



Northeastern University

How to move faster together than alone?

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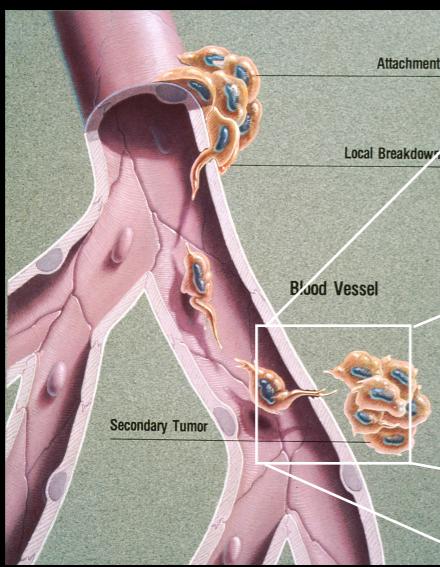
University of Bergen



White blood cells in wound healing



Metastatic cancer



Our focus: The living cell as a moving evolving material

What are we motivated by?

Immune system response, cancer metastasis, embryogenesis

What drives us scientifically?

Governing laws at small scales
Time and spatial dependence
Plasticity/deformability
Higher order structures

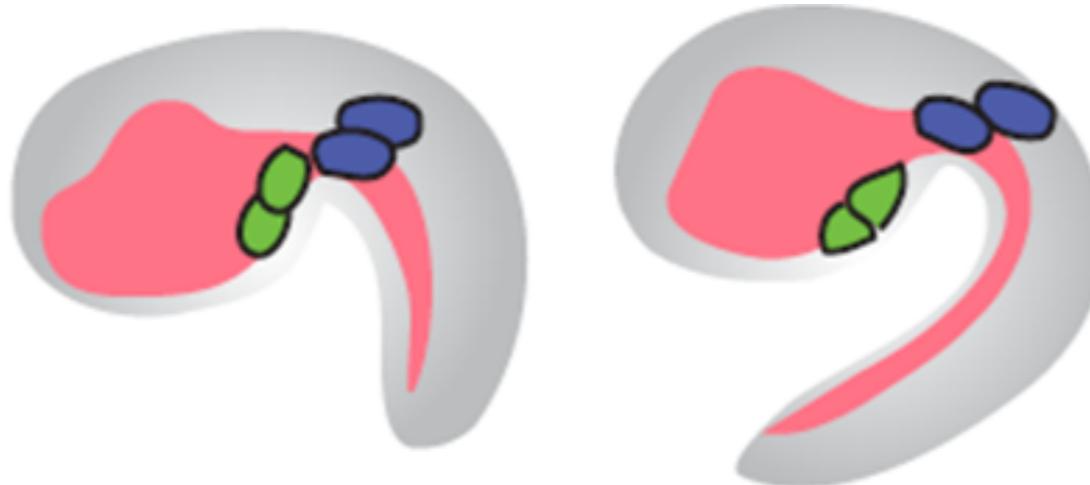
Ciona intestinalis

- Invertebrate chordate model organism in developmental biology and genomics.
- Closest invertebrate relatives of vertebrates.
- Very small genome size, less than 1/20 of the human genome.

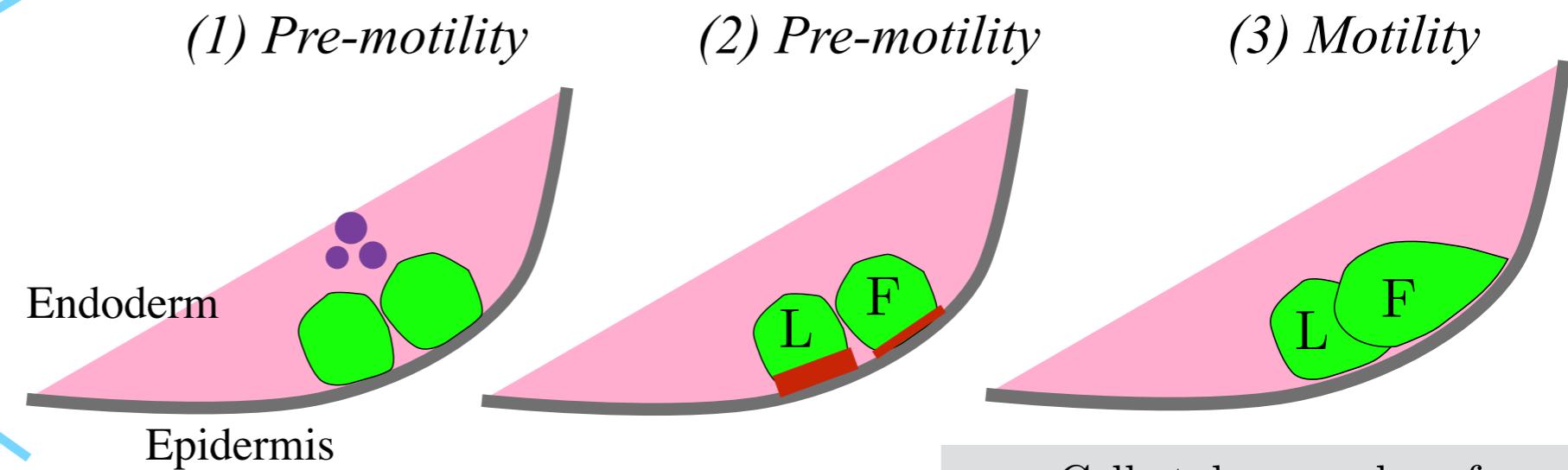
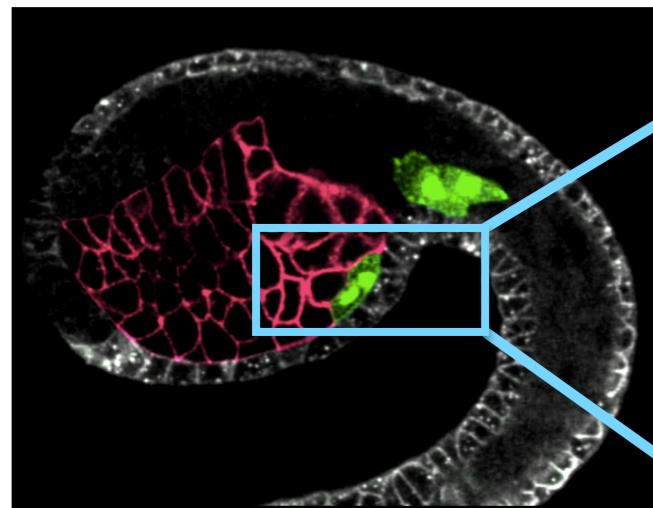
Experimental collaborators: Lionel Christiaen (Univ of Bergen), Yelena Bernadskaya (NYU)



Migration of the trunk ventral cell (TVC) pair: one of the simplest cases of collective cell migration

