Self-Organisation And Flow Of Information Within Confined Flock

Arnab Saha





NSPCS-2024 (KIAS)

dorsal view

03:00:00

Drosophila embryogenesis (Ann. Rev. Cell Dev. Biol. 33, 169-202, 2017)

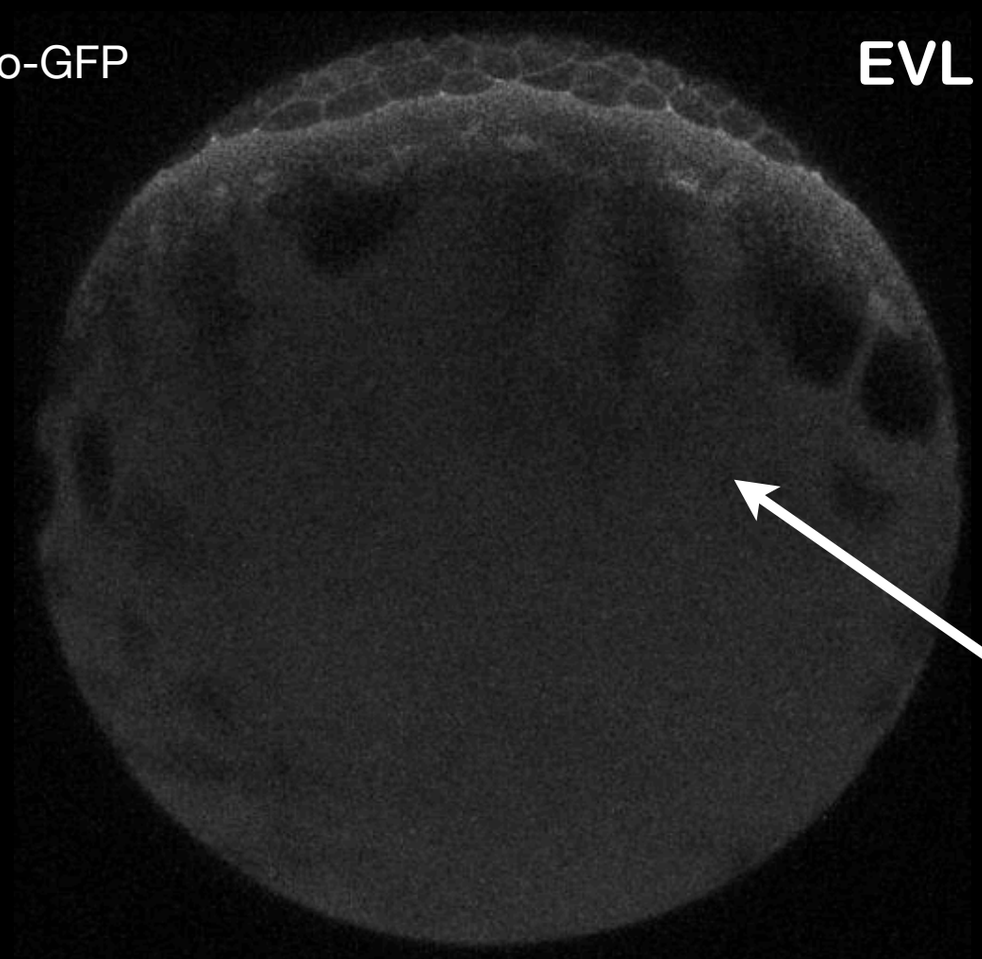
ventral view

50 µm



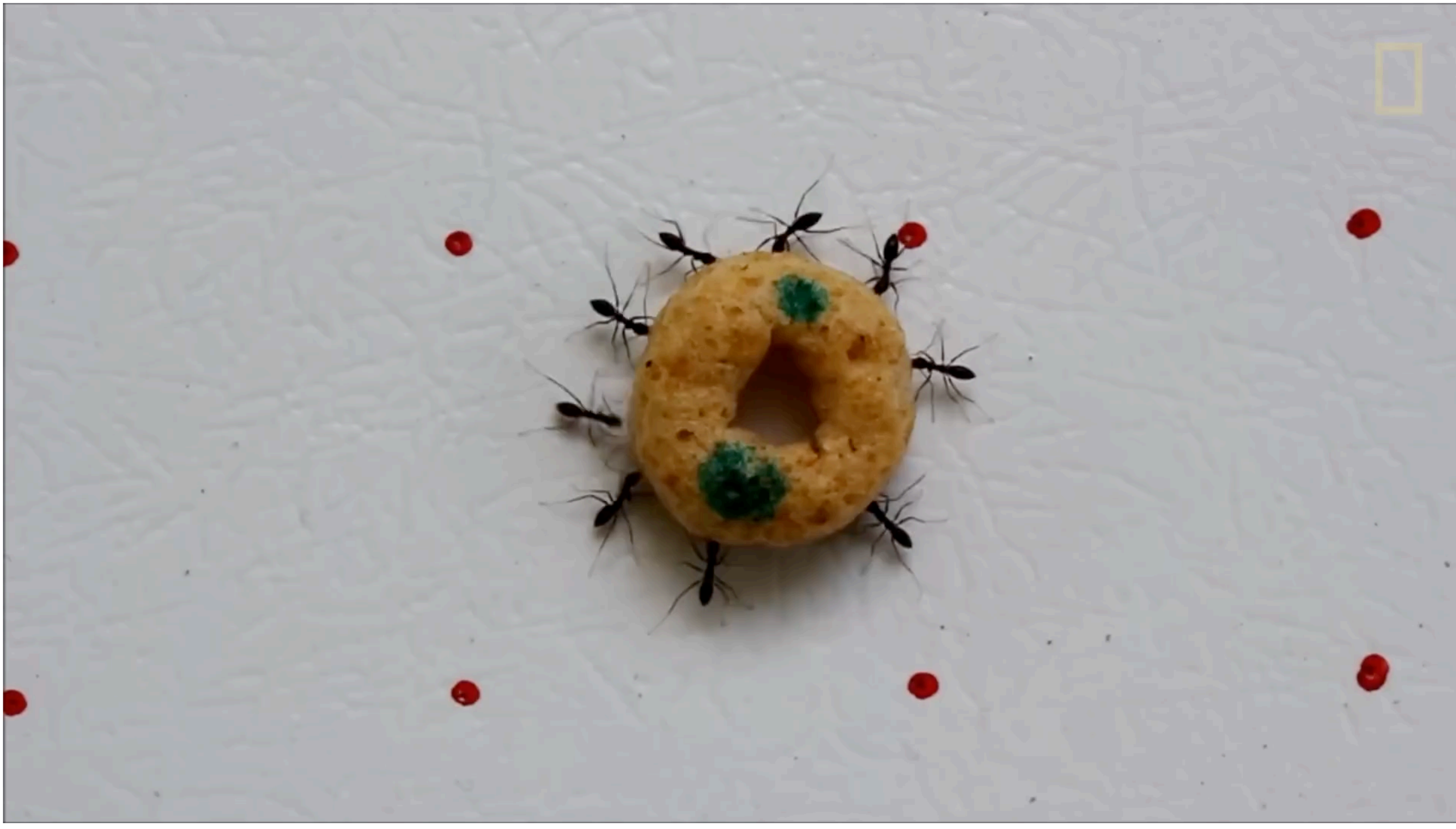
Actomyosin drives developmental rearrangements!

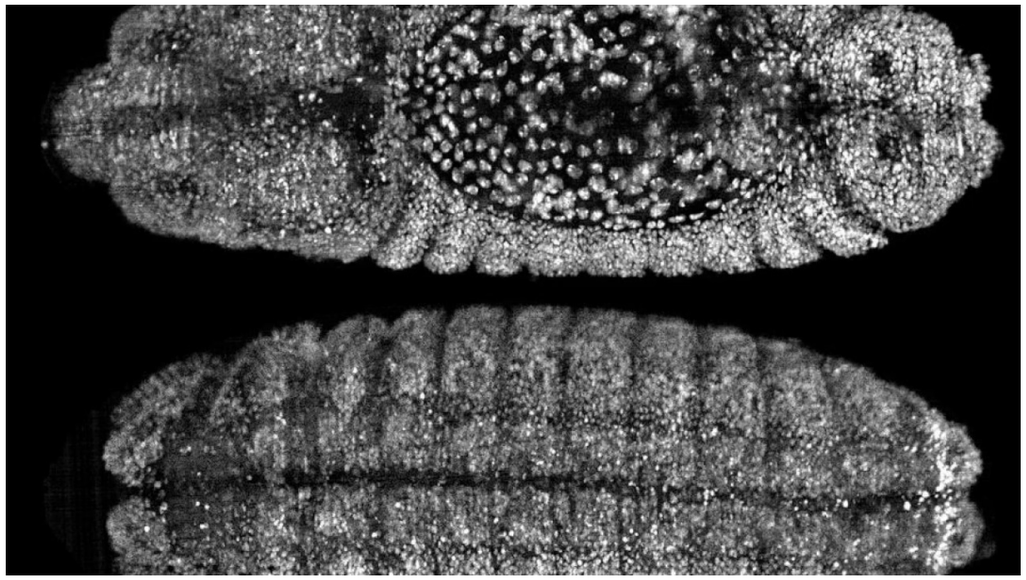


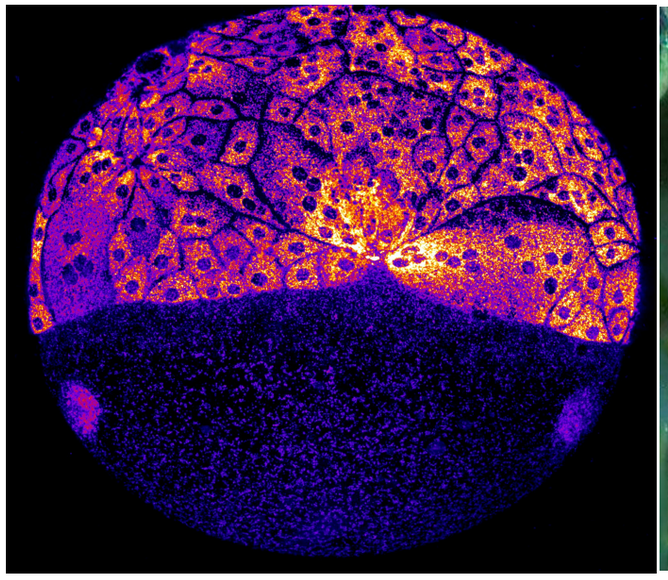


Zebrafish epiboly

Martin Behrndt, Guillaume Salbreux, CP Heisenberg













Orchestrated large-scale motion, complex spatiotemporal pattern formation, co-operative execution of complex tasks - impossible without information exchange/flows

Content

1. **Examples - Active systems-Flocking/collective dynamics with external perturbations.**

2. **A model flock and their self-organisation within a confinement.**

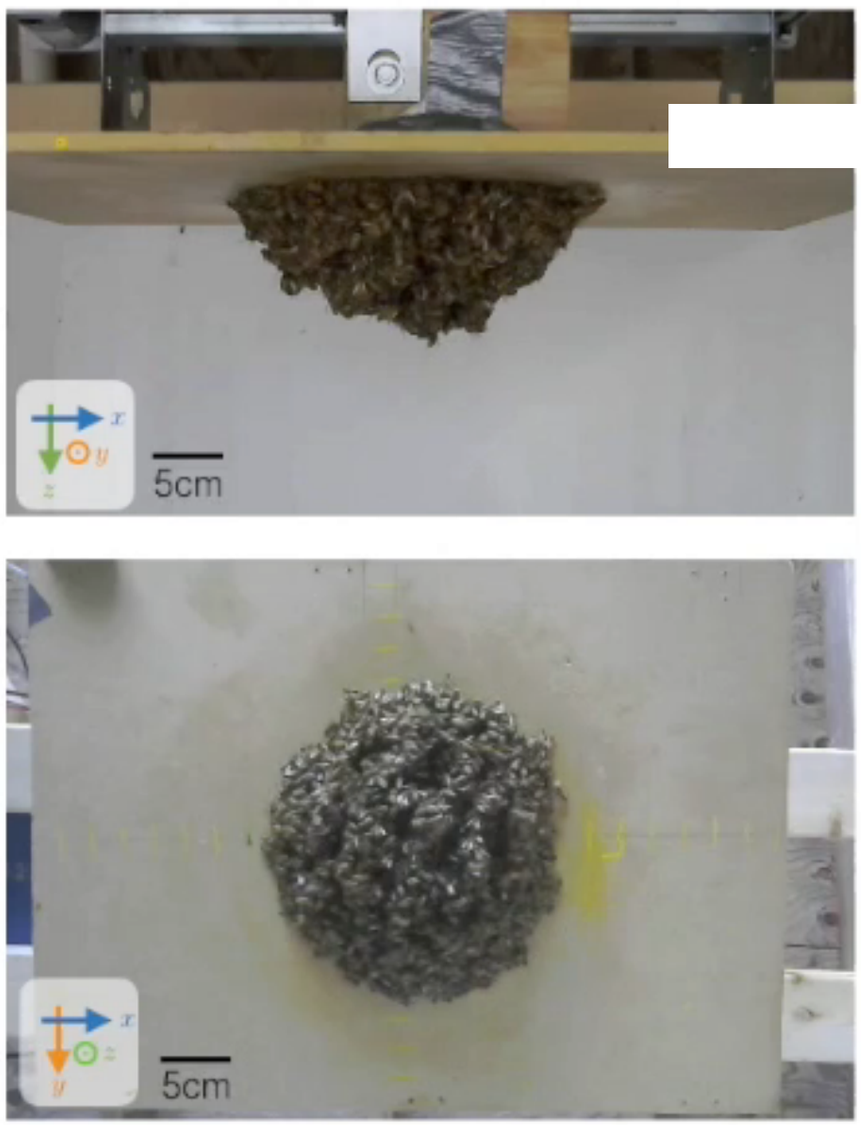
3. **External perturbation to the flock and information flow within it.**

