

# Swarming Models with Repulsive-Attractive Effects

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Lecture 1, Ravello 2013

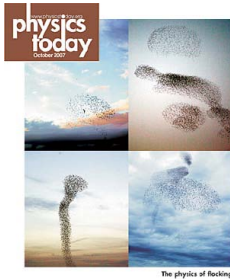
# Outline

- 1 Motivations
  - Collective Behavior Models
  - Variations
  - Fixed Speed models
  - 1st order Models
- 2 Outline of the course
- 3 Transversal Tool: Wasserstein Distances
  - Definition
  - Properties

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# Swarming by Nature or by design?



Fish schools and Birds flocks.

# Individual Based Models (Particle models)

**Swarming** = Aggregation of agents of similar size and body type generally moving in a coordinated way.

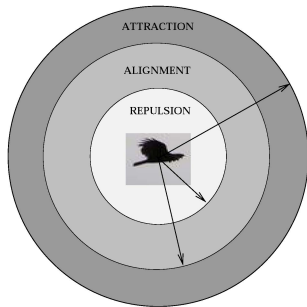
Highly developed social organization: insects (locusts, ants, bees ...), fishes, birds, micro-organisms (myxo-bacteria, ...) and artificial robots for unmanned vehicle operation.

## Interaction regions between individuals<sup>a</sup>

<sup>a</sup>Aoki, Helmerijk et al., Barbaro, Bimir et al.

- **Repulsion** Region:  $R_k$ .
- **Attraction** Region:  $A_k$ .
- **Orientation** Region:  $O_k$ .

## Metric versus Topological Interaction



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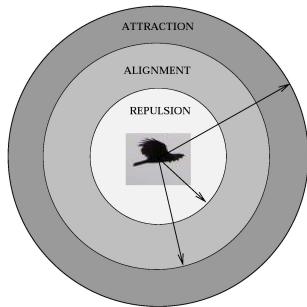
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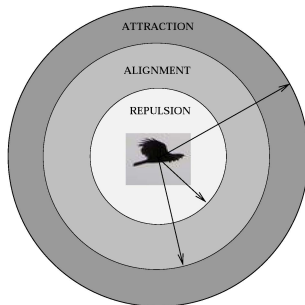
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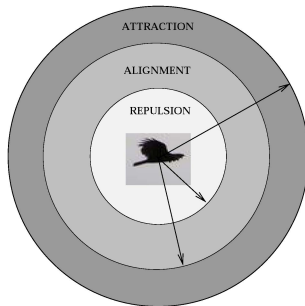
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Metric versus Topological Interaction





## 2nd Order Model: Newton's like equations



D'Orsogna, Bertozzi et al. model (PRL 2006):

$$\begin{cases} \frac{dx_i}{dt} = v_i, \\ m \frac{dv_i}{dt} = (\alpha - \beta |v_i|^2) v_i - \sum_{j \neq i} \nabla U(|x_i - x_j|). \end{cases}$$

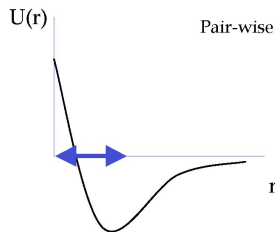
Model assumptions:

- Self-propulsion and friction terms determines an asymptotic speed of  $\sqrt{\alpha/\beta}$ .
- Attraction/Repulsion modeled by an effective pairwise potential  $U(x)$ .

$$U(r) = -C_A e^{-r/\ell_A} + C_R e^{-r/\ell_R}.$$

One can also use Bessel functions in 2D and 3D to produce such a potential.

$C = C_R/C_A > 1$ ,  $\ell = \ell_R/\ell_A < 1$  and  $C\ell^2 < 1$ :