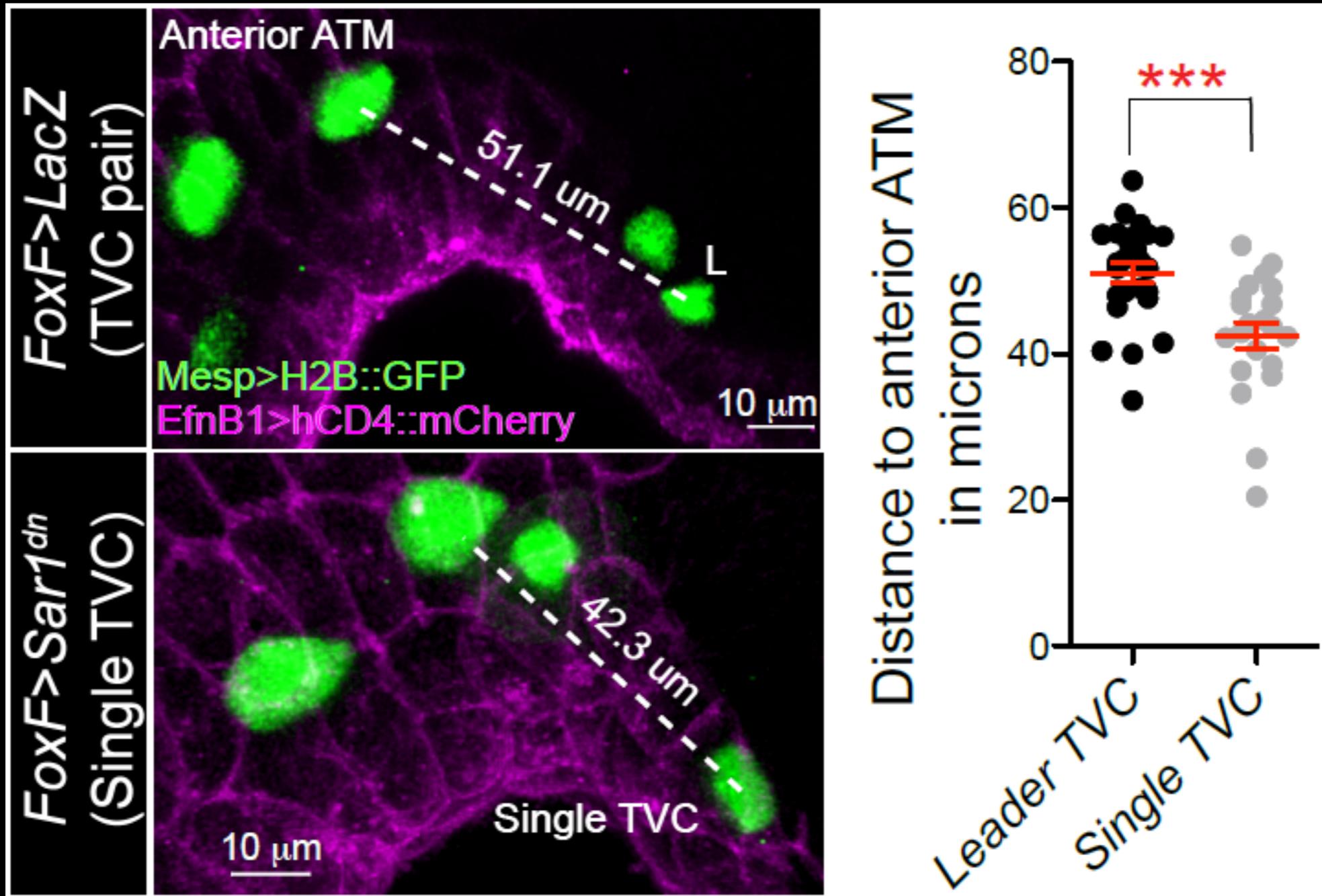


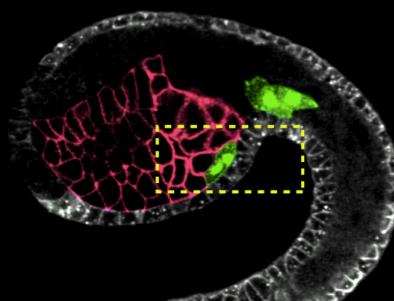
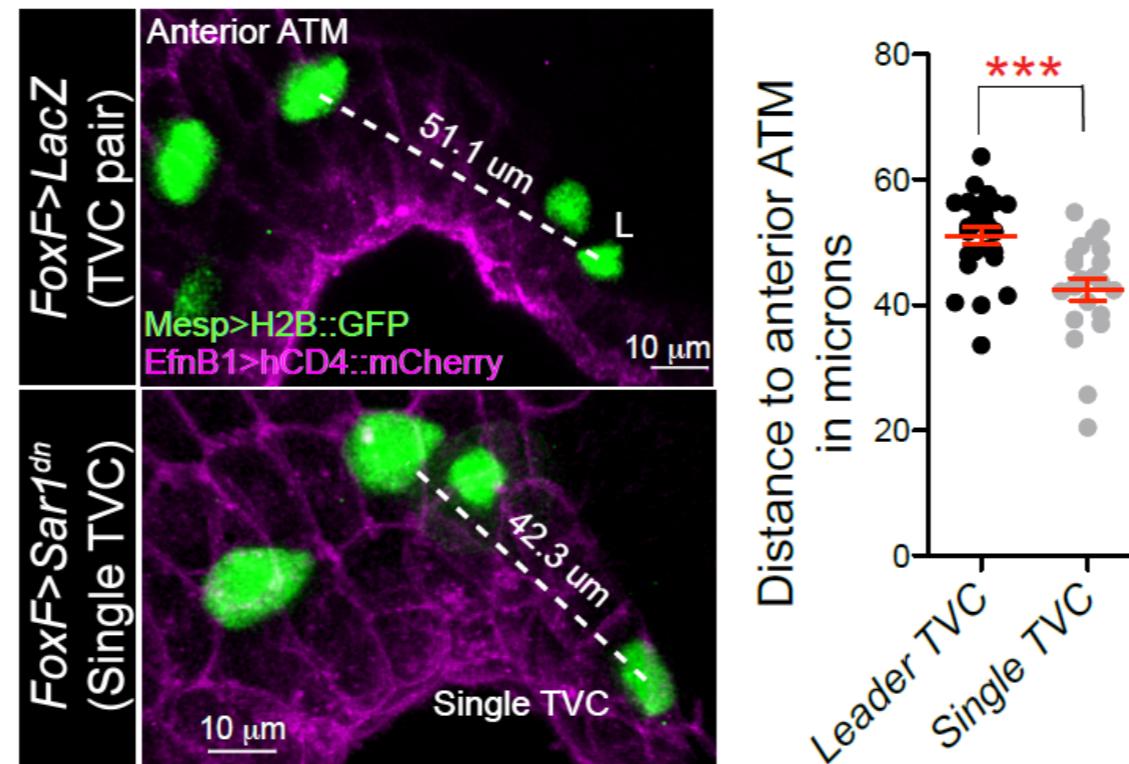
Ciona intestinalis embryo



Cells take on roles of
LEADER & FOLLOWER

Speed of one vs two cells (experiments):





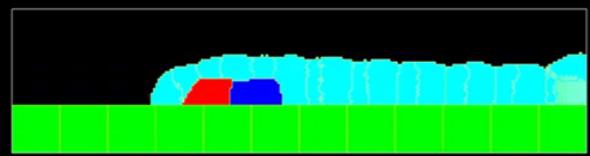
Moving as a pair is “better” than alone

Hypothesis #1: There is a *mechanical* advantage to move as a two-cell system

Hypothesis #2: It is easier to *initiate* locomotion as a pair.

On the mechanical advantage of a pair:

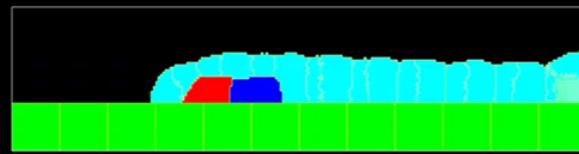
Mechanical (Cellular Potts) model



Y. Bernadskaya, H. Yue, C. Copos, L. Christiaen, A. Mogilner. eLife (2021)

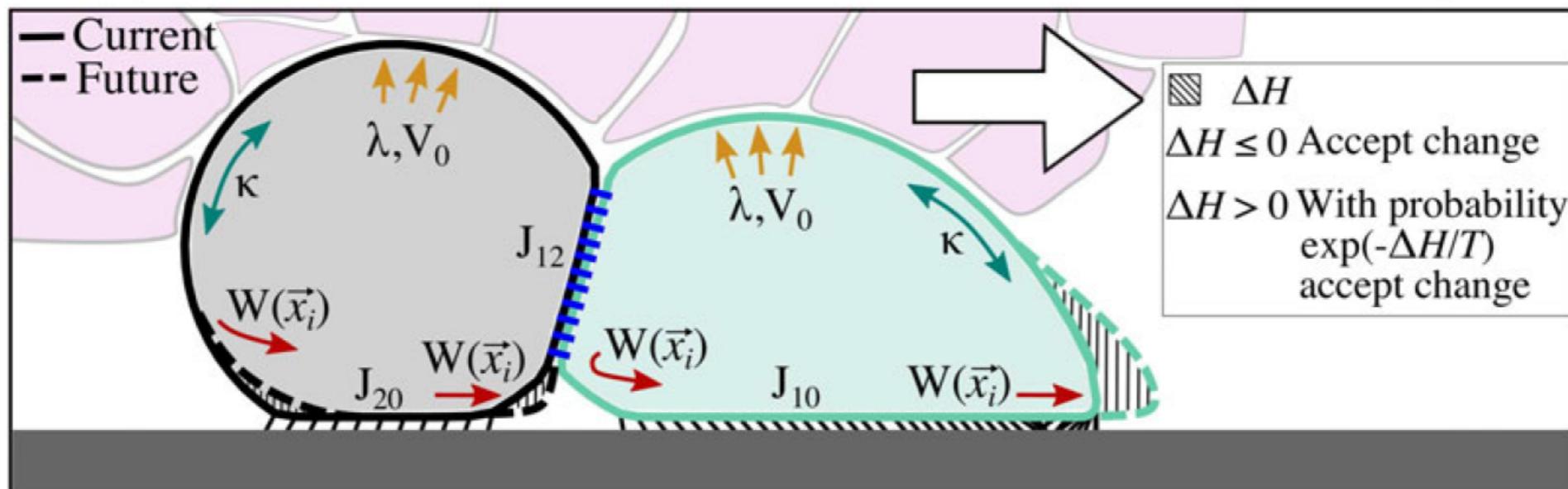
On the mechanical advantage of a pair:

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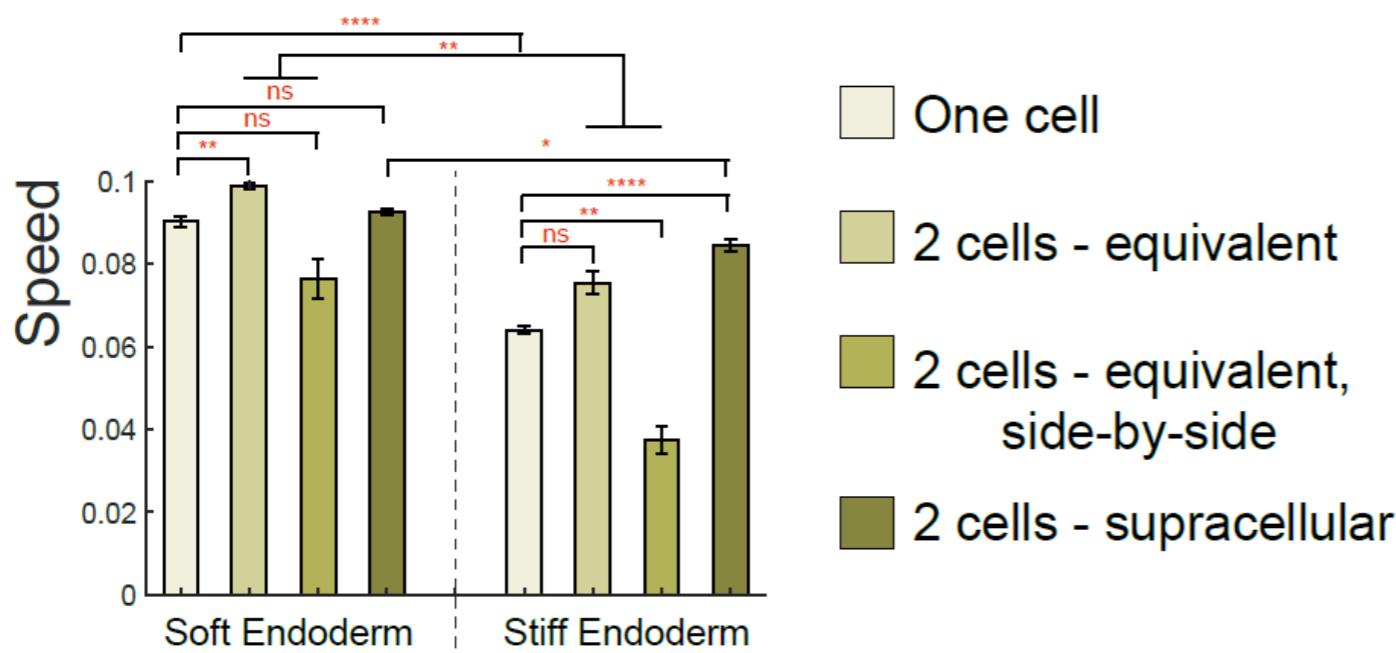
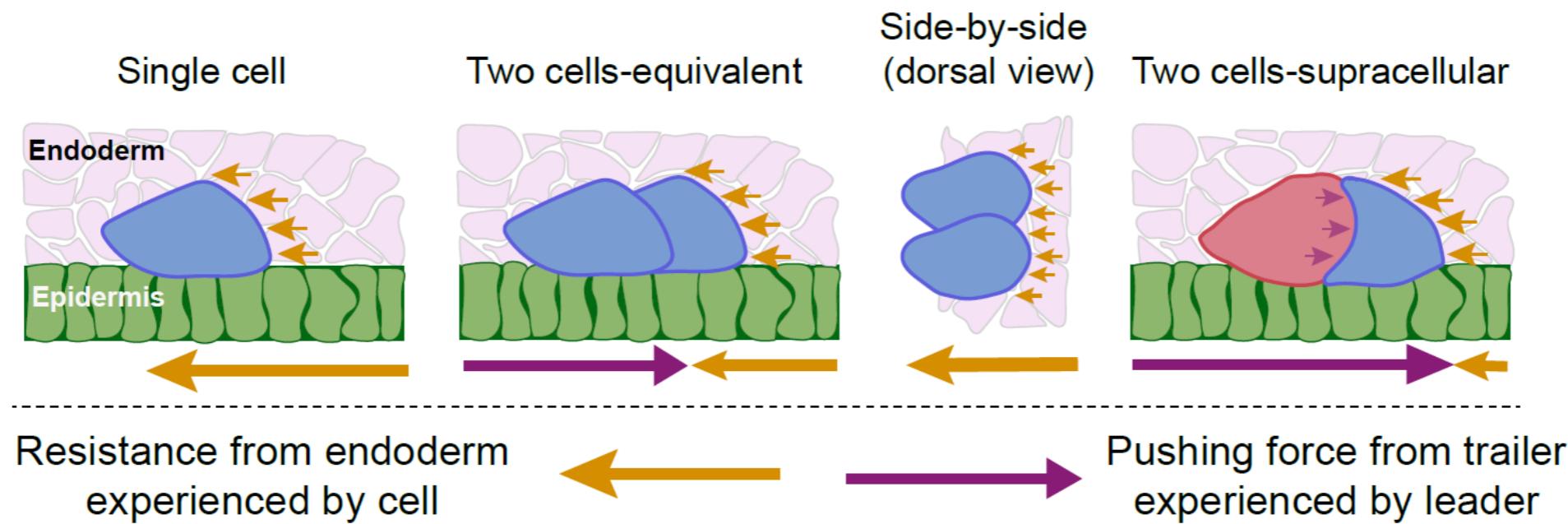
Y. Bernadskaya, H. Yue, C. Copos, L. Christiaen, A. Mogilner. eLife (2021)

$$H = \kappa(a_1^2 + a_2^2) + \lambda((v_1 - v_0)^2 + (v_2 - v_0)^2) + J_{12}a_{12} + J_{10}a_{10} + J_{20}a_{20} + W(\vec{x}_i)$$