Active Adaptive Cluster

Active Adaptive Cluster

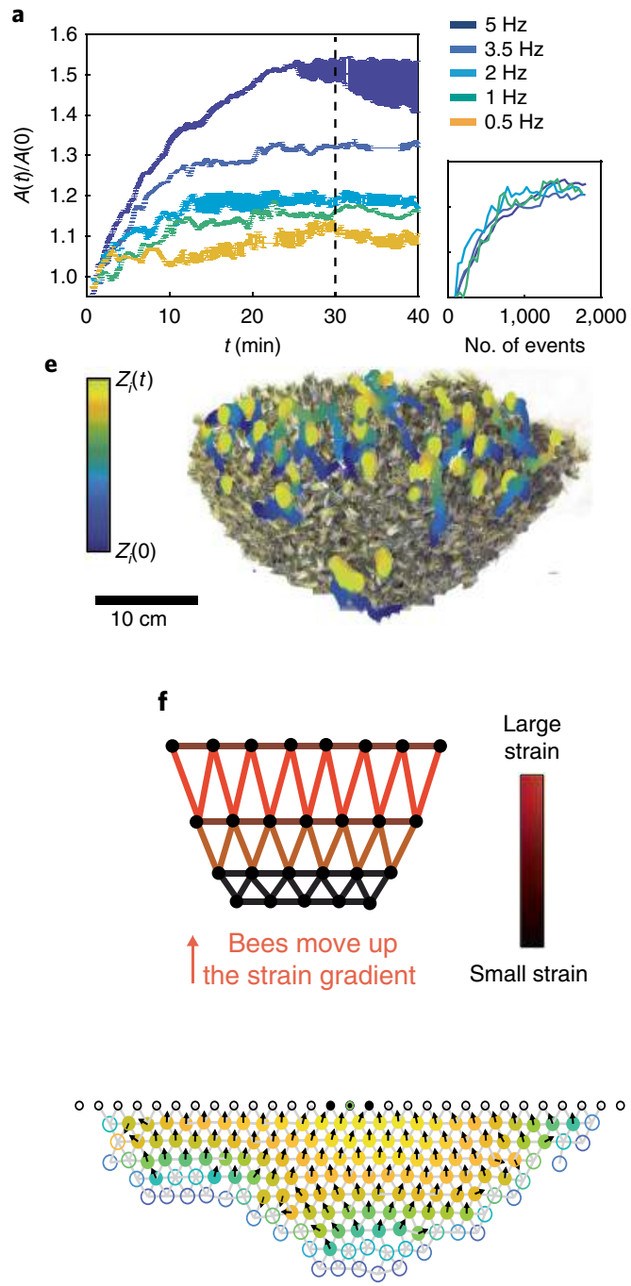
Horizontal shaking

Horizontal discontinuous shaking at 5Hz
time lapse (sped up X600)



Vertical shaking

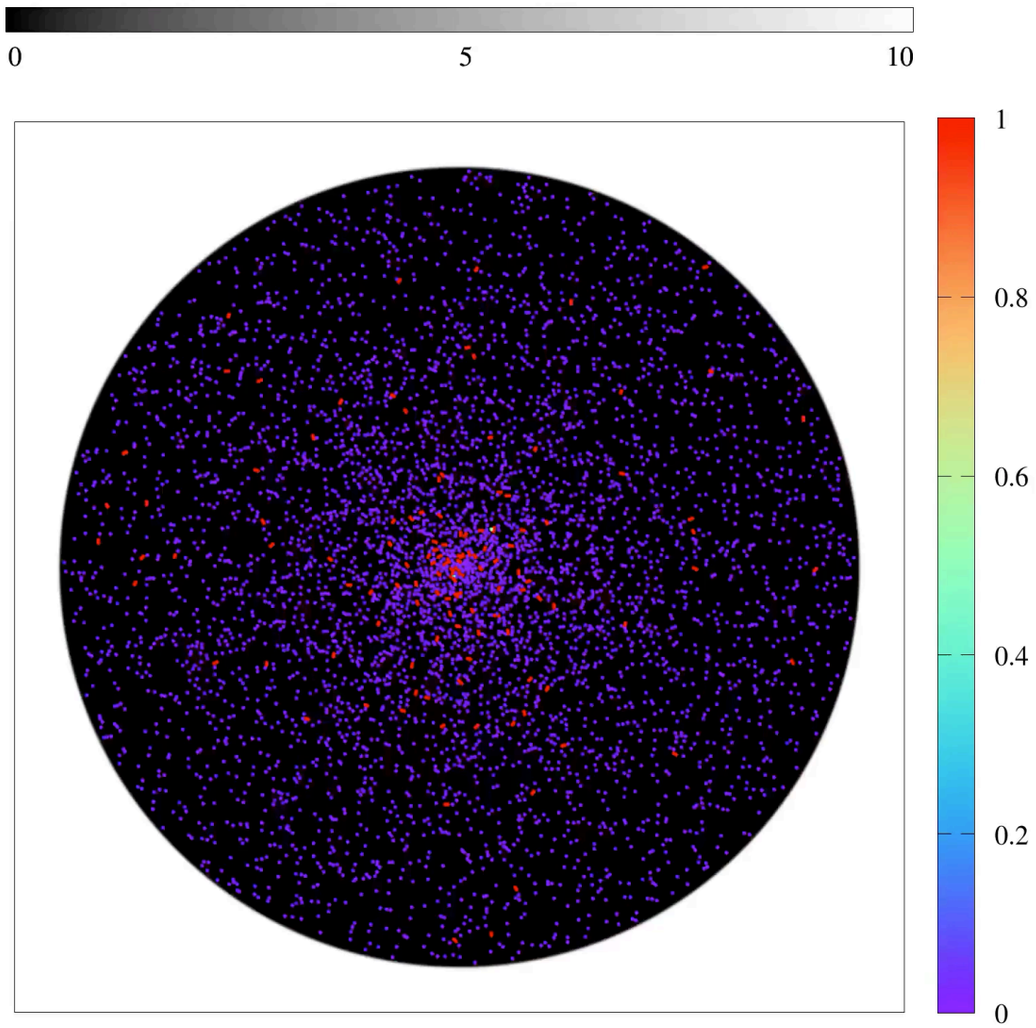




O. Peleg, J. M. Peters, M. K. Salcedo, L. Mahadevan

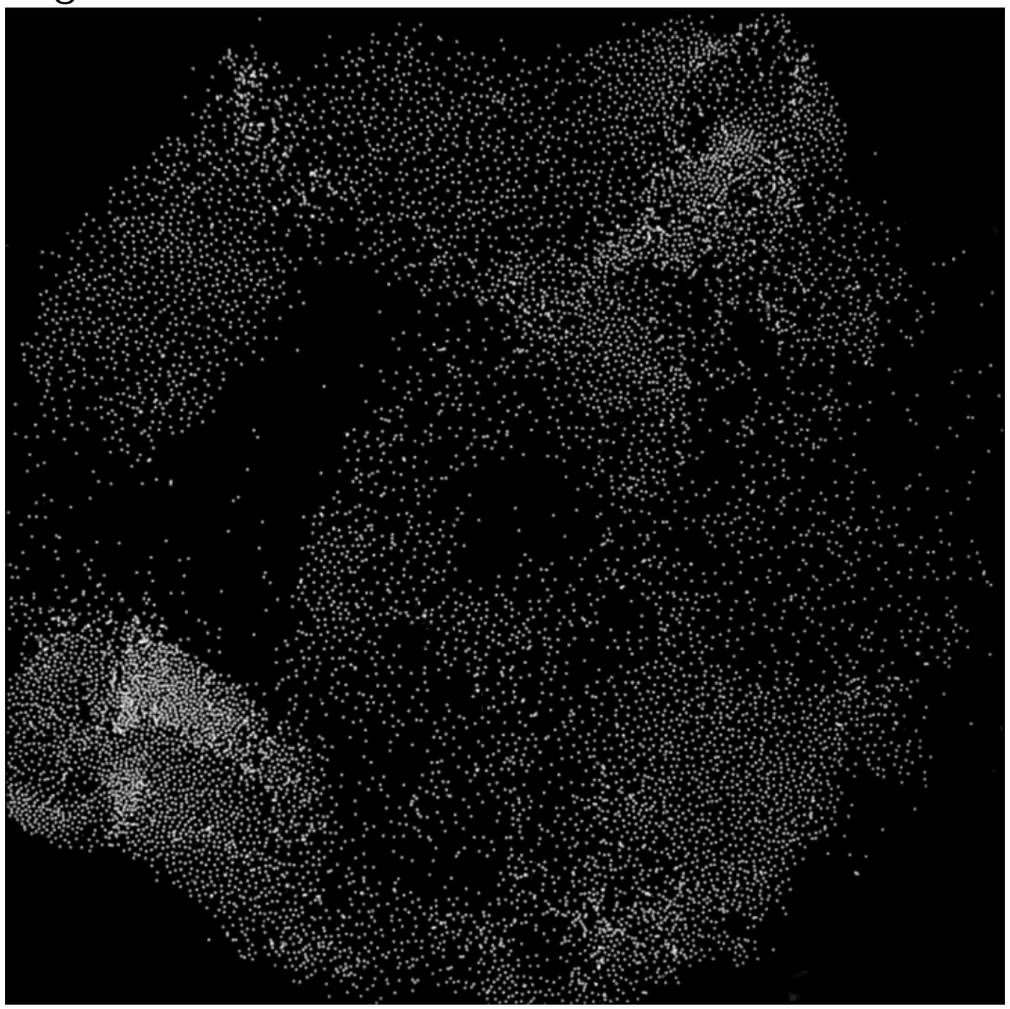
Confined Active Matter

Collective Dynamics & Self-organisation



Rana, Samsuzzaman, Saha, SoftMatter, 2019

polar alignment



Bicard et. al., Nat.Com 2015

Confined Active Matter

Collective Dynamics & Self-organisation

With polar alignment

Model Equations

$$m\frac{d\mathbf{v}_i}{dt} = -\gamma\mathbf{v}_i - \mathbf{F}_i + f_0\hat{\mathbf{n}}_i + \sqrt{2\gamma K_B T}\eta_i$$

$$\hat{\mathbf{n}}_i = R_\xi(\theta) \circ \left(\frac{1}{N_{S_i}}\sum_{k\in S_i}\hat{\mathbf{n}}_k\right)$$

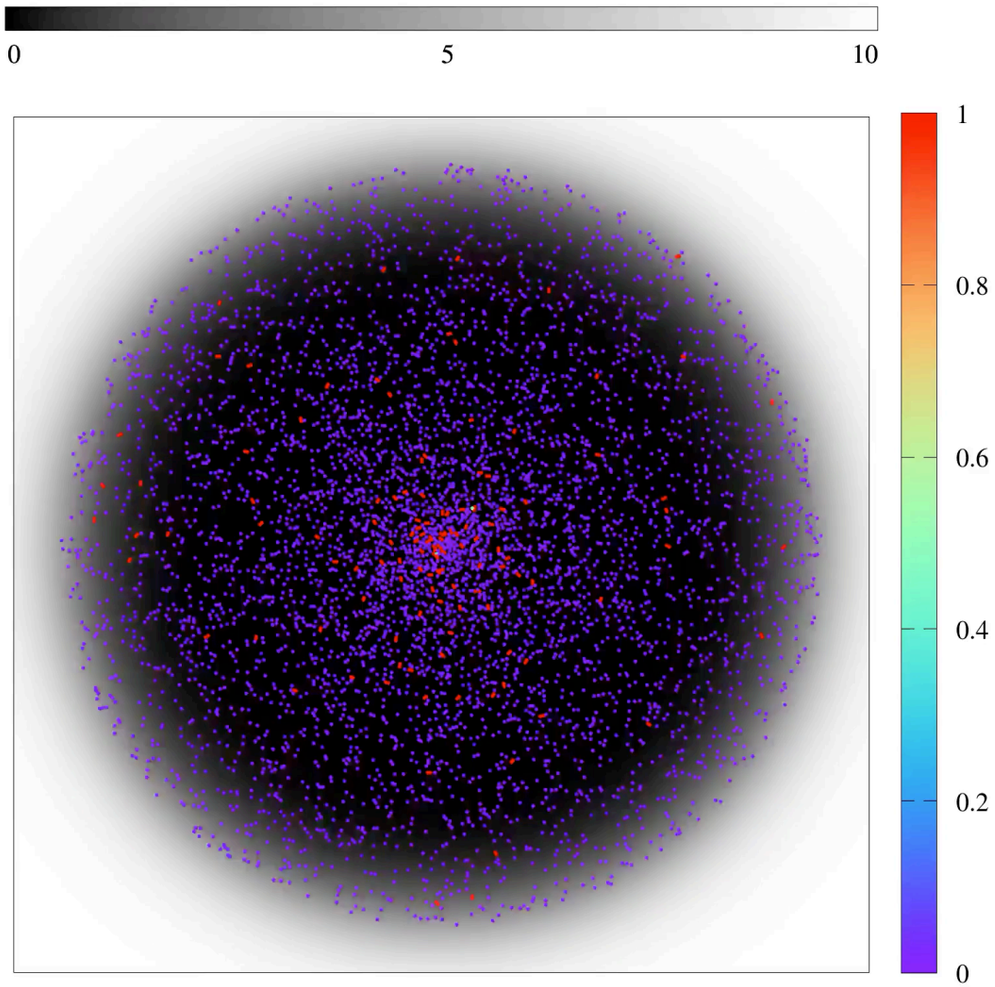
$$\mathbf{F}_i = -\nabla_i U_{trap} + \sum_j \mathbf{F}_{ij}^{WCA}$$

