Stochastic Mean-Field Limit

Conclusions

Swarming Models with Repulsive-Attractive Effects

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Mean-Field Limit for 1st Order Model

Stochastic Mean-Field Limit

Conclusions

Outline

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Kinetic Models and measure solutions

- Vlasov-like Models
- Proof

2 Mean-Field Limit for 1st Order Model

- Setting of the problem
- Ideas of the Proof

Stochastic Mean-Field Limit

- Setting of the problem
- Proof



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 Setting of the problem

Proof

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Kinetic Models and measure solutions	Mean-Field Limit for 1st Order Model	Stochastic Mean-Field Limit	
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Vlasov-like Models			

Mesoscopic models

Model with asymptotic velocity + Attraction/Repulsion:

$$rac{\partial f}{\partial t} + v \cdot
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Velocity consensus Model:

$$\frac{\partial f}{\partial t} + v \cdot \nabla_x f = \nabla_v \cdot \left[\underbrace{\left(\int_{\mathbb{R}^{2d}} \frac{v - w}{(1 + |x - y|^2)^{\gamma}} f(y, w, t) \, dy \, dw \right)}_{:=\xi(f)(x, v, t)} f(x, v, t) \right]$$

Orientation, Attraction and Repulsion:

$$\frac{\partial f}{\partial t} + v \cdot \nabla_{x} f - \operatorname{div}_{v} \left[(\nabla_{x} U \star \rho) f \right] = \nabla_{v} \cdot \left[\xi(f)(x, v, t) f(x, v, t) \right].$$

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Vlasov-like Models

Definition of the distance

Transporting measures:

Given $T : \mathbb{R}^d \longrightarrow \mathbb{R}^d$ mesurable, we say that $\nu = T \# \mu$, if $\nu[K] := \mu[T^{-1}(K)]$ for all mesurable sets $K \subset \mathbb{R}^d$, equivalently

$$\int_{\mathbb{R}^d} \varphi \, d
u = \int_{\mathbb{R}^d} (\varphi \circ T) \, d\mu \qquad ext{for all } \varphi \in C_o(\mathbb{R}^d) \, .$$

Random variables:

Say that *X* is a random variable with law given by μ , is to say $X : (\Omega, \mathcal{A}, P) \longrightarrow (\mathbb{R}^d, \mathcal{B}_d)$ is a mesurable map such that $X \# P = \mu$, i.e.,

$$\int_{\mathbb{R}^d} \varphi(x) \, d\mu = \int_{\Omega} (\varphi \circ X) \, dP = \mathbb{E} \left[\varphi(X) \right].$$

Kantorovich-Rubinstein-Wasserstein Distance p = 1, 2: $W_p^p(\mu, \nu) = \inf_{(X,Y)} \{ \mathbb{E} [|X - Y|^p] \}$

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Vlasov-like Models

Well-posedness in probability measures¹

Existence, uniqueness and stability

Take a potential $U \in C_b^2(\mathbb{R}^d)$, and f_0 a measure on $\mathbb{R}^d \times \mathbb{R}^d$ with compact support. There exists a solution $f \in C([0, +\infty); \mathcal{P}_1(\mathbb{R}^d))$ in the sense of solving the equation through the characteristics: $f_i := P^t \# f_0$ with P^t the flow map associated to the equation.

Moreover, the solutions remains compactly supported for all time with a possibly growing in time support.

Moreover, given any two solutions f and g with initial data f_0 and g_0 , there is an increasing function depending on the size of the support of the solutions and the parameters, such that

 $W_1(f_t,g_t) \leq \alpha(t) W_1(f_0,g_0)$

¹ Dobrushin-Hepp-Neunzert, 1977-79 for the Vlasov.

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Vlasov-like Models

Convergence of the particle method

• Empirical measures: if $x_i, v_i : [0, T) \to \mathbb{R}^d$, for i = 1, ..., N, is a solution to the ODE system,

$$\begin{cases} \frac{dx_i}{dt} = v_i, \\ propulsion-friction \\ \frac{dv_i}{dt} = \overbrace{(\alpha - \beta |v_i|^2)v_i}^{\text{propulsion-friction}} - \overbrace{\sum_{i \neq i}^{\text{attraction-repulsion}}_{i \neq i} m_j \nabla U(|x_i - x_j|)}^{\text{orientation}} + \overbrace{\sum_{j=1}^{N} m_j a_{ij} (v_j - v_i)}^{\text{orientation}}. \end{cases}$$

then the $f:[0,T) \to \mathcal{P}_1(\mathbb{R}^d)$ given by

$$f_N(t) := \sum_{i=1}^N m_i \delta_{(x_i(t), v_i(t))}$$

is the solution corresponding to initial atomic measures.

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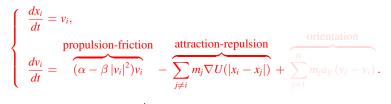
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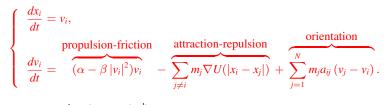
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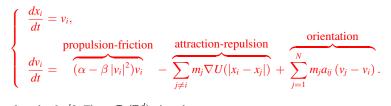
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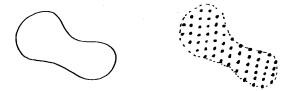
Kinetic Models and measure solutions	Mean-Field Limit for 1st Order Model	Stochastic Mean-Field Limit		
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Just take as many particles as needed in order to have

 $W_1(f_t, f_t^N) \le \alpha(t) W_1(f_0, f_0^N) \to 0 \qquad \text{as } N \to \infty$

by sampling the initial data in a suitable way.

The sequences of particle solutions becomes a Cauchy sequence with the distance W_1 converging to the solution of the kinetic equation.



