Coarse-graining of collective dynamics models Metric vs topological interactions

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Summary

- 1. Topological interactions
- 2. Smooth rank-based dynamics
- 3. Nearest neighbor
- 4. Conclusion

1. Topological interactions

Flocking dynamics

System with locally interacting agents Emergence of spatio-temporal coordination Patterns, structures, correlations, synchronization No leader



 \uparrow Pierre Degond - Metric vs topological interactions - PDE & probabilities, CIRM, 20/04/17 \downarrow

Mean-field (metric) interaction

Particle interact with all particles within a certain distance Examples: Alignment (Vicsek ...) Consensus (Cucker-Smale, Motsch-Tadmor, ...) Attraction-repulsion (Bertozzi, Carrillo, ...)

Binary (ternary, ...)

Particle interacts with a partner at contact Examples: Hard-sphere collisions (Boltzmann ...) Alignment (Bertin, Droz & Grégoire, ...)



Third type: topological interactions

Particles interact with other particles according to their rank [Ballerini et al, PNAS 2008]

Interaction ruling animal collective behavior depends on topological rather than metric distance: Evidence from a field study

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Kinetic models for topological interactions

Kinetic models

Largely investigated for mean-field metric or binary interactions

Almost inexistent for topological interactions 1st work is by J. Haskovec [Physica D 2013] for Cucker-Smale type interactions Also work by Y. Brenier for a competition model

Our work: Boltzmann approach Adapting 'Choose the Leader' model from [Carlen, D., Wennberg, M3AS 2013], [Carlen, Chatelin, D., Wennberg, Physica D 2013]

2. Smooth rank-based dynamics

A. Blanchet & P. D., J. Stat. Phys 163 (2016) 41-60

Rank

N particles
$$(x_i(t), v_i(t))_{i=1,\dots,N}$$
, $(x_i, v_i) \in \mathbb{R}^{2n}$

At given time t, Rank $R^N(i, j)$ of j w.r.t. i: Sort $(|x_k - x_i|)_{k=1,...,n, k \neq i}$ by increasing order $R^N(i, j)$ is rank of $|x_j - x_i|$ in the list $R^N(i, j) \in \{1, ..., N - 1\}$



Interaction probabilities

Normalized rank:
$$r^N(i,j) = \frac{R^N(i,j)}{N-1} \in \bigcup_{k=1}^N \{\frac{k}{N-1}\}$$

Given:
$$K : [0,1] \to [0,\infty)$$
 s.t. $\int_0^1 K(r) dr = 1$
define $K^N(r) = \frac{K(r)}{\sum_{k=1}^{N-1} K(\frac{k}{N-1})}$

Interaction probabilities:

 $\pi_{ij}^{N} \text{ probability of } i \text{ interacting with } j: \pi_{ij}^{N} = K^{N}(r^{N}(i,j))$ Note: $\sum_{\substack{j=1\\j\neq i}}^{N-1} \pi_{ij}^{N} = K^{N}(r^{N}(i,j)) = 1$

N-particle dynamics

Free flights
$$\dot{x}_i = v_i$$
, $\dot{v}_i = 0$

Collisions: at Poisson random times with rate N:

Pick $i \in \{1, ..., N\}$ with uniform probability 1/NPick $j \in \{1, ..., N\}$, $j \neq i$ with probability π_{ij}^N Perform: (x_i, x_j) remains unchanged (v_i, v_j) changed into (v_j, v_j)



Properties & Goal

Properties

Rank is a function of positions $r^N(i,j) = r^N(i,j)(x_1,...,x_N)$ and so is π_{ij}^N : $\pi_{ij}^N = K^N(r^N(i,j)(x_1,...,x_N))$

Rank is permutation-invariant

 $r^{N}(\sigma(i) \sigma(j))(x_{\sigma(1)}, \dots, x_{\sigma(N)}) = r^{N}(i, j)(x_{1}, \dots, x_{N})$

Goal

Derive a Boltzmann operator under Propagation of Chaos assumption

Note: BBGKY does not help

because all particles interact with all particles

Previous work using similar ideas:

[D. & Ringhofer, SIAM Appl. Math. 2007] (min interaction)