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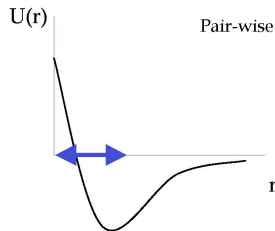
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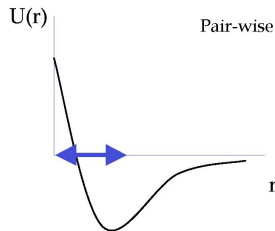
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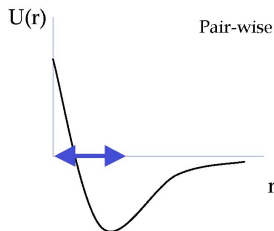
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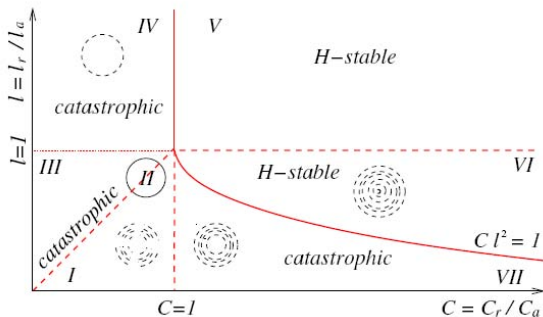
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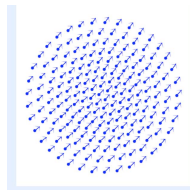
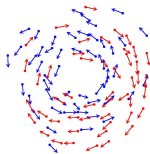
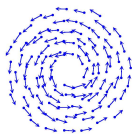
# Model with an asymptotic velocity

Classification of possible patterns: Morse potential. D'Orsogna, Bertozzi et al. model (PRL 2006).



# Model with an asymptotic speed

Typical patterns: milling, double milling or flocking:



# Velocity consensus model

Cucker-Smale Model (IEEE Automatic Control 2007):

$$\left\{ \begin{array}{l} \frac{dx_i}{dt} = v_i, \\ \frac{dv_i}{dt} = \sum_{j=1}^N a_{ij} (v_j - v_i), \end{array} \right.$$

with the communication rate,  $\gamma \geq 0$ :

$$a_{ij} = a(|x_i - x_j|) = \frac{1}{(1 + |x_i - x_j|^2)^\gamma}.$$

**Asymptotic flocking:**  $\gamma < 1/2$ ; Cucker-Smale.

General Proof for  $0 < \gamma \leq 1/2$ ; C.-Fornasier-Rosado-Toscani.

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# Leadership, Geometrical Constraints, and Cone of Influence

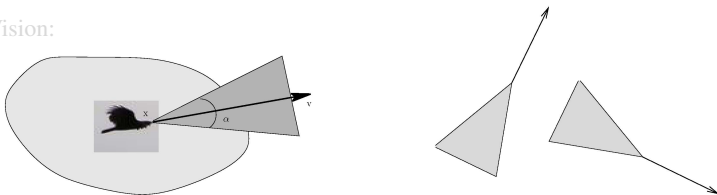
Cucker-Smale with local influence regions:

$$\begin{cases} \frac{dx_i}{dt} = v_i, \\ \frac{dv_i}{dt} = \sum_{j \in \Sigma_i(t)} a(|x_i - x_j|)(v_j - v_i), \end{cases}$$

where  $\Sigma_i(t) \subset \{1, \dots, N\}$  is the set of dependence, given by

$$\Sigma_i(t) := \left\{ 1 \leq \ell \leq N : \frac{(x_\ell - x_i) \cdot v_i}{|x_\ell - x_i| |v_i|} \geq \alpha \right\}.$$

Cone of Vision:



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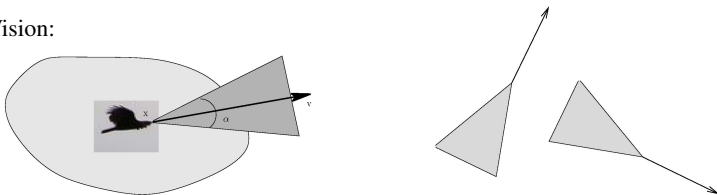
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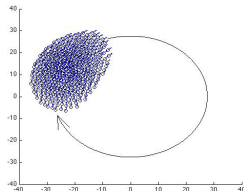
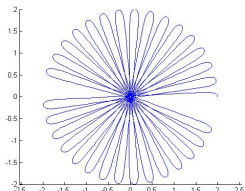
# Roosting Forces

Adding a roosting area to the model:

$$\begin{cases} \frac{dx_i}{dt} = v_i, \\ \frac{dv_i}{dt} = (\alpha - \beta |v_i|^2)v_i - \sum_{j \neq i} \nabla U(|x_i - x_j|) - v_i^\perp \nabla_{x_i} [\phi(x_i) \cdot v_i^\perp]. \end{cases}$$

with the roosting potential  $\phi$  given by  $\phi(x) := \frac{b}{4} \left( \frac{|x|}{R_{\text{Roost}}} \right)^4$ .

Roosting effect: milling flocks  $N = 400$ ,  $R_{\text{roost}} = 20$ .