Hauray-Jabin 2011: mean field limit for Vlasov with potentials such that $|\nabla U| \leq r^{-\alpha}$, with $\alpha < 1$ with initial data for Vlasov in $L^1 \cap L^{\infty}$.

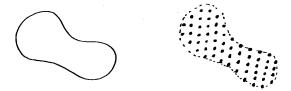
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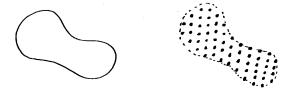
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- Setting of the problem
- Ideas of the Proof

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 Setting of the problem

• Proof

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Proof

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Proof of the Theorem

Conditions on E:

• *E* is continuous on $[0, T] \times \mathbb{R}^d$,

(a) For some C > 0,

 $|E(t,x)| \leq C_E(1+|x|),$ for all $t,x \in [0,T] \times \mathbb{R}^d$, and

Solution E is locally Lipschitz with respect to *x*, i.e., for any compact set $K \subseteq \mathbb{R}^d$ there is some $L_K > 0$ such that

 $|E(t,x) - E(t,y)| \le L_K |x-y|, \quad t \in [0,T], \quad x,y \in K.$

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Proof of the Theorem

Conditions on E:

- *E* is continuous on $[0, T] \times \mathbb{R}^d$,
- (2) For some C > 0,

$|E(t,x)| \leq C_E(1+|x|), \text{ for all } t,x \in [0,T] \times \mathbb{R}^d, \text{ and}$

• *E* is locally Lipschitz with respect to *x*, i.e., for any compact set $K \subseteq \mathbb{R}^d$ there is some $L_K > 0$ such that

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$$\partial_t f + v \cdot \nabla_x f + E \cdot \nabla_v f + \operatorname{div}_v((\alpha - \beta |v|^2)vf) = 0,$$

which is a linear first-order equation. The associated characteristic system of ODE's is

$$\begin{aligned} &\frac{d}{dt}X = V, \\ &\frac{d}{dt}V = E(t,X) + V(\alpha - \beta |V|^2). \end{aligned}$$

Flow Map:

Given $(X_0, V_0) \in \mathbb{R}^d \times \mathbb{R}^d$ there exists a unique solution (X, V) to the ODE system in $C^1([0, T]; \mathbb{R}^d \times \mathbb{R}^d)$ satisfying $X(0) = X_0$ and $V(0) = V_0$. In addition, there exists a constant *C* which depends only on *T*, $|X_0|$, $|V_0|$, α , β and the constant C_E , such that

 $|(X(t), V(t))| \le |(X_0, V_0)| e^{Ct}$ for all $t \in [0, T]$.

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We can thus consider the flow at time $t \in [0, T)$ of ODE's equations

$$\mathcal{T}_E^t: \mathbb{R}^d \times \mathbb{R}^d \to \mathbb{R}^d \times \mathbb{R}^d.$$

Again by basic results in ode's, the map $(t, x, v) \mapsto \mathcal{T}_E^t(x, v) = (X, V)$ with (X, V) the solution at time *t* to the ODE system with initial data (x, v), is jointly continuous in (t, x, v).

For a measure $f_0 \in \mathcal{P}_1(\mathbb{R}^d \times \mathbb{R}^d)$, the function

 $f: [0,T) \to \mathcal{P}_1(\mathbb{R}^d \times \mathbb{R}^d), \quad t \mapsto f_t := \mathcal{T}_E^t \# f_0$

is the unique measure solution to the linear PDE.

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Estimates on characteristics:

- Taking characteristics with initial data inside a fixed ball then there exists R > 0 depending on *T*, in which the whole trajectories are inside a possibly larger ball of radius *R* for all times $t \in [0, T]$.
- For some constant *C* which depends only on α , β , *R* and Lip_{*R*}(*Eⁱ*), for all *P*⁰ in *B*_{*R*}

$$\left|\mathcal{T}_{E^{1}}^{t}(P^{0}) - \mathcal{T}_{E^{2}}^{t}(P^{0})\right| \leq \frac{e^{c_{L}} - 1}{C} \sup_{s \in [0,T)} \left\| E_{s}^{1} - E_{s}^{2} \right\|_{L^{\infty}(B_{R})}.$$

• For some constant *C* as before

 $|\mathcal{T}_{E}^{t}(P_{1}) - \mathcal{T}_{E}^{t}(P_{2})| \leq |P_{1} - P_{2}| e^{C \int_{0}^{t} (\operatorname{Lip}_{R}(E_{s}) + 1) ds}, \quad t \in [0, T].$

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Proof of the Theorem

Estimates on characteristics:

- Taking characteristics with initial data inside a fixed ball then there exists R > 0 depending on *T*, in which the whole trajectories are inside a possibly larger ball of radius *R* for all times $t \in [0, T]$.
- For some constant *C* which depends only on α , β , *R* and Lip_{*R*}(*Eⁱ*), for all *P*⁰ in *B*_{*R*}

$$\left|\mathcal{T}_{E^{1}}^{t}(P^{0})-\mathcal{T}_{E^{2}}^{t}(P^{0})\right|\leq rac{e^{Ct}-1}{C}\sup_{s\in[0,T)}\left\|E_{s}^{1}-E_{s}^{2}\right\|_{L^{\infty}(B_{R})}.$$

• For some constant *C* as before

 $\left|\mathcal{T}_{E}^{t}(P_{1})-\mathcal{T}_{E}^{t}(P_{2})\right|\leq |P_{1}-P_{2}|\,e^{C\int_{0}^{t}(\operatorname{Lip}_{R}(E_{s})+1)\,ds},\quad t\in[0,T].$

Proof

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Proof of the Theorem

Estimates on characteristics:

- Taking characteristics with initial data inside a fixed ball then there exists R > 0 depending on T, in which the whole trajectories are inside a possibly larger ball of radius R for all times $t \in [0, T]$.
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 $|\mathcal{T}_{E}^{t}(P_{1}) - \mathcal{T}_{E}^{t}(P_{2})| \leq |P_{1} - P_{2}| e^{C \int_{0}^{t} (\operatorname{Lip}_{R}(E_{s}) + 1) ds}, \quad t \in [0, T].$

Proof

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Proof of the Theorem

Error on transported measures through different flows:

Let $\mathcal{T}_1, \mathcal{T}_2 : \mathbb{R}^d \to \mathbb{R}^d$ be two Borel measurable functions. Also, take $f \in \mathcal{P}_1(\mathbb{R}^d)$. Then,

 $W_1(\mathcal{T}_1 \# f, \mathcal{T}_2 \# f) \le \|\mathcal{T}_1 - \mathcal{T}_2\|_{L^{\infty}(\mathrm{supp} f)}.$

Continuity in time for solutions of the linear transport:

 $W_1(\mathcal{T}_E^s \# f, \mathcal{T}_E^t \# f) \leq C |t-s|, \quad \text{ for any } t, s \in [0,T].$

Error on transported measures through different initial data:

Take a locally Lipschitz map $\mathcal{T} : \mathbb{R}^d \to \mathbb{R}^d$ and $f, g \in \mathcal{P}_1(\mathbb{R}^d)$, both with compact support contained in the ball B_R . Then,

 $W_1(\mathcal{T}\#f,\mathcal{T}\#g) \leq LW_1(f,g),$

where *L* is the Lipschitz constant of \mathcal{T} on the ball B_R .

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Proof

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Proof of the Theorem

$$\begin{split} W_{1}(f_{t},g_{t}) &= W_{1}(\mathcal{T}_{f}^{t} \#f_{0},\mathcal{T}_{g}^{t} \#g_{0}) \\ &\leq W_{1}(\mathcal{T}_{f}^{t} \#f_{0},\mathcal{T}_{g}^{t} \#f_{0}) + W_{1}(\mathcal{T}_{g}^{t} \#f_{0},\mathcal{T}_{g}^{t} \#g_{0}) \\ &\leq \|\mathcal{T}_{f}^{t}-\mathcal{T}_{g}^{t}\|_{L^{\infty}(\mathrm{supp}f_{0})} + L_{t} W_{1}(f_{0},g_{0}) \\ &\leq C_{2} \int_{0}^{t} e^{C_{2}(t-s)} \|E[f_{s}] - E[g_{s}]\|_{L^{\infty}(B_{R})} ds + L_{t} W_{1}(f_{0},g_{0}) \\ &\leq C_{3} \mathrm{Lip}_{2R}(\nabla U) \int_{0}^{t} e^{C_{4}(t-s)} W_{1}(f_{s},g_{s}) ds + e^{C_{1}t} W_{1}(f_{0},g_{0}). \end{split}$$

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3 Stochastic Mean-Field Limit

- Setting of the problem
- Proof



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Rigorous Statement of the Mean-Field Limit

Aggregation Equation:

$$\begin{cases} \partial_t \rho + \nabla \cdot (\rho u) = 0, \text{ with } u(t, x) := -\nabla U * \rho, \qquad t > 0, \quad x \in \mathbb{R}^d, \\ \rho(0, x) := \rho_0(x), \qquad x \in \mathbb{R}^d, \end{cases}$$

Particle Approximation and Empirical distribution $\mu_N(t)$:

$$\begin{cases} \dot{X}_{i}(t) = -\sum_{j \neq i} m_{j} \nabla U(X_{i}(t) - X_{j}(t)), \\ X_{i}(0) = X_{i}^{0}, \quad i = 1, \dots, N. \\ \mu_{N}(t) = \sum_{i=1}^{N} m_{i} \delta_{X_{i}(t)}, \quad \sum_{i=1}^{N} m_{i} = \int_{\mathbb{R}^{d}} \rho_{0}(x) dx = 1, \end{cases}$$

with $m_i > 0, i = 1, ..., N$. We set $\nabla U(0) = 0$ even if singular at the origin.

The convergence:

 $(\mu_N^0 \rightarrow \rho^0 \text{ weakly-* as measures} \Longrightarrow \mu_N(t) \rightarrow \rho(t) \text{ weakly-* as measures}$ for small time or for every time?"

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Setting of the problem

Rigorous Statement of the Mean-Field Limit

Quantities to Control: the W_{∞} -distance between $\rho(t)$ and $\mu_N(t)$, and the minimum inter-particle distance:

 $\eta(t) := W_{\infty}(\mu_N(t), \rho(t)), \quad \eta_m(t) := \min_{1 \le i \ne j \le N} (|X_i(t) - X_j(t)|),$

with $\eta^0 := \eta(0)$ and $\eta^0_m := \eta_m(0)$.

Assumptions on the potential U: it is C^2 except at the origin, where it might have a singularity. We set U(0) = 0 by definition, and

$$\begin{aligned} |\nabla U(x)| &\leq \frac{C}{|x|^{\alpha}}, \quad \text{and} \quad |D^2 U(x)| \leq \frac{C}{|x|^{1+\alpha}}, \quad \forall x \in \mathbb{R}^d \setminus \{0\}, \\ &\leq \alpha < d-1. \end{aligned}$$

Note that due to the assumptions on U, we can always find $1 such that <math>(\alpha + 1)p' < d$, and thus ∇U belongs to $\mathcal{W}_{loc}^{1,p'}(\mathbb{R}^d)$.

