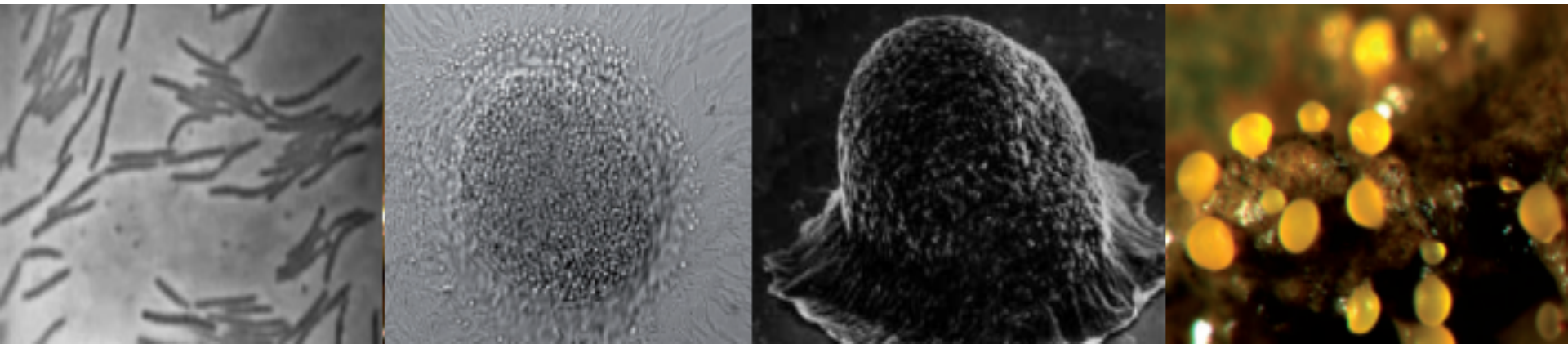


Disordered Active Matter: **On how time-independent disorder affects the motion of self-propelled particles**

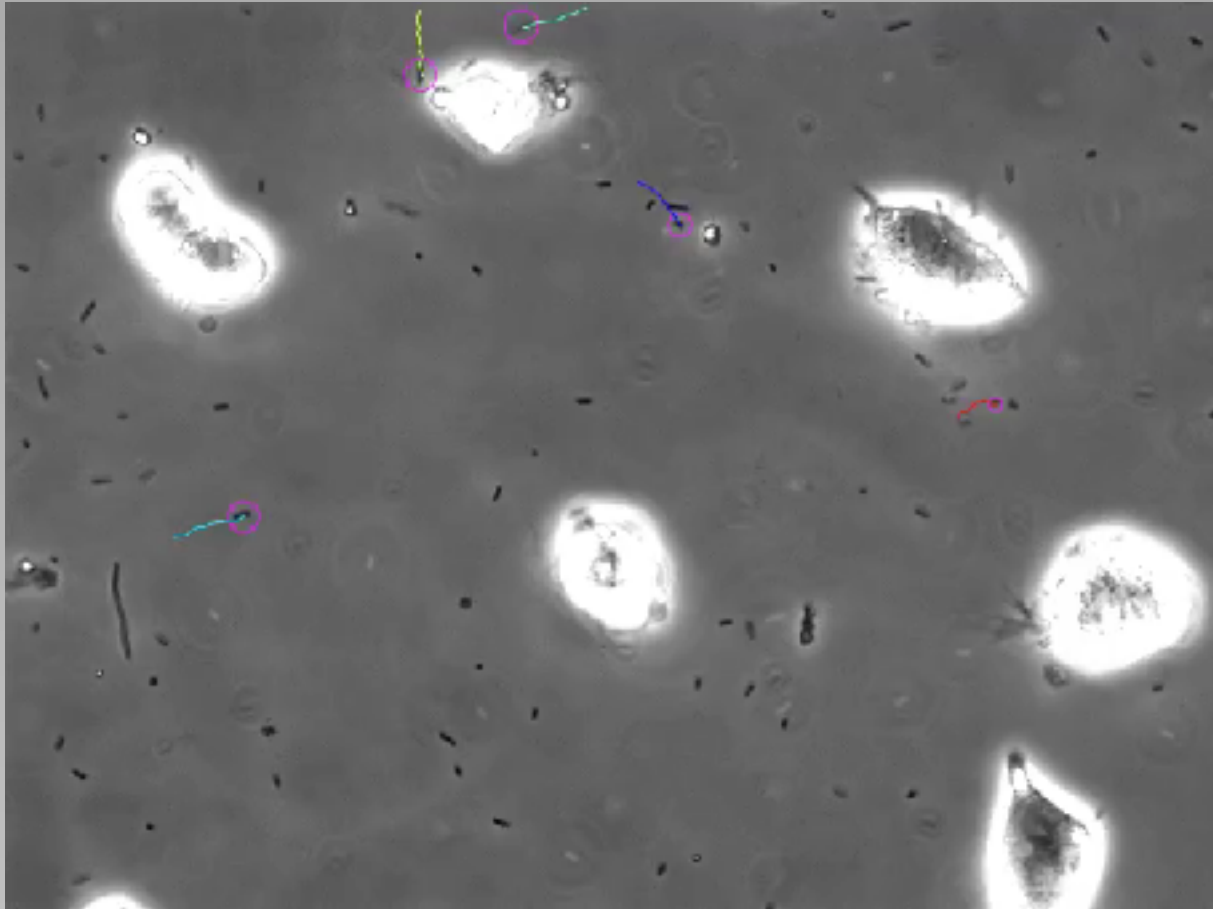
Fernando Peruani

LPTM, CY Cergy Paris University

Japan-France joint seminar "Physics of dense and active disordered materials"



Active particles in the presence of quenched disorder

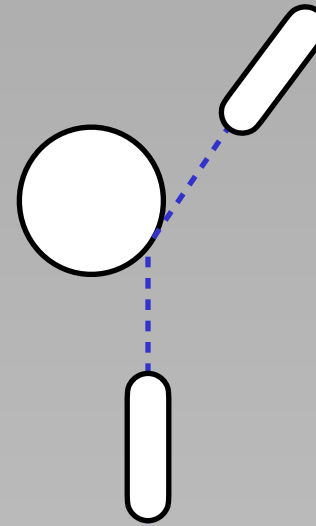


Otte, Perez-Ipiña, Czerucka, Peruani, Nat. Comm. 2021

Example of active matter in heterogeneous medium:

Bacterial trajectories are deflected each time that they hit an obstacles (here a human epithelial cell).

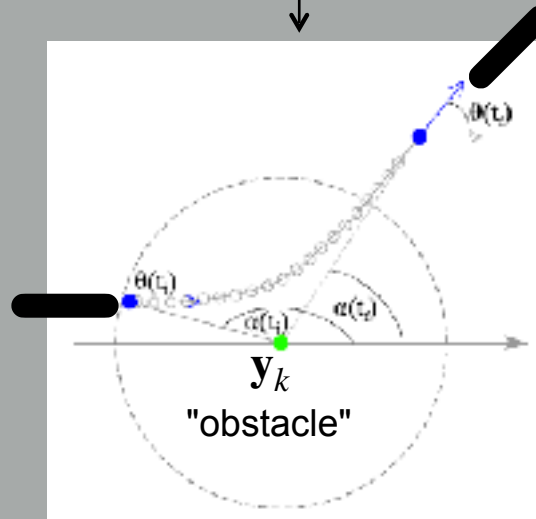
Active particles in the presence of quenched disorder



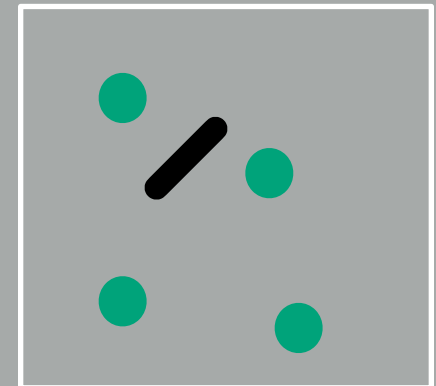
during the time the bacterium is in contact with the obstacle, it experiences a **torque!**
(and note that the speed remains roughly constant)

Active Particle moving in the presence of quenched disorder (a minimal model)

$$\begin{aligned}\dot{\mathbf{x}}_i &= v_o \mathbf{V}(\theta_i) \longrightarrow \mathbf{V}(\theta_i) = \cos(\theta_i) \hat{x} + \sin(\theta_i) \hat{y} \\ \dot{\theta}_i &= h(\mathbf{x}_i, \theta_i) + \eta \xi_i(t)\end{aligned}$$



medium with obst.



turning strength

$$h(\mathbf{x}_i, \theta_i) = \frac{\gamma}{n(\mathbf{x}_i)} \sum_{|\mathbf{x}_i - \mathbf{y}_k| < R} f(|\mathbf{x}_i - \mathbf{y}_k|) \sin(\alpha_{k,i} - \theta_i)$$

of obstacles inside R

$$\mathbf{x}_i - \mathbf{y}_k = r_{k,i} (\cos \alpha_{k,i}, \sin \alpha_{k,i})$$

Active Particle moving in the presence of quenched disorder (a minimal model)

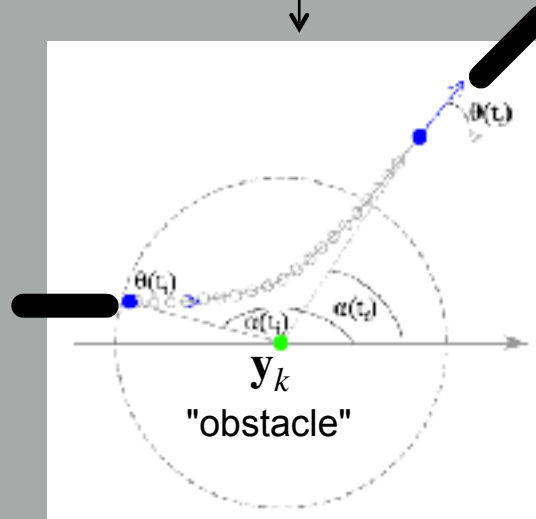
with $h = 0$

$$D = \frac{v_0^2}{\eta^2} = \frac{v_0^2}{2D_\theta}$$

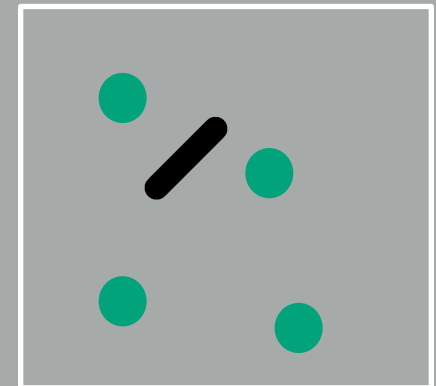
where $D_\theta = \frac{\eta^2}{2}$

$$\dot{\mathbf{x}}_i = v_0 \mathbf{V}(\theta_i) \longrightarrow \mathbf{V}(\theta_i) = \cos(\theta_i) \hat{x} + \sin(\theta_i) \hat{y}$$

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of obstacles inside R

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Active Particle moving in the presence of quenched disorder (a minimal model)

Quincke
Roller



obstacle

(speed is const.!)

from Desreumaux
PhD thesis

50 μm

turning strength

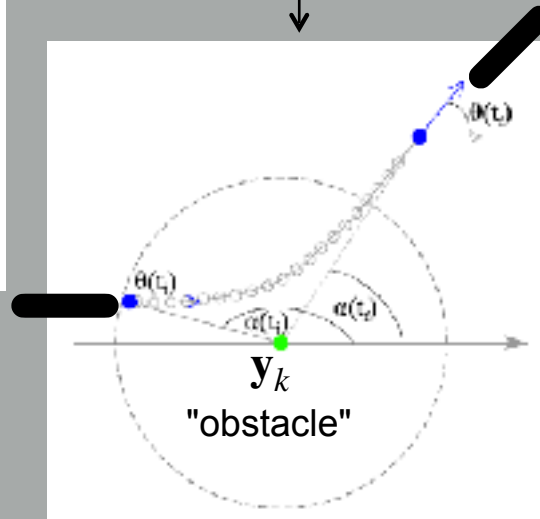
$$h(\mathbf{x}_i, \theta_i) = \frac{\gamma}{n(\mathbf{x}_i)} \sum_{|\mathbf{x}_i - \mathbf{y}_k| < R} f(|\mathbf{x}_i - \mathbf{y}_k|) \sin(\alpha_{k,i} - \theta_i)$$

of obstacles inside R

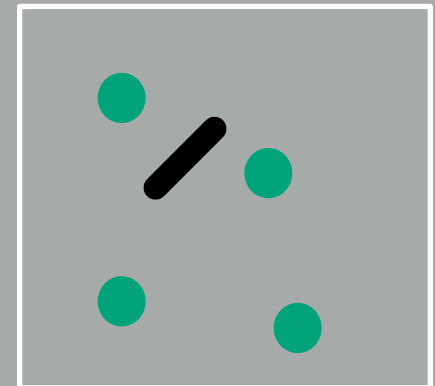
$$\mathbf{x}_i \quad \mathbf{y}_k = r_{k,i} (\cos \alpha_{k,i}, \sin \alpha_{k,i})$$

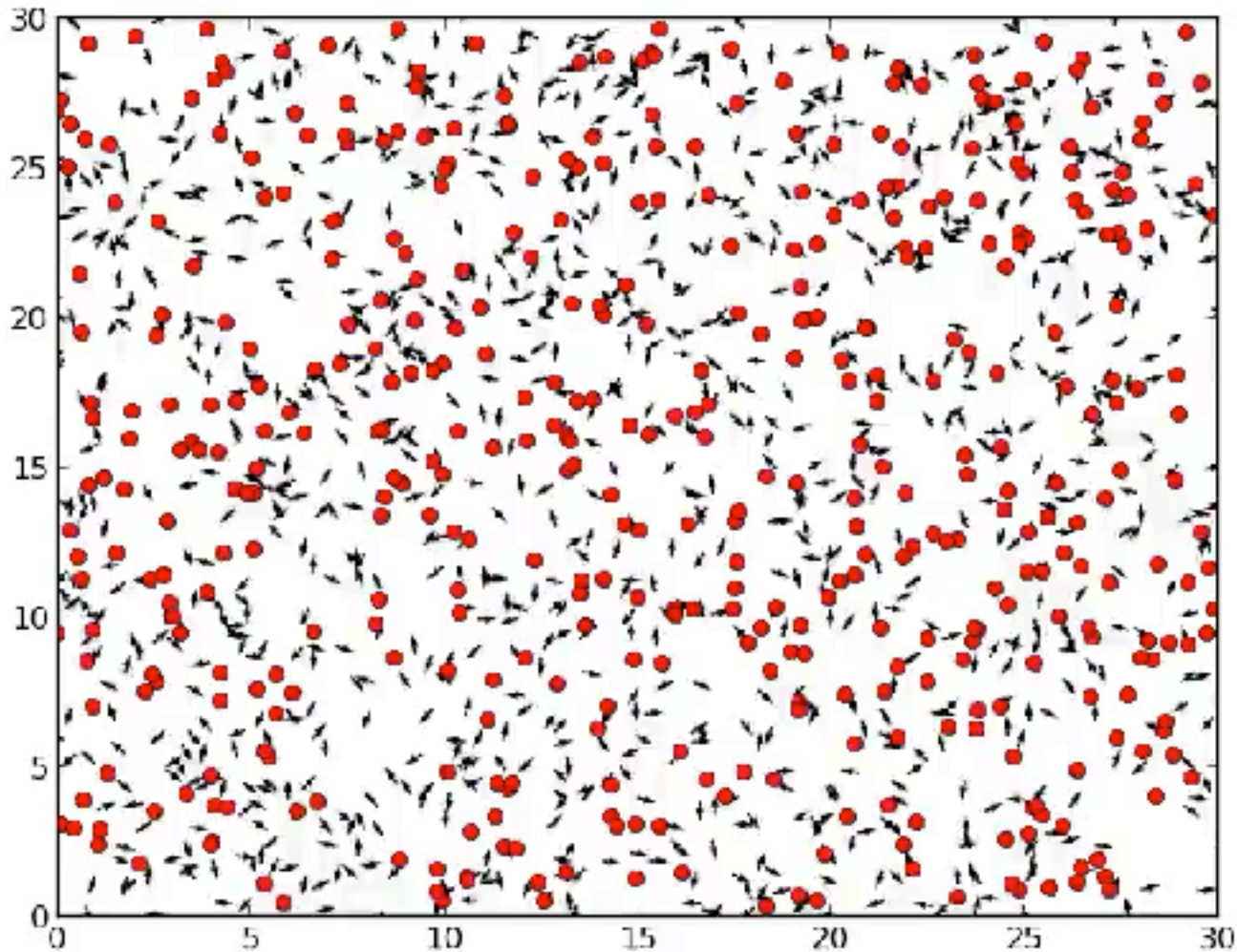
$$\begin{aligned} \dot{\mathbf{x}}_i &= v_o \mathbf{V}(\theta_i) \\ \dot{\theta}_i &= h(\mathbf{x}_i, \theta_i) + \eta \xi_i(t) \end{aligned}$$

$$\mathbf{V}(\theta_i) = \cos(\theta_i) \hat{x} + \sin(\theta_i) \hat{y}$$



medium with obst.

