  $t \in I$ .
- **Pathwise** propagation of chaos holds towards a distribution  $f_I \in \mathcal{P}(D(I, E))$  on the space  $D(I, E)$  of càdlàg functions when the law  $f_I^N \in \mathcal{P}(D(I, E)^N)$  of the process  $\mathcal{X}_I^N$  seen as a random element in  $D(I, E)^N$  is  $f_I$ -chaotic.

## Example.

$$(Pointwise) \quad W_2^2(f_t^{s,N}, f_t^{\otimes s}) \leq s \mathbb{E} |X_t^1 - \bar{X}_t^1|^2 \leq s \sup_{t \in I} \mathbb{E} |X_t^1 - \bar{X}_t^1|^2.$$

$$(Pathwise) \quad \mathcal{W}_2^2(f_I^{s,N}, f_I^{\otimes s}) \leq s \mathbb{E} \|X_I^1 - \bar{X}_I^1\|_{C(I,E)}^2 = s \mathbb{E} \left[ \sup_{t \in I} |X_t^1 - \bar{X}_t^1|^2 \right].$$

There are **two** pathwise empirical measure processes:

- The measure-valued process  $(\mu_{\mathcal{X}_t^N})_t$  with law  $F_I^{\mu,N} \in \mathcal{P}(D(I, \mathcal{P}(E)))$ .
- The empirical measure of the processes  $\mu_{\mathcal{X}_I^N}$  with law  $F_I^N \in \mathcal{P}(\mathcal{P}(D(I, E)))$ .

$$[F_I^N \rightarrow \delta_{f_I}] \implies [F_I^{\mu,N} \rightarrow \delta_{(f_t)_t}] \implies [F_t^N \rightarrow \delta_{f_t}]$$

**Pathwise p.o.c.**  
 $\mathcal{P}(\mathcal{P}(D(I, E)))$

**Functional L.L.N.**  
 $\mathcal{P}(D(I, \mathcal{P}(E)))$

**Pointwise p.o.c.**  
 $\mathcal{P}(\mathcal{P}(E))$

# Pathwise point of view: Martingale problems

→ The  $N$ -particle process is defined as the solution of a **martingale problem**.

## Pathwise particle martingale problem

$$\forall \varphi_N \in \text{Dom}(\mathcal{L}_N), M_t^{\varphi_N} := \varphi_N(\mathbf{X}_t^N) - \varphi_N(\mathbf{X}_0^N) - \int_0^t \mathcal{L}_N \varphi_N(\mathbf{X}_s^N) ds,$$

is a  $f_I^N$ -martingale, where  $\mathbf{X}_t^N(\omega) = \omega(t)$  is the canonical process in  $D(I, E^N)$ .

→ Similarly for the limit nonlinear processes. . .

## Pathwise nonlinear Boltzmann-Kac martingale problem

$$\forall \varphi_N \in C_b(E), M_t^\varphi := \varphi(\mathbf{X}_t) - \varphi(\mathbf{X}_0) - \int_0^t \langle f_s, \mathbf{D}\varphi(\mathbf{X}_s, \cdot) \rangle ds,$$

is a  $f_I$ -martingale, where  $\mathbf{X}_t(\omega) = \omega(t)$  and  $f_s = (\mathbf{X}_s)_\# f_I \in \mathcal{P}(E)$ .

## Pathwise nonlinear McKean-Vlasov martingale problem

$$\forall \varphi_N \in C_b(E), M_t^\varphi := \varphi(\mathbf{X}_t) - \varphi(\mathbf{X}_0) - \int_0^t L_{f_s} \varphi(\mathbf{X}_s) ds,$$

is a  $f_I$ -martingale, where  $\mathbf{X}_t(\omega) = \omega(t)$  and  $f_s = (\mathbf{X}_s)_\# f_I \in \mathcal{P}(E)$ .

## General outline of the proof

1. Show that  $(F_I^N)_N$  is tight using classical **tightness criteria**: Aldous, Rebolledo, Joffe-Métivier. . .  
By Prokhorov theorem, there exists a limit point  $\pi \in \mathcal{P}(\mathcal{P}(D(I, E)))$ .
2. Identify the  $\pi$ -distributed limit points as solutions of the limit martingale problem (this provides an **existence** result).
3. Prove the **uniqueness** of the limit martingale problem. This implies that  $\pi$  is a Dirac mass at this point.

## A very general methodology!

For the Boltzmann-equation. . .

[Tanaka, *Proc. IFIP-WG 7/1, Bangalore 1982, 1983*], [Sznitman, *Zeit. Wah. Ver. Geb. 66, 1984*], [Wagner, *Sto. An. App. 14, 1996*]. . .