On the mechanical advantage of a pair:

Mechanical (Cellular Potts) model

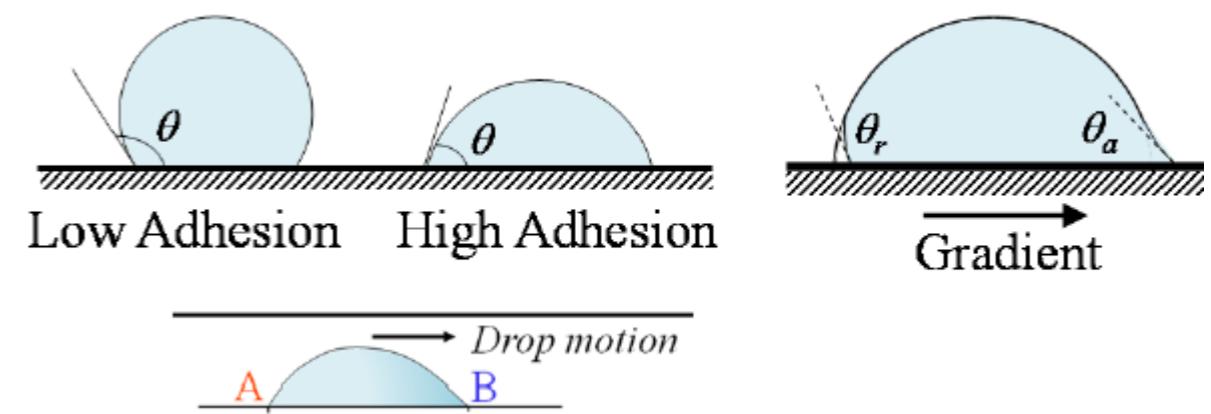


On the mechanical advantage of a pair:

Active Drop model

Generation of Motion of Drops with Interfacial Contact

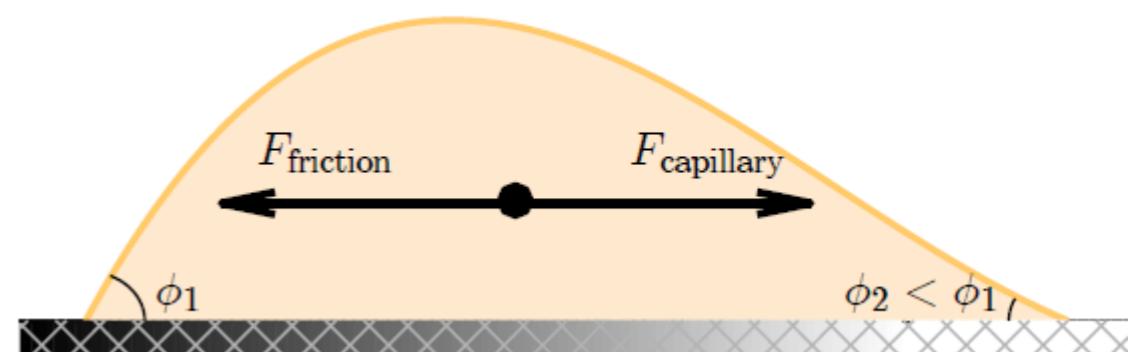
Manoj K. Chaudhury,^{*†} Aditi Chakrabarti,[†] and Susan Daniel[‡]



How many ways a cell can move: the modes of self-propulsion of an active drop

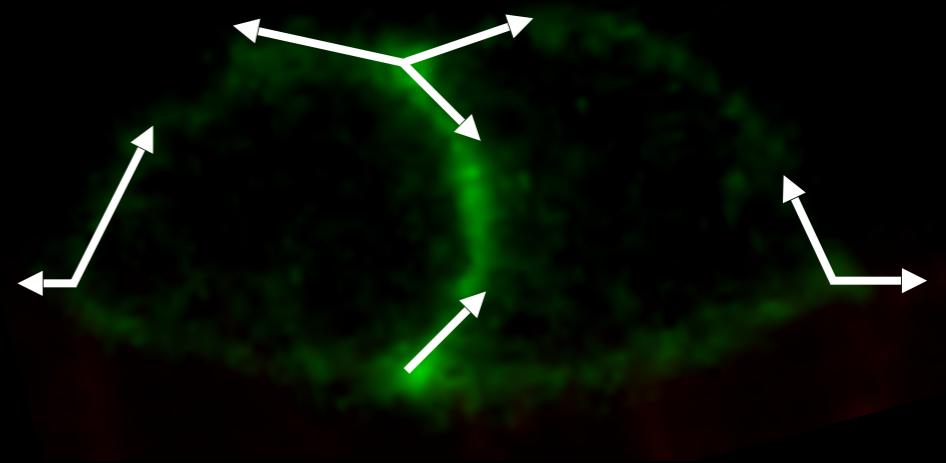
Aurore Loisy, ^{*a} Jens Eggers ^a and Tanniemola B. Liverpool ^{*a}

sliding driven by capillarity



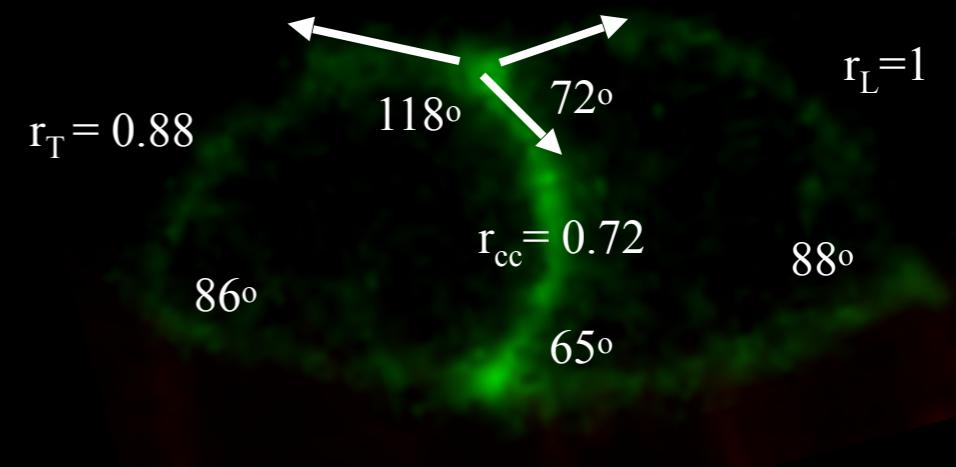
On the mechanical advantage of a pair:

Active Drop model



On the mechanical advantage of a pair:

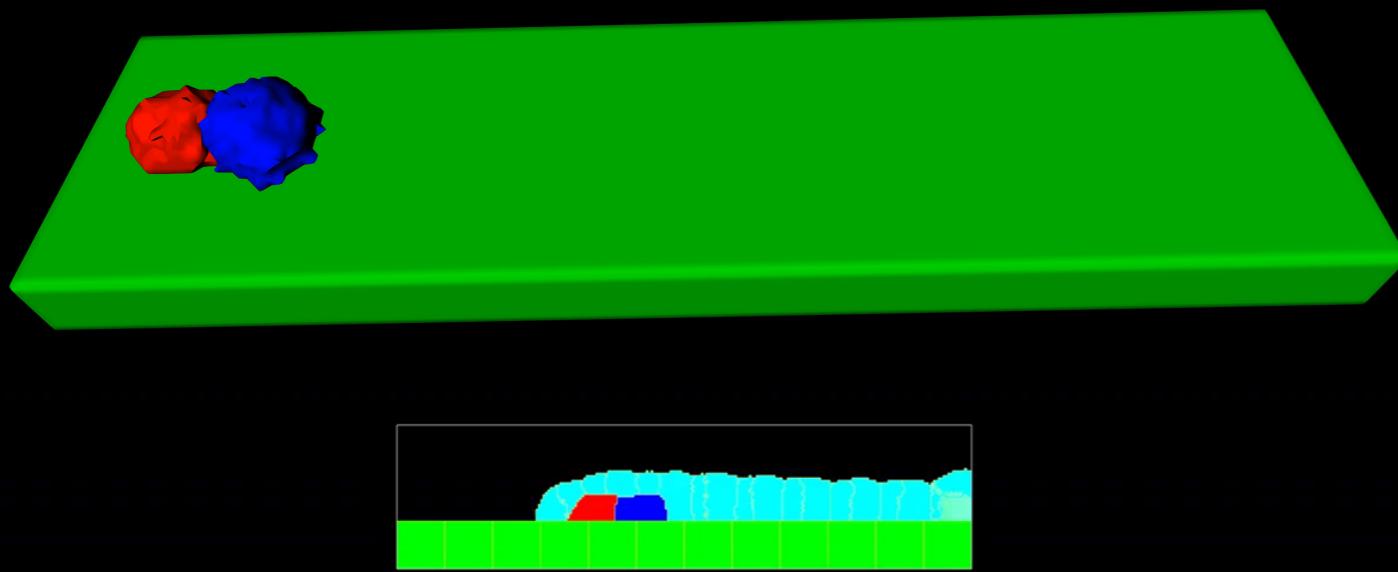
Active Drop model



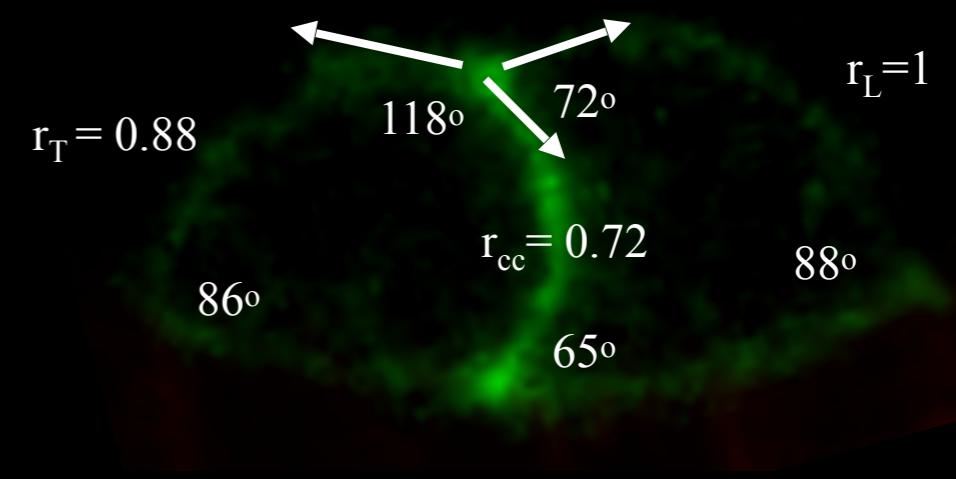
Morphological Measurements
to Forces to Velocities

On the mechanical advantage of a pair:

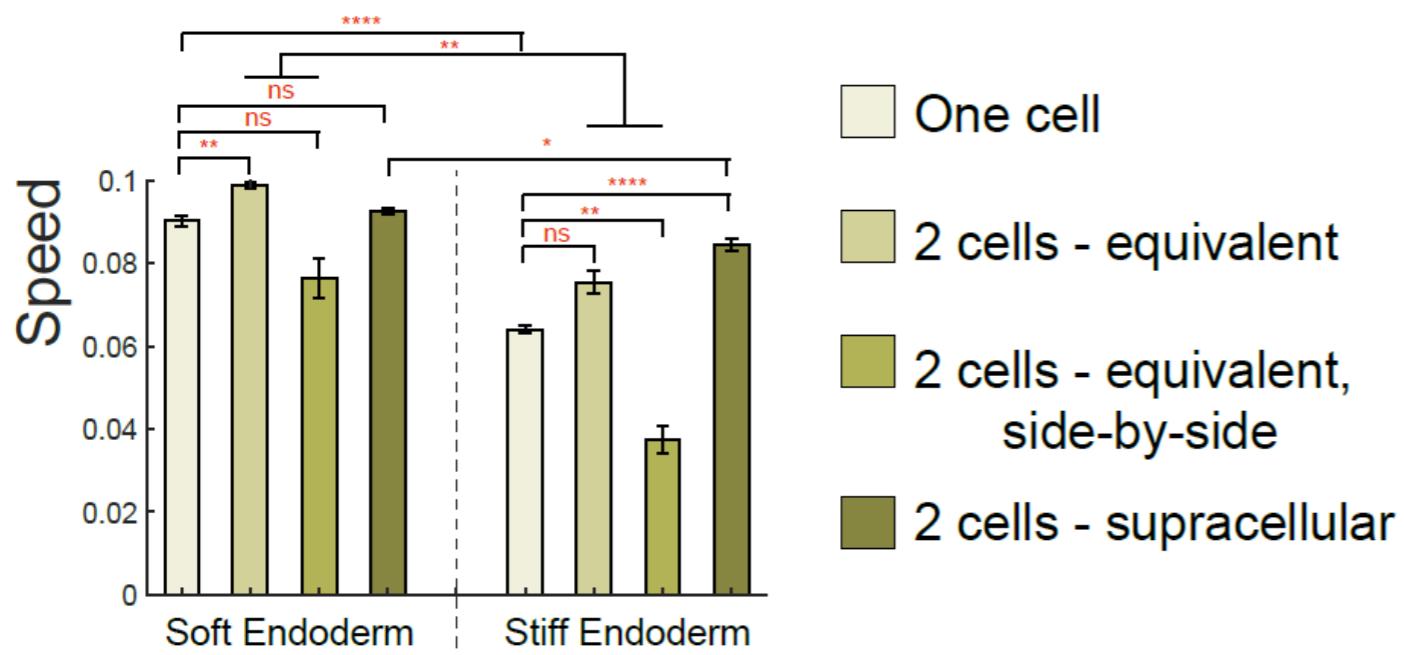
Mechanical (Cellular Potts) model



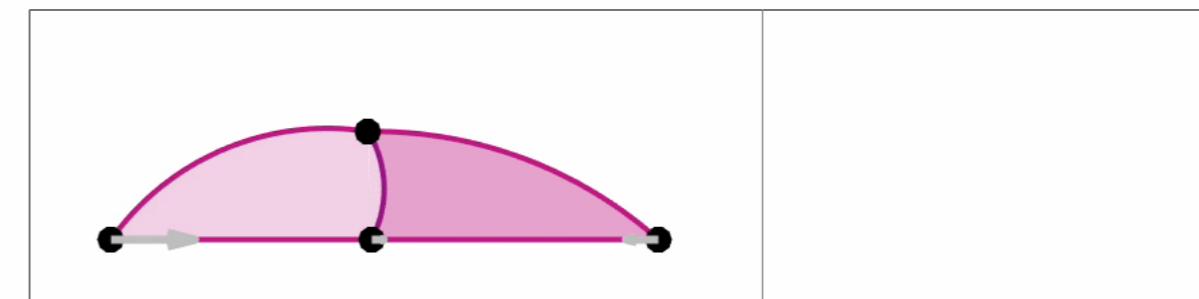
Active Drop model

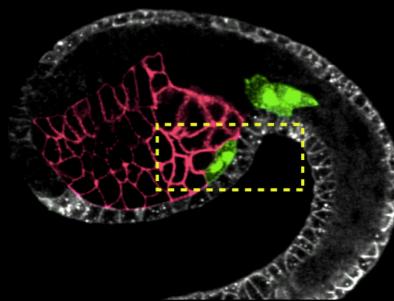
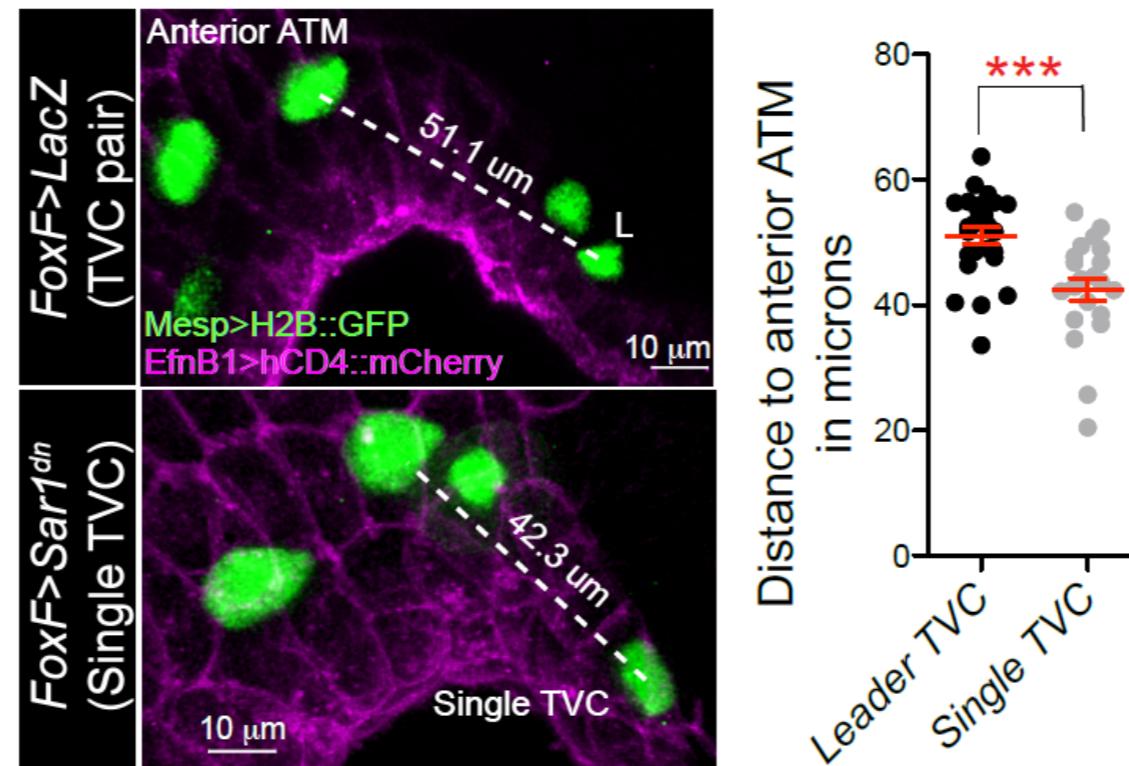


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Morphological Measurements
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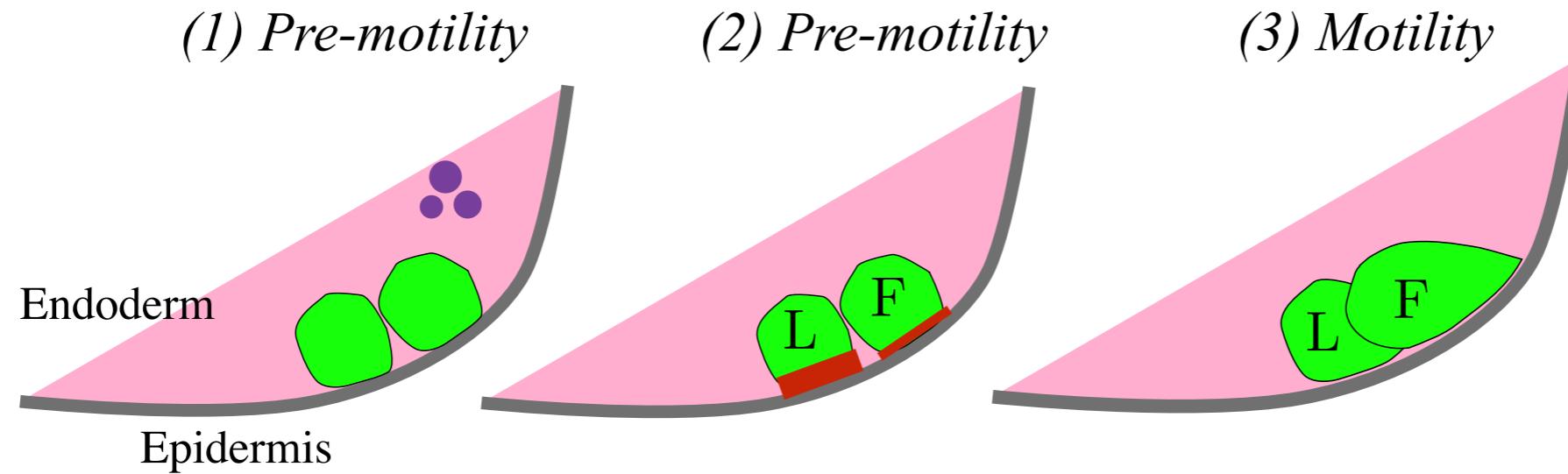


Moving as a pair is “better” than alone

Hypothesis #1: There is a *mechanical* advantage to move as a two-cell system

Hypothesis #2: It is easier to *initiate* locomotion as a pair.

On the biochemical advantage of a pair



- Literature search revealed a lot of polymerization / symmetry breaking theoretical models focus on specific pathways with nonlinearities (accessory proteins)
- **Wanted:** general framework (mechanics & signaling are integrated)
- **Is it easier to polarize in a pair? Role of cell-cell junction proteins?**

Big step back:

Construct general framework for symmetry breaking in a SINGLE cell

For any interested students: the big question remains to be answered...