Master equation

Notations: $\vec{x} = (x_1, ..., x_N), \quad \vec{v} = (v_1, ..., v_N)$ $Z_{i} = (x_{i}, v_{i}), \quad \vec{Z} = (Z_{1}, \dots, Z_{N}), \quad d\vec{Z} = dZ_{1} \dots dZ_{N}$ $f^N(\vec{Z},t)$: N-particle distribution function Find eq. for f^N (master equation) Follow strategy of [Carlen, D., Wennberg, M3AS 2013] Take $\Phi^N(\vec{Z})$ a test function Drop drift term for simplicity $\frac{d}{dt}\int f_N \Phi^N d\vec{Z} =$ $N \int \left[\frac{1}{N} \sum \pi_{ij}^N(\vec{x}) \Phi^N(Z_1, \dots, x_i, v_j, \dots, x_j, v_j, \dots, Z_N) - \Phi^N(\vec{Z})\right] f^N(\vec{Z}, t) d\vec{Z}$

> If $f^N|_{t=0}$ is permutation invariant then $f^N(t)$ is permutation invariant

Marginals and propagation of chaos

Marginal:
$$f_N^k(Z_1, \ldots, Z_k, t) = \int f^N(\vec{Z}, t) dZ_{k+1} \ldots dZ_N$$

To compute eq. for f_N^1 , use $\Phi^N(\vec{Z}) = \phi(Z_1)$

Propagation of chaos

Assume
$$f^N(\vec{Z},t) = \prod_{\ell=1}^N f^1_N(Z_\ell,t) + \text{negligible terms as } N \to \infty$$

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Define
$$\rho_N^1(x,t) = \int f_N^1(x,v,t) \, dv$$

Eq. for first marginal

$$\frac{d}{dt} \int f_1^N(Z_1) \,\phi(Z_1) \,dZ_1 = \frac{1}{S^N(K)} \int \left(\phi(x_1, v_2) - \phi(x_1, v_1)\right) f_1^N(Z_1) \,f_1^N(Z_2) \\ \left(\int K\left(r^N(1, 2)(\vec{x})\right) \prod_{\ell=3}^N \rho_N^1(x_\ell) \,dx_\ell\right) dZ_1 \,dZ_2$$

where

$$S^{N}(K) = \frac{1}{N-1} \sum_{k=1}^{N-1} K\left(\frac{k}{N-1}\right) \approx \int_{0}^{1} K(r) \, dr = 1$$

Need to estimate the behavior as $N \to \infty$ of:

$$\int K(r^N(1,2)(\vec{x})) \prod_{\ell=3}^N \rho_N^1(x_\ell) \, dx_\ell$$

Estimate of interaction term

$$\int K(r^N(1,2)(\vec{x})) \prod_{\ell=3}^N \rho_N^1(x_\ell) \, dx_\ell = \mathbb{E}\Big\{K(r^N(1,2)(x_1,x_2,x_3,\dots,x_N))\Big\}$$

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when x_3, \ldots, x_N are iid random variables following the law ρ_N^1

$$= \sum_{j=0}^{N-2} K\left(\frac{j+1}{N-1}\right) \binom{N-2}{j} \operatorname{Prob}\left(\operatorname{Card}\left\{k \in \{3, \dots, N\} \text{ s.t. } |x_k - x_1| \le |x_2 - x_1|\right\} = j\right)$$
$$= \sum_{j=0}^{N-2} K\left(\frac{j+1}{N-1}\right) \binom{N-2}{j} m^j (1-m)^{(N-2)-j}$$
where $m = M_{\rho_N^1}(x_1, |x_2 - x_1|) = \int_{|x-x_1| \le |x_2 - x_1|} \rho_N^1(x) \, dx$

 \approx Bernstein polynomial approximation of K(m)

 $= K(m) + \mathcal{O}(\frac{1}{N})$

Kinetic equation (smooth dynamics)

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In the limit $N \to \infty$, if $f_N^1(Z_1) \to f(Z_1)$, then

$$\frac{d}{dt} \int f(Z_1, t) \,\phi(Z_1) \,dZ_1 = \\ \int \left(\phi(x_1, v_2) - \phi(x_1, v_1)\right) f(Z_1) \,f(Z_2) \,K\left(M_\rho(x_1, |x_2 - x_1|)\right) dZ_1 \,dZ_2$$