For McKean-Vlasov systems and more. . .

[Sznitman, *J. Fun. An. 56, 1984*], [Oelschläger, *An. Prob. 12, 1984*], [Gärtner, *Math. Nachr. 137, 1988*], [Graham, Méléard, *Ann. Probab. 25, 1997*]. . .

Some drawbacks: no convergence rate, typically much more technical.

# Two important questions and some applications...

1. Long-time behaviour and uniform-in-time propagation of chaos
2. Low regularity, singular and abstract interactions

**(One) motivation.** Understand the long-time behaviour of **mesoscopic nonlinear** systems via their particle representation.

**Example:** trend to equilibrium for the **granular media equation:**

$$\partial_t f_t = \nabla \cdot (f_t \nabla (V + W \star f_t)) + \Delta f_t.$$

- $V$  confinement potential (e.g.  $V(x) = |x|^2/2$ ).
- $W$  (symmetric) interaction potential.

[Carrillo, McCann, Villani, *Rev. Ma. Iberoica*. 19, 2003], [Bolley, Gentil, Guillin, *ARMA* 208, 2013]

**Mean-field particle representation:**

$$dX_t^i = -\nabla V(X_t^i)dt - \frac{1}{N} \sum_{j=1}^N \nabla W(X_t^j - X_t^i)dt + \sqrt{2}dB_t^i.$$

**High-dimensional Langevin dynamics with invariant measure:**

$$\pi_\infty^N(d\mathbf{x}^N) \propto \exp \left( -\sum_{i=1}^N V(x^i) - \frac{1}{2N} \sum_{i,j=1}^N W(x^i - x^j) \right) dx^1 \dots dx^N.$$

# Long-time behaviour: Malrieu's theorem

**Earlier work in 1D:** [Benachour, Roynette, Vallois, *Sto. Pro. App.* 75, 1998]

## Theorem (Malrieu, *Sto. Pro. App.* 95, 2001)

If  $V$  is  $\beta$ -uniformly convex,  $W$  is symmetric, convex,  $\nabla W$  is locally Lipschitz with polynomial growth then the synchronous coupling is uniform in time:

$$\sup_{t \geq 0} \mathbb{E} |X_t^i - \bar{X}_t^i|^2 \leq \frac{C}{N}.$$

It implies the exponential convergence of  $f_t$  towards a unique invariant measure.

*Key idea:* With Itô's formula,

$$\frac{d}{dt} |X_t^i - \bar{X}_t^i|^2 \leq -2(X_t^i - \bar{X}_t^i) \cdot (\nabla V(X_t^i) - \nabla V(\bar{X}_t^i)) + \dots \leq -2\beta |X_t^i - \bar{X}_t^i|^2 + \dots$$

## Extensions, and related works...

Non uniformly convex  $V$ : [Cattiaux, Guillin, Malrieu, *Pr. Th. Rel. Fi.* 140, 2008]...

Kinetic (2nd order) systems: [Bolley, Guillin, Malrieu, *ESAIM Ma. Mo. Nu. An.* 44, 2010], [Monmarché, *Sto. Pro. App.*, 127, 2017]...

*New coupling methods:* [Durmus, Eberle, Guillin, Zimmer, *Proc. Amer. Math. Soc.* 148, 2020], [Guillin, Le Bris, Monmarché, *EJP* 27, 2022]...



# Long-time behaviour: Phase transitions

Unlike the particle system, the mean-field limit can have **several** invariant measures.

**The Kuramoto model:** synchronization of oscillators  $\theta_t^i \in \mathbb{S}^1$  with strength  $\gamma > 0$

$$d\theta_t^i = \frac{\gamma}{N} \sum_{j=1}^N \sin(\theta_t^j - \theta_t^i) dt + dB_t^i, \quad \partial_t f_t(\theta) = -\gamma \nabla_{\theta} \cdot (f_t(\sin \star f_t)) + \frac{1}{2} \Delta f_t$$

**Stable invariant measure of the mean-field equation:** for  $\theta_0 \in \mathbb{R}$ ,

$$M_{\kappa, \theta_0}(\theta) \propto \exp(-\kappa \cos(\theta - \theta_0)), \quad \kappa = 2\gamma \frac{I_1(\kappa)}{I_0(\kappa)}.$$

**Phase transition:**

- If  $\gamma < 1$ ,  $\kappa = 0$  is the unique solution.
- If  $\gamma > 1$ , there is another solution  $\kappa^* > 0$  and  $M_{\kappa^*, \theta_0}$  is asymptotically stable.