Emergent organization inside cells
to initiate locomotion

Breaking symmetry to initiate locomotion



Yam...Theriot 2007

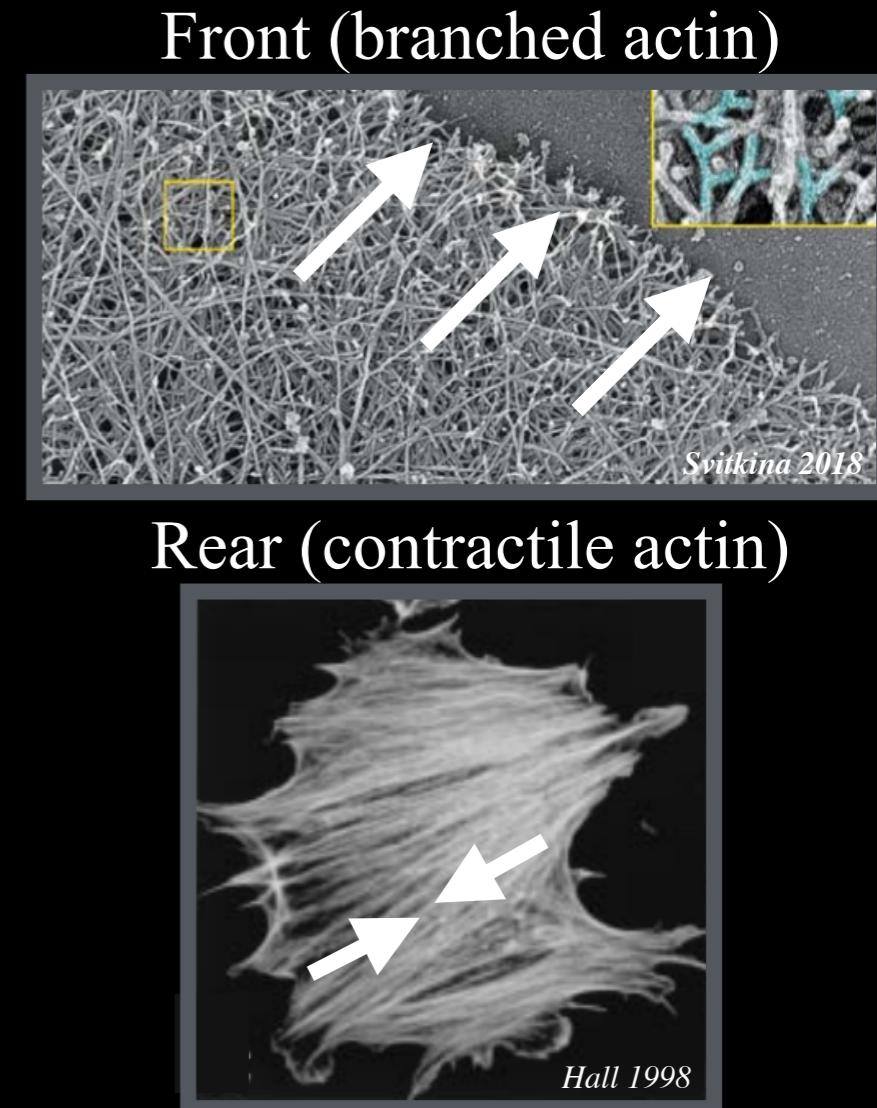
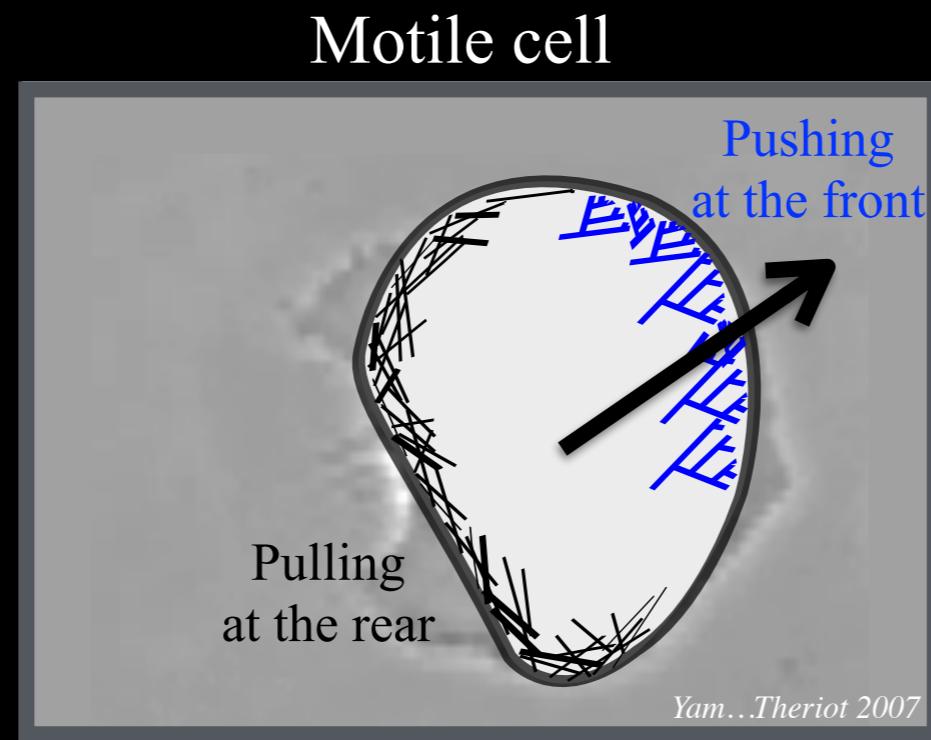
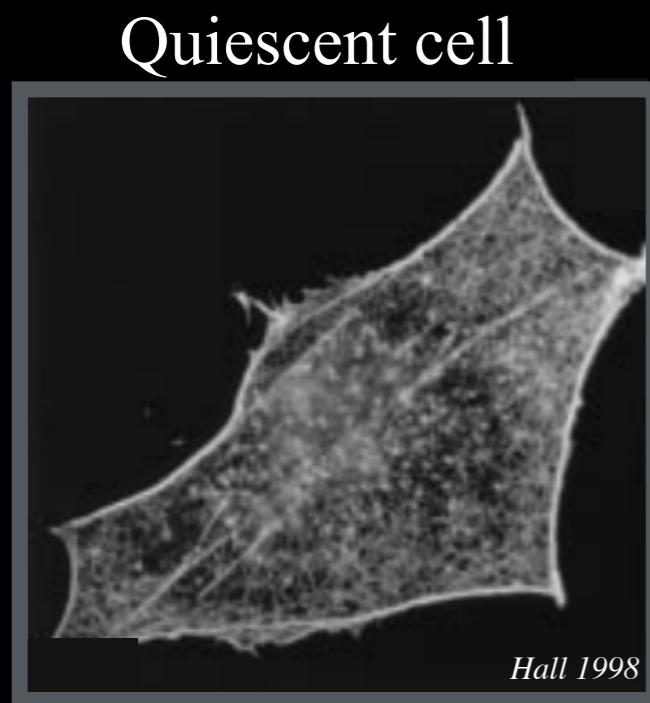
Breaking symmetry to initiate locomotion



Yam...Theriot 2007

- Breaking symmetry = Form a cell “front” and “rear” = Cell ‘polarization’

Breaking symmetry to initiate locomotion

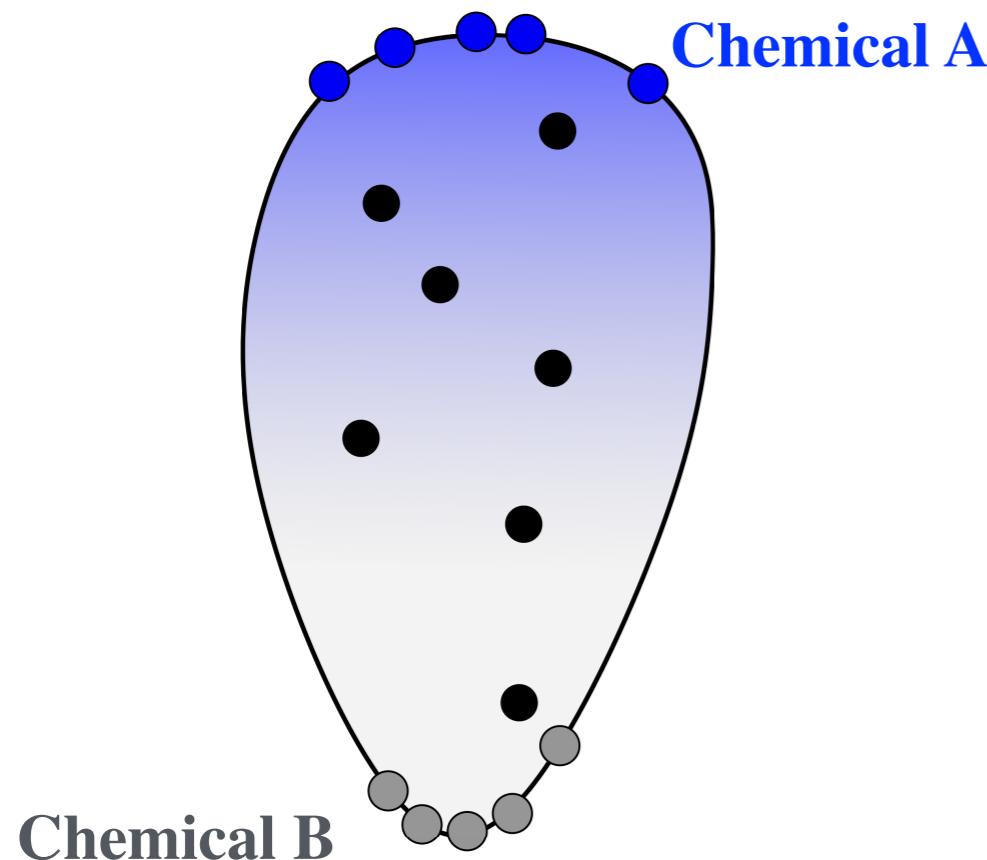


- Breaking symmetry = Form a cell “front” and “rear” = Cell ‘polarization’
- This process happens prior to movement

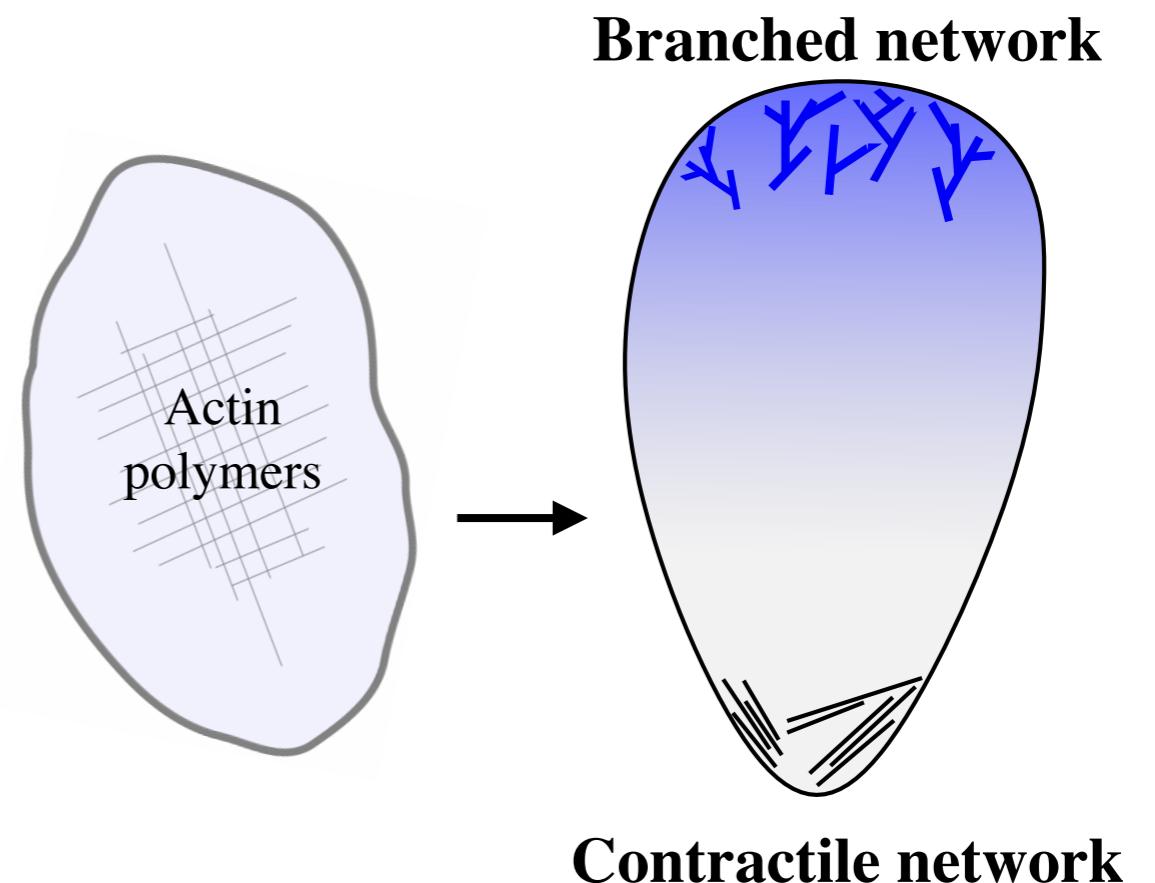
What triggers symmetry breaking
(i.e. formation of front and rear)?