In strong form (adding back the drift term):

$$\begin{split} \partial_t f + v \cdot \nabla_x f &= Q(f) \\ Q(f)(x,v) &= \rho(x) \int f(x',v) \, K \big(M_\rho(x,|x'-x|) \big) \, dx' - f(x,v) \\ \text{with} \quad M_\rho(x,s) &= \int_{|x'-x| \le s} \rho(x') \, dx' \end{split}$$

Mass conservation

$$\int Q(f) dv = \rho(x) \left(\int \rho(x') K(M_{\rho}(x, |x'-x|)) dx' - 1 \right)$$
$$= \rho(x) \left(\int K(m) dm - 1 \right) = 0$$

So, the continuity eq. is satified

$$\partial_t \rho + \nabla_x \cdot j = 0, \qquad j(x,t) = \int_{\mathbb{R}^n} f(x,v,t) v \, dv$$

3. Nearest neighbor

A. Blanchet & P. D., arXiv:1703.05131

Nearest neighbor interaction

At each collision event:

A particle is selected randomly with uniform probability When selected, particle *i* follows its nearest neighbor i.e. the probability π_{ij}^N of *i* interacting with *j* is

$$\pi_{ij}^N = \delta\Big(R^N(i,j) - 1\Big)$$

here: rank is un-normalized: $R^N(i,j) \in \{1,\ldots,N-1\}$, so: $\pi_{ij}^N = 0$ except if j = nearest neighbor in which case $\pi_{ij}^N = 1$

Rate of collision events: $\lambda(N) N$ with $\lambda(N) \to \infty$ TBD

Master eq. unchanged: - multiply by $\lambda(N)$

- replace $K^N(r^N(i,j))$ by $\delta(R^N(i,j)-1)$

Eq. for first marginal

$$\frac{d}{dt} \int f_1^N(Z_1) \,\phi(Z_1) \,dZ_1 = \int \left(\phi(x_1, v_2) - \phi(x_1, v_1)\right) f_1^N(Z_1) \,f_1^N(Z_2) \\ \left(\lambda(N) \left(N-1\right) \int \delta\left(R^N(1, 2)(\vec{x}) - 1\right) \prod_{\ell=3}^N \rho_N^1(x_\ell) \,dx_\ell\right) dZ_1 \,dZ_2$$

Need to estimate the behavior as $N \to \infty$ of:

$$\lambda(N) (N-1) \int \delta(R^N(1,2)(\vec{x}) - 1) \prod_{\ell=3}^N \rho_N^1(x_\ell) \, dx_\ell$$

Drop scripts N and 1 for clarity i.e. $f_1^N \to f, \, \rho_1^N \to \rho$

Estimate of interaction term

$$\int \delta(R^N(1,2)(\vec{x})-1) \prod_{\ell=3}^N \rho(x_\ell) \, dx_\ell = \mathbb{E}\Big\{\delta(R^N(1,2)(\vec{x})-1)\Big\}$$

when x_3,\ldots,x_N are iid random variables following the law ho

$$= \operatorname{Prob}\left(\operatorname{Card}\left\{k \in \{3, \dots, N\} \text{ s.t. } |x_k - x_1| \le |x_2 - x_1|\right\} = 0\right)$$
$$= (1 - m)^{(N-2)}$$
where $m = M_{\rho}(x_1, |x_2 - x_1|) = \int_{|x - x_1| \le |x_2 - x_1|} \rho(x) \, dx$

So:
$$\lambda(N) (N-1) \int \delta (R^N(1,2)(\vec{x})-1) \prod_{\ell=3}^N \rho(x_\ell) dx_\ell$$

= $\lambda(N) (N-1) (1 - M_\rho(x_1, |x_2 - x_1|))^{(N-2)}$

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Estimate of first marginal

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$$\frac{d}{dt} \int f(Z_1) \,\phi(Z_1) \,dZ_1 = \int \left(\phi(x_1, v_2) - \phi(x_1, v_1) \right) f(x_1, v_1) \,f(x_2, v_2) \\$$
$$\lambda(N) \,(N-1) \left(1 - M_\rho(x_1, |x_2 - x_1|) \right)^{(N-2)} \,dx_1 \,dx_2 \,dv_1 \,dv_2$$