**Long-time behaviour:** there exists a Brownian noise  $(W_t)_t$

$$\frac{1}{N} \sum_{i=1}^N \delta_{\theta_{Nt}^i} \approx M_{\kappa^*, \theta_0 + W_t} \neq M_{\kappa^*, \theta_0}.$$

[Bertini, Giacomin, Poquet, *Prob. Th. Rel. Fi.* 160, 2014]

→ The propagation of chaos breaks down at time proportional to  $N$ .

# Long-time behaviour: some research directions

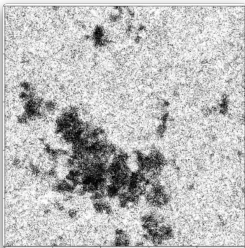
**A (not so) recent trend:** explore the links between phase transitions, uniform in time propagation of chaos and log-Sobolev inequalities. . .

[Malrieu, *Sto. Pro. App.* 95, 2001], [Delgadino, Gvalani, Pavliotis, *Ar. Ra. Me. An.* 241, 2021], [Delgadino, Gvalani, Pavliotis, Smith, *Comm. Math. Phys.*, 2023], [Guillin, Monmarché, *J. Stat. Phys.* 185, 2021]. . .

**A long-standing problem:** Trend to equilibrium for Boltzmann models [Kac, 1956], [Grünbaum, *ARMA* 42, 1971], [Mischler, Mouhot, *Inv. Math.* 193, 2013]. . .

**An open problem:** phase transitions in the Vicsek model (and other kinetic models)

$$\partial_t f_t(x, v) + v \cdot \nabla_x f_t = [\text{some mean-field operator acting on } v \text{ with phase transition}].$$



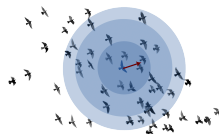
*Local alignment + noise*

# Two important questions and some applications...

1. Long-time behaviour and uniform-in-time propagation of chaos
2. Low regularity, singular and abstract interactions

# Low-regularity and singular interactions

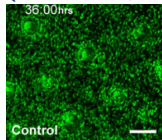
- Interaction kernel in collective dynamics models



Flocking in the Cucker-Smale model.

$$dX_t^i = V_t^i dt, \quad dV_t^i = \frac{1}{N} \sum_{j=1}^N \frac{V_t^j - V_t^i}{(1 + |X_t^j - X_t^i|^2)^\gamma} dt + dB_t^i$$

- (Overdamped) Keller-Segel and Coulomb-type interactions



[Glover et al., 2017]

$$\partial_t \rho = -\nabla \cdot (\rho \nabla c) + \frac{1}{2} \Delta \rho, \quad -\Delta c = \rho.$$

$$dX_t^i = \frac{1}{N} \sum_{j=1}^N K(X_t^j - X_t^i) dt + dB_t^i, \quad K(r) = \xi \frac{x}{|x|^d}.$$

- Unbounded jump rates in Boltzmann-Kac and mean-field jumps models

Spiking neurons rate  $\lambda(r) = (r/r_0)^\alpha$  [Fournier, Löcherbach, *Ann. IHP Pr. St.* 52, 2015]

$$X_t^i = X_0^i - \lambda \int_0^t \left( X_s^i - \frac{1}{N} \sum_{j=1}^N X_s^j \right) ds - \int_0^t \int_0^{+\infty} X_{s-}^i \mathbf{1}_{z \leq \lambda(X_{s-}^i)} \mathcal{N}^i(ds, dz) \\ + \frac{1}{N} \sum_{j \neq i} \int_0^t \int_0^{+\infty} \mathbf{1}_{z \leq \lambda(X_{s-}^j)} \mathcal{N}^j(ds, dz).$$

## ► Cut-off and mollifiers.

- Define  $K_\varepsilon \rightarrow K$  as  $\varepsilon \rightarrow 0$  where  $K_\varepsilon$  sufficiently nice to prove propagation of chaos with convergence speed  $r_N(K_\varepsilon) \xrightarrow{N \rightarrow +\infty} 0$  for a fixed  $\varepsilon > 0$ .
- Use a sequence  $\varepsilon_N \xrightarrow{N \rightarrow +\infty} 0$  depending on  $N$ .
- Try to prove propagation of chaos such that  $r_N(K_{\varepsilon_N}) \xrightarrow{N \rightarrow +\infty} 0$ .

*Example 1.*  $K_\varepsilon(x) = \frac{x}{\max(|x|, \varepsilon)^d} \rightarrow x/|x|^d$ .