What triggers symmetry breaking?

(1) Biochemical signaling



(2) Polymer mechanics

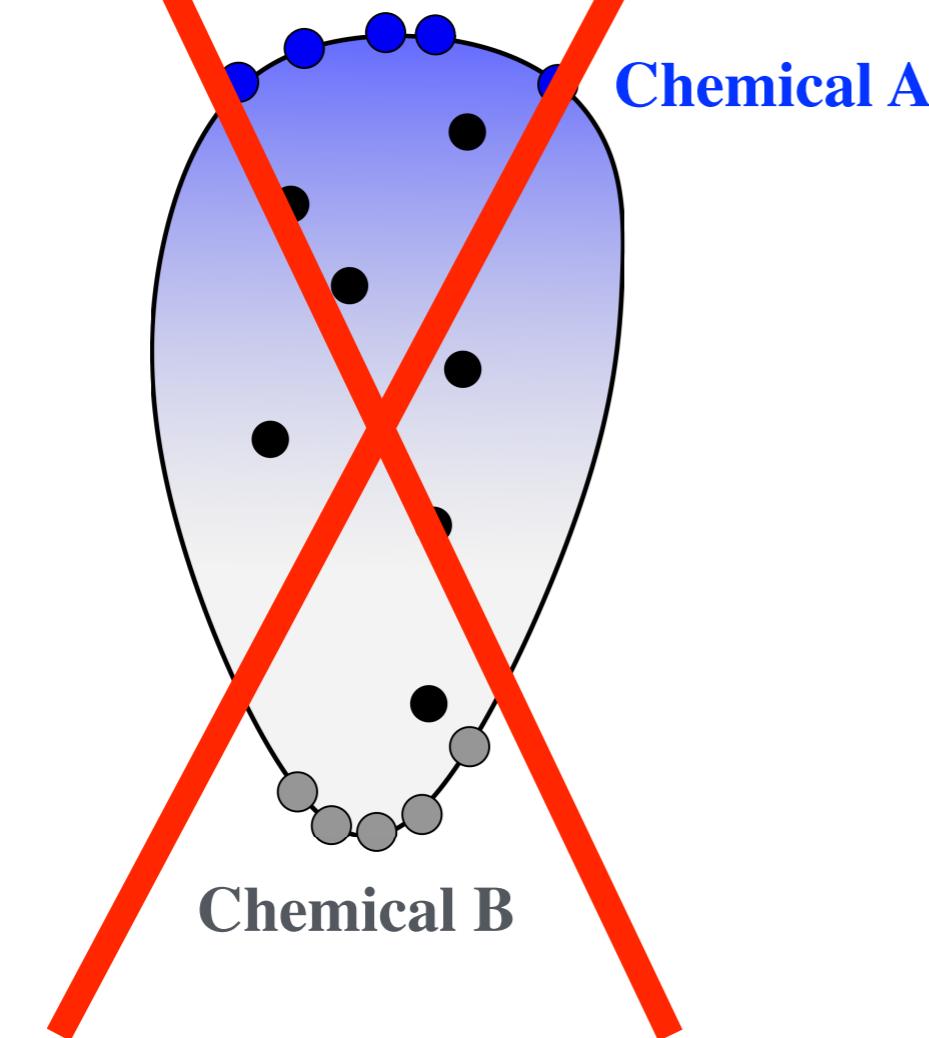


Spatial segregation of chemicals through kinetics

Rearrangement of cytoskeleton

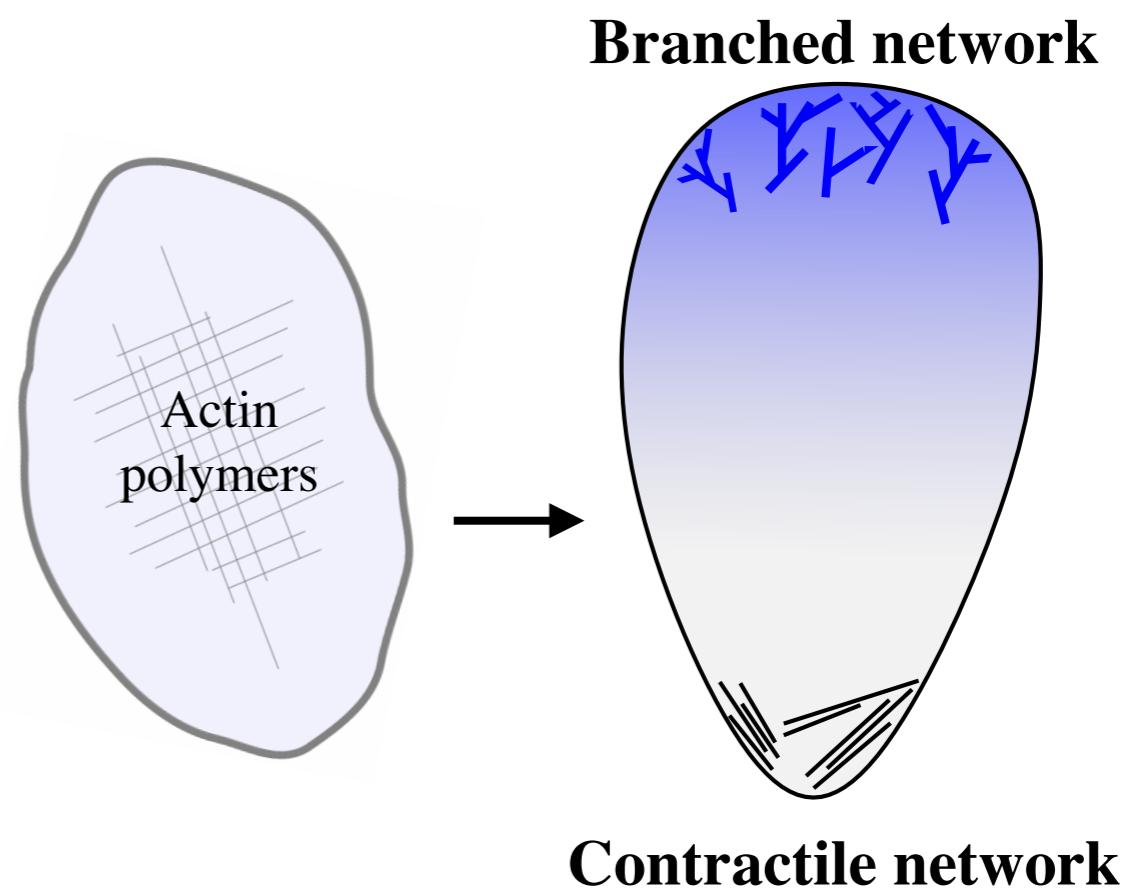
In reality, both are necessary

(1) Biochemical signaling



Spatial segregation of chemicals through kinetics

(2) Polymer mechanics

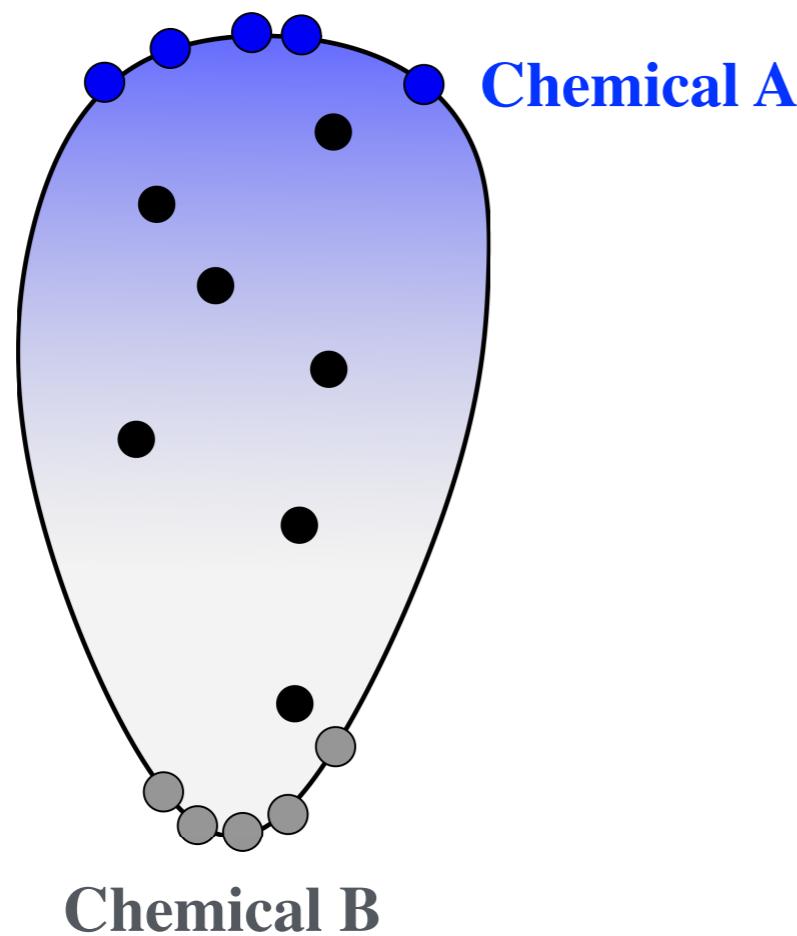


Rearrangement of cytoskeleton

In neutrophils, **inhibition of signaling chemicals (Rac)**: no front edge formation
(Schwarz 2004)

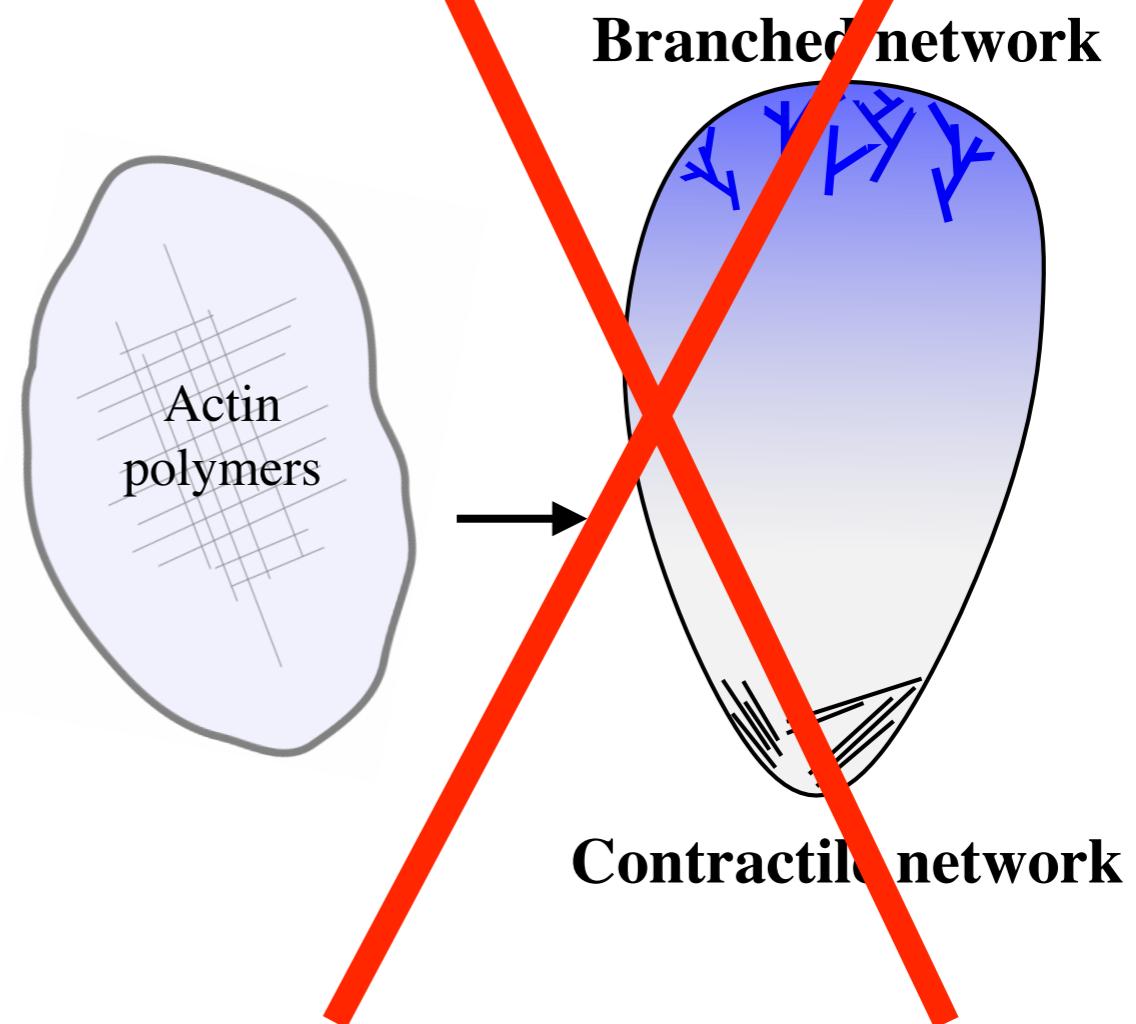
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(1) Biochemical signaling