$$U_{trap} = U_0(\tanh(q(r_i - r_0)) + 1)$$

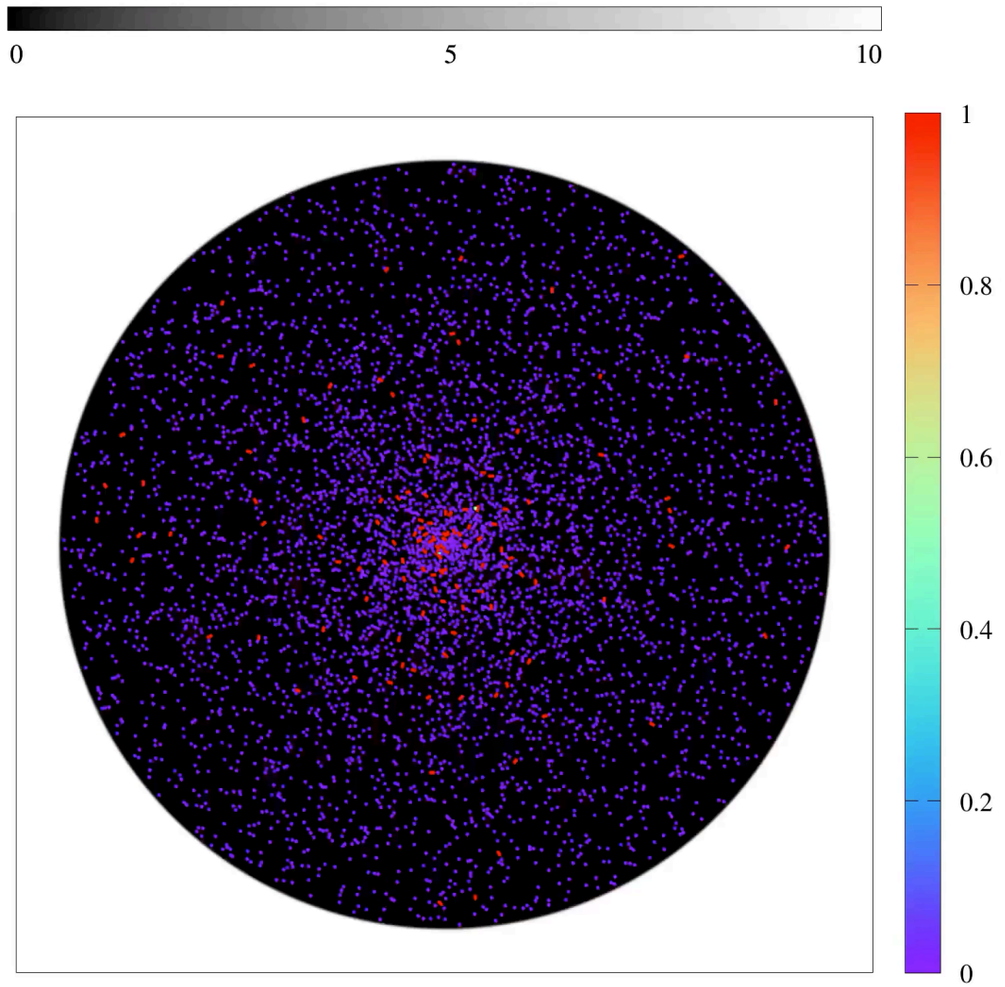
$$S = q\sigma$$

Confined Active Matter

Collective Dynamics & Self-organisation - Boundary effects



Soft Boundary

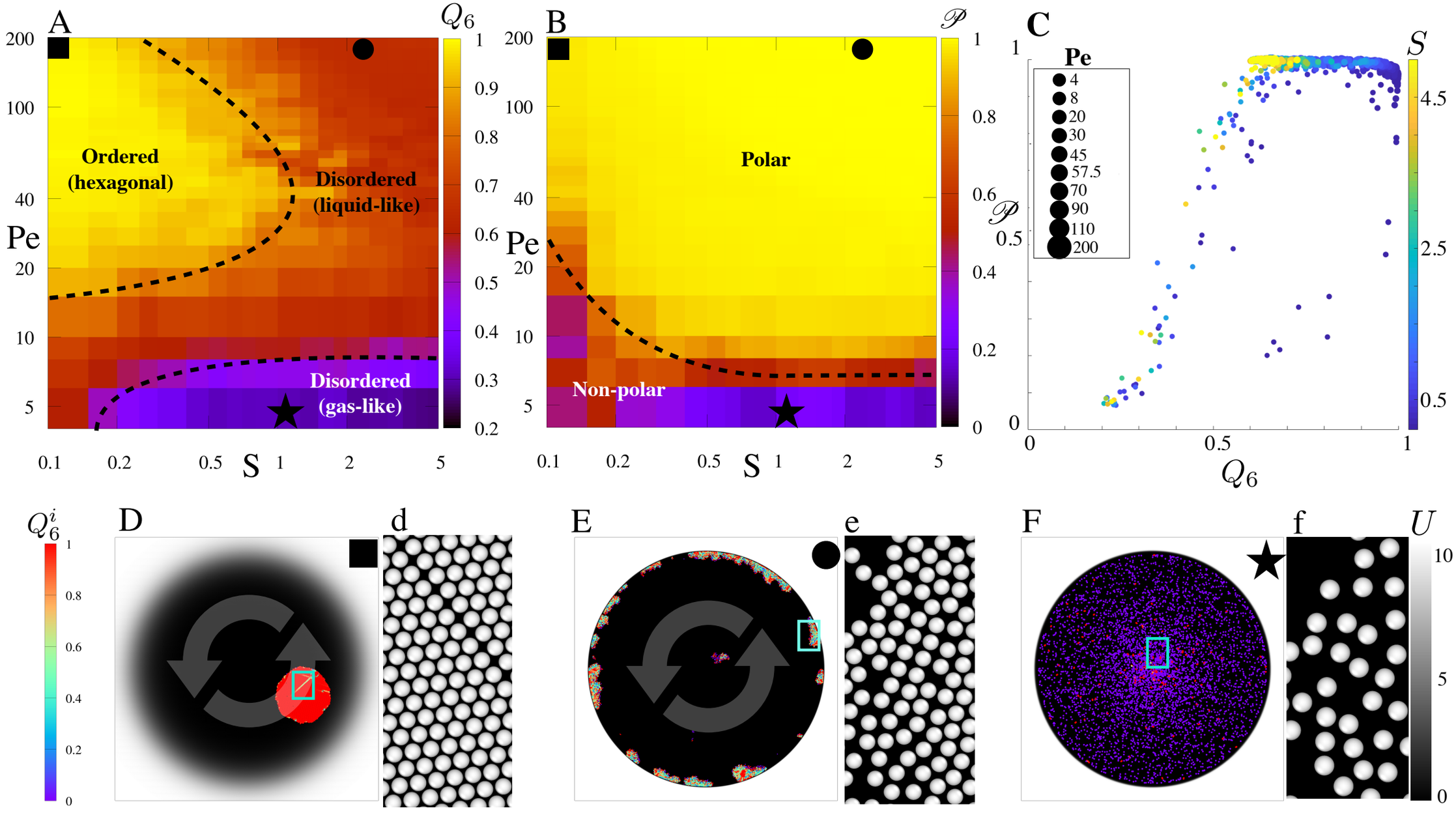


Hard Boundary

Color-scale : local hexatic order parameter

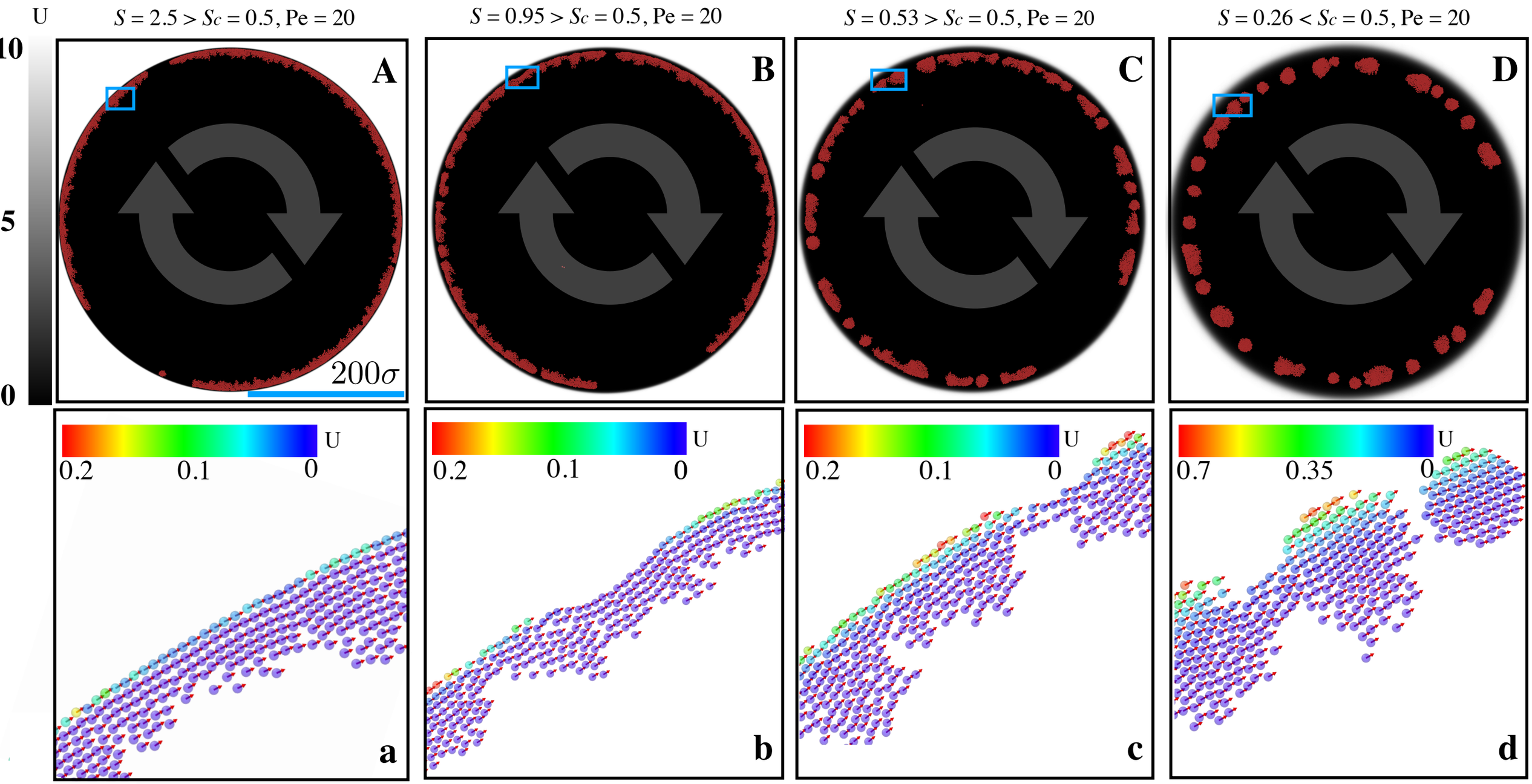
Phase diagram