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Rigorous Statement of the Mean-Field Limit

Main Result.-

Let ρ be a solution to the aggregation equation up to time T > 0, such that $\rho \in L^{\infty}(0, T; (L^1 \cap L^p)(\mathbb{R}^d)) \cap C([0, T], \mathcal{P}_1(\mathbb{R}^d))$, with initial data $\rho^0 \in (\mathcal{P}_1 \cap L^p)(\mathbb{R}^d), 0 \le \alpha < -1 + d/p'$, and $1 . Furthermore, we assume <math>\mu_N^0$ converges to ρ^0 for the distance d_∞ as the number of particles *N* goes to infinity,

 $W_\infty(\mu^0_N,
ho^0) o 0 \quad ext{as} \quad N o\infty,$

and that the initial quantities η^0 , η^0_m satisfy

$$\lim_{N\to\infty}\frac{(\eta^0)^{d/p'}}{(\eta^0_m)^{1+\alpha}}=0.$$

Under the previous assumptions on the potential, for N large enough the associated particle system is well-defined up to time T, in the sense that there is no collision between particles before that time, and moreover

 $\mu_N(t) \rightarrow \rho(t)$ weakly-* as measures as $N \rightarrow \infty$, for all $t \in [0, T]$.

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Ideas of the Proof

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Kinetic Models and measure solutions

- Vlasov-like Models
- Proof

2 Mean-Field Limit for 1st Order Model

- Setting of the problem
- Ideas of the Proof

3 Stochastic Mean-Field Limit

- Setting of the problem
- Proof

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Kinetic Models and measure solutions	Mean-Field Limit for 1st Order Model	Stochastic Mean-Field Limit				
Ideas of the Proof						
Strategy of the Proof						

In Step A, we estimate the growth of the W_∞ Wasserstein distance between the continuum and the discrete solutions η that involves η itself and η_m in the form:

$$rac{d\eta}{dt} \leq C\eta \|
ho\| \left(1+\eta^{d/p'}\eta_m^{-(1+lpha)}
ight).$$

• In Step B, we estimate the decay of the minimum inter-particle distance η_m , which also involves the terms η and η_m in the form:

$$\frac{d\eta_m}{dt} \ge -C\eta_m \|\rho\| \left(1 + \eta^{d/p'} \eta_m^{-(1+\alpha)}\right).$$

• In Step C, under the assumption of a well prepared initial approximation, we combine the estimates above to conclude the desired result.

Kinetic Models and measure solutions	Mean-Field Limit for 1st Order Model	Stochastic Mean-Field Limit	
Ideas of the Proof		000000000000000000000000000000000000000	
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Ideas of the Proof

Step A: Well-defined characteristics

The assumptions on the potential lead to

$$|\nabla U(x) - \nabla U(y)| \le \frac{2|x-y|}{\min(|x|, |y|)^{\alpha+1}}.$$

Given the velocity fields $u(x, t) = -\nabla U * \rho$ and " $u_N := -\nabla U * \mu_N$ ". We define the flows:

$$\begin{cases} \frac{d}{dt}(\Psi(t;s,x)) = u(t;s,\Psi(t;s,x)),\\ \Psi(s;s,x) = x, \end{cases}$$

for all $s, t \in [0, T]$, and

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defined for all $s, t \in [0, T_0^N]$ since $\eta_m^0 > 0$.

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Ideas of the Proof

Step A: Well-defined characteristics

The assumptions on the potential lead to

$$|\nabla U(x) - \nabla U(y)| \le \frac{2|x-y|}{\min(|x|, |y|)^{\alpha+1}}.$$

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Ideas of the Proof

Step A: Well-defined Flows

$$\begin{aligned} |u(t,x) - u(t,y)| &\leq \int_{\mathbb{R}^d} |\nabla U(x-z) - \nabla U(y-z)| \rho(t,z) \, dz \\ &\leq 2|x-y| \int_{\mathbb{R}^d} \frac{1}{\min(|x-z|, |y-z|)^{\alpha+1}} \rho(t,z) \, dz \\ &\leq 4|x-y| \sup_{x \in \mathbb{R}^d} \int_{\mathbb{R}^d} \frac{1}{|x-z|^{\alpha+1}} \rho(t,z) \, dz \, . \end{aligned}$$

Now, splitting the last integral into the near- and far-field sets $\mathcal{A} := \{z : |x - z| \ge 1\}$ and $\mathcal{B} := \mathbb{R}^d - \mathcal{A}$ and estimating the two terms, we deduce

$$\begin{split} \int_{\mathbb{R}^d} \frac{1}{|x-z|^{\alpha+1}} \rho(t,z) \, dz &\leq \|\rho(t)\|_1 + \left(\int_{\mathcal{B}} \frac{1}{|x-y|^{(1+\alpha)p'}} \, dy \right)^{1/p'} \|\rho(t)\|_p \\ &\leq C \|\rho\| \,, \end{split}$$

for all $x \in \mathbb{R}^d$ due to the assumption $(1 + \alpha)p' < d$.

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Conclusions

Ideas of the Proof

Step A: Estimate of the evolution of W_{∞}

Fixed $0 \le t_0 < \min(T, T_0^N)$ and choose an optimal transport map for W_∞ denoted by \mathcal{T}^0 between $\rho(t_0)$ and $\mu_N(t_0)$; $\mu_N(t_0) = \mathcal{T}^0 \# \rho(t_0)$.