Spatial segregation of chemicals through kinetics

(2) Polymer mechanics

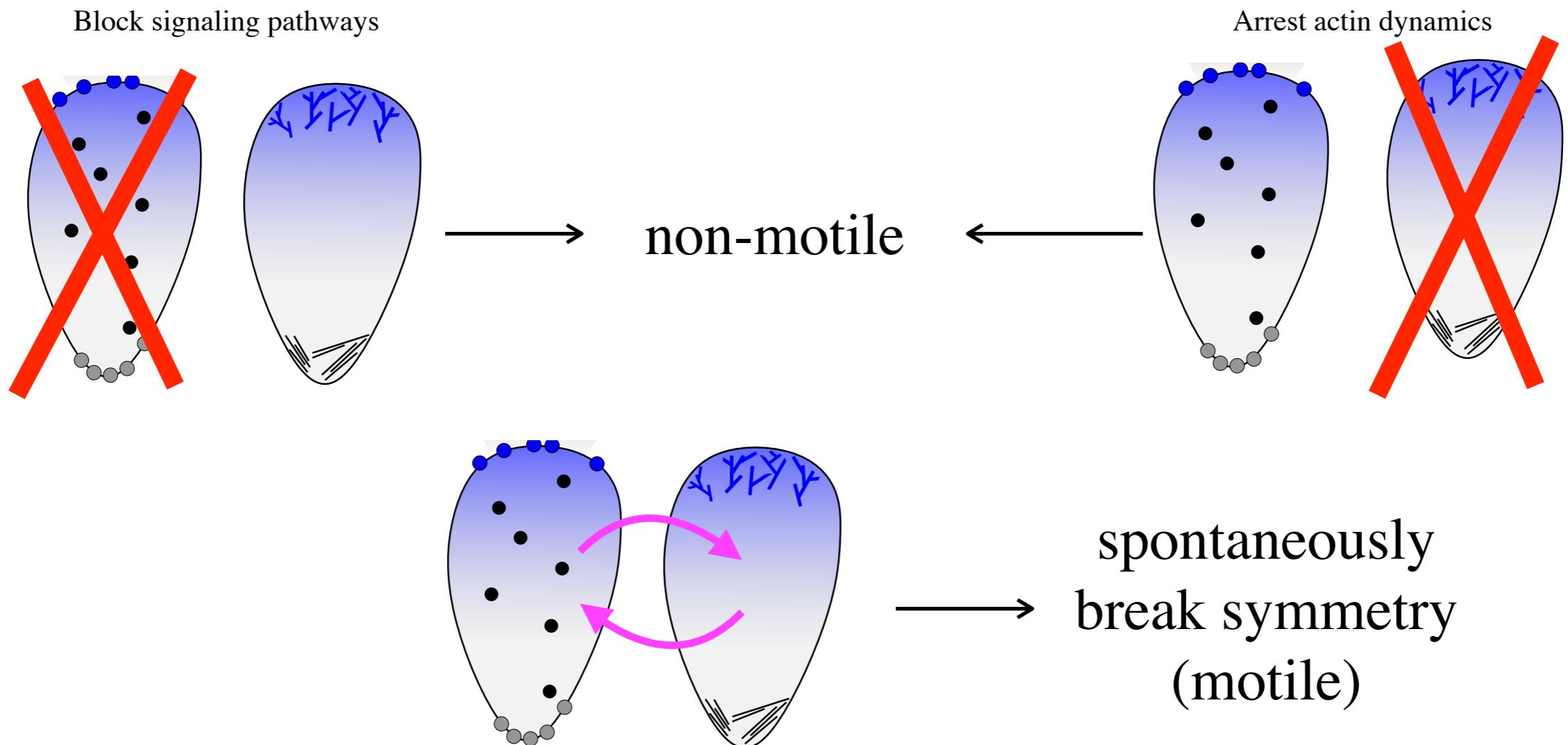


Rearrangement of cytoskeleton

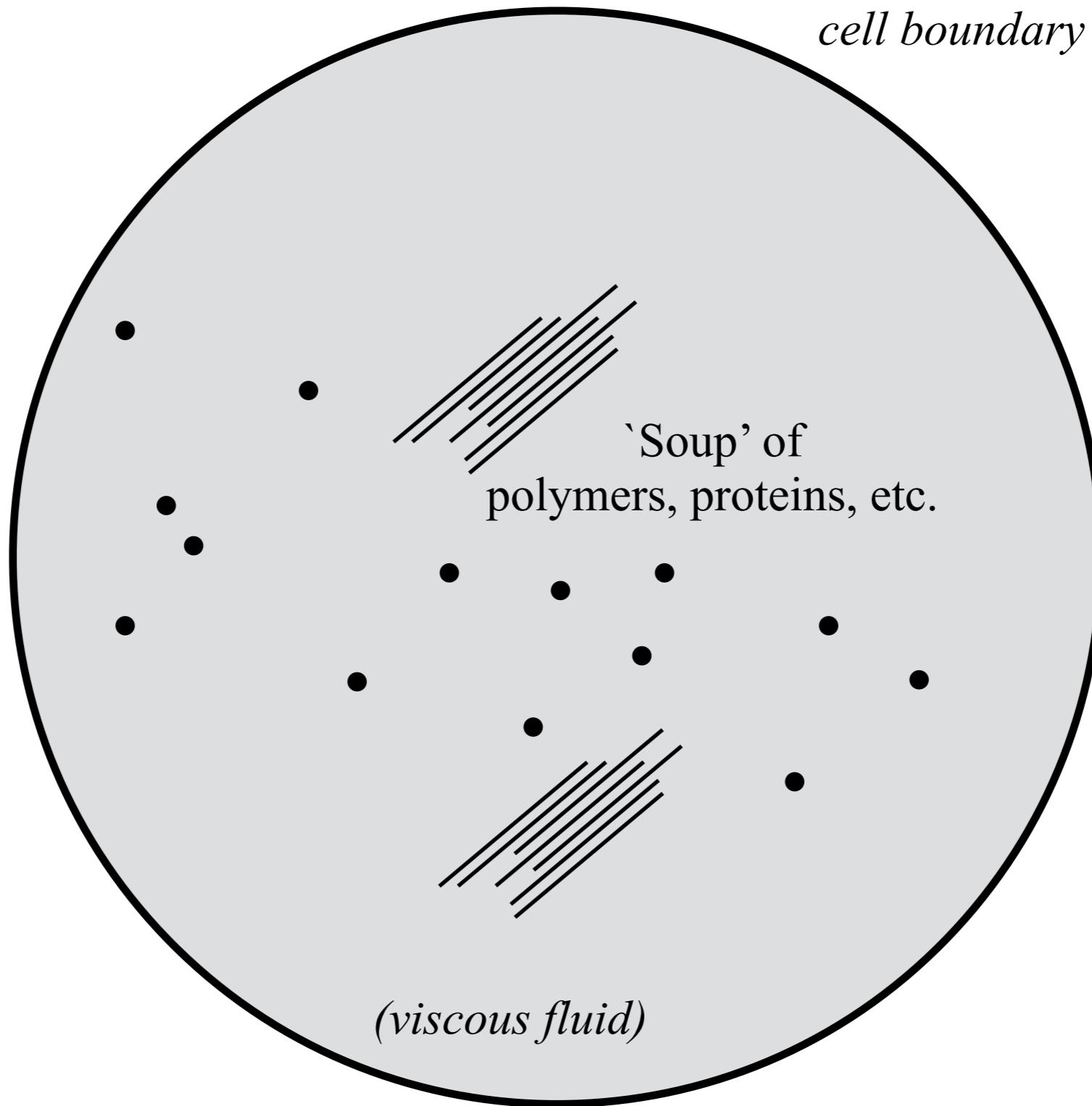
In neutrophils, **arresting the actin polymer dynamics**: desensitization to new incoming signals (*Dandekar et al. 2013*)

Hypothesis: Not only both (mechanics and biochemical pathways) are at play. Their **coupling/reinforcement** leads to a polarized cell state.

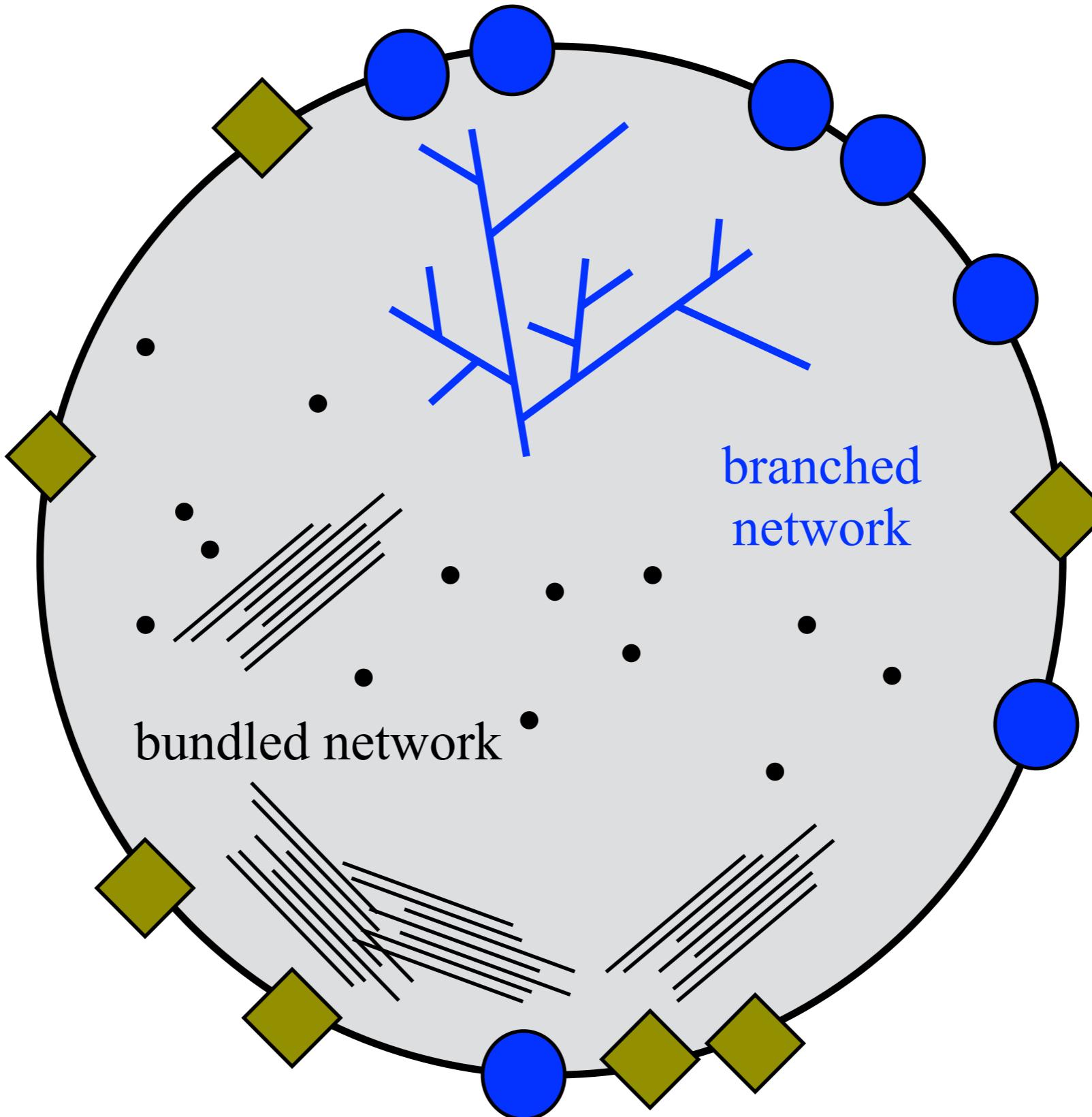
What are the necessary and sufficient conditions?