Phase diagram

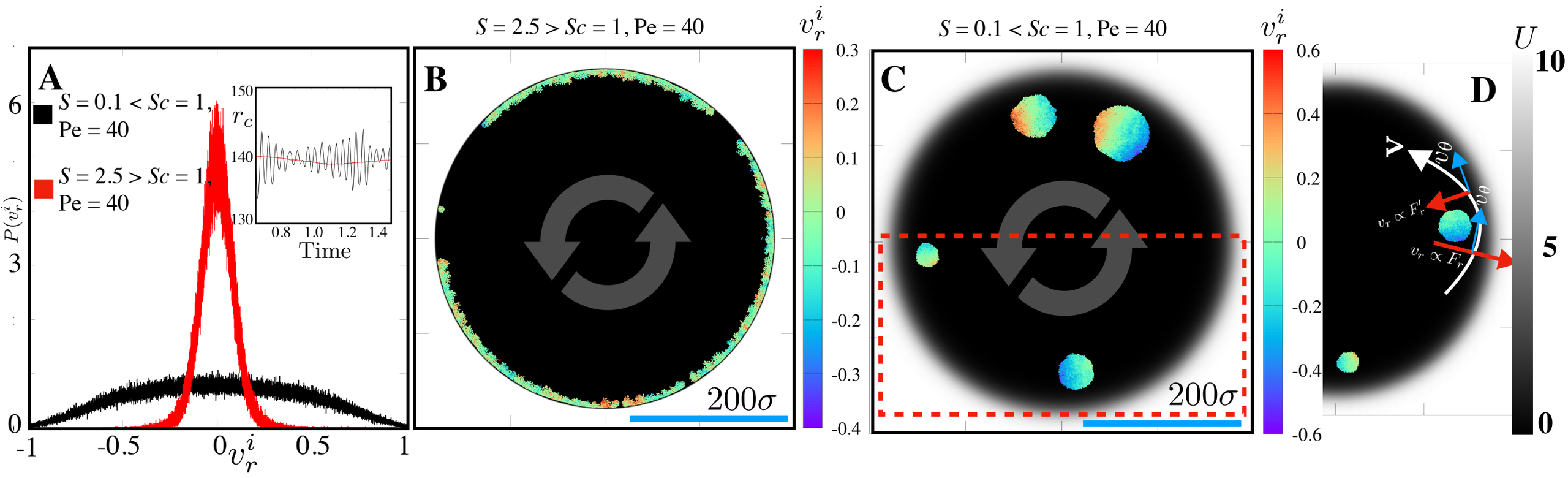


Kinetics

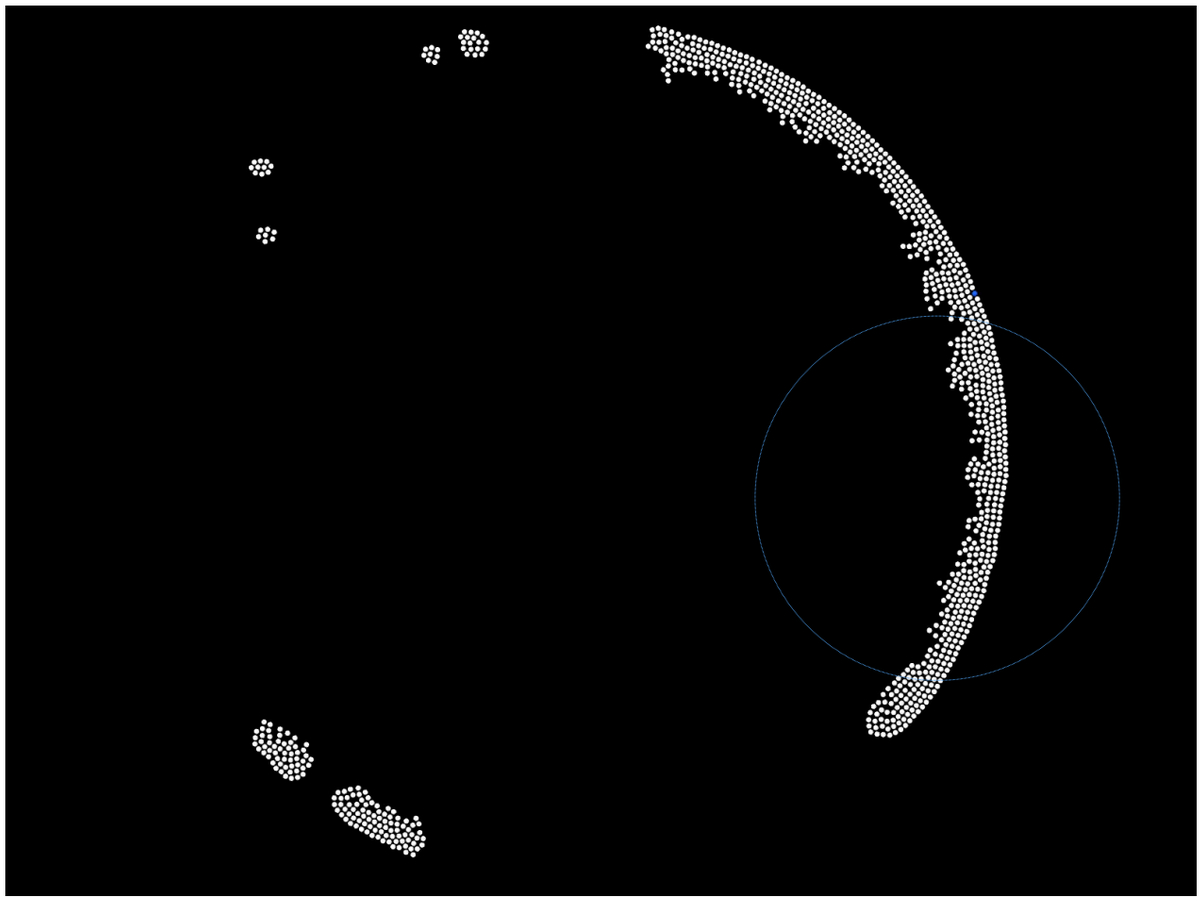
Fragmentation



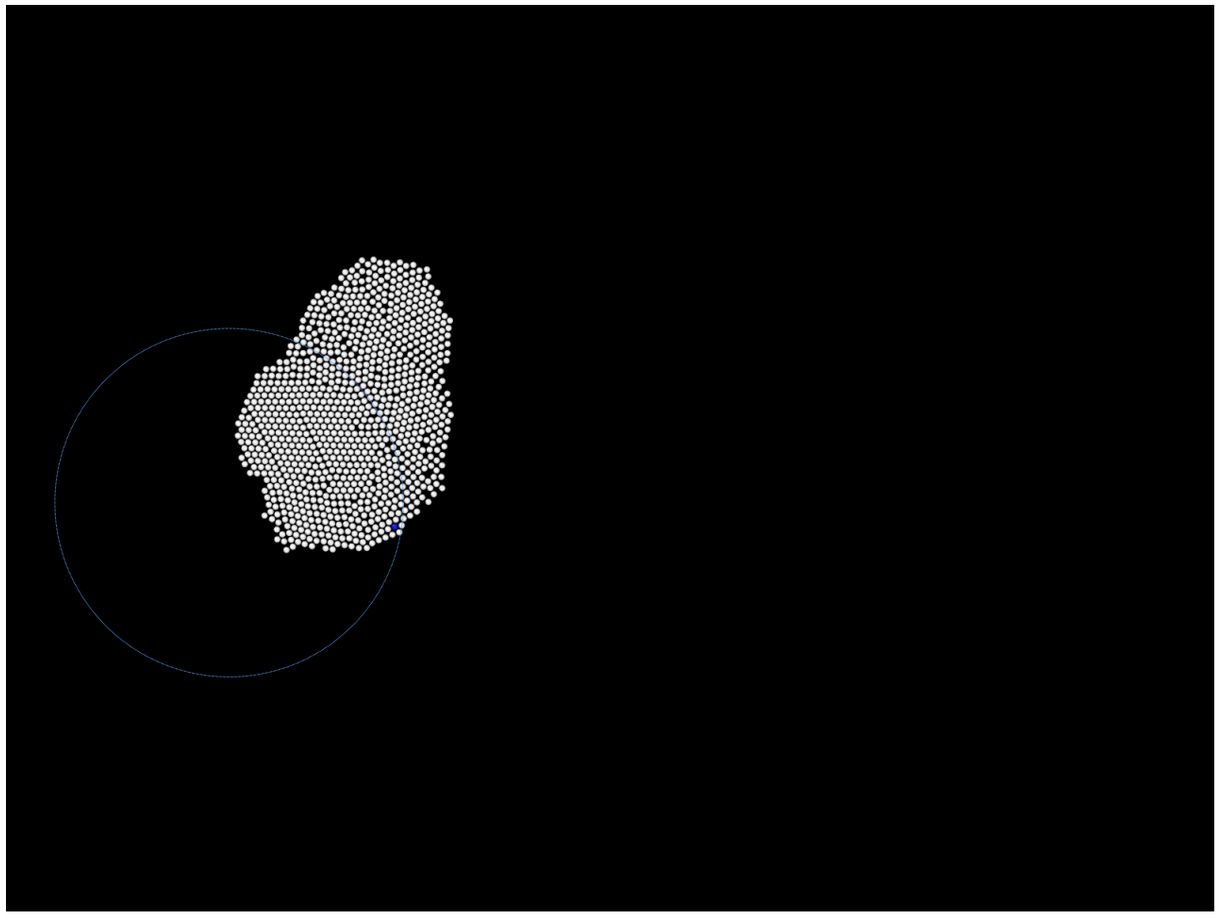
Rolling


A
S = 0.1 < Sc = 1, Pe = 40
S = 2.5 > Sc = 1, Pe = 40
$P(v_r^i)$
v_r^i
r_c
Time
B
S = 2.5 > Sc = 1, Pe = 40
200σ
C
S = 0.1 < Sc = 1, Pe = 40
200σ
v_r^i
D
v
v_θ
$v_r \propto F_r'$
$v_r \propto F_r$
U