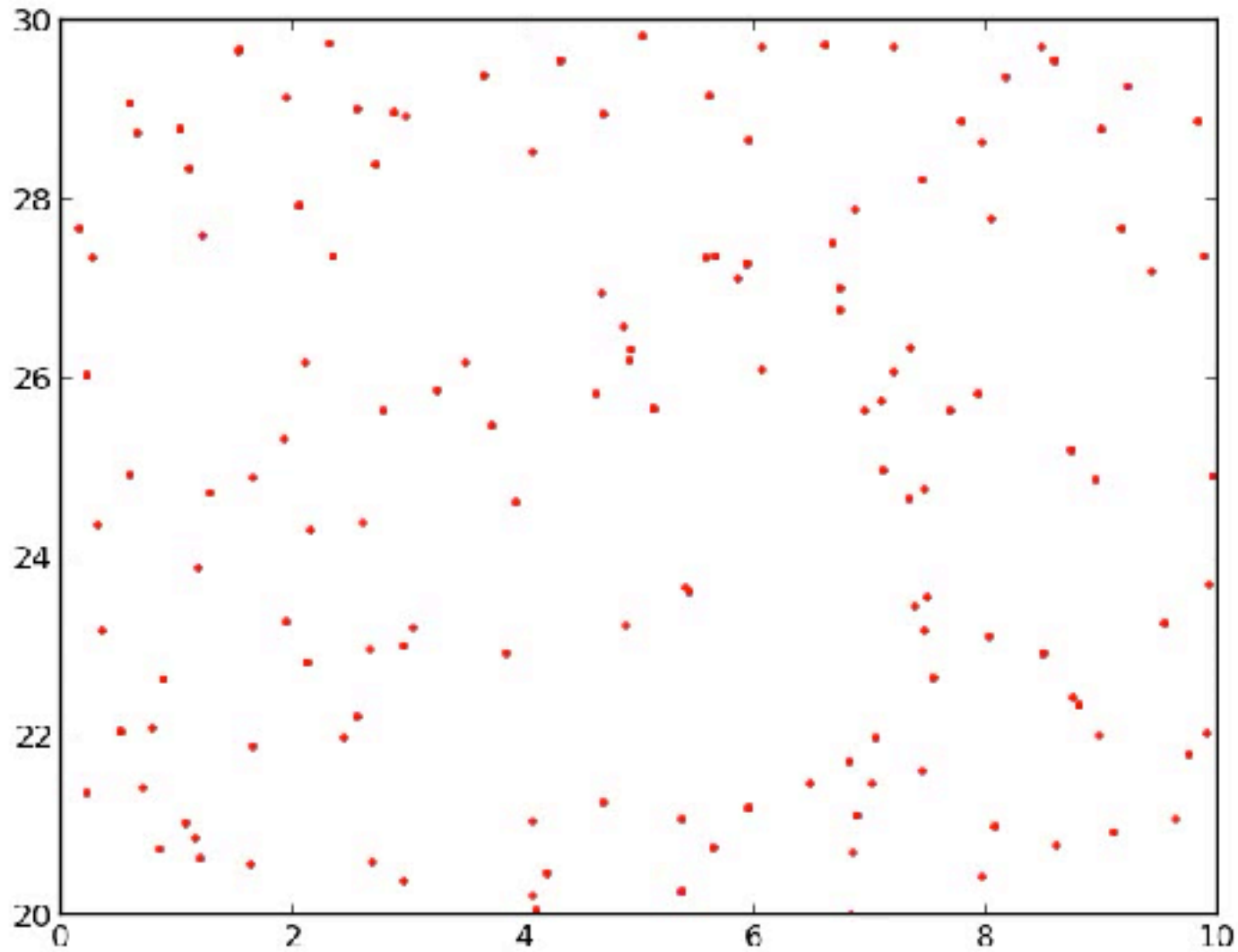




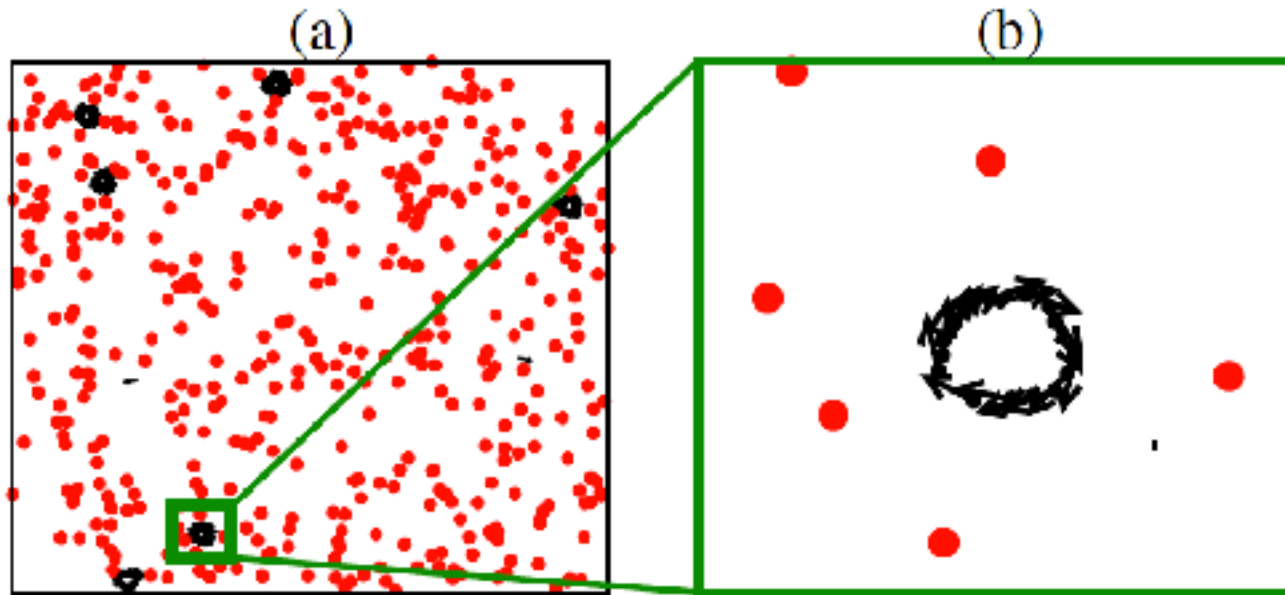
Starting from a random initial condition, traps emerge. The time that particles spend in a particular trap depends on the particular configuration of obstacles.

An active “Lorentz” gas

Peruani



Looking at a small part of a large system at real time



These traps are closed stable orbits that are found by the active particles in the landscape of obstacles.

Remember that noise is present. These orbits are not absorbing, and particle can escape.

- How can we understand the observed behavior?

We look for a coarse-grained description of the problem in terms of $p(\mathbf{x}, \theta, t)$ whose temporal evolution can be expressed as:

$$\partial_t p + v_0 \nabla \cdot [\mathbf{V}(\theta)p] = D_\theta \partial_{\theta\theta} p + F[p(\mathbf{x}, \theta, t), \rho_o(\mathbf{x})]$$

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Interactions with obstacles

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\downarrow
 $D_\theta = \eta^2/2$

Interactions with obstacles

In absence of interactions, we will see that we recover Fürth’s formula for MSD, and a diffusion coefficient:

$$D_{x_o} = v_0^2 / (2D_\theta)$$

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Interactions with obstacles

There are two limiting cases where $F[.]$ can be specified:

- Low density (LD) approximation
- High density (HD) approximation

(with respect obstacle density)

- Low density (LD) approximation

We assume that $\longrightarrow D_{\theta}^{-1} v_0 \gg \rho_o^{-1/2}$

This implies that in between obstacles we can assume that particles move ballistically.

If we look at time-scales larger than R/v_0 , we can assume that the interactions with obstacles can be described as sudden jumps in the moving direction of the particle:

$$\begin{aligned} F[p] &= -\lambda(\rho_o) p(x, \theta, t) + \int_0^{2\pi} d\theta' T(\theta, \theta') p(x, \theta', t) \\ &\approx \frac{\lambda(\rho_o) \epsilon_{\theta}^2}{6} \partial_{\theta\theta} p, \end{aligned} \quad (5)$$

Top-hat simplification: $T(\theta, \theta'; \mathbf{x}) \simeq \lambda(\rho_o) T(\theta, \theta') \approx [\lambda(\rho_o)/(2\epsilon_{\theta})] \Theta(\epsilon_{\theta} - |\theta - \theta'|)$

where $\lambda(\rho_o) \approx v_o \rho_o \sigma_o$ and $\sigma_o = 2R$

- Low density (LD) approximation

Under all these assumptions, we arrive to the following asymptotic equation for $\rho(x,t)$:

$$\partial_t \rho = \nabla \cdot \left[\frac{v_0^2}{2\tilde{D}_\theta} \nabla \rho \right]$$



$$D_x = v_0^2 / [2 (D_\theta + \Lambda_0 \rho_o)]$$



$$\Lambda_0 = v_0 \sigma_0 \epsilon_\theta^2 / 6$$

- High density (HD) approximation

At high obstacle densities, active particles sense always several obstacle around them, which forces us to leave the Boltzmann for the Fokker-Planck approach.

At high obstacle densities, the interaction with obstacles can then be modeled as:

$$F = \partial_\theta [I p(\mathbf{x}, \theta, t)]$$



where I is the average “torque” felt by a particle at (\mathbf{x}, θ) , which takes the form:

$$I = \frac{\gamma}{n(\mathbf{x})} \sum_j \sin(\theta - \alpha_j) = \frac{\gamma \Gamma(\mathbf{x})}{n(\mathbf{x})} \sin(\theta - \psi(\mathbf{x}))$$

Since obstacles are located at random, this is equivalent to summing $n(\mathbf{x})$ random vectors!

$$I \sim \sin(\theta - \psi(\mathbf{x})) / \sqrt{n} \quad \text{where} \quad n \approx \pi R^2 \rho_o$$

- High density (HD) approximation

After performing the moment expansion procedure used for the LD approximation, we arrive to:

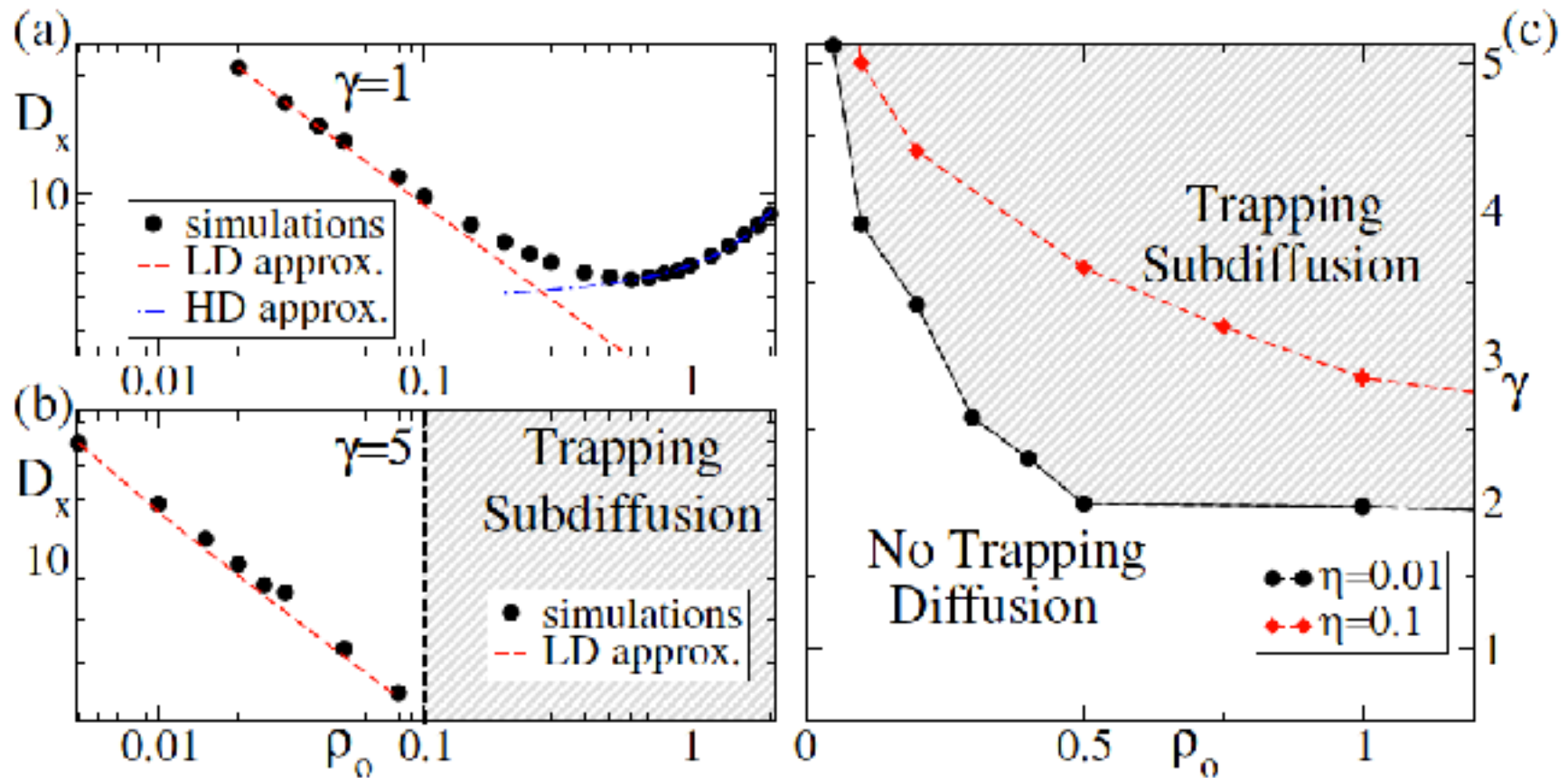
$$\begin{aligned}\partial_t \rho &= \frac{v_0^2}{2D_\theta} \nabla^2 \rho - \frac{\gamma v_0}{2D_\theta R \sqrt{\pi \rho_0}} \nabla \cdot [(\cos(\psi), \sin(\psi)) \rho] \\ &= \frac{v_0^2}{2D_\theta} \nabla^2 \rho - \frac{\gamma v_0}{2D_\theta R \sqrt{\pi \rho_0}} \nabla \cdot \left[\frac{\rho \nabla \rho_o(\mathbf{x})}{\|\nabla \rho_o(\mathbf{x})\|} \right], \quad (11)\end{aligned}$$

From this we learn two important things:

- The convective term dominates the asymptotic dynamics of ρ .
- As the density of obstacles increases, the diff. coeff. increase.

$$D_x \sim 1 / [\rho_c - \Lambda_1 \rho_o]$$

• Comparison between the LD and HD and simulations

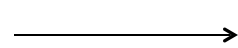


• Why do we observe subdiffusion?

$$\sigma^2(t) = \langle \mathbf{x}^2(t) \rangle$$

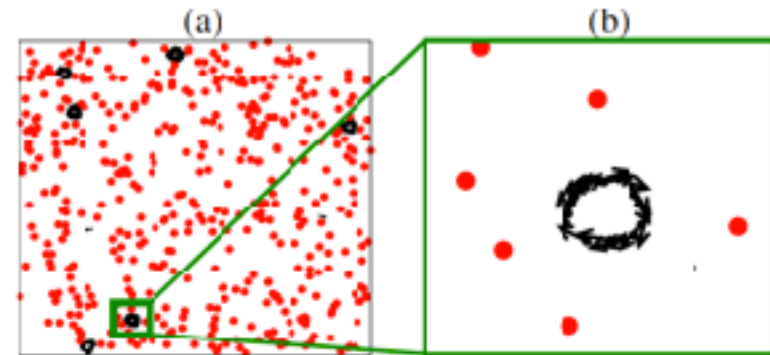
If we imagine an array of traps, the MSD has to be proportional to the number of jumps made according to the CLT.

$$\sigma^2(t) \propto n_J(t)$$



The problem reduces to know how many jumps our particle performs during t !