The solution of the aggregation equation is given by $\rho(t) = \Psi(t; t_0, \cdot) \# \rho(t_0)$ and obviously $\mu_N(t) = \Psi_N(t; t_0, \cdot) \# \mu_N(t_0)$ for $t \ge t_0$. We also notice that for $t \ge t_0$

$$\mathcal{T}^t \# \rho(t) = \mu_N(t), \quad \text{where} \quad \mathcal{T}^t = \Psi_N(t; t_0, \cdot) \circ \mathcal{T}^0 \circ \Psi(t_0; t, \cdot).$$

By Definition of the W_{∞} Wasserstein distance, we get

$$\eta(t) = W_{\infty}(\mu_N(t), \rho(t)) \leq \|\Psi(t; t_0, \cdot) - \Psi_N(t; t_0, \cdot) \circ \mathcal{T}^0\|_{\infty}.$$

We notice that

$$\frac{d}{dt}\left(\Psi_N(t;t_0,\mathcal{T}^0(x))-\Psi(t;t_0,x)\right)\Big|_{t=t_0}=u_N(t_0,\mathcal{T}^0(x))-u(t_0,x).$$

$$\frac{d}{dt} \|\Psi_N(t;t_0,\cdot) \circ \mathcal{T}^0 - \Psi(t;t_0,\cdot)\|_{\infty}\Big|_{t=t_0^+} \le \|u_N(t_0,\cdot) \circ \mathcal{T}^0 - u(t_0,\cdot)\|_{\infty}.$$

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Ideas of the Proof

Step A: Estimate of the evolution of W_{∞}

We now note that

$$u_{N}(t_{0}, \mathcal{T}^{0}(x)) - u(t_{0}, x) = -\int_{\mathbb{R}^{d}} \nabla U(\mathcal{T}^{0}(x) - y) d\mu_{N}(t_{0}, y) + \int_{\mathbb{R}^{d}} \nabla U(x - y) \rho(t_{0}, y) dy$$

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$$\frac{d^{+}\eta}{dt} \leq C \sup_{x \in \mathbb{R}^{d}} \int_{\mathbb{R}^{d}} |\nabla U(\mathcal{T}(x) - \mathcal{T}(y)) - \nabla U(x - y)|\rho(y)dy$$

We decompose the integral on \mathbb{R}^d into the near- and the far-field parts as $\mathcal{A} := \{z : |x - z| \ge 4\eta\}$ and $\mathcal{B} := \mathbb{R}^d - \mathcal{A}$, to get

$$\mathcal{I}_1 \leq \int_{\mathcal{A}} \frac{2\left(|x - \mathcal{T}(x)| + |y - \mathcal{T}(y)|\right)}{\min(|x - y|, |\mathcal{T}(x) - \mathcal{T}(y)|)^{\alpha + 1}} \rho(y) dy \leq C\eta \|\rho\|.$$

and

$$\mathcal{I}_2 \leq \int_{\mathcal{B}} \frac{\rho(y)}{|x-y|^{\alpha}} dy + \int_{\mathcal{B}} \frac{\rho(y)}{\eta_m^{\alpha}} dy \leq C(\eta^{d/p'-\alpha} + \eta^{d/p'} \eta_m^{-\alpha}) \|\rho\|.$$

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Ideas of the Proof

Step B: Estimate of the evolution of η_m

Pick *i*, *j* so that $|X_i - X_j| = \eta_m$.

$$\begin{aligned} \frac{d}{t} |X_i - X_j| &\ge -|u_N(X_i) - u_N(X_j)| \\ &\ge -\int_{\mathbb{R}^d} |\nabla U(X_i - y) - \nabla U(X_j - y)| \, d\mu_N(y) \\ &= -\int_{\mathbb{R}^d} |\nabla U(X_i - \mathcal{T}(y)) - \nabla U(X_j - \mathcal{T}(y))| \, \rho(y) dy \,, \end{aligned}$$

where \mathcal{T} is the optimal map satisfying $\mu_N(t) = \mathcal{T} \# \rho(t)$.

Decomposing in near- and far-field parts the domain \mathbb{R}^d as $\mathcal{A} := \{y : |X_i - y| \ge 2\eta \text{ and } |X_j - y| \ge 2\eta\}$ and $\mathcal{B} := \mathbb{R}^d - \mathcal{A}$, we can estimate

$$\begin{split} \int_{\mathcal{A}} |\nabla U(X_i - \mathcal{T}(y)) - \nabla U(X_j - \mathcal{T}(y))| \,\rho(y) dy \\ &\leq \int_{\mathcal{A}} \frac{2|X_i - X_j|}{\min(|X_i - \mathcal{T}(y)|, |X_j - \mathcal{T}(y)|)^{\alpha + 1}} \,\rho(y) dy \\ &\leq 2^{2 + \alpha} |X_i - X_j| \int_{\mathcal{A}} \left(\frac{1}{|X_i - y|^{\alpha + 1}} + \frac{1}{|X_j - y|^{\alpha + 1}} \right) \rho(y) dy \leq C \eta_m \|\rho\|, \end{split}$$

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Step B: Estimate of the evolution of η_m

Pick *i*, *j* so that $|X_i - X_j| = \eta_m$.

$$\begin{split} \frac{d}{dt} |X_i - X_j| &\geq -|u_N(X_i) - u_N(X_j)| \\ &\geq -\int_{\mathbb{R}^d} |\nabla U(X_i - y) - \nabla U(X_j - y)| \, d\mu_N(y) \\ &= -\int_{\mathbb{R}^d} |\nabla U(X_i - \mathcal{T}(y)) - \nabla U(X_j - \mathcal{T}(y))| \, \rho(y) dy \,, \end{split}$$

where \mathcal{T} is the optimal map satisfying $\mu_N(t) = \mathcal{T} \# \rho(t)$.