Rolling



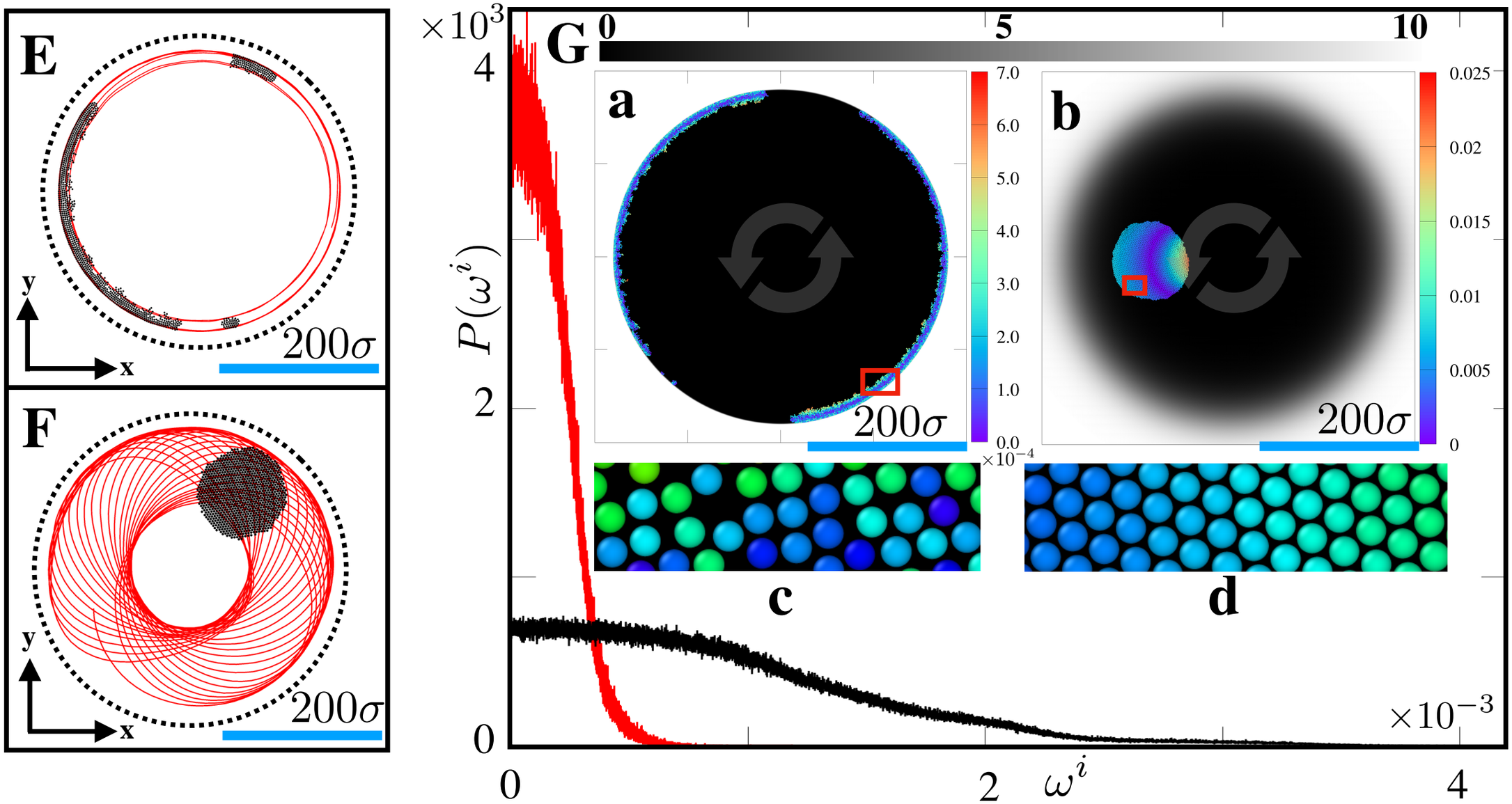
Hard Boundary



Soft Boundary

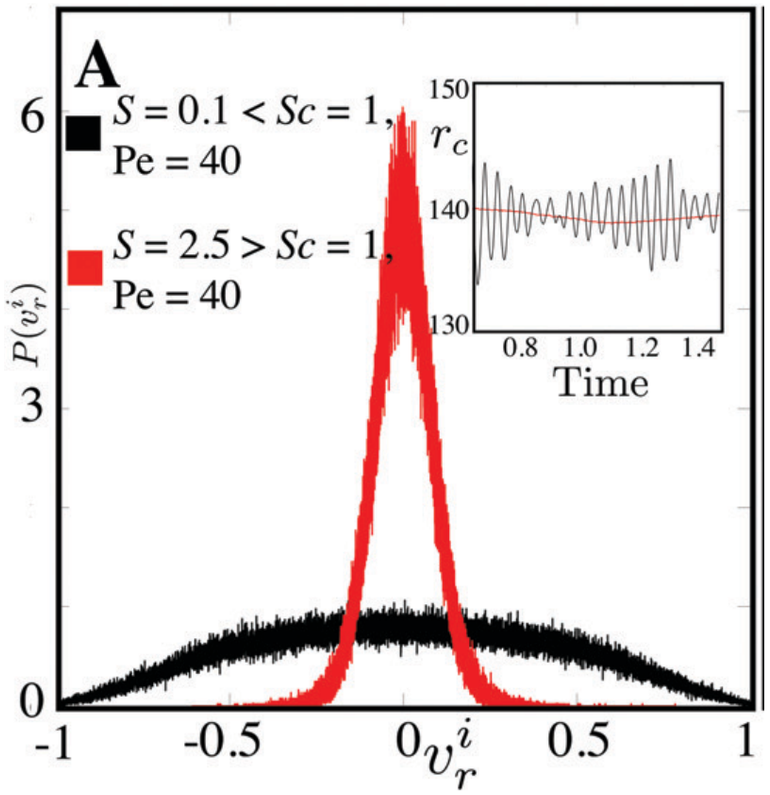
With trajectory of a typical particle

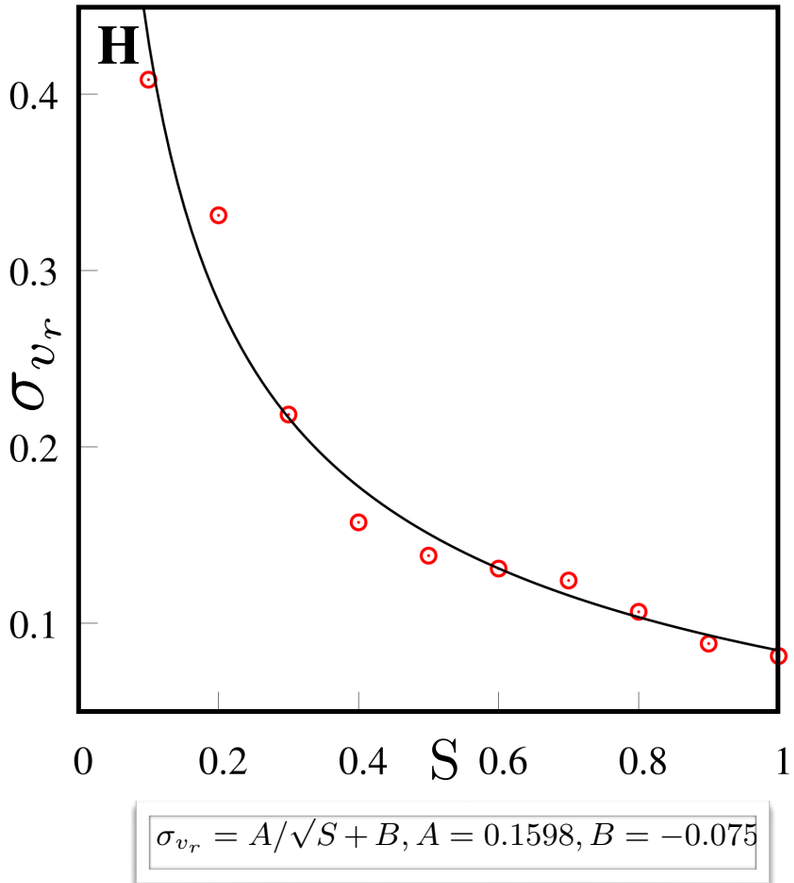
Rolling



How does rolling frequency scale with steepness of the trap?

Rolling With Soft Boundary





$\sigma_{v_r} = A/\sqrt{S} + B, A = 0.1598, B = -0.075$

$$e_r \propto I\omega_c^2 \qquad I \propto m_c l^2$$

$$e_r \propto m_c l^2 \omega_c^2$$

In large scale (cluster scale), f_0 — force / area

$$e_r \propto f_0 l^3$$

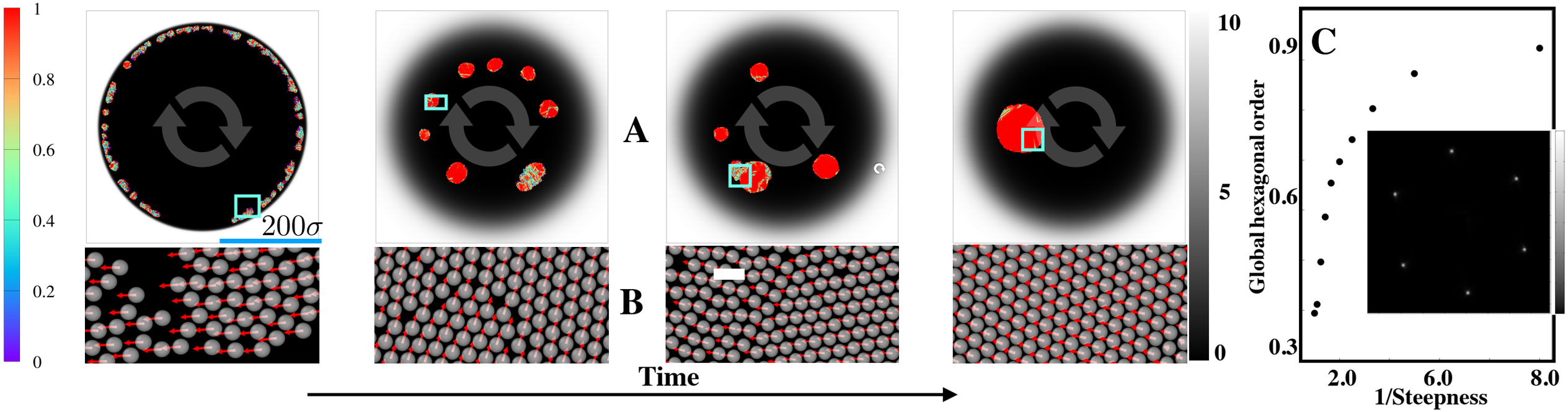
$$l \sim S^{-1}$$

$$\omega_c \propto f_0^{1/2} l^{1/2} \propto f_0^{1/2} S^{-1/2}$$

$$\omega_c \sim \sigma_{v_r}$$

$$\sigma_{v_r} \propto S^{-1/2}$$

Spatial Order
&
Wall softness



wall-
softness

Theory

IOP PUBLISHING JOURNAL OF PHYSICS A: MATHEMATICAL AND THEORETICAL

J. Phys. A: Math. Theor. **42** (2009) 445001 (31pp) doi:10.1088/1751-8113/42/44/445001

Hydrodynamic equations for self-propelled particles: microscopic derivation and stability analysis

Eric Bertin[1,2], **Michel Droz**[2] **and Guillaume Grégoire**[3]

$$\partial_t \mathbf{w} + \lambda(\mathbf{w}\cdot\nabla)\mathbf{w} = \nu\nabla^2\mathbf{w} - \frac{1}{2}\nabla(\rho - k|\mathbf{w}|^2) - (\nabla\cdot\mathbf{w})(\nu'\nabla\rho + k\mathbf{w}) + \left(\mu - \zeta|\mathbf{w}|^2\right)\mathbf{w} + \nu'\nabla\rho\cdot\left(\nabla\mathbf{w} + \nabla\mathbf{w}^T\right)$$

$$\mathbf{w} = \rho\mathbf{v}$$

Complemented with

Soft Matter

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Cite this: *Soft Matter*, 2019, 15, 8865

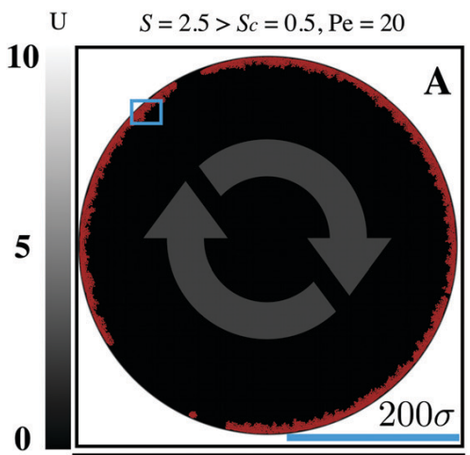
Tuning the self-organization of confined active particles by the steepness of the trap†

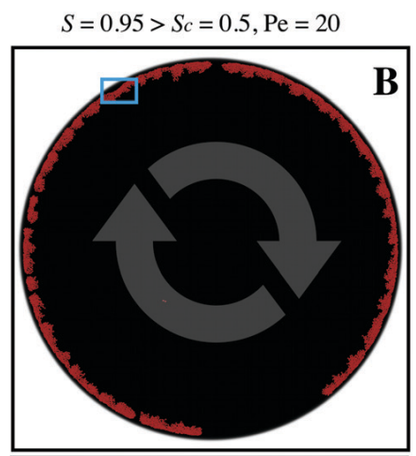
Shubhashis Rana,‡[a] Md. Samsuzzaman‡[b] and Arnab Saha *[b]

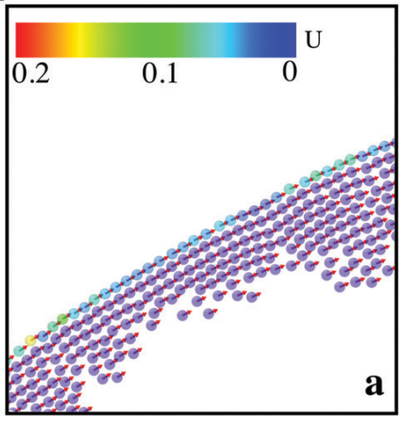
$$\partial_t \rho(\mathbf{r},t) + \nabla\cdot\mathbf{w} = -\nabla\cdot(\mathbf{J}_{\text{diffusion}} + \mathbf{J}_{\text{drift}} + \mathbf{J}_{\text{WCA}})$$

Theory

Ripple formation

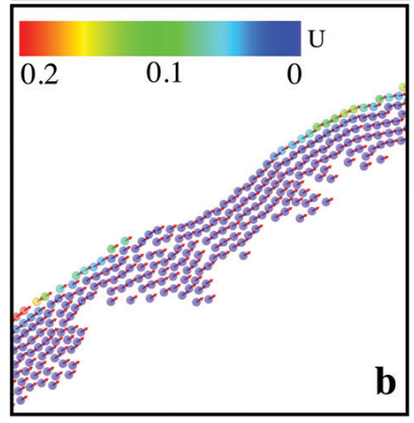






$$\mathbf{w} = \sqrt{\mu/\zeta}\hat{\theta} = \mathbf{w}_0$$
$$w_r = \mathbf{w}.\hat{\mathbf{r}} = 0$$

Linear perturbation



$$\mathbf{w} = \mathbf{w}_0 + \delta\mathbf{w}(\mathbf{r},t)$$
$$\delta\mathbf{w} = \delta w_r\hat{\mathbf{r}} + \delta w_\theta\hat{\theta}$$
$$\delta w_{\theta,r} \simeq \exp(st + i\mathbf{k}.\mathbf{r})$$

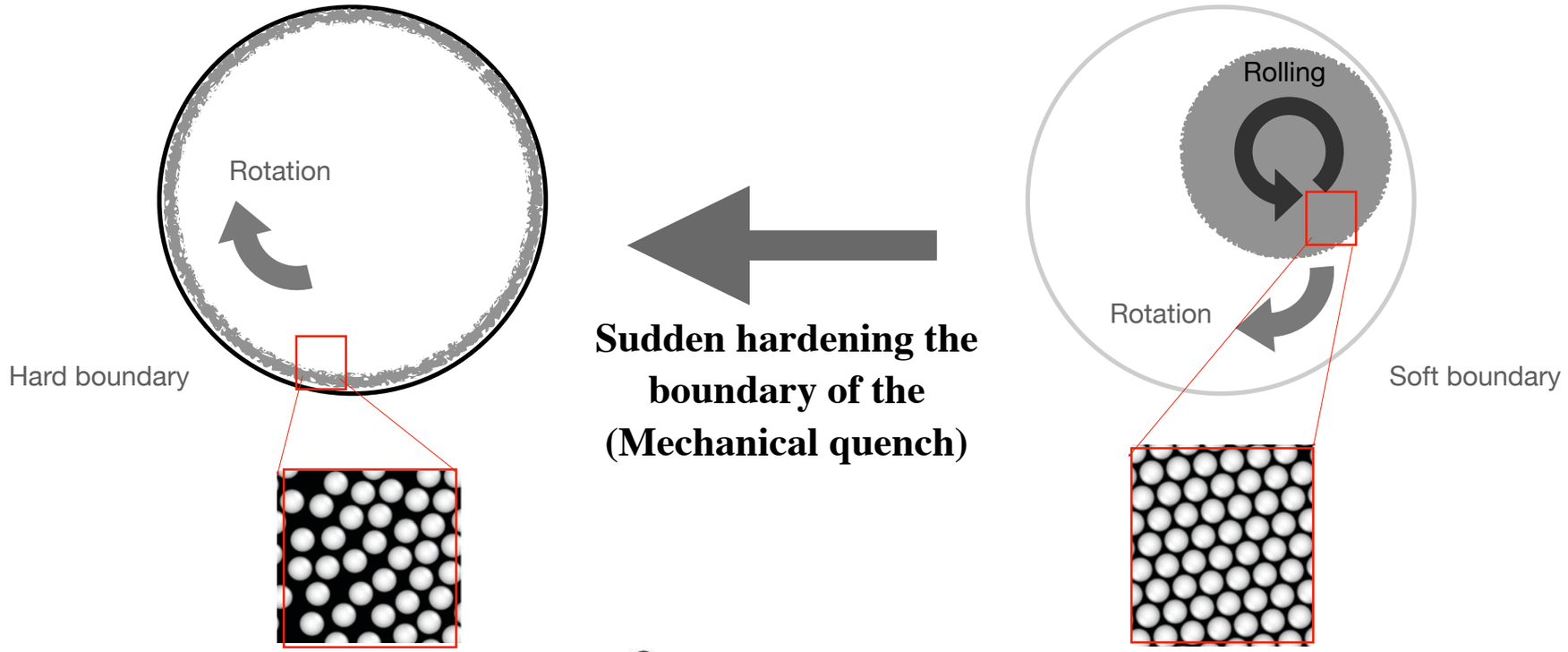
$$s > 0$$
$$\therefore (\delta w_r, \delta w_\theta) > 0 \quad \text{For} \quad S < S_c$$