If every trap is characterized by an average $\langle \tau_t \rangle$, this is simply $t / \langle \tau_t \rangle$



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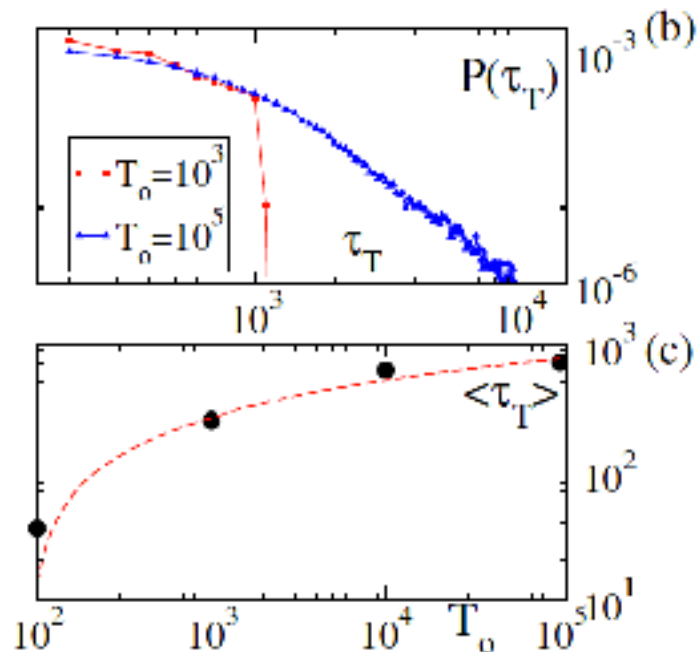
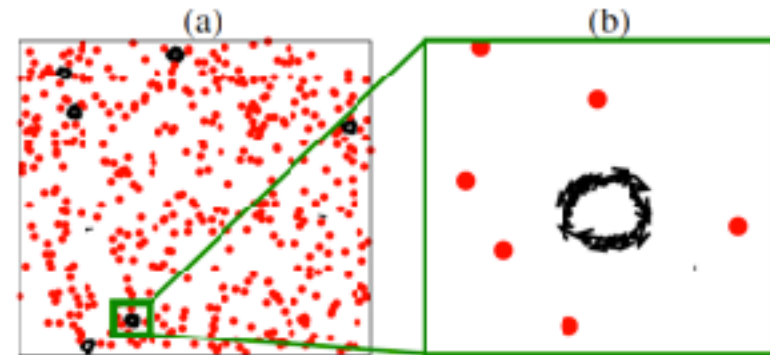
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• Measurement on $\langle \tau_t \rangle$

$\langle \tau_t \rangle$ depends on the observation time !!!



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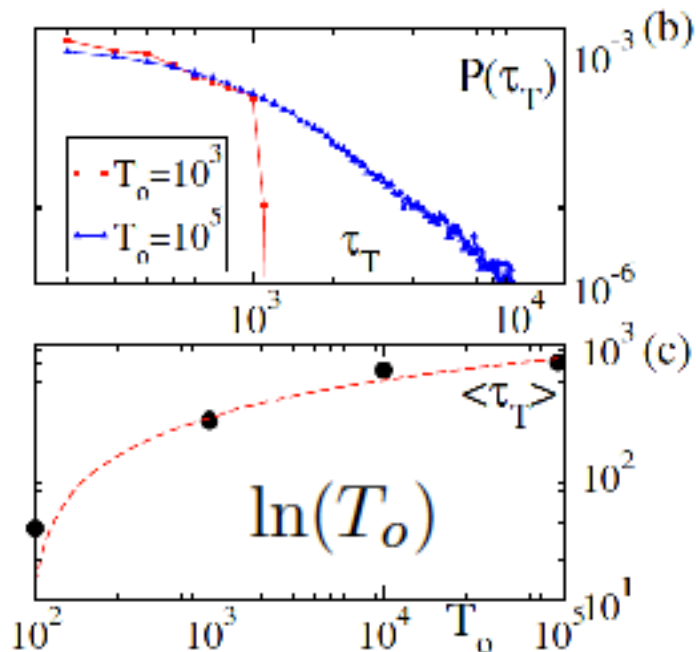
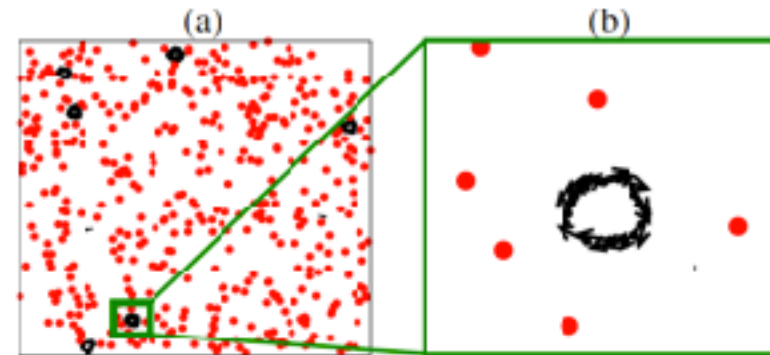
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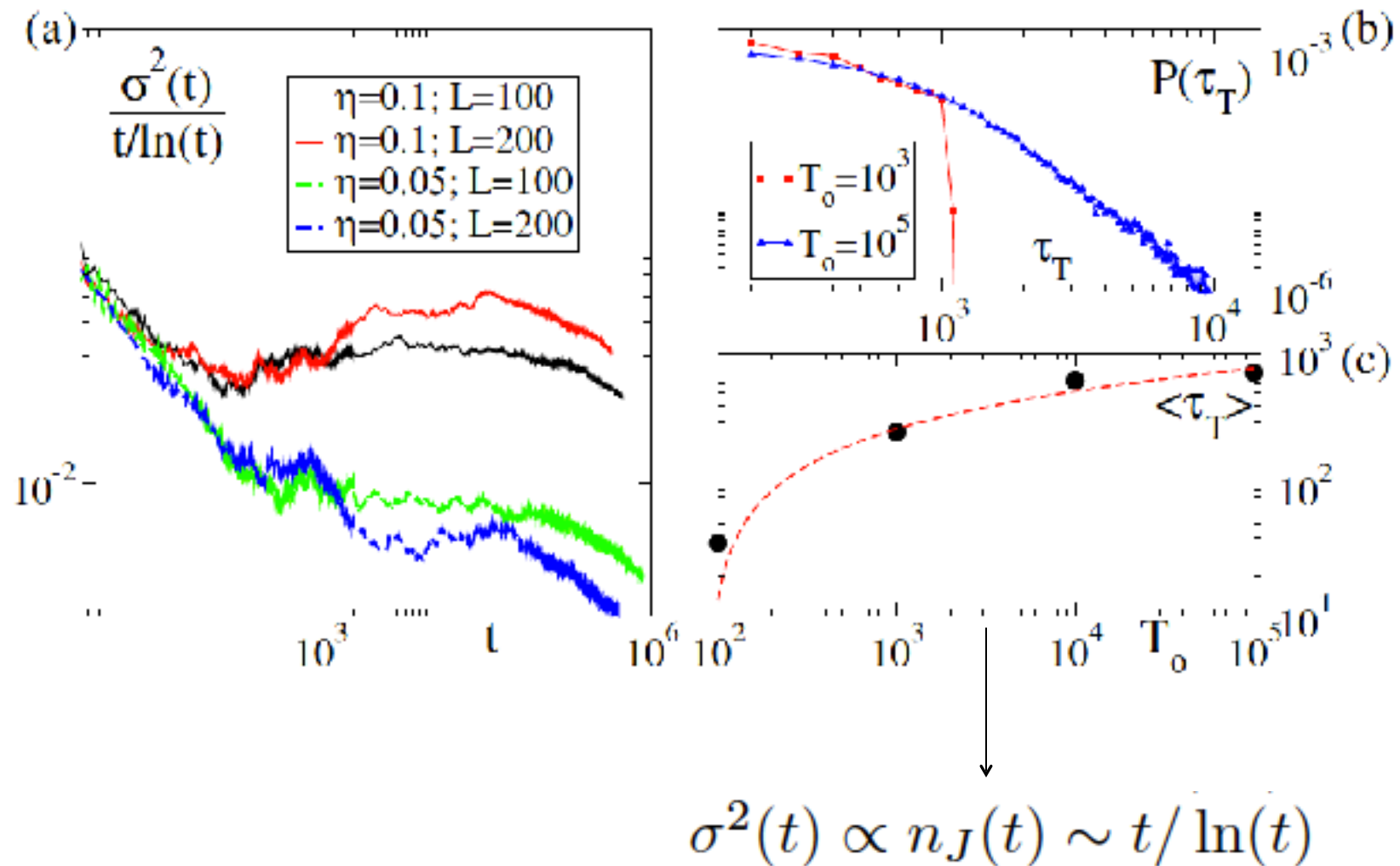
• Measurement on $\langle \tau_t \rangle$

$\langle \tau_t \rangle$ depends on the observation time !!!

$$\sigma^2(t) \propto n_J(t) \sim t / \ln(t)$$

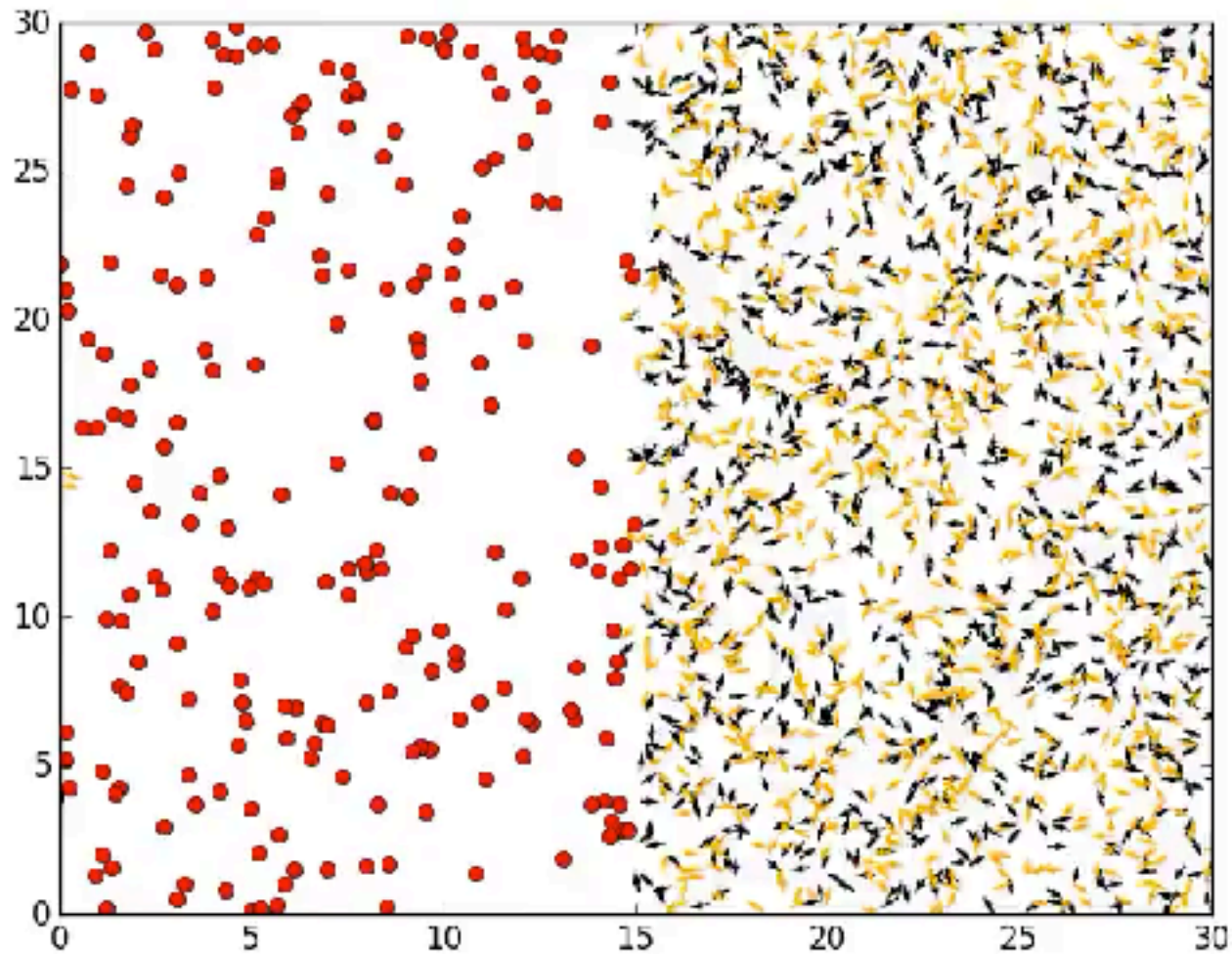


• Why do we observe subdiffusion?