# Adding Noise

Self-Propelling/Friction/Interaction with Noise Particle Model:

$$\left\{ \begin{array}{l} \dot{x}_i = v_i, \\ dv_i = \left[ (\alpha - \beta |v_i|^2)v_i - \nabla_{x_i} \sum_{j \neq i} U(|x_i - x_j|) \right] dt + \sqrt{2\sigma} d\Gamma_i(t), \end{array} \right.$$

where  $\Gamma_i(t)$  are  $N$  independent copies of standard Wiener processes with values in  $\mathbb{R}^d$  and  $\sigma > 0$  is the noise strength. The Cucker–Smale Particle Model with Noise:

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# Vicsek's model

Assume  $N$  particles moving at **unit speed**: reorientation & diffusion:

$$\begin{cases} dX_t^i = V_t^i dt, \\ dV_t^i = \sqrt{2} P(V_t^i) \circ dB_t^i - P(V_t^i) \left( \frac{1}{N} \sum_{j=1}^N K(X_t^i - X_t^j) (V_t^i - V_t^j) \right) dt. \end{cases}$$

Here  $P(v)$  is the projection operator on the tangent space at  $v/|v|$  to the unit sphere in  $\mathbb{R}^d$ , i.e.,

$$P(v) = I - \frac{v \otimes v}{|v|^2}.$$

Noise in the **Stratonovich sense**: imposed by the rigorous construction of the Brownian motion on a manifold. Rigorous derivation: Bolley-Cañizo-C.

Main issue: **phase transition?** Degond-Liu-Frouvelle.



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# 1st Order Friction Model:

Edelshtein-Keshet, Mogilner (JMB 2000): Assume the variations of the velocity and speed are much smaller than spatial variations, then from Newton's equation:

$$m \frac{d^2 x_i}{dt^2} + \alpha \frac{dx_i}{dt} + \sum_{j \neq i} \nabla U(|x_i - x_j|) = 0$$

so finally, we obtain

$$\frac{dx_i}{dt} = - \sum_{j \neq i} \nabla U(|x_i - x_j|) \quad \text{in the continuum setting} \Rightarrow \begin{cases} \frac{\partial \rho}{\partial t} + \operatorname{div}(\rho v) = 0 \\ v = -\nabla U * \rho \end{cases}$$

**Flock Solutions:** stationary states  $x_i^s$  of the 1st order model are connected to particular solutions of the Bertozzi et al 2nd order model of the form

$$x_i(t) = x_i^s + tv_0$$

with  $v_0$  fixed with  $|v_0|^2 = \frac{\alpha}{\beta}$ .

For which potentials do we evolve towards some nontrivial steady states/patterns?  
Is there any implication of the stability from first to 2nd order models?

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# Mathematical Questions:

- What are the continuum models associated to these systems as the number of individuals gets larger and larger? Mean-field limits.
- What is the good analytical framework to deal with the possible concentration of mass in finite/infinite time in space or in velocity?
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# Schedule:

- **Lecture 2: Second order Models - Kinetic Equations for Swarming:** measure solutions - mean field limit with/without noise.
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# Outline

- 1 Motivations
  - Collective Behavior Models
  - Variations
  - Fixed Speed models
  - 1st order Models
- 2 Outline of the course
- 3 **Transversal Tool: Wasserstein Distances**
  - **Definition**
  - Properties

# Definition of the distance<sup>1</sup>

Transporting measures:

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

$$\int_{\mathbb{R}^d} \varphi d\nu = \int_{\mathbb{R}^d} (\varphi \circ T) d\mu$$

for all  $\varphi \in C_o(\mathbb{R}^d)$ .

Random variables:

Say that  $X$  is a random variable with law given by  $\mu$ , is to say

$X : (\Omega, \mathcal{A}, P) \rightarrow (\mathbb{R}^d, \mathcal{B}_d)$  is a measurable map such that  $X\#P = \mu$ , i.e.,

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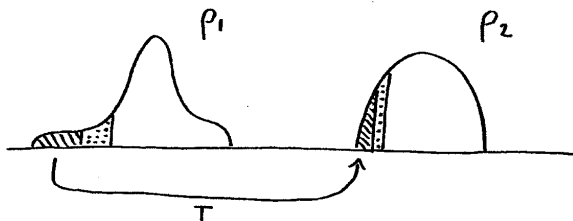
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# Two piles of sand!