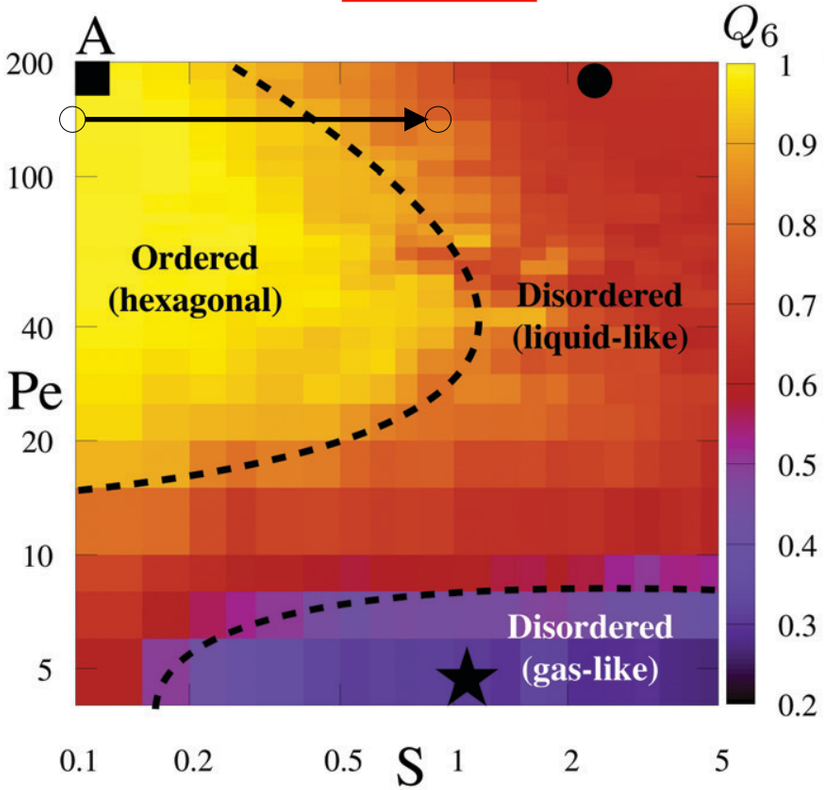
How Does The Flock Respond To A Sudden Change?

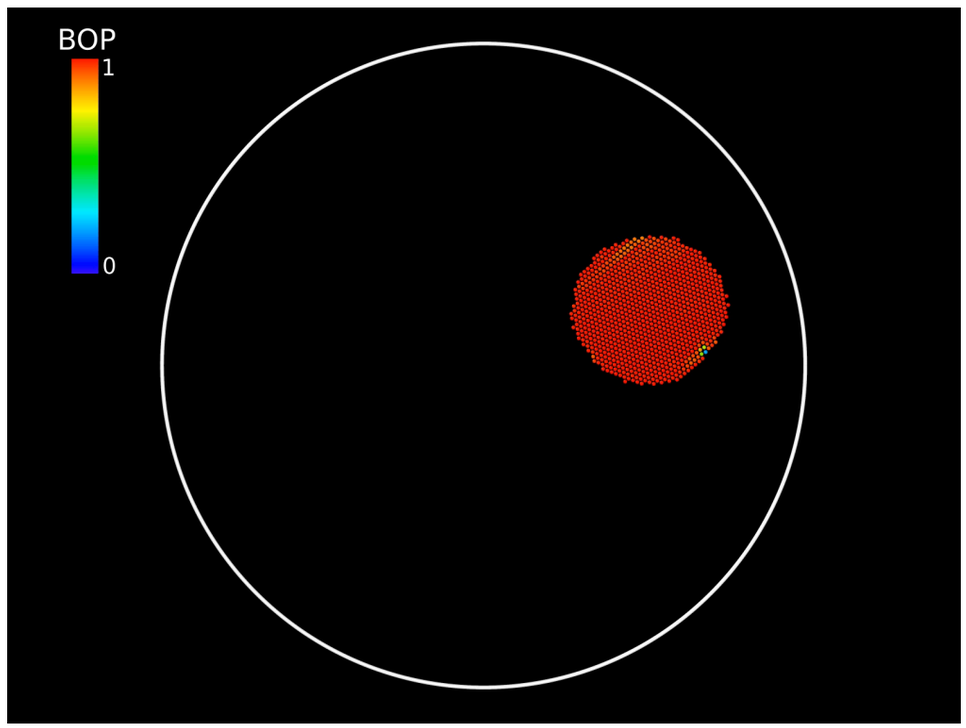
….. Flow Of Information

WWW.DAVIDPALFREY.COM

Mechanical Response To Quench

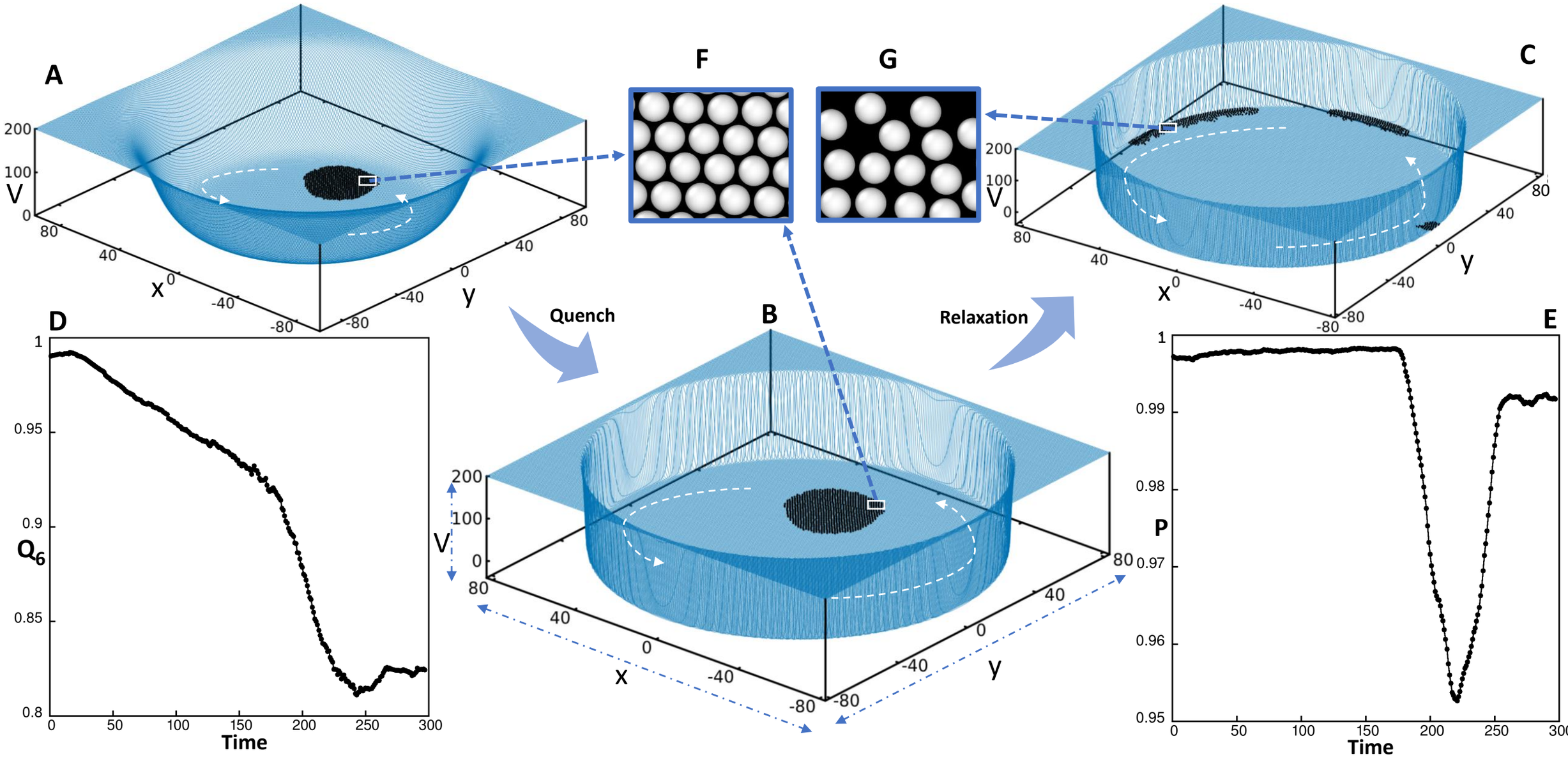






Quenching S from 0.1 tp 1.0

Mechanical Response To Quench



Questions we ask …

* **How are the flocking particles informed about the quench? ….Quantification of the information?**

* **Information flow (from the boundary to the bulk) time and length scales ?**

* **Comparison between time scales of information-flow and structural relaxation ?**

Information

X ⟶ Random variable with outcomes $\{\mathbf{x_i}\}$

i runs from 1 to N (number of possible outcomes)

P(x) ⟶ Probability of getting **x** as outcome

Less (more) probable event is more (less) informative

Information ⟶ $\mathcal{I} = \log_2 \frac{1}{\mathbf{P}}$

Average information content ⟶ $\langle \mathcal{I} \rangle = -\sum \mathbf{P} \log_2 \mathbf{P}$

Entropy

Mutual Information (I)

X,Y ⟶ Two random variable with outcomes {**x,y**}

How much **X** (**Y**) is known to **Y** (**X**)? ⟶ Difference between **P(x,y)** and **P(x)P(y)**

$$I = D_{KL} = \sum P(x,y) \log_2 \frac{P(x,y)}{P(x)P(y)}$$

Relative Entropy

*** Amount of X known to Y = Amount of Y known to X**

Information Flow

*** Amount of X known to Y = Amount of Y known to X**

(When information flows from X to Y or Y to X)

X & Y are two random time series. The **information flows** from Y to X :

$$TE_{Y\to X} = \sum P(x(t+1), x(t), y(t)) \log_2 \frac{P(x(t+1)|x(t), y(t))}{P(x(t+1)|x(t))}$$

VOLUME 85, NUMBER 2 PHYSICAL REVIEW LETTERS 10 JULY 2000

Measuring Information Transfer

Thomas Schreiber

Max Planck Institute for the Physics of Complex Systems, Nöthnitzer Strasse 38, 01187 Dresden, Germany

(Received 19 January 2000)

Information Flow

$$TE_{Y\to X} = \sum P(x(t+1), x(t), y(t)) \log_2 \frac{P(x(t+1)|x(t), y(t))}{P(x(t+1)|x(t))}$$