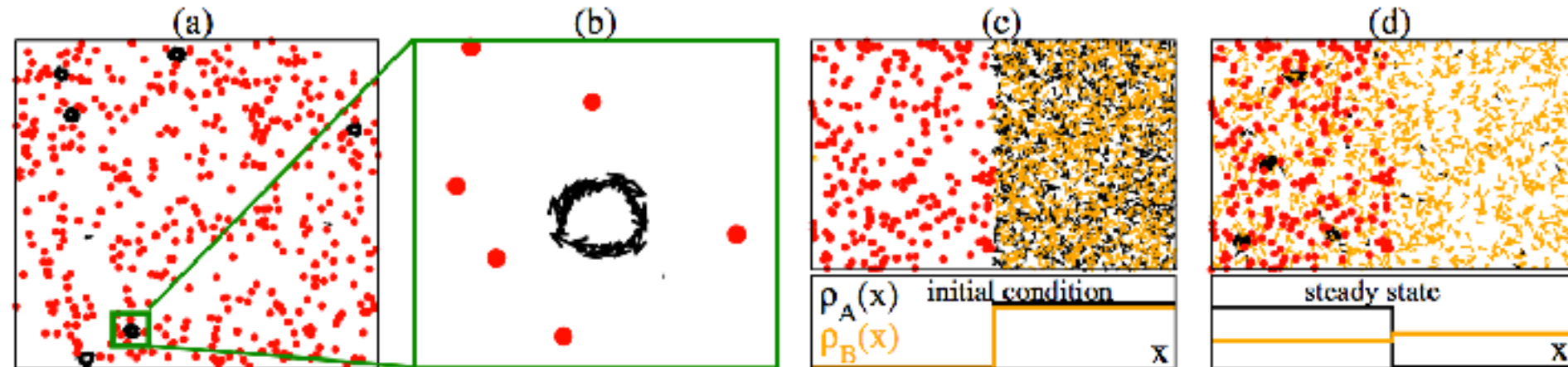
- Filtering

$$\lambda_A > \lambda_B$$



- We can use the traps to fabricate a filter of SPPs!

$$\lambda_A > \lambda_B$$



Results:

- The diffusion coefficient exhibits a minimum with obstacle density (small λ)
- Spontaneous trapping of particles (moving at constant speed) occurs
- Trapping leads to subdiffusive behavior
- These findings can be used to fabricate a filter of active particles!

Adding particle-particle interactions:

Does the environment have an impact on the collective behavior?

- A minimal continuum time SPP model with obstacles:

$$\begin{aligned}\dot{\mathbf{x}}_i &= v_0 \mathbf{V}(\theta_i) \\ \dot{\theta}_i &= g(\mathbf{x}_i) \left[\frac{\gamma_b}{n_b(\mathbf{x}_i)} \sum_{|\mathbf{x}_i - \mathbf{x}_j| < R_b} \sin(\theta_j - \theta_i) \right] \\ &\quad + h(\mathbf{x}_i) + \eta \xi_i(t),\end{aligned}$$



$$h(\mathbf{x}_i) = \begin{cases} \frac{\gamma_o}{n_o(\mathbf{x}_i)} \sum_{|\mathbf{x}_i - \mathbf{y}_k| < R_o} \sin(\alpha_{k,i} - \theta_i) & \text{if } n_o(\mathbf{x}_i) > 0 \\ 0 & \text{if } n_o(\mathbf{x}_i) = 0 \end{cases},$$

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Continuum time version of Vicsek model

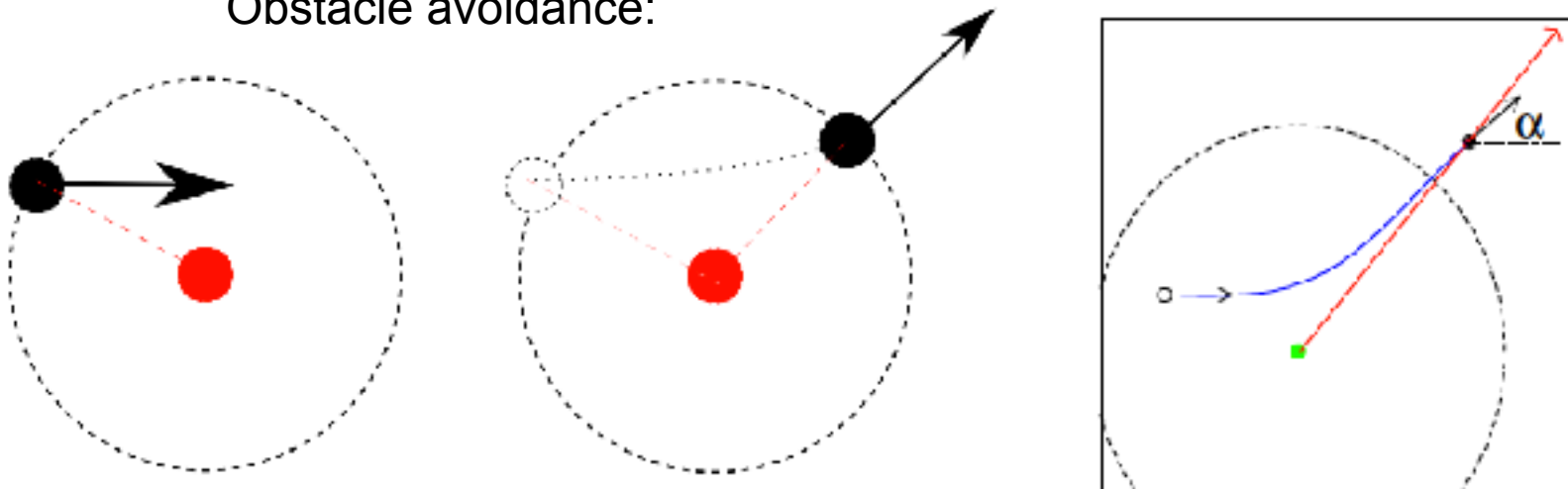
$$h(\mathbf{x}_i) = \begin{cases} \frac{\gamma_o}{n_o(\mathbf{x}_i)} \sum_{|\mathbf{x}_i - \mathbf{y}_k| < R_o} \sin(\alpha_{k,i} - \theta_i) & \text{if } n_o(\mathbf{x}_i) > 0 \\ 0 & \text{if } n_o(\mathbf{x}_i) = 0 \end{cases},$$

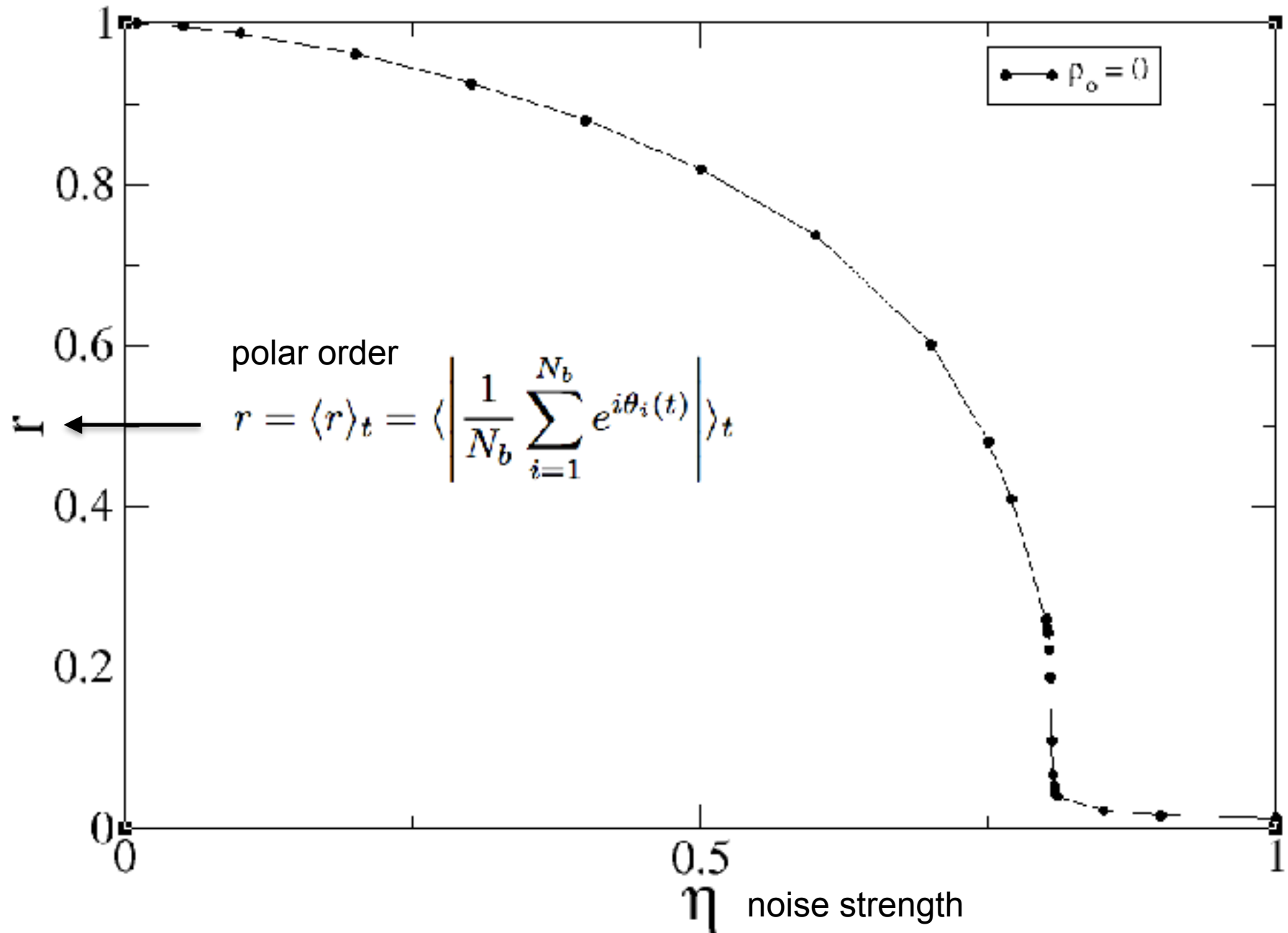
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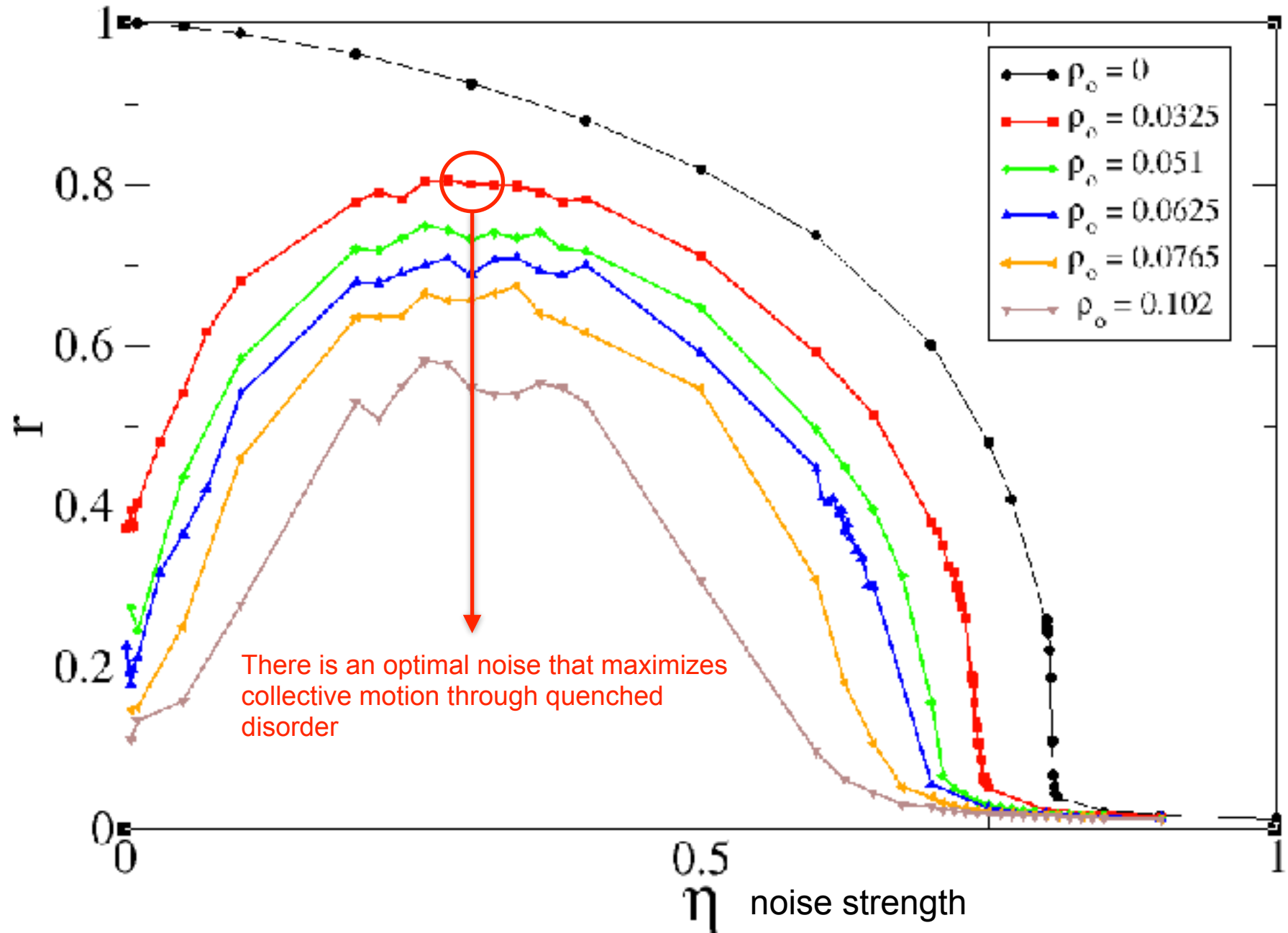
$$\begin{aligned}\dot{\mathbf{x}}_i &= v_0 \mathbf{V}(\theta_i) \\ \dot{\theta}_i &= g(\mathbf{x}_i) \left[\frac{\gamma_b}{n_b(\mathbf{x}_i)} \sum_{|\mathbf{x}_i - \mathbf{x}_j| < R_b} \sin(\theta_j - \theta_i) \right] \\ &\quad + h(\mathbf{x}_i) + \eta \xi_i(t),\end{aligned}$$

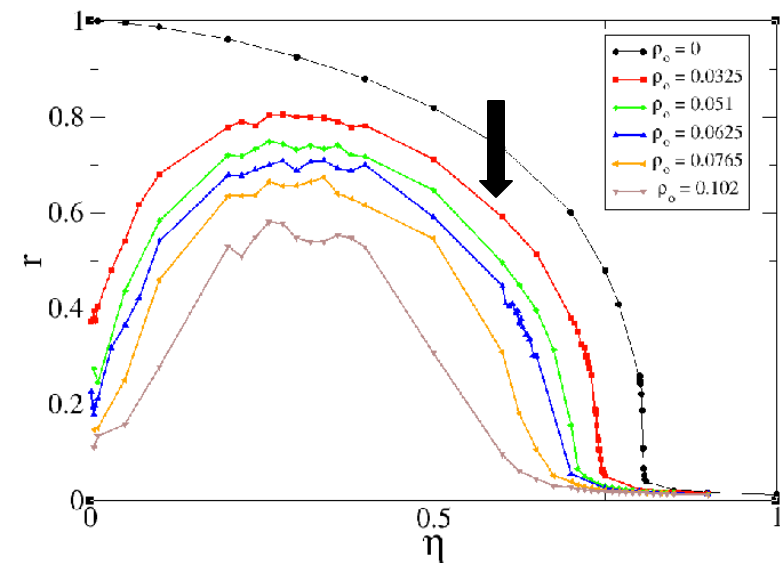
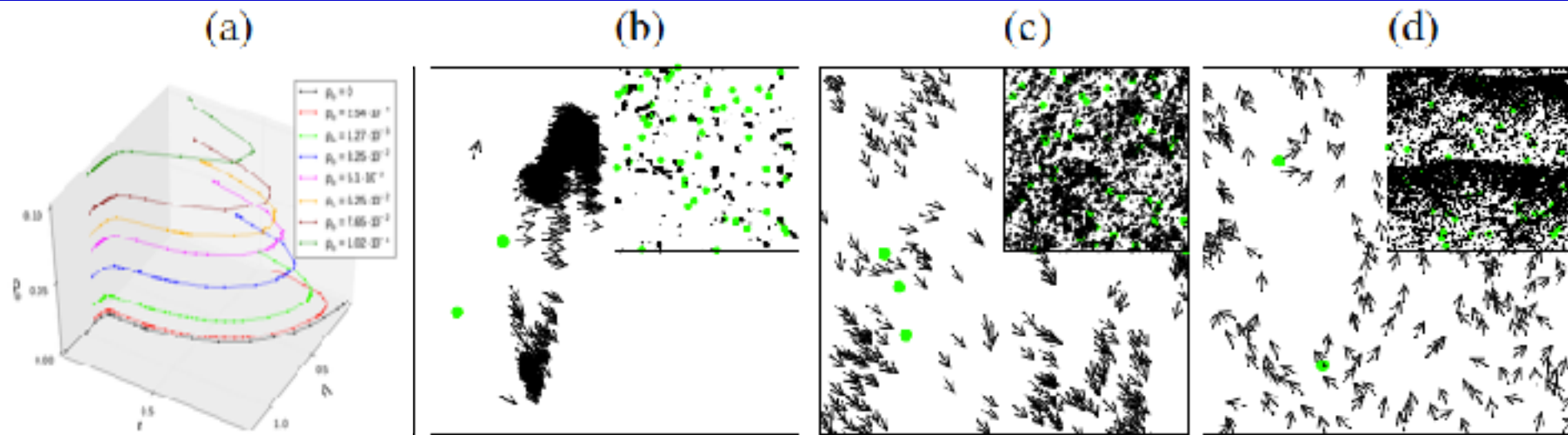
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Obstacle avoidance:

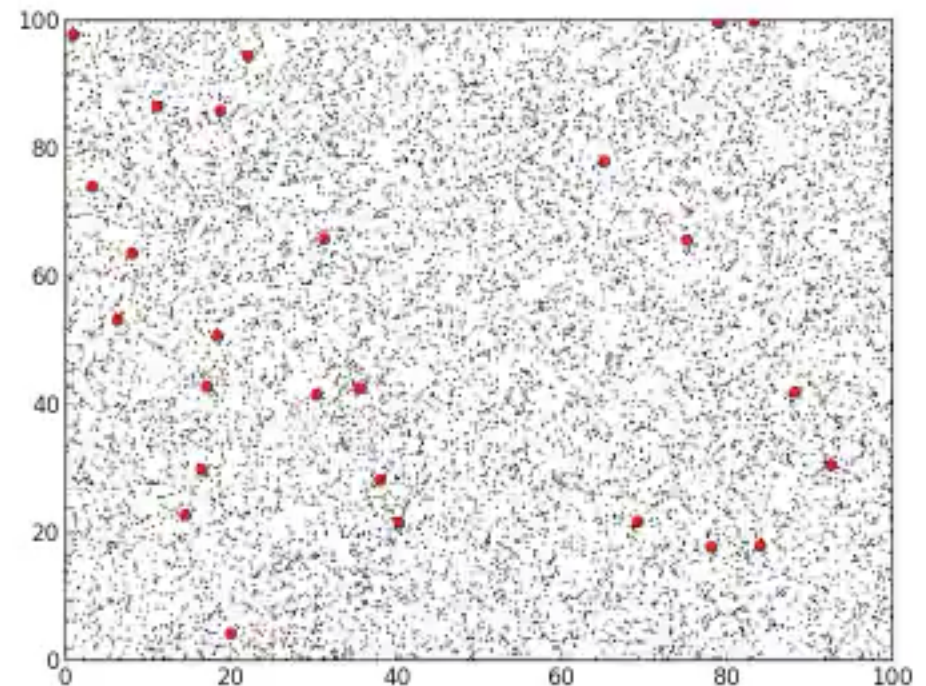


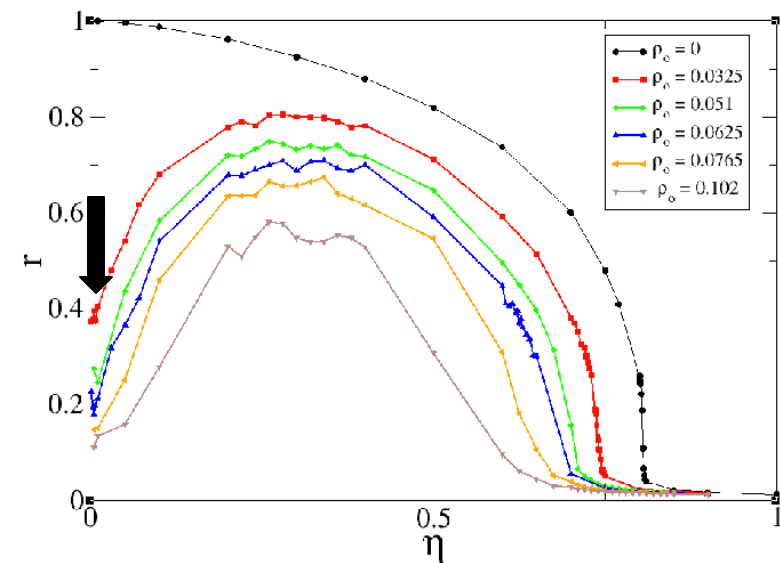
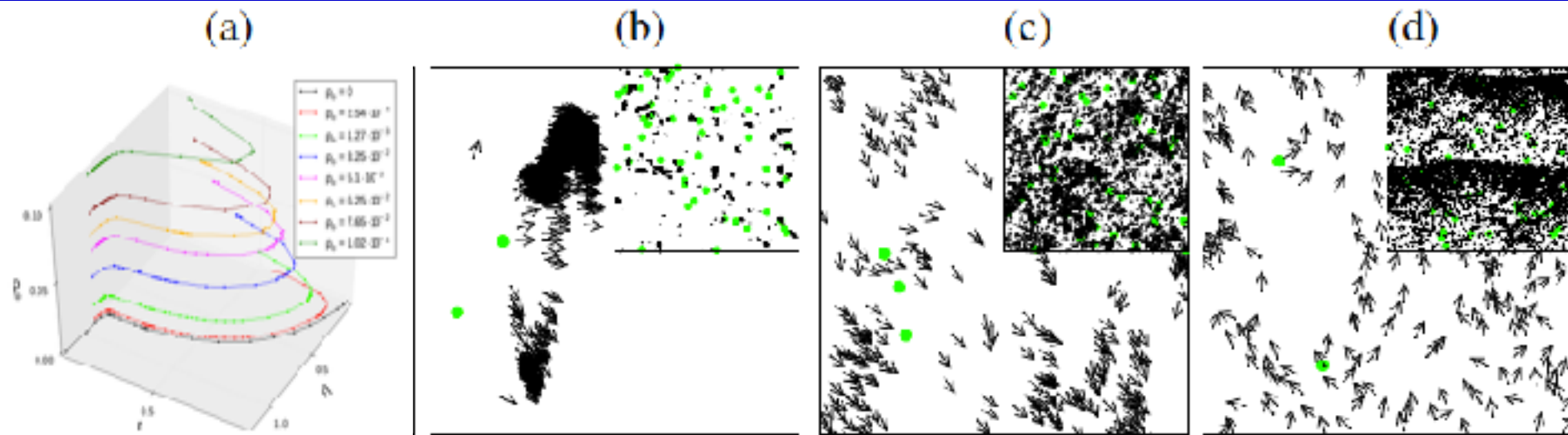




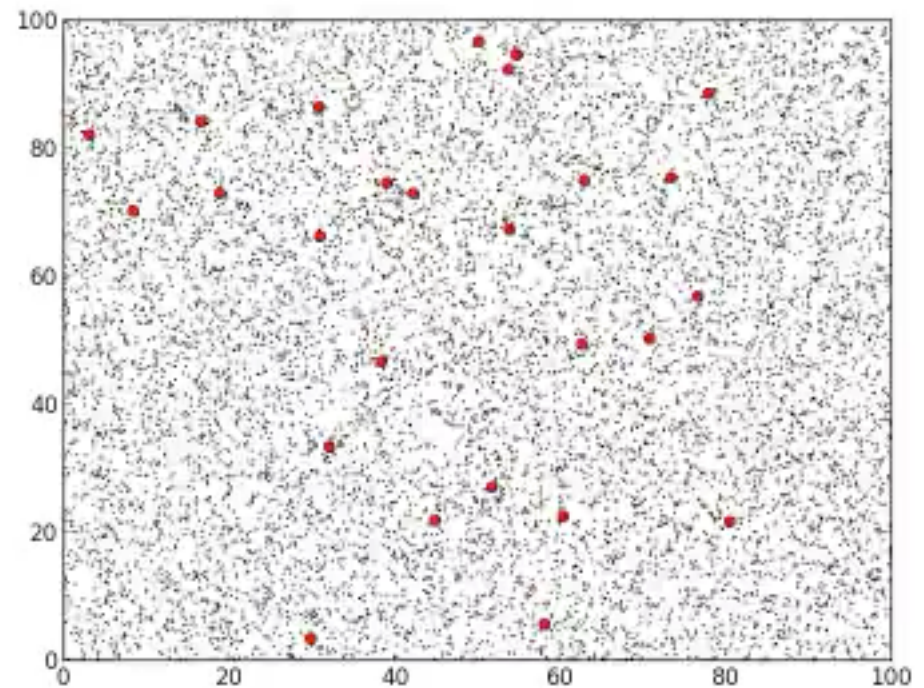


N=10000

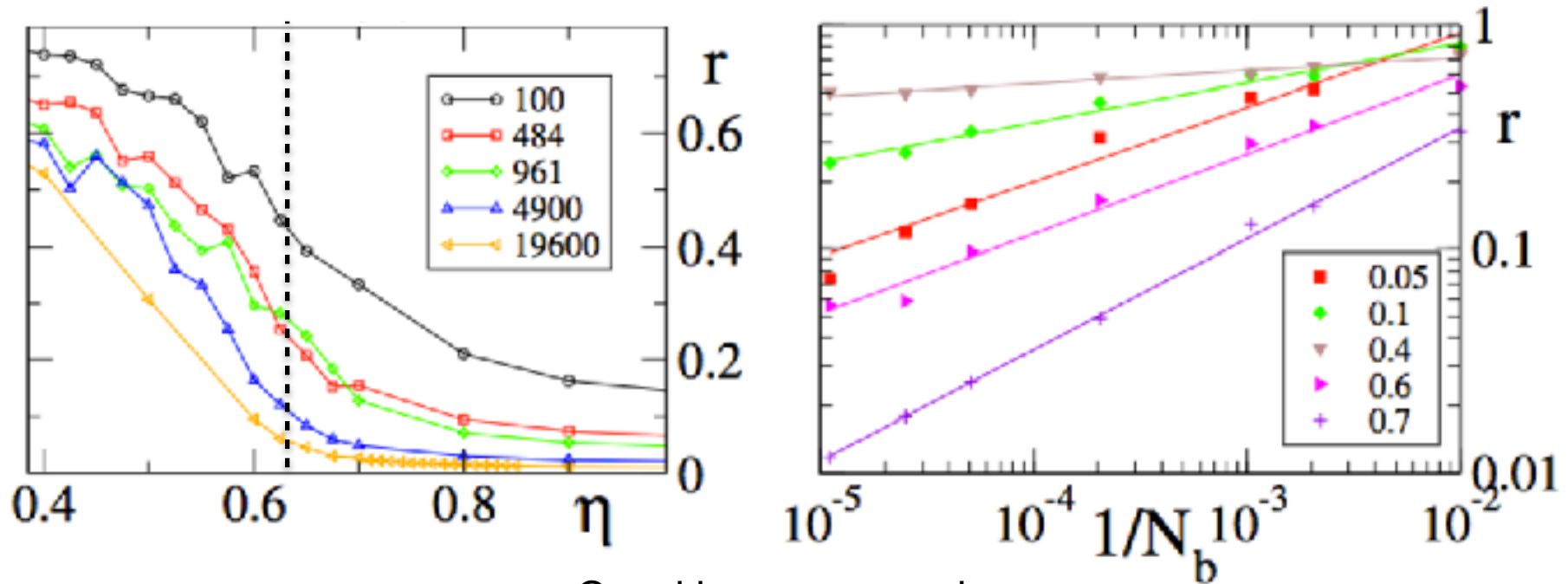




$N=10000$



- Long-range order vs. quasi long-range order:



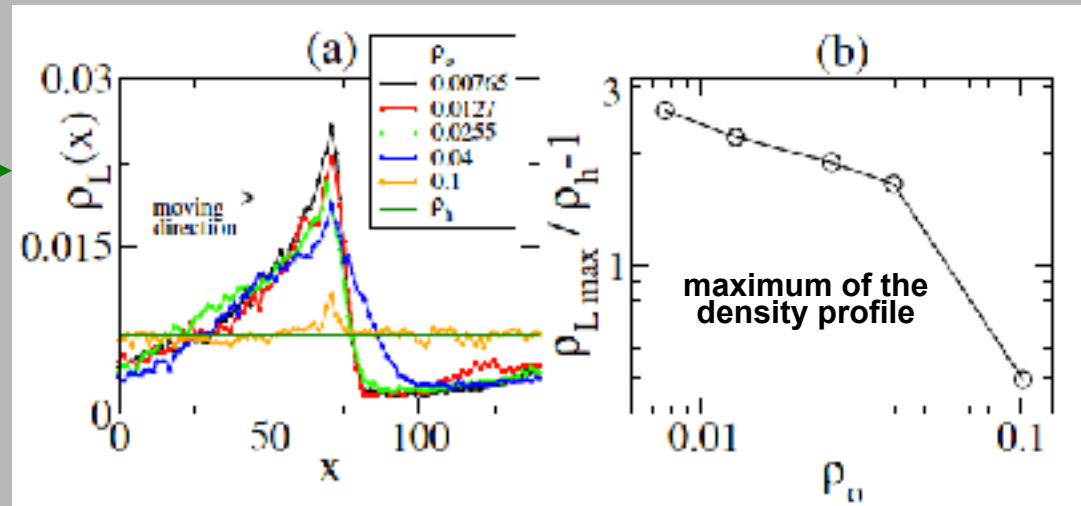
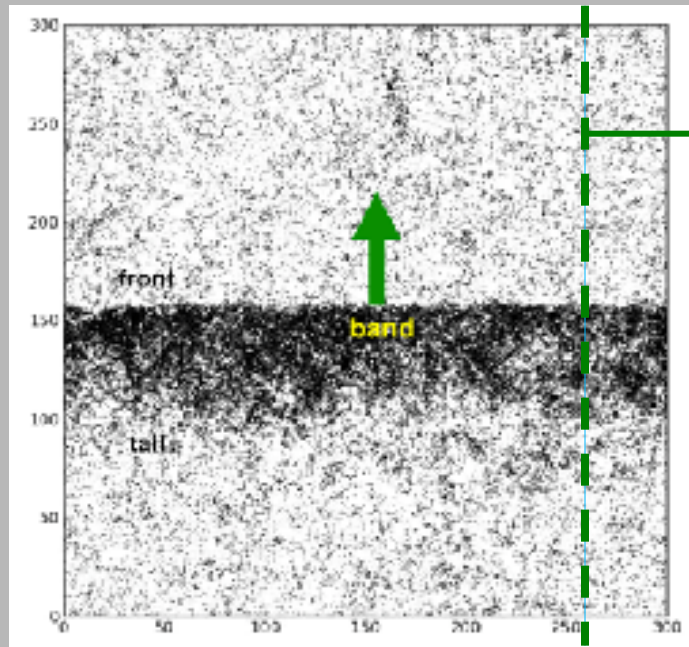
Quasi long-range order

$$r \propto N_b^{-\nu(D_\theta, \rho_\sigma)}$$

Context:

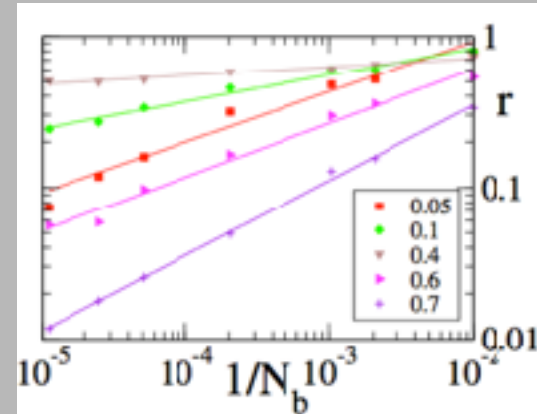
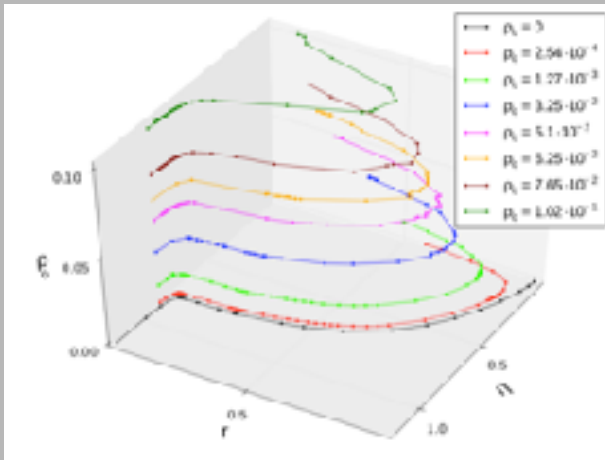
In the XY model in 2D, order is QLRO, while in the Vicsek model (in 2D) is LRO. Here, we are finding that in the presence of quenched disorder, the emergent polar order becomes QLRO!