Energy needed to transport  $m$  kg of sand from  $x = a$  to  $x = b$ :

$$\text{energy} = m |a - b|^2$$



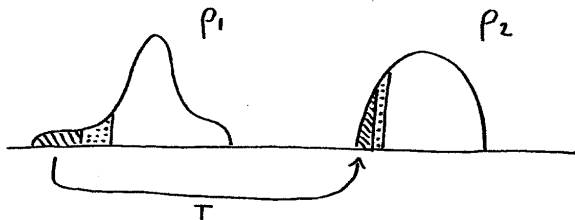
$W_2^2(\rho_1, \rho_2)$  = Among all possible ways to transport the mass from  $\rho_1$  to  $\rho_2$ , find the one that minimizes the total energy

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Kantorovich-Rubinstein-Wasserstein Distance  $p = 1, 2, \infty$ :

$$W_p^p(\mu, \nu) = \inf_{\pi} \left\{ \iint_{\mathbb{R}^d \times \mathbb{R}^d} |x - y|^p d\pi(x, y) \right\} = \inf_{(X, Y)} \{ \mathbb{E} [|X - Y|^p] \}$$

where the transference plan  $\pi$  runs over the set of joint probability measures on  $\mathbb{R}^d \times \mathbb{R}^d$  with marginals  $\mu$  and  $\nu \in \mathcal{P}_p(\mathbb{R}^d)$  and  $(X, Y)$  are all possible couples of random variables with  $\mu$  and  $\nu$  as respective laws.

$$W_{\infty}(\mu, \nu) = \inf_{\pi \in \Pi(\mu, \nu)} \sup_{(x, y) \in \text{supp}(\pi)} |x - y|,$$

Monge's optimal mass transport problem:

Find

$$I := \inf_T \left\{ \int_{\mathbb{R}^d} |x - T(x)|^p d\mu(x); \nu = T\#\mu \right\}^{1/p}.$$

Take  $\gamma_T = (1_{\mathbb{R}^d} \times T)\#\mu$  as transference plan  $\pi$ .



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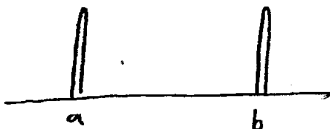
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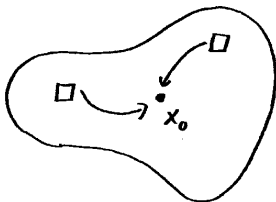
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# Three examples



$$W_2^2(\delta_a, \delta_b) = |a - b|^2$$



$$\begin{aligned} W_2^2(\rho, \delta_{x_0}) &= \int |x_0 - y|^2 d\rho(y) \\ &= \text{Var}(\rho) \end{aligned}$$

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# Euclidean Wasserstein Distance

## Convergence Properties

1 **Convergence of measures:**  $W_2(\mu_n, \mu) \rightarrow 0$  is equivalent to  $\mu_n \rightarrow \mu$  weakly-\* as measures and convergence of second moments.

2 **Weak lower semicontinuity:** Given  $\mu_n \rightarrow \mu$  and  $\nu_n \rightarrow \nu$  weakly-\* as measures, then

$$W_2(\mu, \nu) \leq \liminf_{n \rightarrow \infty} W_2(\mu_n, \nu_n).$$

3 **Completeness:** The space  $\mathcal{P}_2(\mathbb{R}^d)$  endowed with the distance  $W_2$  is a complete metric space.

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# One dimensional Case

## Distribution functions:

In one dimension, denoting by  $F(x)$  the **distribution function** of  $\mu$ ,

$$F(x) = \int_{-\infty}^x d\mu,$$

we can define its **pseudo inverse**:

$$F^{-1}(\eta) = \inf\{x : F(x) > \eta\} \quad \text{for } \eta \in (0, 1),$$

we have  $F^{-1} : ((0, 1), \mathcal{B}_1), d\eta) \rightarrow (\mathbb{R}, \mathcal{B}_1)$  is a random variable with law  $\mu$ , i.e.,  $F^{-1} \# d\eta = \mu$

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## Wasserstein distance:

In one dimension, it can be checked<sup>a</sup> that given two measures  $\mu$  and  $\nu$  with distribution functions  $F(x)$  and  $G(y)$  then,  $(F^{-1} \times G^{-1})\#d\eta$  has joint distribution function  $H(x, y) = \min(F(x), G(y))$ . Therefore, in one dimension, the optimal plan is given by  $\pi_{opt}(x, y) = (F^{-1} \times G^{-1})\#d\eta$ , and thus

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