E.g. : {x(t)},{y(t)} are dynamical variables of two interacting active particles

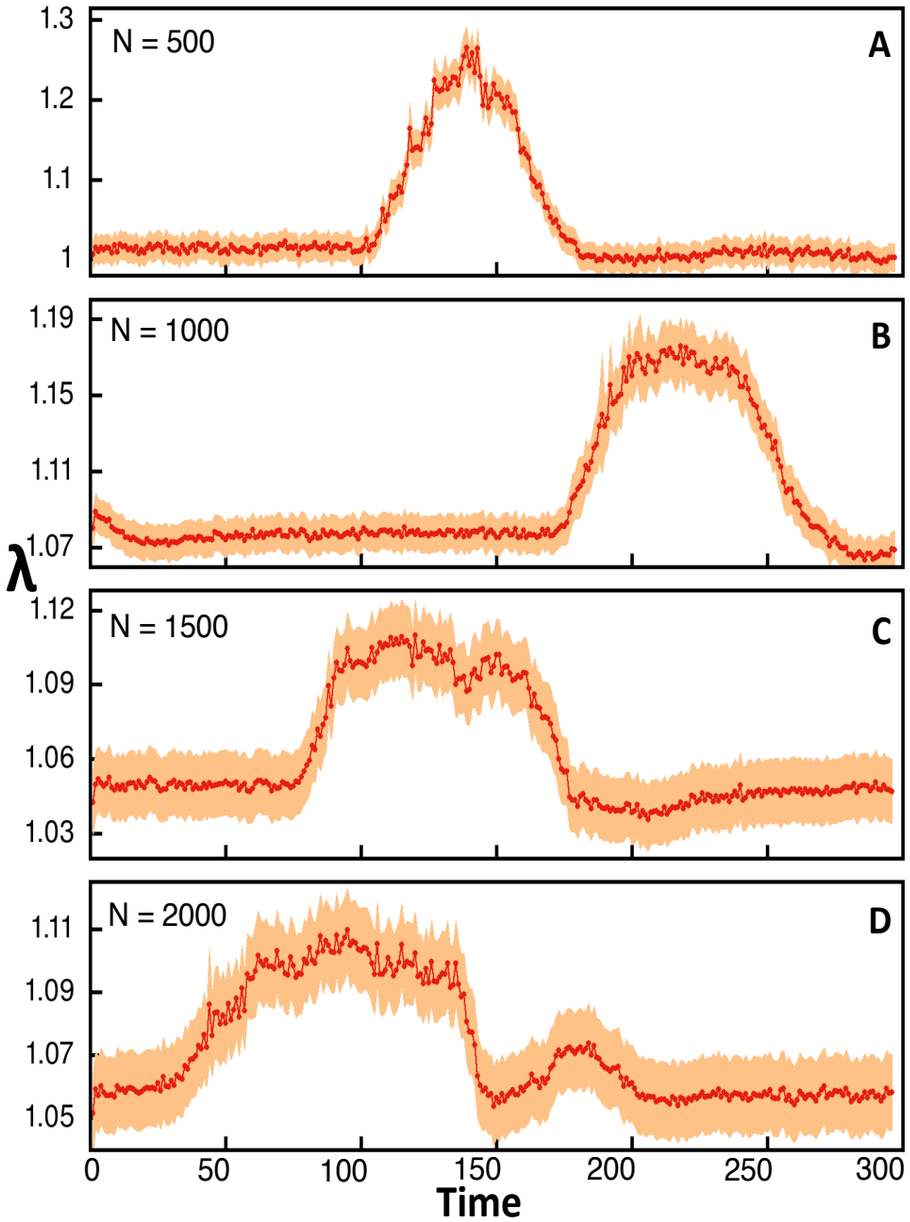
$TE_{Y\to X}$: Information flow from Y to X. Not same as X to Y

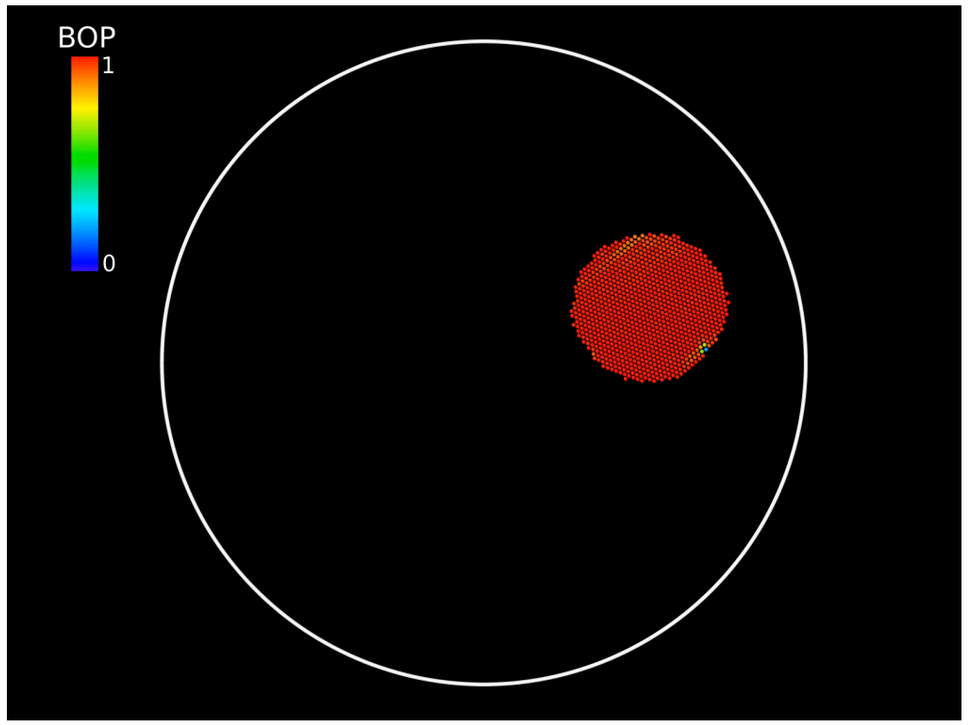
VOLUME 85, NUMBER 2 PHYSICAL REVIEW LETTERS 10 JULY 2000

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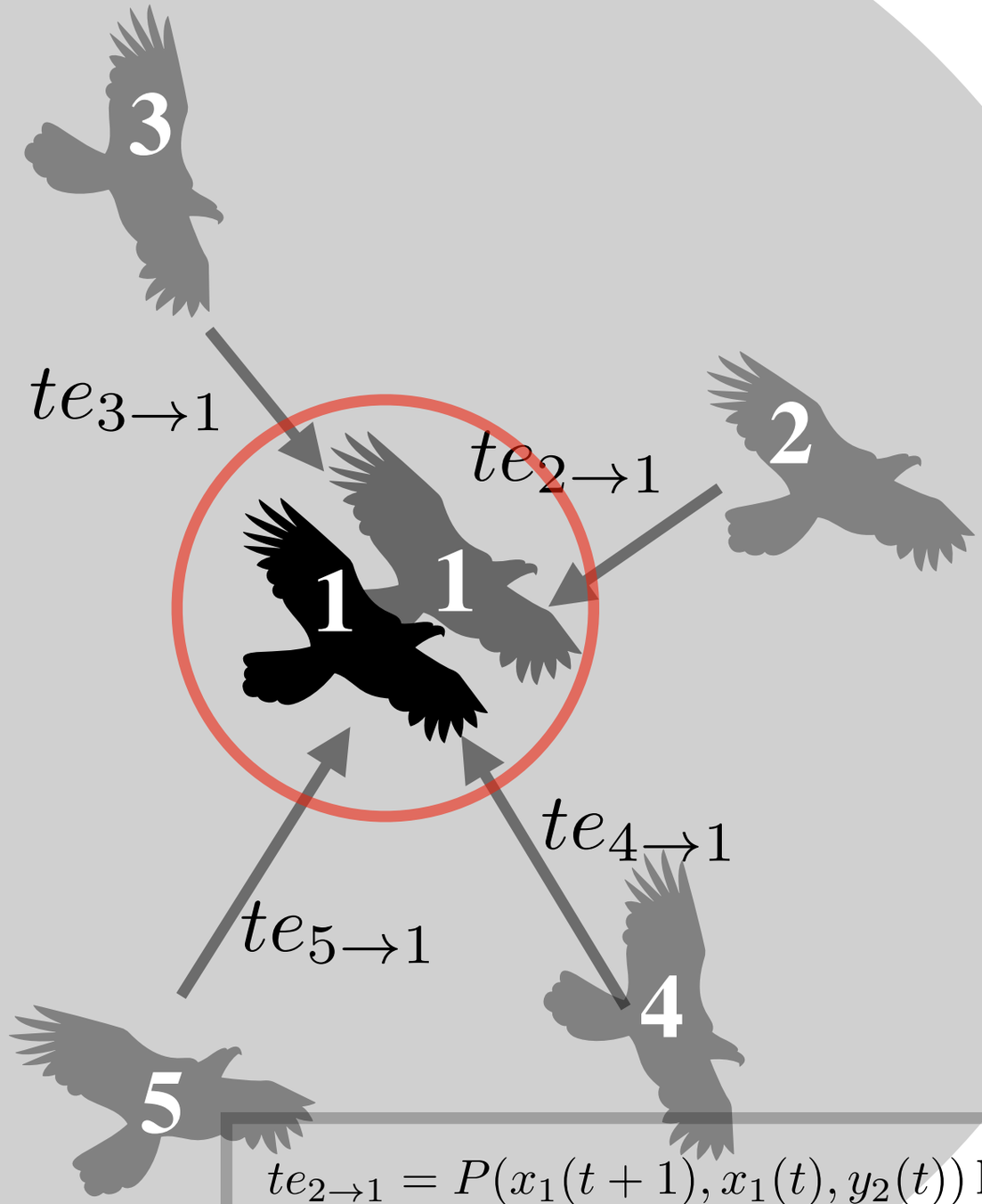
Computing Global Information Transfer

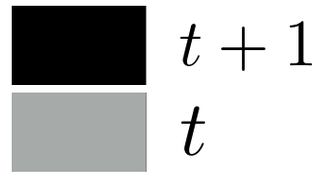




$$TE_{Y\to X} = \sum P(x(t+1), x(t), y(t)) \log_2 \frac{P(x(t+1)|x(t), y(t))}{P(x(t+1)|x(t))}$$