[Carrillo, Choi, Salem, *Comm. Con. Math.* 21, 2019]

*Example 2 (moderate interaction).*  $K_\varepsilon(x) = \varepsilon^{-d} K_0(x/\varepsilon) \rightarrow \delta_x$ .

[Oelschläger, *Ze. Wa. Ve. Ge.* 69, 1985]. [Jourdain, Méléard, *Ann. IHP Pro. St.* 34, 1998]

## ► Local Lipschitz and exponential moments.

[Bolley, Cañizo, Carrillo, *Ma. Mo. Me. App. Sc.* 21, 2011]

- $K$  local Lipschitz with polynomial growth or order  $p$ .
- The exponential moments  $\mathbb{E}[e^{\kappa|X_t^i|^{p'}}]$  and  $\mathbb{E}[e^{\kappa|\bar{X}_t^i|^{p'}}]$  are bounded on  $(0, T)$  for some  $\kappa > 0$  and  $p' \geq p$ .
- $\int |K(y-x)|^2 f_t(dx) f_t(dy) < +\infty$ .

# Entropy methods

For two probability measures  $\mu, \nu \in \mathcal{P}(\mathcal{E})$ , the relative entropy is defined by

$$H(\nu|\mu) := \int_{\mathcal{E}} \frac{d\nu}{d\mu} \log \left( \frac{d\nu}{d\mu} \right) d\mu.$$

## Lemma: chaos from entropy bounds

For any  $k \leq N$ ,  $f^N \in \mathcal{P}(E^N)$  and  $f \in \mathcal{P}(E)$ ,

$$\frac{1}{2} \|f^{k,N} - f^{\otimes k}\|_{\text{TV}}^2 \leq H(f^{k,N}|f^{\otimes k}) \leq \frac{k}{N} H(f^N|f^{\otimes N}).$$

[Ben Arous, Zeitouni, *Ann. IHP Prob. Sta.* 35, 1999]

[Ben Arous, Brunaud, *Sto. and Sto. Rep.* 31, 1990]

## Lemma: bounding the entropy

Let  $dX_t^i = b(X_t^i, \mu_{\mathcal{X}_t^N})dt + \sigma dB_t^i$  be a **McKean-Vlasov process**,

$$H(f_I^N|f_I^{\otimes N}) = \frac{N}{2} \mathbb{E} \left[ \int_0^T |b(X_t^1, \mu_{\mathcal{X}_t^N}) - b(X_t^1, f_t)|^2 dt \right].$$

*Key idea:* Girsanov theorem

# Entropy methods

- ▶ With the global Lipschitz bounded assumption of McKean's theorem, this is a **strengthening** result from Wasserstein to Total Variation convergence.  
[Malrieu, *Sto. Pro. App.* 95, 2001]
- ▶ **No regularity assumption** on  $b$  (*only* the well-posedness of the limit system).  
For linear interactions  $b(x, \mu) = K \star \mu(x)$  with interaction kernel  $K$ :  
Bounded forces:  $K \in L^\infty$  [Jabin, Wang, *J. Fun. An.* 271, 2016],  
Less than bounded  $K \in W^{-1, \infty}$  : [Jabin, Wang, *Inv. Math.* 214, 2018]  
Singular gradient systems  $K = -\nabla W$ : [Bresch, Jabin, Wang, *Duke Math. Journal*, 2022], [Serfaty, *ICM 2018*], [Duerinckx, *SIAM J. Ma. An.* 48, 2016]...  
Stochastic version: [Jabir, *arXiv:1907.09096*, 2019]  
→ Change of measure argument: bound observables for  $f_t$  instead of  $f_t^N$ .
- ▶ **No assumption on the form** of  $b$  [Lacker, *Elec. Com. Pro.* 23, 2018].
- ▶ Hierarchy of marginal entropies, quantitative chaos with **optimal rate**  $\mathcal{O}(k/N)$ .  
[Lacker, *arXiv:2105.02983*, 2021]

Entropy methods for jump and Boltzmann-Kac models via Girsanov transform?  
[Léonard, *Séminaire de Probabilités XLIV*, 2012]

# Beyond the classical theory

1. Some extensions
2. Some applications in numerical analysis, data science and optimization



# Some extensions (check the program!)

## ► Changing the noise...

$$dX_t^i = b(X_t^i, \mu_{\mathcal{X}_t^N})dt + dM_t^i + dB_t, \quad X_T^i = \xi^i.$$

- **Individual noise:**  $M_t^i$  martingale measure,  $\alpha$ -stable Lévy driven noise, terminal condition  $\xi^i \dots$
- **Environmental noise**  $B_t$ : SPDE limit, conditional propagation of chaos.