Bands disappear as the density is increased:



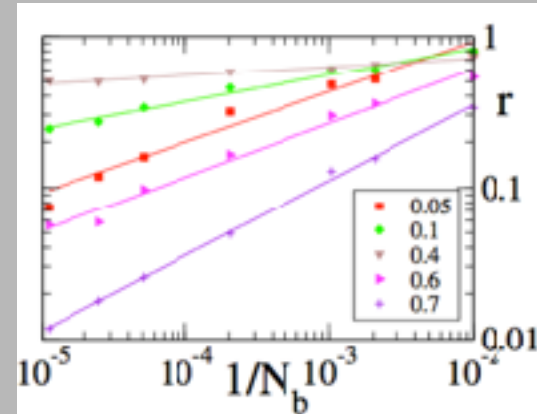
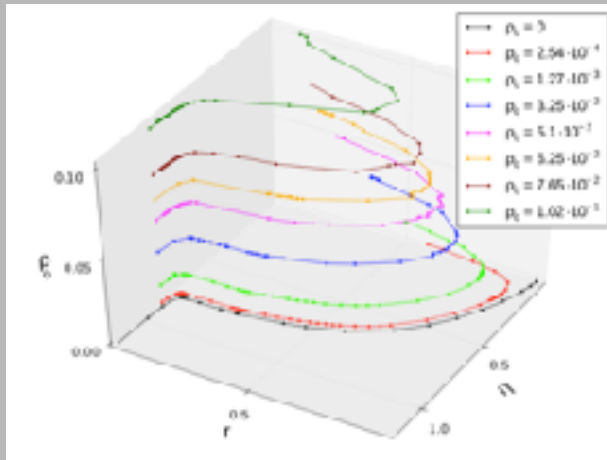
as before this occurs due to...

$$\begin{aligned} \partial_t \rho &= \frac{v_0^2}{2D_\theta} \nabla^2 \rho - \frac{\gamma v_0}{2D_\theta R \sqrt{\pi \rho_0}} \nabla \cdot [(\cos(\psi), \sin(\psi)) \rho] \\ &= \frac{v_0^2}{2D_\theta} \nabla^2 \rho - \frac{\gamma v_0}{2D_\theta R \sqrt{\pi \rho_0}} \nabla \cdot \left[\frac{\rho \nabla \rho_o(\mathbf{x})}{\|\nabla \rho_o(\mathbf{x})\|} \right], \quad (11) \end{aligned}$$



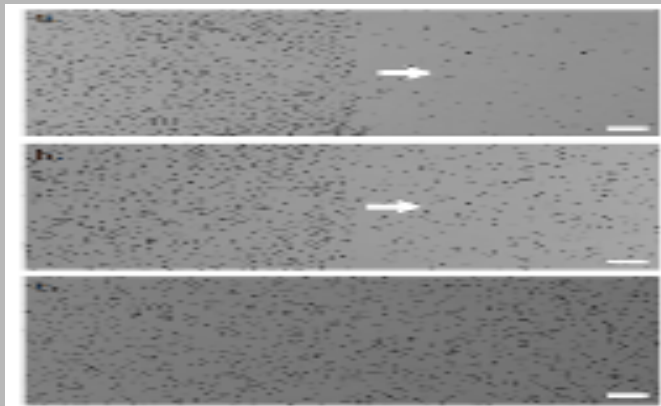
Results:

- There is an optimal noise that maximizes collective motion
- Due to the presence of “obstacles”, the system exhibits QLRO and bands disappear

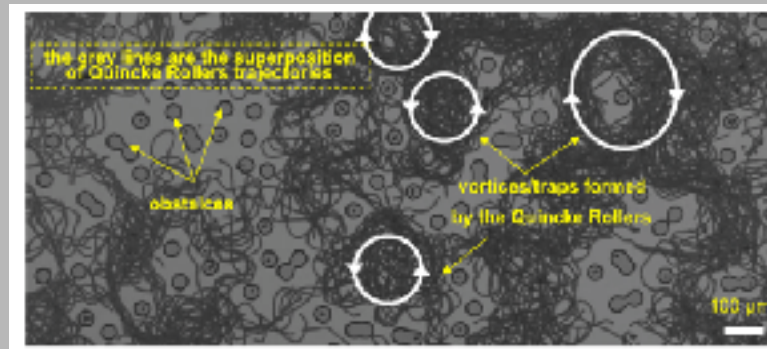


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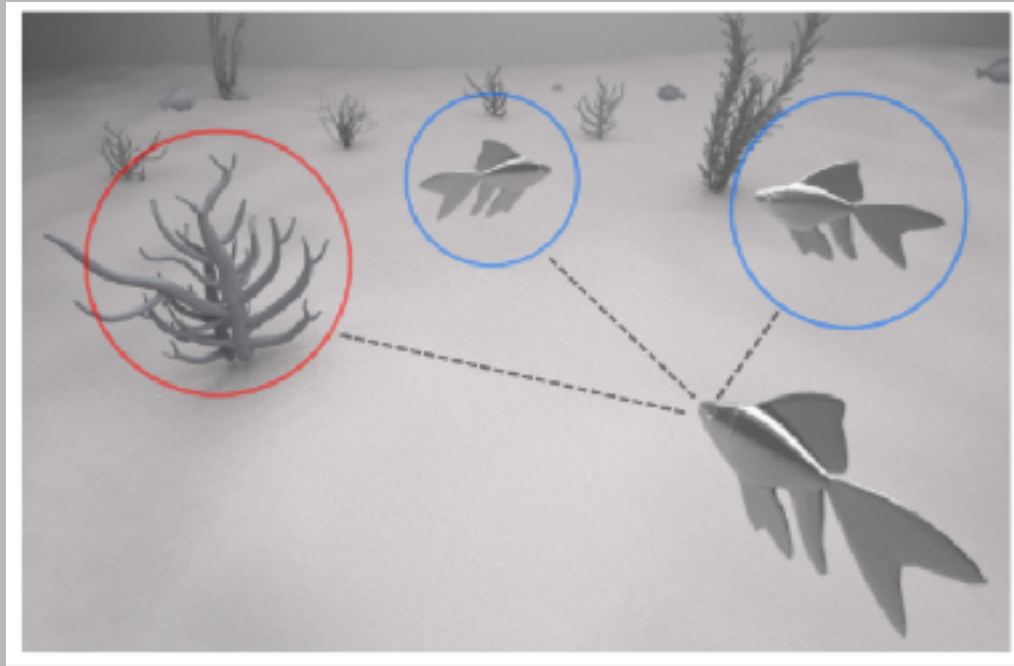
- There is an optimal noise that maximizes collective motion
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predictions observed in experiments:
Briccard, Desreumaux et al. Nature Phys (2016)



Flocking through disorder with topological interactions



$$\dot{\mathbf{x}}_i = v_0 \mathbf{V}(\theta_i)$$

$$\dot{\theta}_i = g_i(n_{o,i}) \left[\frac{\gamma}{n_{b,i}} \sum_{j \in \text{TN}} \sin(\theta_j - \theta_i) \right]$$

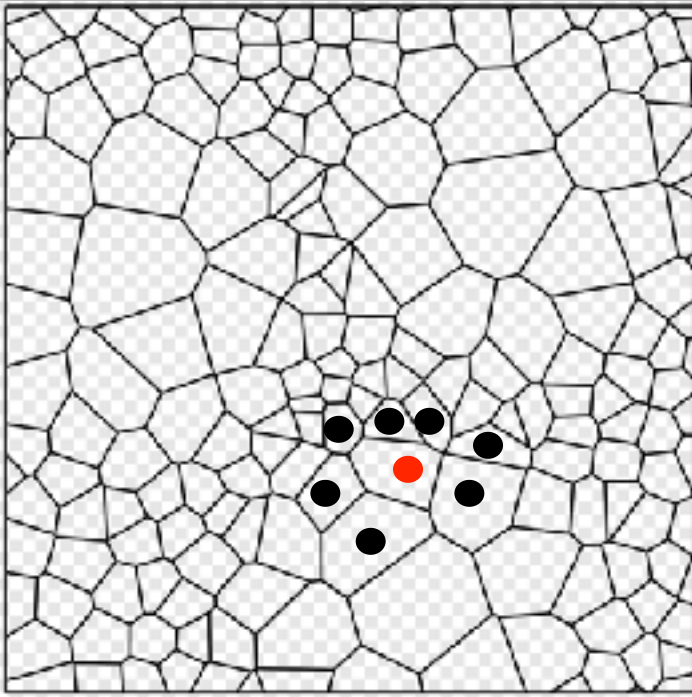
$$+ \frac{\gamma}{n_{o,i}} \sum_{s \in \text{TN}} \sin(\alpha_{s,i} - \theta_i) + \eta \xi_i(t)$$

topo neighbor particles

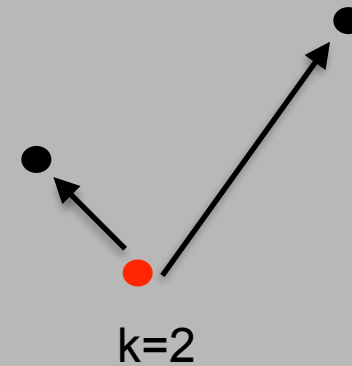
topo neighbor obstacles

Flocking through disorder with topological interactions

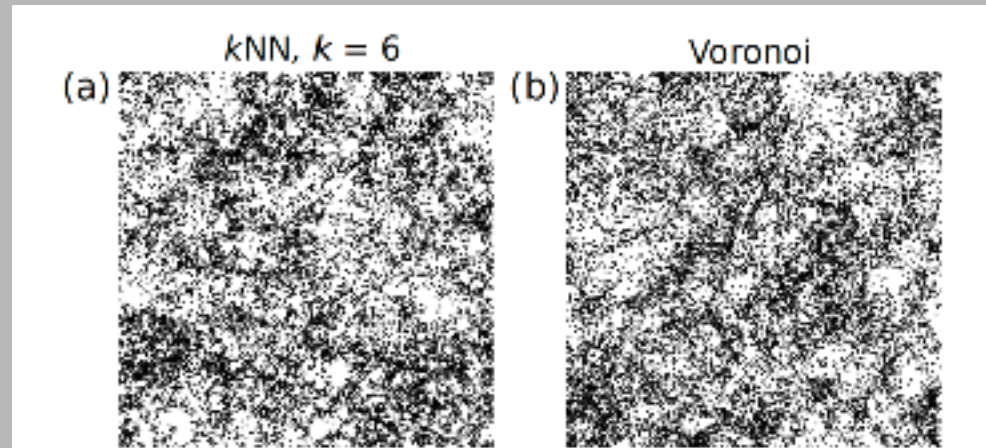
Voronoi neighbors



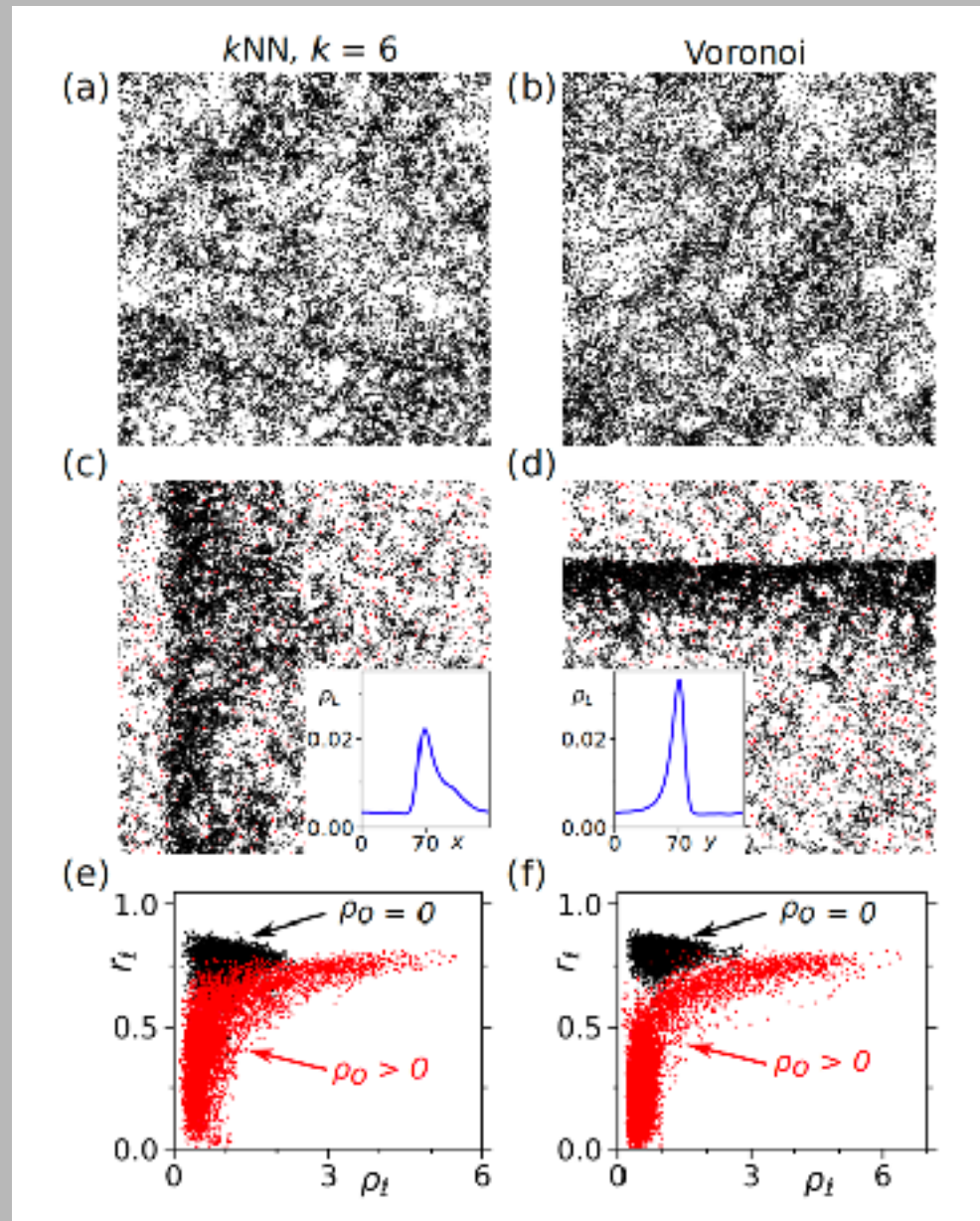
Knn neighbors



Flocking through disorder with topological interactions:



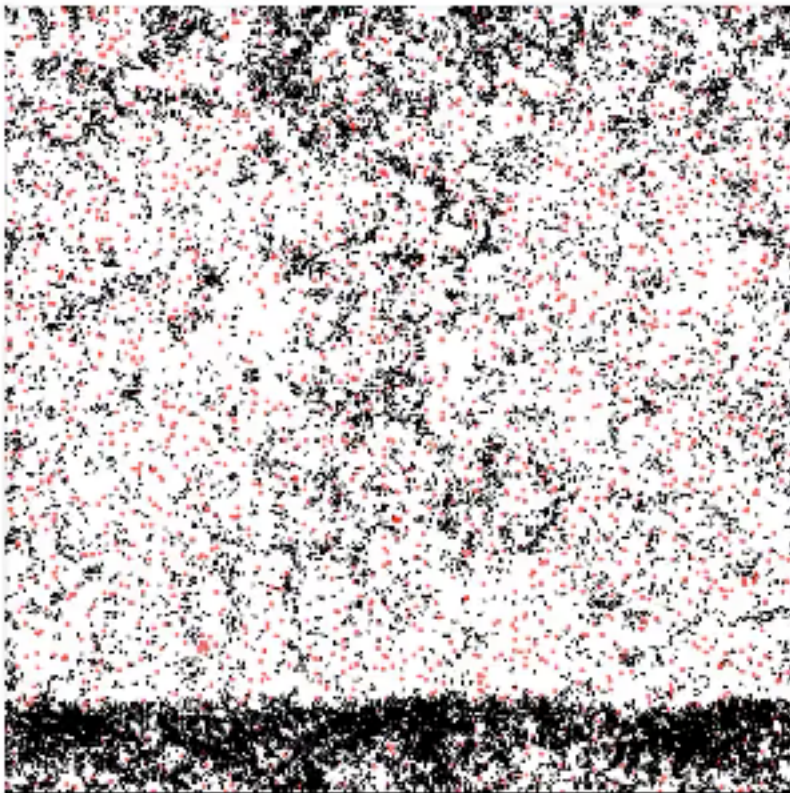
Flocking through disorder with topological interactions:



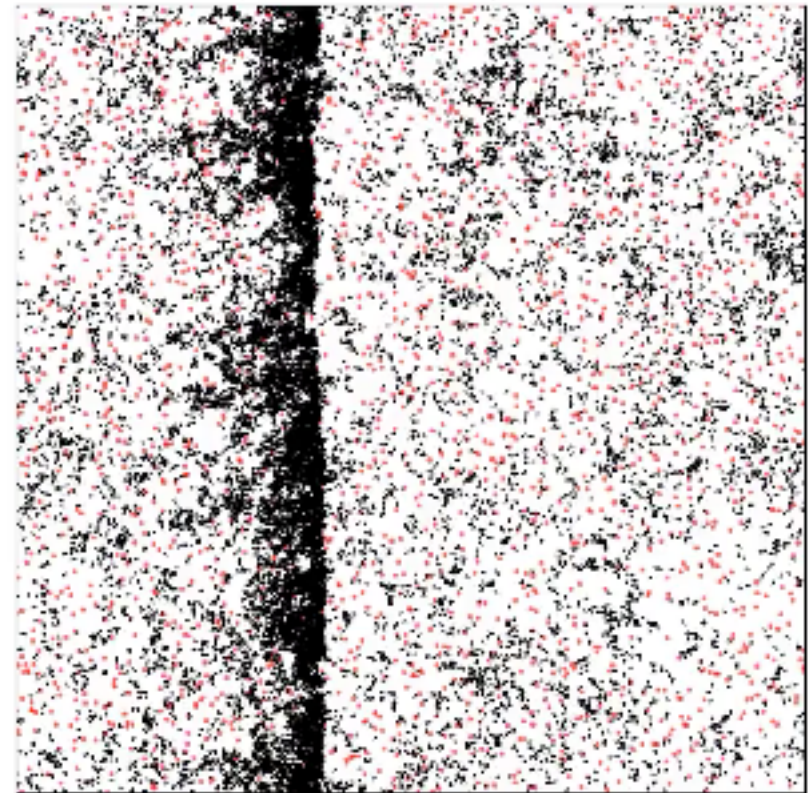
a coupling
local order-local density
emerges

Flocking through disorder with topological interactions:
quenched disorder promotes the formation of bands!

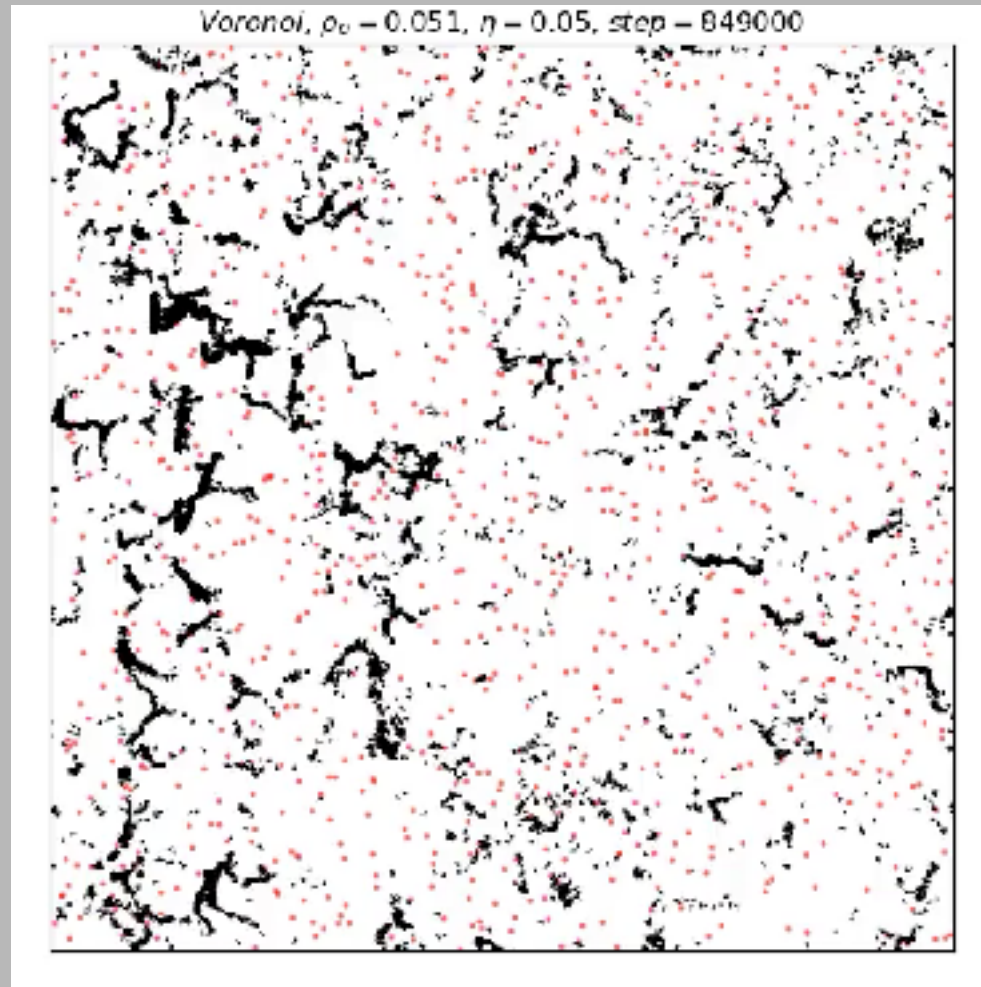
kNN, $k = 6$, $p_0 = 0.102$, $\eta = 0.55$, step = 602000



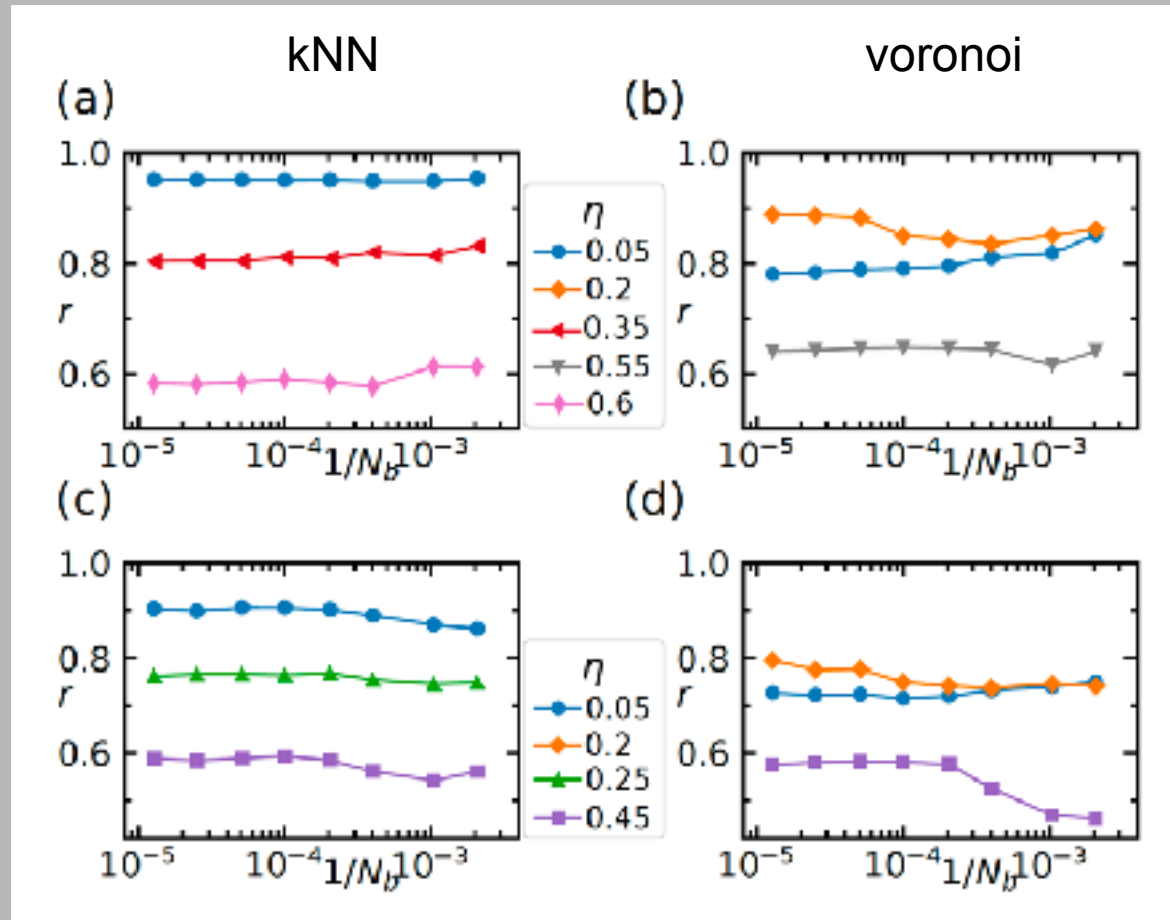
Voronoi, $p_0 = 0.102$, $\eta = 0.55$, step = 849000



Flocking through disorder with topological interactions:

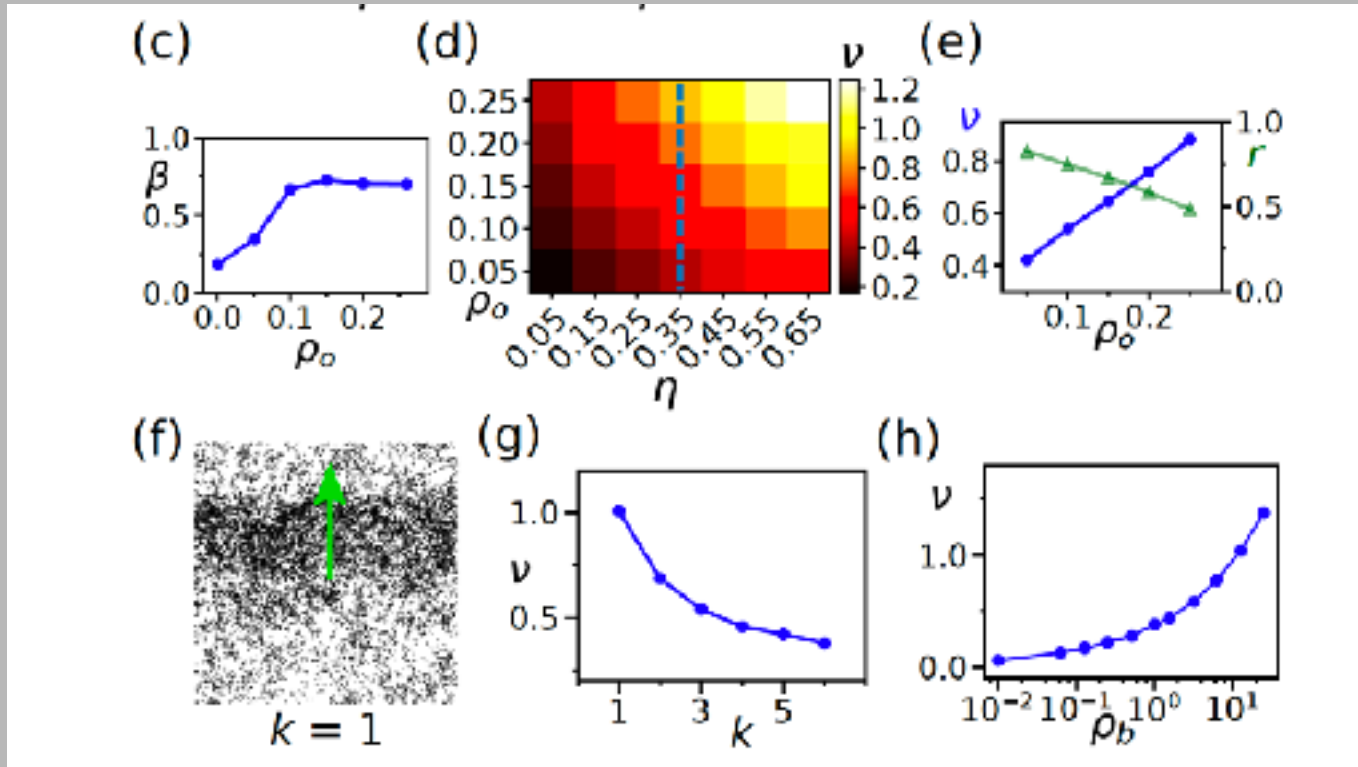


Flocking through disorder with topological interactions:



in contrast to the metric case, order is long-range!