Local Information Flow

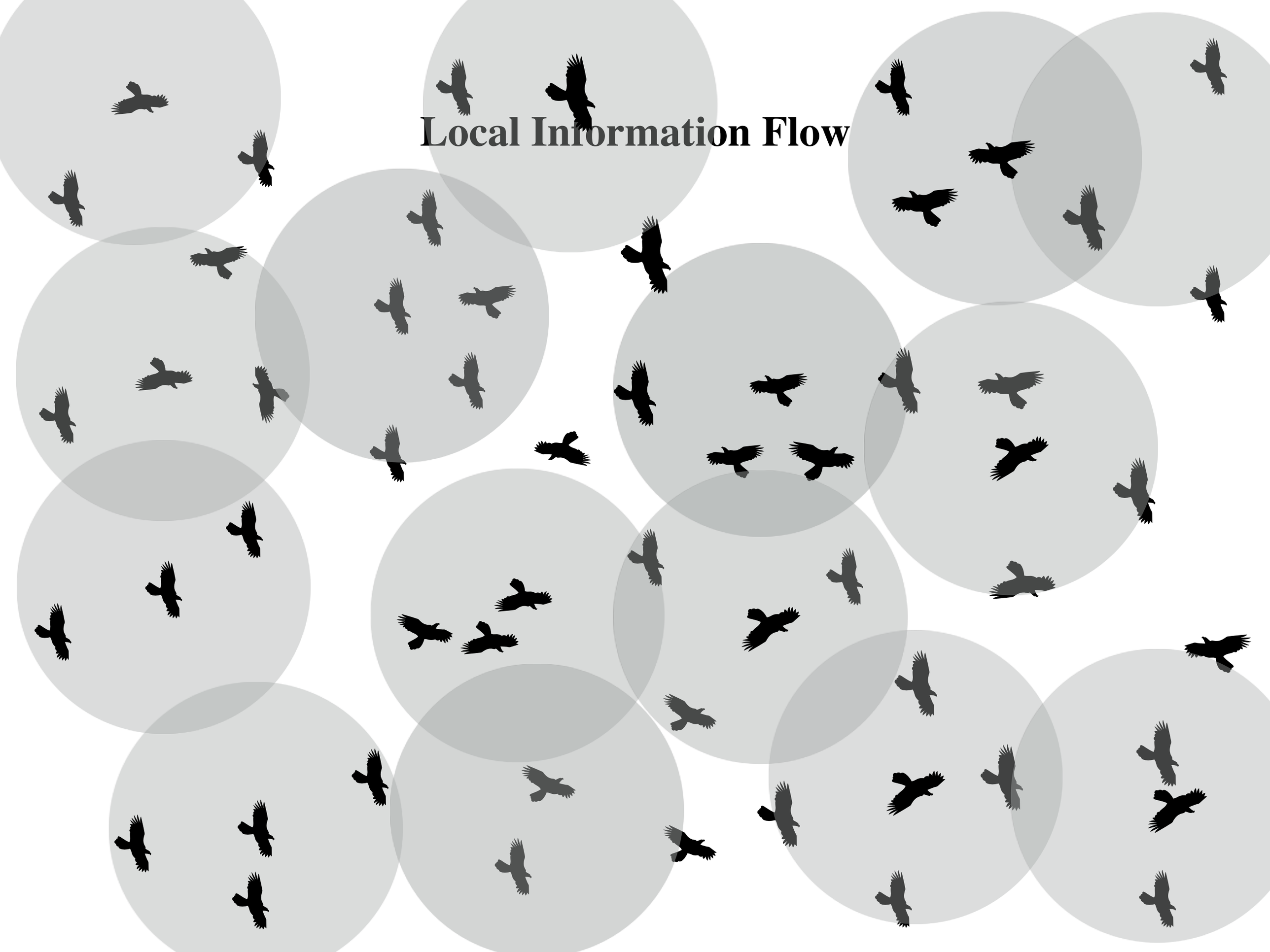




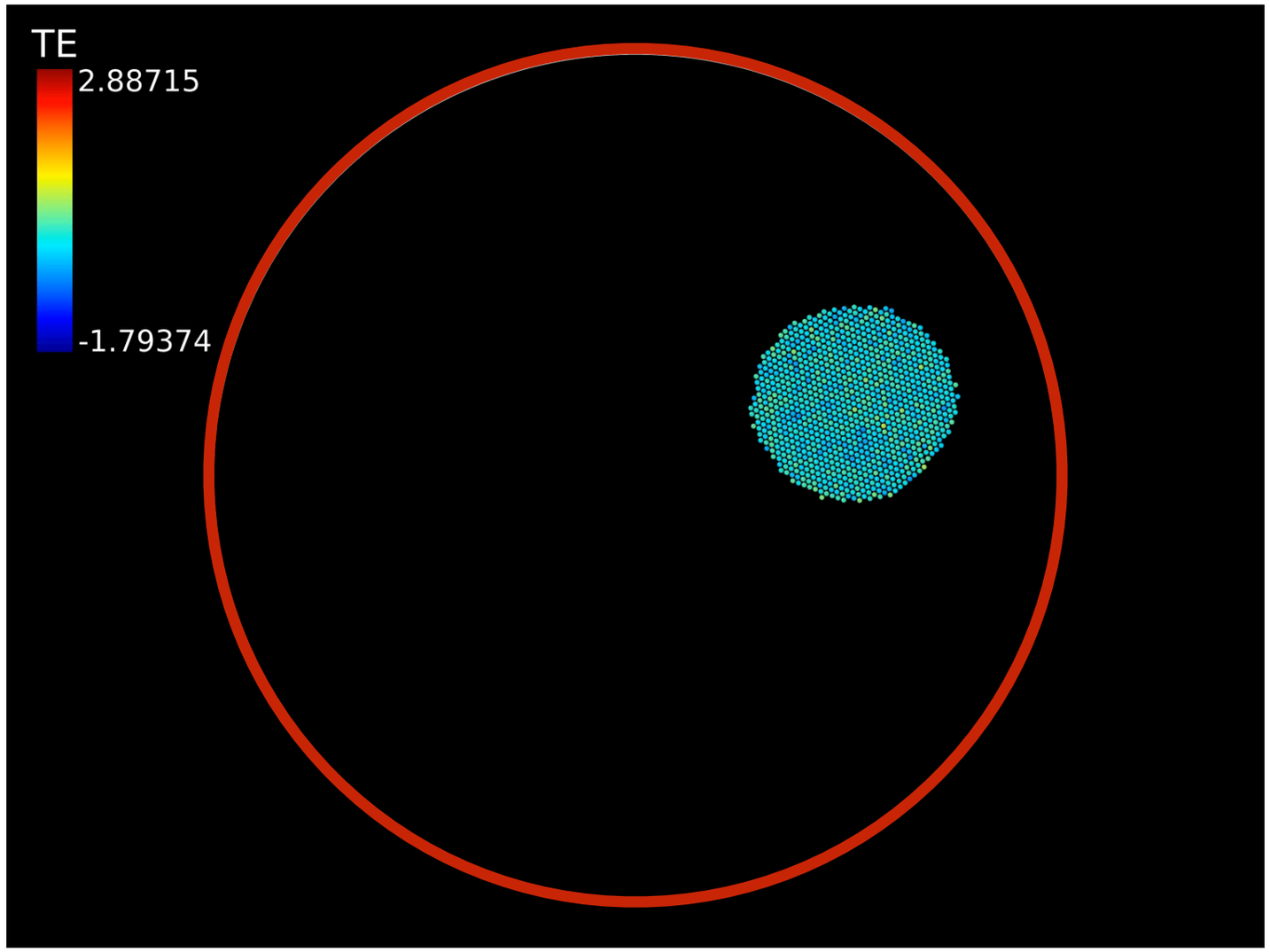
$$te_{2\to1} = P(x_1(t+1), x_1(t), y_2(t)) \log_2 \frac{P(x_1(t+1)|x_1(t), y_2(t))}{P(x_1(t+1)|x_1(t))}$$

$$te_1 = \frac{1}{4}(te_{2\to1} + te_{3\to1} + te_{4\to1} + te_{5\to1})$$

Local Information Flow



Computing Local Information Transfer

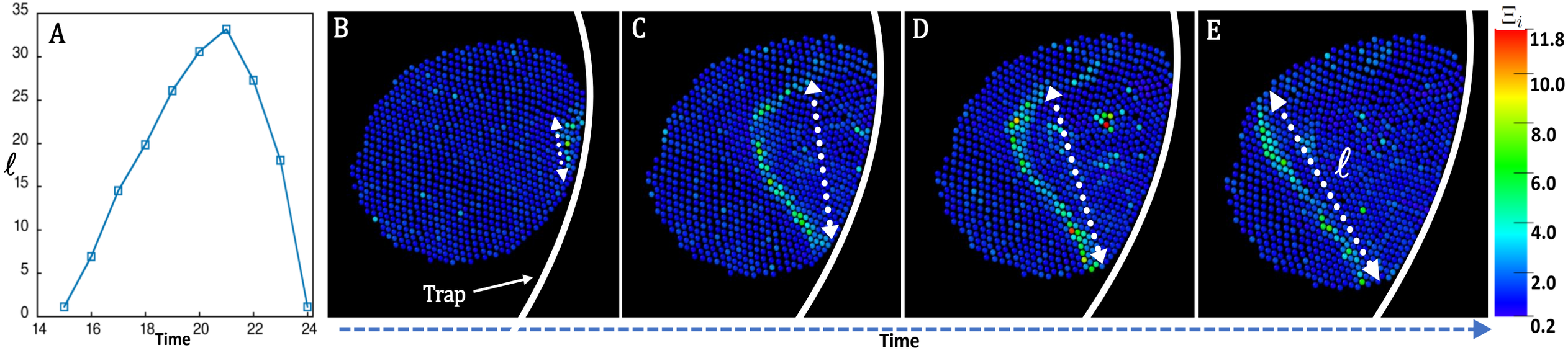


$$te_{j\to i} = P(x_i(t+1), x_i(t), y_j(t)) \log_2 \frac{P(x_i(t+1)|x_i(t), y_j(t))}{P(x_i(t+1)|x_i(t))}$$

$$te_i = \sum_j te_{j\to i}$$

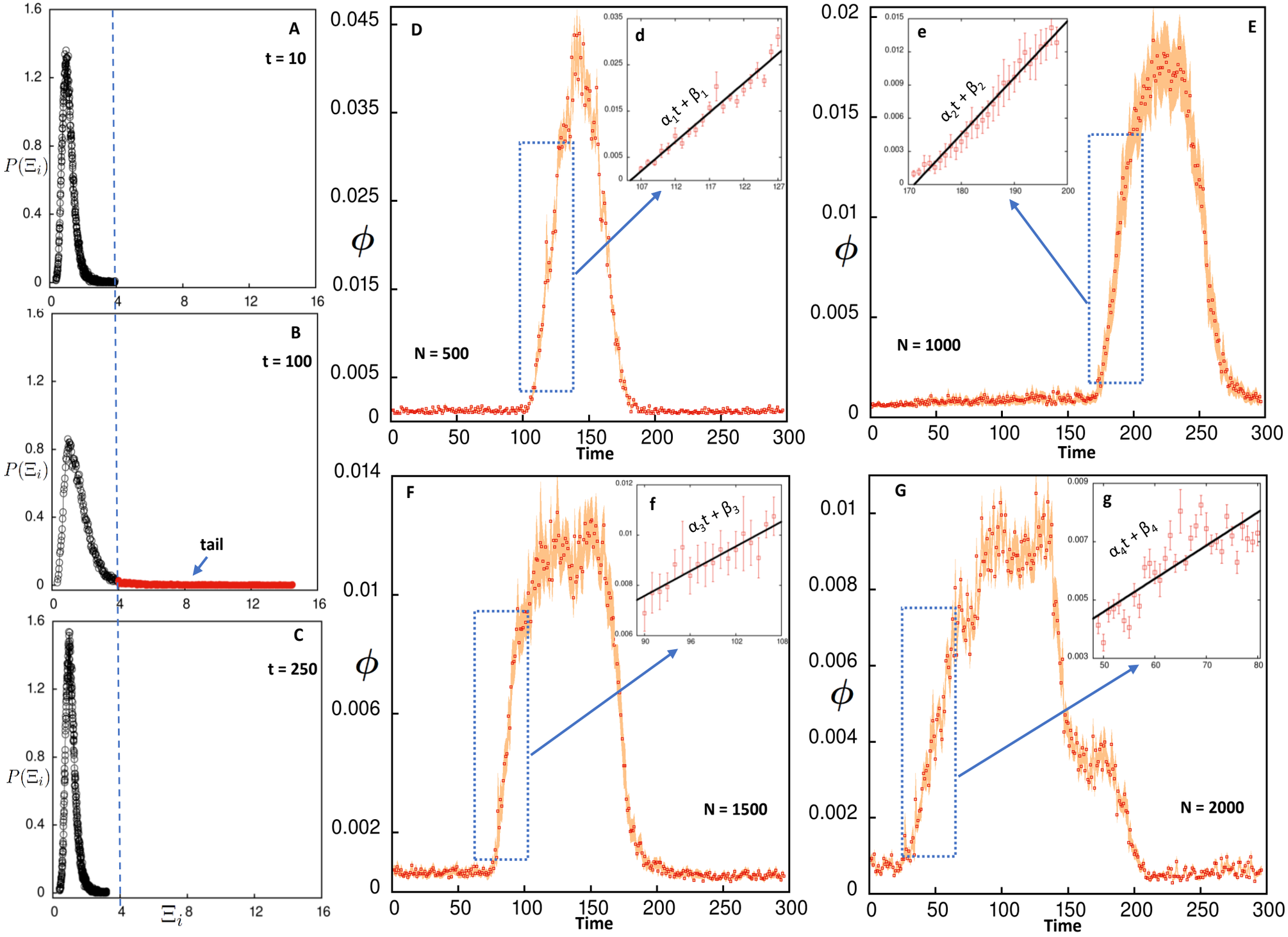
Computing Local Information Transfer

Information flow length scales

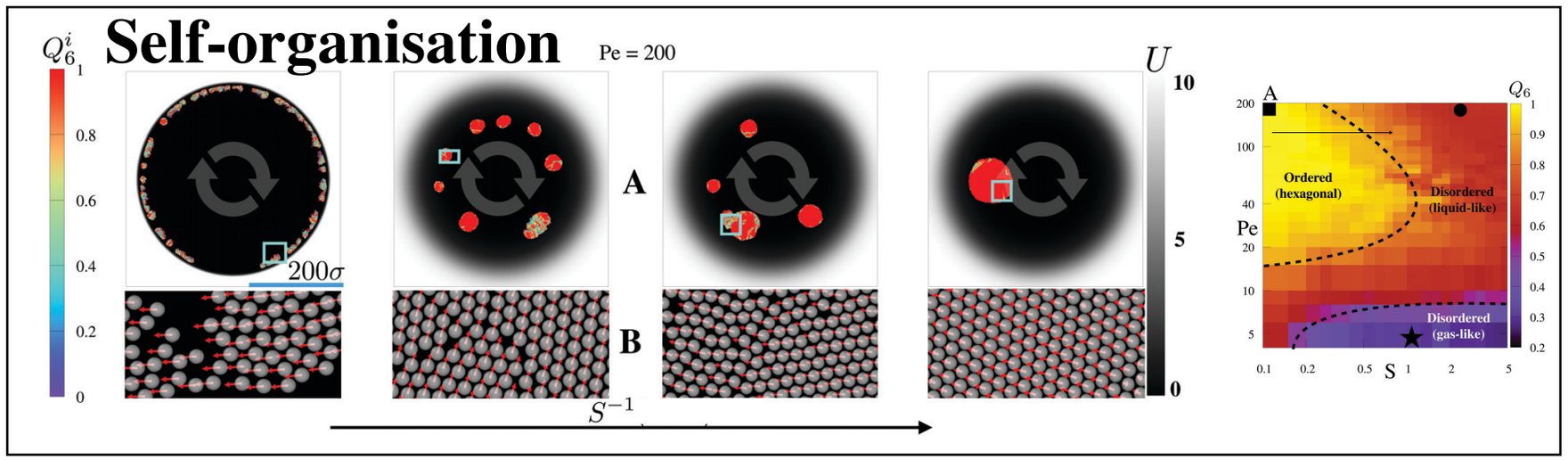


Computing Local Information Transfer

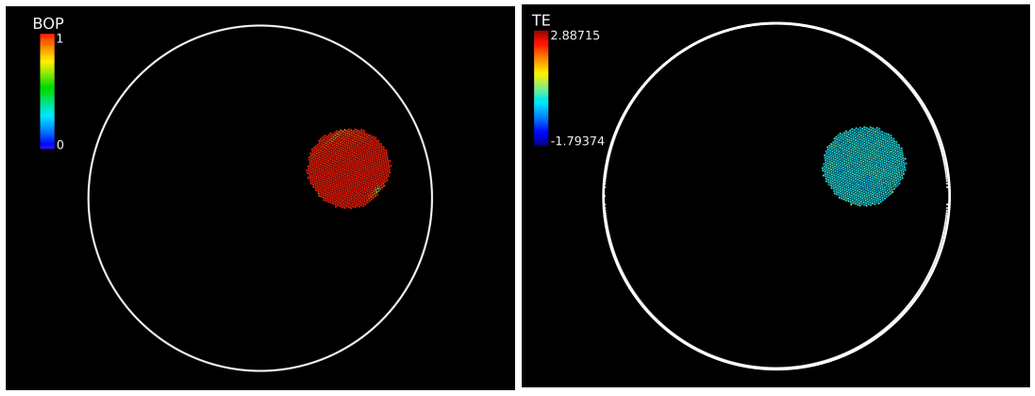
Ballistic flow of information



Summary



Information flow



Flow of information is quantified by per-particle transfer entropy (TE).

Length scale of the flow ~ flock-size.

Information flow is much faster than Structural relaxation.

Information flow is ballistic.

Thank You


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