Use polar coordinates $x_2 = x_1 + r\omega$, $r \in [0, \infty)$, $\omega \in \mathbb{S}^{n-1}$

$$\frac{d}{dt} \int f(Z_1) \,\phi(Z_1) \,dZ_1 = \int \left(\phi(x_1, v_2) - \phi(x_1, v_1)\right) f(x_1, v_1) \,F_f^N(x_1, v_2) \,dx_1 \,dv_1 \,dv_2$$
$$F_f^N(x_1, v_2) = \lambda(N) \,(N-1) \int f(x_1 + r\omega, v_2) \left(1 - M_\rho(x_1, r)\right)^{(N-2)} r^{n-1} \,dr \,d\omega$$

Estimate of F_f^N

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Change of variables $m = M_{\rho}(x_1, r) \Leftrightarrow r = R_{\rho}(x_1, m)$, $m \in [0, 1)$

$$F_f^N(x_1, v_2) = \lambda(N) \left(N - 1\right) \int_0^1 G_f(x_1, v_2, m) \left(1 - m\right)^{N-2} dm$$
$$G_f(x_1, v_2, m) = \frac{\int f(x_1 + R_\rho(x_1, m)\omega, v_2) d\omega}{\int \rho(x_1 + R_\rho(x_1, m)\omega) d\omega}$$

As
$$m \to 0$$

$$G_f(x_1, v_2, m) = \frac{f(x_1, v_2)}{\rho(x_1)} + \frac{1}{2n} \left(\frac{m}{\rho(x_1)}\right)^{\frac{2}{n-1}} D(\rho, f)(x_1, v_2) + o\left(m^{\frac{2}{n-1}}\right)$$

$$D(\rho, f)(x_1, v_2) = \frac{1}{\rho(x_1)} \left(\Delta_x f(x_1, v_2) - \frac{f(x_1, v_2)}{\rho(x_1)} \Delta_x \rho(x_1)\right)$$

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Collision frequency scaling

Denote:

$$C_{N,n} = (N-1)\frac{n^{\frac{2}{n}-1}}{2} \int_0^1 m^{\frac{2}{n}} (1-m)^{N-2} dm$$

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 $C_{N,n} \to 0$ as $N \to \infty$. For instance: $C_{N,2} = \frac{1}{2N}$

Choose: $\lambda(N) = 1/C_{N,n}$

larger frequency: $\lambda(N) \rightarrow \infty$ as $N \rightarrow \infty$

Then, as $N \to \infty$: $F_f^N(x_1, v_2) - \lambda(N) \frac{f(x_1, v_2)}{\rho(x_1)} \longrightarrow \left(\frac{1}{\rho(x_1)}\right)^{\frac{2}{n-1}} D(\rho, f)(x_1, v_2)$ Probability $p_{N,n}(dm) \sim m^{\frac{2}{n-1}} (1-m)^{N-2} dm \to \delta_0$ as $N \to \infty$

Kinetic equation (nearest neighbor)

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In the limit $N \to \infty$, if $f_N^1(Z_1) \to f(Z_1)$, then

$$\frac{d}{dt'} \int f(x_1, v_1, t') \,\phi(x_1, v_1) \,dx_1 \,dv_1 = \\ \int \left(\phi(x_1, v_2) - \phi(x_1, v_1)\right) f(x_1, v_1) \,\Delta_x f(x_1, v_2) \,\frac{1}{\rho(x_1)^{\frac{n+1}{n-1}}} \,dx_1 \,dx_2 \,dv_2$$

In strong form (adding back the drift term):

$$\partial_t f + v \cdot \nabla_x f = Q(f)$$
$$Q(f)(x,v) = \frac{1}{\rho(x)^{\frac{2}{n-1}}} \left(\Delta_x f(x,v) - \frac{f(x,v)}{\rho(x)} \Delta_x \rho(x) \right)$$

Mass conservation

$$\int Q(f) \, dv = 0 \qquad \text{(obvious)}$$

So, the continuity eq. is satisfied

$$\partial_t \rho + \nabla_x \cdot j = 0, \qquad j(x,t) = \int_{\mathbb{R}^n} f(x,v,t) v \, dv$$

4. Conclusion

Conclusion and perspectives

Smooth rank-based topological interaction Derivation of spatially non-local Boltzmann model Highly nonlinear new collision operator

Nearest-neighbor interaction

gives rise to spatial nonlinear diffusion

Still preserves continuity eq.

Perspectives

Well-posedness of the resulting eqs.

Proof of propagation of chaos and convergence

Hydrodynamic limits

Extension to more complex interaction rules