Rewiring of the underlying interaction network



rewiring explains the emergence of the coupling order-density

rewiring also occurs in the absence of obstacles. For $k=1$, we can observe bands

Hot vs Cold Active Matter

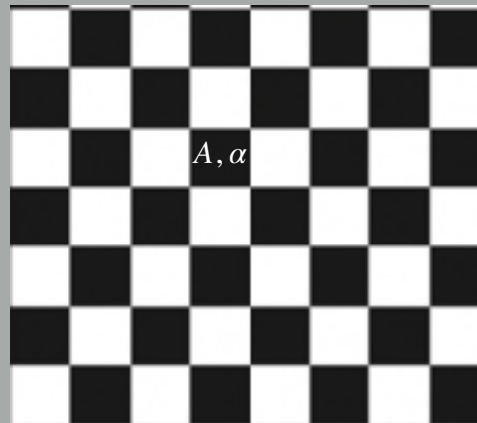
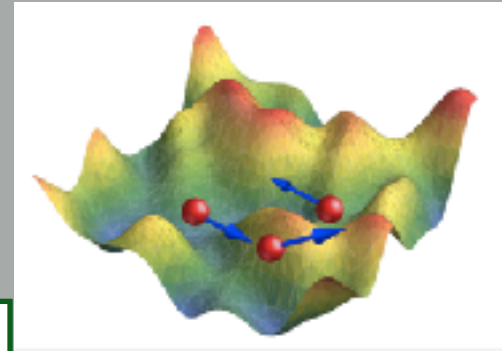
$$\dot{\mathbf{x}}_i = v_0 \mathbf{V}(\theta_i), \quad \dot{\theta}_i = I_q(\mathbf{x}_i, \theta_i) + R_s(\mathbf{x}_i, \theta_i),$$

$$I_q(\mathbf{x}_i, \theta_i) = \frac{1}{n(\mathbf{x}_i)} \sum_{|\mathbf{x}_i - \mathbf{x}_j| < 1} \sin(q(\theta_j - \theta_i)),$$

$$R_{RT}(\mathbf{x}_i, \theta_i) = A\Gamma(\mathbf{x}_i),$$

$$R_{RF}(\mathbf{x}_i, \theta_i) = A \sin(\alpha(\mathbf{x}_i) - \theta_i),$$

$$R_{RS}(\mathbf{x}_i, \theta_i) = A \sin(2(\alpha(\mathbf{x}_i) - \theta_i)),$$


 A, α
 x
 y

Hot vs Cold Active Matter

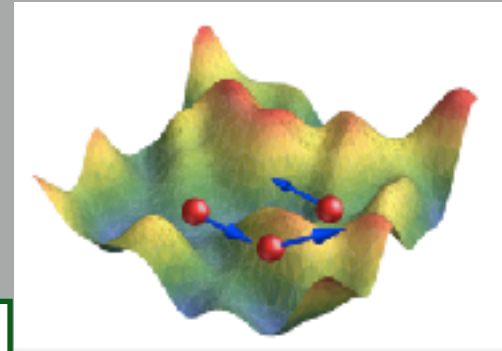
$$\dot{\mathbf{x}}_i = v_0 \mathbf{V}(\theta_i), \quad \dot{\theta}_i = I_q(\mathbf{x}_i, \theta_i) + R_s(\mathbf{x}_i, \theta_i),$$

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$$R_{RS}(\mathbf{x}_i, \theta_i) = A \sin(2(a(\mathbf{x}_i) - \theta_i)),$$



When the equations of motion exhibit a **Hamiltonian structure**, then particles trajectories cannot fall (asymptotically) into a trap [by Poincaré-Bendixon Theorem], and thus motion is **diffusive**.

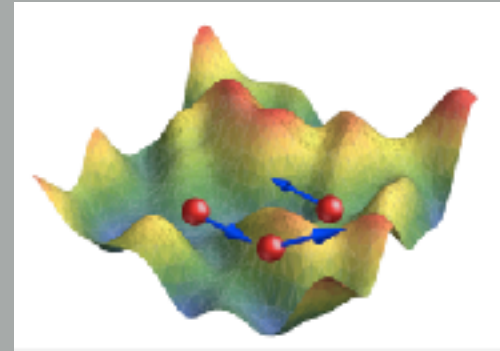
On the other hand, when the equations of motion display a **dissipative structure**, traps emerge in the system and particles asymptotically fall into **traps**.

Hot vs Cold Active Matter

When do we have a Hamiltonian structure?

$$\dot{\mathbf{x}}_i = v_0 \mathbf{V}(\theta_i),$$

$$\dot{\theta}_i = R_s(\mathbf{x}_i, \theta_i)$$



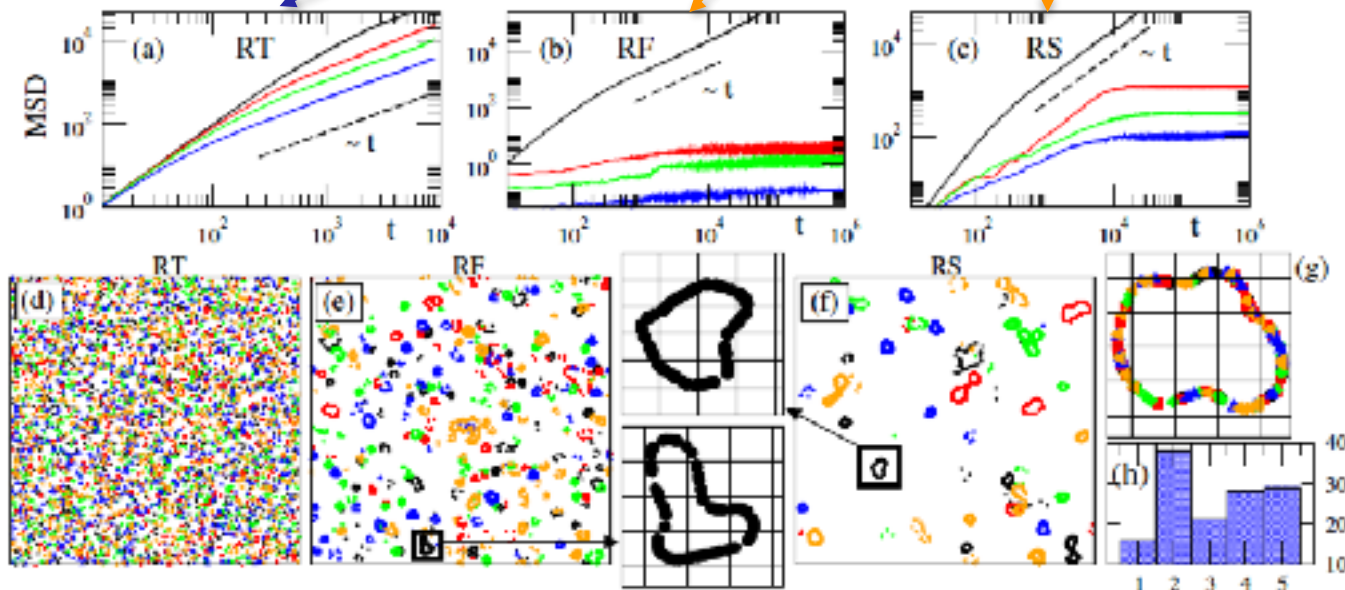
$$R_{RT}(\mathbf{x}_i, \theta_i) = A\Gamma(\mathbf{x}_i),$$

yes

$$R_{RF}(\mathbf{x}_i, \theta_i) = A \sin(a(\mathbf{x}_i) - \theta_i),$$

no

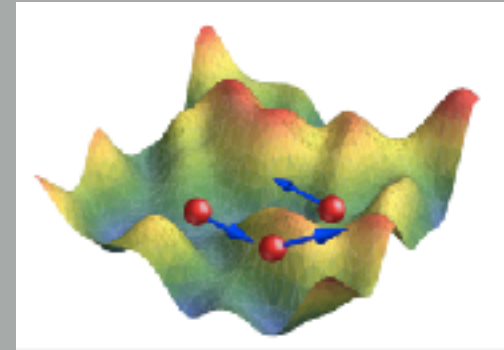
$$R_{RS}(\mathbf{x}_i, \theta_i) = A \sin(2(a(\mathbf{x}_i) - \theta_i)).$$



Hot vs Cold Active Matter

When do we have a Hamiltonian structure?

$$\ddot{\mathbf{x}} = \dot{\mathbf{x}} \times (-A\Gamma(\mathbf{x})\mathbf{z}_0) \text{ for RT}$$



diffusion coefficient

$$\begin{aligned} \langle \theta_i^2(t) \rangle &= 2A^2 \int_0^t dt' \int_0^{t'} dt'' \langle \Gamma(\mathbf{u}_0 v_0 t'') \Gamma(\mathbf{u}_0 v_0 t') \rangle \\ &\approx 2 \frac{A^2 \langle \Gamma(\mathbf{x})^2 \rangle_c \Delta_x}{v_0} t = 2T_{\text{sh}} t. \end{aligned}$$

$$D_\theta = T_{\text{sh}} = \frac{A^2 \Delta_x}{3v_0}$$

shaking temp.

$$D_{\text{tr}} = \frac{v_0^2}{2D_\theta} = \frac{3v_0^3}{2A^2 \Delta_x}$$

Hot vs Cold Active Matter

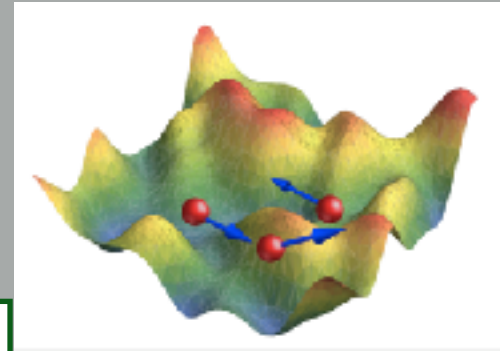
$$\dot{\mathbf{x}}_i = v_0 \mathbf{V}(\theta_i), \quad \dot{\theta}_i = I_q(\mathbf{x}_i, \theta_i) + R_s(\mathbf{x}_i, \theta_i),$$

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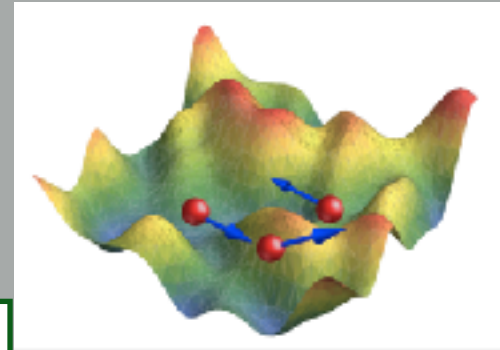
When do we find a dissipative structure?

$$\ddot{\mathbf{x}}_i = -\dot{\mathbf{x}}_i \times A\Gamma(\mathbf{x}_i)\mathbf{z}_0 + \frac{1}{v_0^2 n(\mathbf{x}_i)} \dot{\mathbf{x}}_i \times \sum_{|\mathbf{x}_i - \mathbf{x}_j| < 1} \dot{\mathbf{x}}_i \times \dot{\mathbf{x}}_j$$

interactions

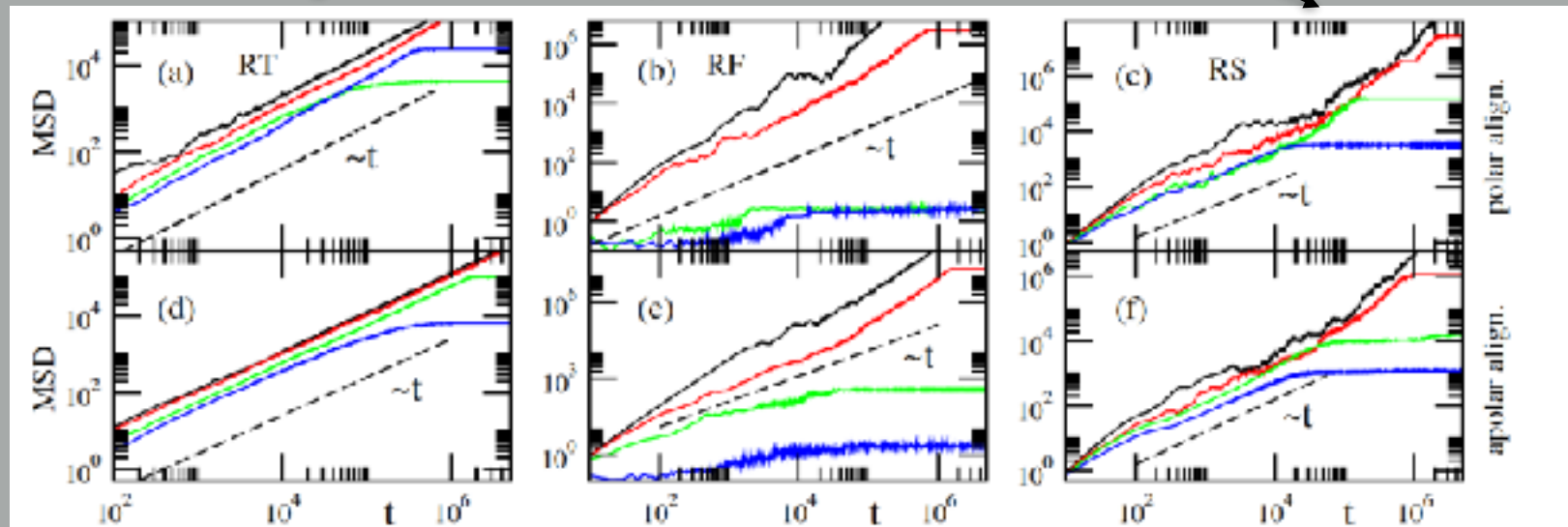
Hot vs Cold Active Matter

$$\dot{\mathbf{x}}_i = v_0 \mathbf{V}(\theta_i), \quad \dot{\theta}_i = I_q(\mathbf{x}_i, \theta_i) + R_s(\mathbf{x}_i, \theta_i),$$



$$I_q(\mathbf{x}_i, \theta_i) = \frac{1}{n(\mathbf{x}_i)} \sum_{|\mathbf{x}_i - \mathbf{x}_j| < 1} \sin(q(\theta_j - \theta_i)),$$

$$\begin{aligned} R_{RT}(\mathbf{x}_i, \theta_i) &= A\Gamma(\mathbf{x}_i), \\ R_{RF}(\mathbf{x}_i, \theta_i) &= A \sin(a(\mathbf{x}_i) - \theta_i), \\ R_{RS}(\mathbf{x}_i, \theta_i) &= A \sin(2(a(\mathbf{x}_i) - \theta_i)), \end{aligned}$$

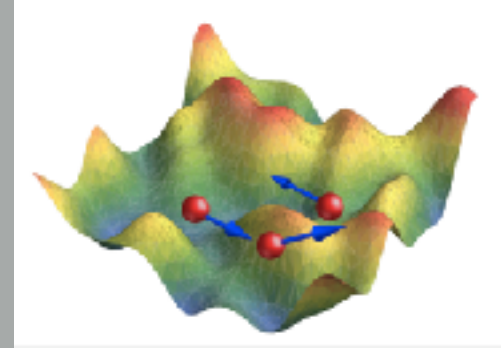


And for interacting active particles, we always find trapping!

Hot vs Cold Active Matter

Hamiltonian structure \rightarrow diffusive-like behavior

Dissipative structure \rightarrow trapping



Aranson



from PennState

Chepizhko



from Univ. Innsbruck

Romanczuk



Humb. Univ.

Rahmani



CYU

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Thanks for you attention!