Decomposing in near- and far-field parts the domain \mathbb{R}^d as $\mathcal{A} := \{y : |X_i - y| \ge 2\eta \text{ and } |X_j - y| \ge 2\eta\}$ and $\mathcal{B} := \mathbb{R}^d - \mathcal{A}$, we can estimate

$$\begin{split} &\int_{\mathcal{A}} |\nabla U(X_i - \mathcal{T}(y)) - \nabla U(X_j - \mathcal{T}(y))| \,\rho(y) dy \\ &\leq \int_{\mathcal{A}} \frac{2|X_i - X_j|}{\min(|X_i - \mathcal{T}(y)|, |X_j - \mathcal{T}(y)|)^{\alpha + 1}} \,\rho(y) dy \\ &\leq 2^{2+\alpha} |X_i - X_j| \int_{\mathcal{A}} \left(\frac{1}{|X_i - y|^{\alpha + 1}} + \frac{1}{|X_j - y|^{\alpha + 1}} \right) \rho(y) dy \leq C \eta_m \|\rho\|, \end{split}$$

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Ideas of the Proof

Step B: Estimate of the evolution of W_{∞}

For the integral over \mathcal{B} , we use that as soon as $X_i \neq \mathcal{T}(y)$, then

$$|\nabla U(X_i - \mathcal{T}(y))| \leq \frac{1}{|X_j - \mathcal{T}(y)|^{\alpha}} \leq \frac{1}{\eta_m^{\alpha}},$$

and $\nabla U(X_i - \mathcal{T}(y)) = 0$ otherwise, and similarly for X_j .

A simple Hölder computation implies that

$$\int_{\mathcal{B}} |\nabla U(X_i - \mathcal{T}(y)) - \nabla U(X_j - \mathcal{T}(y))| \, \rho(y) dy \leq C \eta^{d/p'} \eta_m^{-\alpha} ||\rho||.$$

Putting together we finally conclude the estimate in Step B.

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Ideas of the Proof

Step C: Closing the Argument

$$\begin{aligned} \frac{d^+\eta}{dt} &\leq C\eta \|\rho\| \left(1+\eta^{d/p'}\eta_m^{-(1+\alpha)}\right), \\ \frac{d\eta_m}{dt} &\geq -C\eta_m \|\rho\| \left(1+\eta^{d/p'}\eta_m^{-(1+\alpha)}\right), \end{aligned}$$

for $t \in [0, \min(T, T_0^N))$.

For this, we set

$$f(t) := rac{\eta(t)}{\eta^0}, \quad g(t) := rac{\eta_m(t)}{\eta_m^0} \quad ext{and} \quad \xi_N := (\eta^0)^{d/p'} (\eta_m^0)^{-(1+lpha)}.$$

Note that ξ_N depends on the number of particles N. It yields

$$\begin{aligned} \frac{d^{+}f}{dt} &\leq C \|\rho\| f\left(1 + \xi_{N} f^{d/p'} g^{-(1+\alpha)}\right), \\ \frac{dg}{dt} &\geq -C \|\rho\| g\left(1 + \xi_{N} f^{d/p'} g^{-(1+\alpha)}\right). \end{aligned}$$

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Ideas of the Proof

Step C: Closing the Argument

Then, there exists a positive constant $T_*^N \leq T_0^N$ for sufficiently large N such that

 $\xi_N f^{d/p'} g^{-(1+\alpha)} \le 1 \quad \text{for} \quad t \in [0, T^N_*],$

Then it follows that $f(t) \leq e^{2\|\rho\|t}$ and $g(t) \geq e^{-2\|\rho\|t}$. This yields $\xi_N f^{d/p'} g^{-(1+\alpha)} \leq \xi_N e^{2(d/p'+(1+\alpha))\|\rho\|t}$, that is,

$$\xi_N f^{d/p'} g^{-(1+\alpha)} \le 1$$
 holds for $t \le -\frac{\log(\xi_N)}{2(d/p' + (1+\alpha))\|\rho\|}$

so that

$$-\frac{\log(\xi_N)}{2(d/p'+(1+\alpha))\|\rho\|} \le T_*^N \,.$$

Our assumption for the initial data finally implies

$$\liminf_{N\to\infty} T^N_* \geq \lim_{N\to\infty} -\frac{\log(\xi_N)}{2(d/p'+(1+\alpha))\|\rho\|} = \infty,$$

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Outline

Kinetic Models and measure solutions

- Vlasov-like Models
- Proof

Mean-Field Limit for 1st Order Model

- Setting of the problem
- Ideas of the Proof

Stochastic Mean-Field Limit
 Setting of the problem
 Proof

4 Conclusions

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Conclusions

Setting of the problem

Stochastic Particle System

General Interacting Particle System with Noise:

N interacting \mathbb{R}^{2d} -valued processes $(X_t^i, V_t^i)_{t\geq 0}$ with $1 \leq i \leq N$ solution of

$$\begin{cases} dX_t^i = V_t^i dt, \\ dV_t^i = \sqrt{2} dB_t^i - F(X_t^i, V_t^i) dt - \frac{1}{N} \sum_{j=1}^N H(X_t^i - X_t^j, V_t^i - V_t^j) dt, \end{cases}$$

with independent and commonly distributed initial data (X_0^i, V_0^i) with $1 \le i \le N$.

Empirical Measure:

$$\hat{f}^N_t = rac{1}{N}\sum_{i=1}^N \delta_{(X^i_t,V^i_t)}$$

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Setting of the problem

Coupling Method 1

Stochastic Particle System Associated to PDE:

N interacting processes $(\overline{X}_t^i, \overline{V}_t^i)_{t\geq 0}$ solutions of the kinetic McKean-Vlasov type equation on \mathbb{R}^{2d} :

$$\begin{cases} d\overline{X}_t^i = \overline{V}_t^i dt \\ d\overline{V}_t^i = \sqrt{2} dB_t^i - F(\overline{X}_t^i, \overline{V}_t^i) dt - H * f_t(\overline{X}_t^i, \overline{V}_t^i) dt, \\ (\overline{X}_0^i, \overline{V}_0^i) = (X_0^i, V_0^i), \quad f_t = \text{law}(\overline{X}_t^i, \overline{V}_t^i). \end{cases}$$

The stochastic processes are independent and identically distributed according to

 $\partial_t f_t + v \cdot \nabla_x f_t = \Delta_v f_t + \nabla_v \cdot ((F + H * f_t) f_t), \quad t > 0, x, v \in \mathbb{R}^d.$

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Coupling Method 2

Conjecture: The *N* interacting processes $(X_t^i, V_t^i)_{t\geq 0}$ behave as $N \to \infty$ like the processes $(\overline{X}_t^i, \overline{V}_t^i)_{t\geq 0}$ associated to the PDE.