## ► Changing the interactions...

$$dX_t^i = \frac{1}{N} \sum_{j=1}^N \Gamma_{ij} b(X_t^i, X_t^j, \mu_{\mathcal{X}_t^N}, \alpha_t^i)dt + dB_t^i.$$

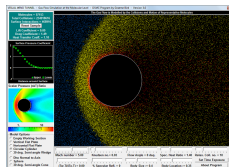
- **Non-exchangeable systems:** (random) graph interactions  $(\Gamma_{ij})_{ij}$ , non-metric interactions (“topological”) with  $K$ -nearest neighbors...
- **Control** process  $\alpha_t^i$  maximizing  $J^i(\alpha^1, \dots, \alpha^N)$ .

## ► Changing the scaling...

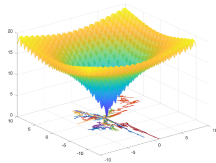
- **Boltzmann-Grad** scaling: binary interactions in a **dilute** regime.
- **Diffusion scaling:**  $1/\sqrt{N}$  instead of  $1/N$ .
- **Fluctuation** process:  $\eta_t^N = \sqrt{N}(\mu_{\mathcal{X}_t^N} - f_t)$ .
- **Measure-valued** limit: e.g. Fleming-Viot process

# Beyond the classical theory

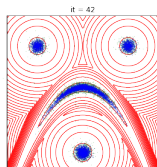
1. Some extensions
2. Some applications for the numerical analysis of PDE, data science and optimization



[Bird, *DSMC algorithm*, 1970]



[Totzeck, *Active Particles* 3, 2021]



[Clarté, D., Feydy, *EJS* 16, 2022]

# Some applications in PDE, data science and optimization

- **Particle methods for nonlinear PDEs:** construct  $X_t^1, \dots, X_t^N$  such that

$$\text{(some functional of)} \mu_{\mathcal{X}_t^N} \approx f_t,$$

where  $f_t$  is the solution of a complicated PDE (e.g. Boltzmann, Burgers, vortex, Landau...).

- **Particle swarm optimization:** construct  $X_t^1, \dots, X_t^N$  such that

$$X_t^1, \dots, X_t^N \xrightarrow{t \rightarrow +\infty} x^*$$

where  $x^*$  is the minimizer of an objective function  $G$ .

- **MCMC sampling:** construct  $X_t^1, \dots, X_t^N$  such that as  $t \rightarrow +\infty$ ,

$$(X_t^1, \dots, X_t^N) \sim \pi^{\otimes N},$$

where  $\pi$  is a probability density known up to a multiplicative constant.

- **Neural networks:** construct  $\theta^1, \dots, \theta^N$  which minimize the risk functional

$$R(\theta^N) := \sum_{\ell} \text{Loss} \left( Y^{\ell}, \frac{1}{N} \sum_{i=1}^N \sigma(X^{\ell}, \theta^i) \right),$$

where  $(X^{\ell}, Y^{\ell})$  are some labelled data and  $\sigma$  is an activation function.

→ In all the previous applications, a **critical** limitation comes from the **high-computational cost**  $\mathcal{O}(N^2)$  of discrete convolutions:

$$\text{Compute } y_i = \sum_{j=1}^N K(x_i, x_j) \text{ for } i \in \{1, \dots, N\}$$

- ▶ **Verlet list methods** in MD simulations for short-range interactions.  
[Leimkuhler, Matthews, *Molecular Dynamics*, 2015]
- ▶ **Super particles and tree methods** for long-range interactions.  
[Rokhlin, *J. Comp. Phys.* 60, 1985]
- ▶ “Approximate”  $K$  using so-called **kernel methods**.  
[Yang et al., *NeurIPS* 25, 2012]
- ▶ Randomly subsample the interactions via **random batch methods**.  
[Jin, Li, Liu, *J. Comp. Phys.* 400, 2020]
- ▶ Massively parallelized symbolic computations using **GPU routines**.

▶ **KeOps** ◀

[Charlier, Feydy, Glaunès, Collin, Durif, *J. Mach. Lea. Res.* 22, 2021]

# Thank you for your attention!

## References (lecture notes and review articles).

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[Sznitman, *Lecture at St Flour*, 1989]

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[Jabin, Wang, in *Active Particles, Volume 1*, 2017]

[Villani, *Cours de DEA*, 2001]

[Jabin, *Kinet. Relat. Models* 7, 2014]

[Golse, *Lecture notes. arXiv:1301.5494*, 2016]

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