More precisely, the objective is to estimate the convergence as $N \rightarrow \infty$ of

 $\mathbb{E}ig[|X^i_t - \overline{X}^i_t|^2 + |V^i_t - \overline{V}^i_t|^2ig] \leq arepsilon(N)$

Consequences

1. $f_t^{(1)}$ of any of the particles X_t^i at time *t* converges to f_t as *N* goes to infinity: $W_2^2(f_t^{(1)}, f_t) \leq \mathbb{E}\left[|X_t^i - \overline{X}_t^i|^2 + |V_t^i - \overline{V}_t^i|^2\right] \leq \varepsilon(N)$.

Kinetic Models and measure solutions	Mean-Field Limit for 1st Order Model	Stochastic Mean-Field Limit	
		000000000000	
Setting of the problem			

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Setting of the problem

Coupling Method 3

Consequences

2. Propagation of chaos: The law $f_t^{(k)}$ of any k particles (X_t^i, V_t^i) converges to the tensor product $f_t^{\otimes k}$ as N goes to infinity:

 $W_2^2(f_t^{(k)}, f_t^{\otimes k}) \leq k\varepsilon(N).$

3. Convergence of the empirical measure \hat{f}_t^N to f_t : if φ is a Lipschitz map on \mathbb{R}^{2d} , then

$$\begin{split} & \mathbb{E}\left[\left|\frac{1}{N}\sum_{i=1}^{N}\varphi(X_{t}^{i},V_{t}^{i})-\int_{\mathbb{R}^{2d}}\varphi\,df_{t}\right|^{2}\right] \\ & \leq 2\,\mathbb{E}\left[\left|\varphi(X_{t}^{i},V_{t}^{i})-\varphi(\overline{X}_{t}^{i},\overline{V}_{t}^{i})\right|^{2}+\left|\frac{1}{N}\sum_{i=1}^{N}\varphi(\overline{X}_{t}^{i},\overline{V}_{t}^{i})-\int_{\mathbb{R}^{2d}}\varphi\,df_{t}\right|^{2}\right] \\ & \leq \varepsilon(N)+\frac{C}{N} \end{split}$$

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Kinetic Models and measure solutions OOOOOOOOOOOOOOOOOOOOOOOOOOOOOOOOOOOO	Mean-Field Limit for 1st Order Model	Stochastic Mean-Field Limit	Conclusions
Main Result			

Previous Results: If the functions involved F and H are globally Lipschitz then there are classical results by Snitzman and Meleard, implying that

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

The typical F and H in our Cucker-Smale and D'Orsogna et al model are not globally Lipschitz.

Hypotheses:

Assume that *F* and *H* with H(-x, -v) = -H(x, v), satisfy

$$-(v - w) \cdot (F(x, v) - F(x, w)) \le A |v - w|^2$$
$$|F(x, v) - F(y, v)| \le L \min\{|x - y|, 1\}(1 + |v|^p)$$

for all x, y, v, w in \mathbb{R}^d , and analogously for *H* instead of *F*.

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Setting of the problem			
Main Result			

Previous Results: If the functions involved F and H are globally Lipschitz then there are classical results by Snitzman and Meleard, implying that

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

The typical F and H in our Cucker-Smale and D'Orsogna et al model are not globally Lipschitz.

Hypotheses:

Assume that *F* and *H* with H(-x, -v) = -H(x, v), satisfy

$$-(v - w) \cdot (F(x, v) - F(x, w)) \le A |v - w|^2$$

|F(x, v) - F(y, v)| \le L min{|x - y|, 1}(1 + |v|^p)

for all x, y, v, w in \mathbb{R}^d , and analogously for *H* instead of *F*.

Kinetic Models and measure solutions	Mean-Field Limit for 1st Order Model	Stochastic Mean-Field Limit	
		000000000000	
Setting of the problem			

Main Result 2

Properties of the Stochastic Processes and PDE:

Assume that the particle system and the processes have global solutions on [0, T] with initial data (X_0^i, V_0^i) such that the uniform moment condition holds:

$$\sup_{0 \le t \le T} \left\{ \int_{\mathbb{R}^{4d}} |H(x-y,v-w)|^2 df_t(x,v) df_t(y,w) + \int_{\mathbb{R}^{2d}} (|x|^2 + e^{a|v|^{p'}}) df_t(x,v) \right\} < +\infty$$

with
$$f_t = law(\overline{X}_t^i, \overline{V}_t^i)$$
 and some $p' > p$.

Result:

For all $0 < \epsilon < 1$ there exists a constant *C* such that

$$\mathbb{E}\big[|X_t^i - \overline{X}_t^i|^2 + |V_t^i - \overline{V}_t^i|^2\big] \le \frac{C}{N^{1-\epsilon}}$$

for all $0 \le t \le T$ and $N \ge 1$.

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Outline

Proof

Kinetic Models and measure solutions

- Vlasov-like Models
- Proof

Mean-Field Limit for 1st Order Model

- Setting of the problem
- Ideas of the Proof

3 Stochastic Mean-Field Limit

- Setting of the problem
- Proof

4 Conclusions

Proof

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Conclusions

Step 0.- Fluctuations:

Fluctuations:
$$x_t^i := X_t^i - \overline{X}_t^i, v_t^i := V_t^i - \overline{V}_t^i, i = 1, \dots, N.$$

Coupling: the Brownian motions $(B_t^t)_{t\geq 0}$ are equal for the stochastic interacting particle system and for the processes

$$\begin{split} dx^{i} &= v^{i} dt , \\ dv^{i} &= -\left(F(X^{i}, V^{i}) - F(\overline{X}^{i}, \overline{V}^{i})\right) dt \\ &- \frac{1}{N} \sum_{j=1}^{N} \left(H(X^{i} - \overline{X}^{j}, V^{i} - V^{j}) - (H * f_{t})(\overline{X}^{i}, \overline{V}^{i})\right) dt. \end{split}$$

Consider the quantity

$$\alpha(t) = \mathbb{E}\left[|x^i|^2 + |v^i|^2\right]$$

independent of the label *i* by symmetry.

Proof

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Step 0.- Fluctuations:

$$\frac{1}{2}\frac{d}{dt}\mathbb{E}\left[|x^{i}|^{2}\right] = \mathbb{E}\left[x^{i}\cdot v^{i}\right] \leq \frac{1}{2}\alpha(t)$$

and

$$\frac{1}{2}\frac{d}{dt}\mathbb{E}\left[|v^{i}|^{2}\right] = -\mathbb{E}\left[v^{i}\cdot\left(F(X^{i},V^{i})-F(\overline{X}^{i},\overline{V}^{i})\right)\right] \\ -\frac{1}{N}\mathbb{E}\left[\sum_{j=1}^{N}v^{i}\cdot\left(H(X^{i}-X^{j},V^{i}-V^{j})-H*f_{l}(\overline{X}^{i},\overline{V}^{i})\right)\right] =:I_{1}+I_{2}.$$

Proof

Mean-Field Limit for 1st Order Model

Stochastic Mean-Field Limit

Conclusions

Step 1.- Localization Estimate for I_1 :

Using the hypotheses on F:

 $I_{1} \leq A \mathbb{E}\left[|v^{i}|^{2}\right] + L \mathbb{E}\left[|v^{i}|\min\{|x^{i}|,1\}\left(1+|\overline{V}^{i}|^{p}\right)\right] := I_{11} + L I_{12}.$

Localizing in *V* + Markov's inequality:

$$I_{12} \leq (1+R^p)\alpha(t) + \frac{1}{2} \left(\mathbb{E}\left[|\overline{V}^i|^{4p} \right] \right)^{1/2} \left(e^{-aR^p} \mathbb{E}\left[e^{a|\overline{V}_i|^p} \right] \right)^{1/2}$$

Final Estimate: given T > 0, there exists C > 0 such that

 $I_1 \le C(1+r)\,\alpha(t) + C\,e^{-r}$

holds for all r > 0 and all $0 \le t \le T$.

Proof

Mean-Field Limit for 1st Order Model

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Mean-Field Limit for 1st Order Model

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Proof

Step 2.- Localization Estimate for *I*₂:

$$I_{2} = -\frac{1}{N}\mathbb{E}\left[\sum_{j=1}^{N} v^{i} \cdot \left(H(X^{i} - X^{j}, V^{i} - V^{j}) - H(\overline{X}^{i} - \overline{X}^{j}, \overline{V}^{i} - \overline{V}^{j})\right)\right]$$
$$-\frac{1}{N}\mathbb{E}\left[v^{i} \cdot \left(H(0, 0) - (H * f_{t})(\overline{X}^{i}, \overline{V}^{i})\right)\right]$$
$$-\frac{1}{N}\mathbb{E}\left[\sum_{j\neq i}^{N} v^{i} \cdot \left(H(\overline{X}^{i} - \overline{X}^{j}, \overline{V}^{i} - \overline{V}^{j}) - (H * f_{t})(\overline{X}^{i}, \overline{V}^{i})\right)\right]$$
$$=: I_{21} + I_{22} + I_{23}.$$

Localization in *I*₂₁ and *I*₂₂ + Argument of Law of Large Numbers (Snitzman):

$$I_{23} \leq \frac{1}{N} \left(\mathbb{E} \left[|v^1|^2 \right] \right)^{1/2} \left(\mathbb{E} \left[\left| \sum_{j=2}^N Y^j \right|^2 \right] \right)^{1/2} \leq \frac{C}{\sqrt{N}} \sqrt{\alpha(t)}$$

where $Y^j := H(\overline{X}^1 - \overline{X}^j, \overline{V}^1 - \overline{V}^j) - (H * f_t)(\overline{X}^1, \overline{V}^1)$ for $j \ge 2$.

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Step 3.- Conclusion:

First Result: given T > 0, there exists C > 0 such that

$$\alpha'(t) \le C(1+r)\alpha(t) + Ce^{-r} + \frac{C}{\sqrt{N}}\sqrt{\alpha(t)} \le C(1+r)\alpha(t) + Ce^{-r} + \frac{C}{N}$$

for all $t \in [0, T]$, all $N \ge 1$ and all r > 0. This implies due to changes of variables:

$$u' \le -u\log u + \frac{1}{N}$$

implying that $\alpha(t) \leq CN^{-e^{-Ct}}$

Second Result: A better localization implies that given T > 0, there exists C > 0 such that

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Stochastic Mean-Field Limit

Conclusions

- Simple modelling of the three main mechanisms leads to complicated patterns. More information from particular species should be included to make more realistic models (Helmelrijk & collaborators, ...)
- Mean-field limit under reasonable conditions leads to rigorous derivation of the mesoscopic/kinetic models with/without noise.
- References:
 - Orsogna-Panferov (KRM 2008).
 - C.-Fornasier-Toscani-Vecil (Birkhäuser 2011).
 - Oc.-Klar-Martin-Tiwari (M3AS 2010).
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