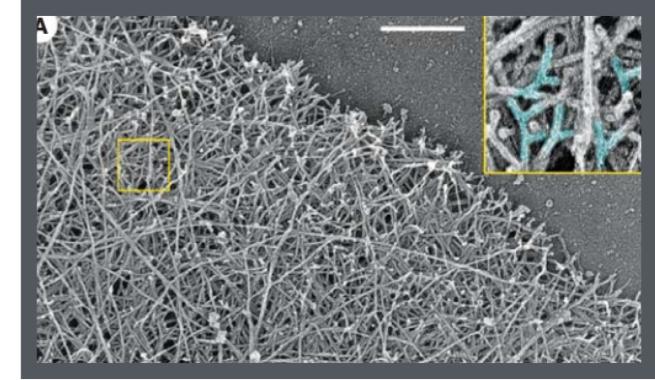
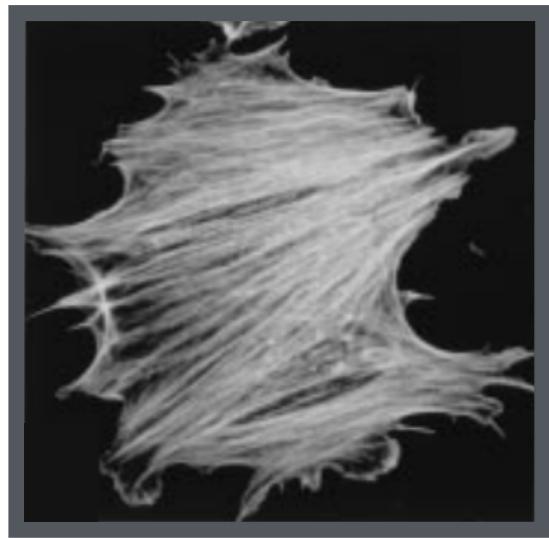
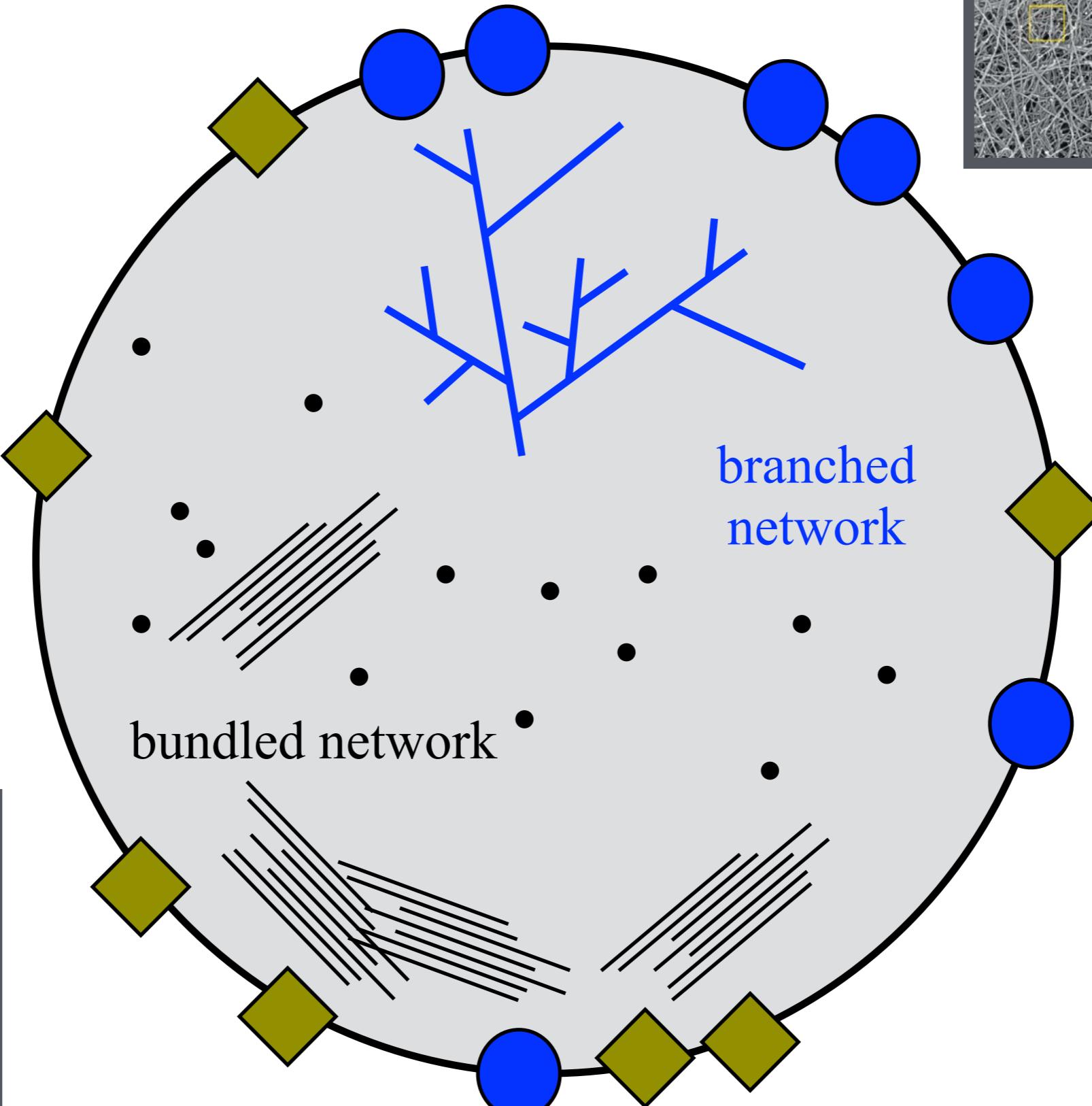
The 'spherical' eow cell



The model overview



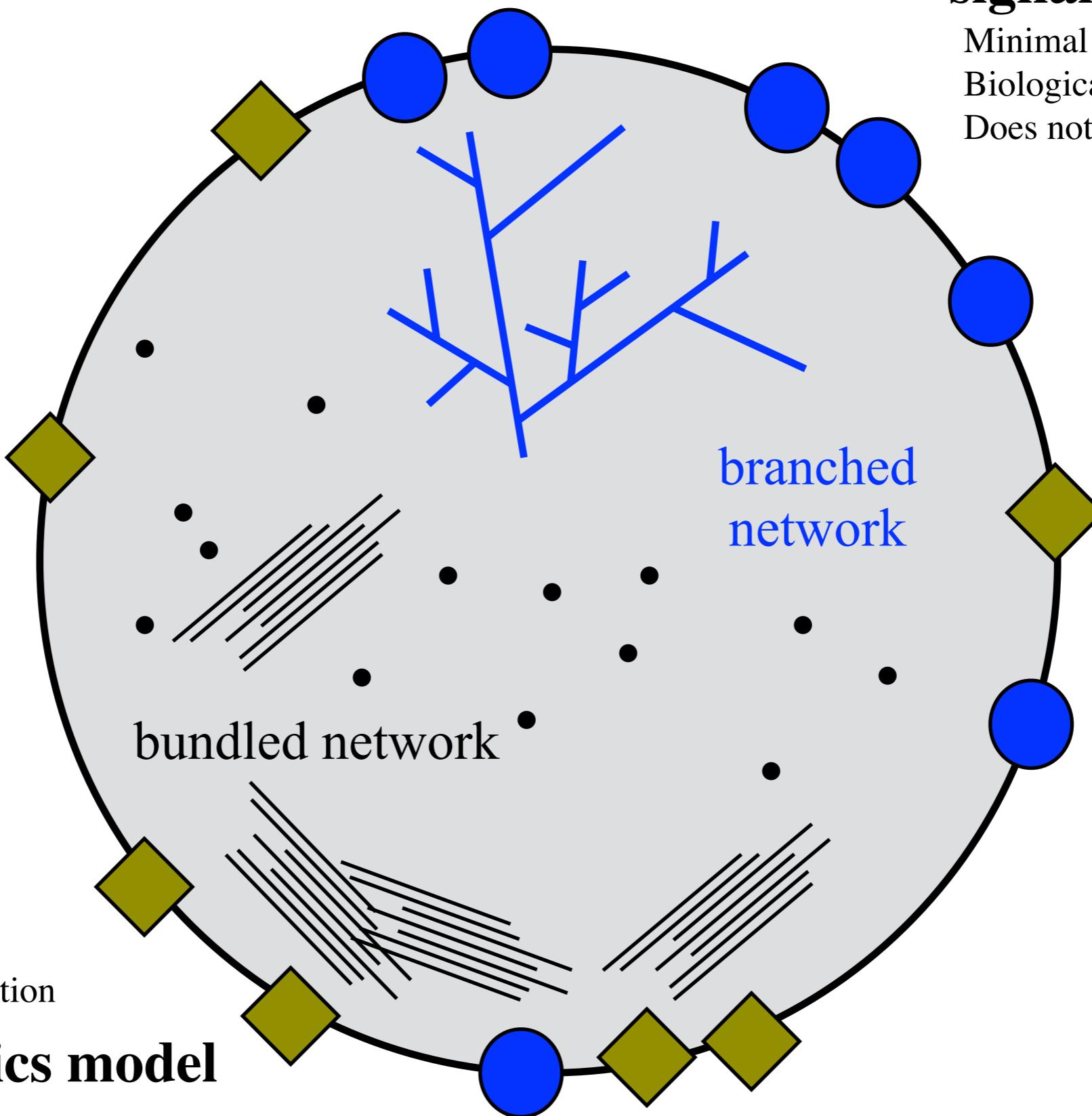
The model overview



The model overview

1. Biochemical signaling model

Minimal
Biologically inspired
Does not produce polarization on its own



Minimal model
Does not produce polarization

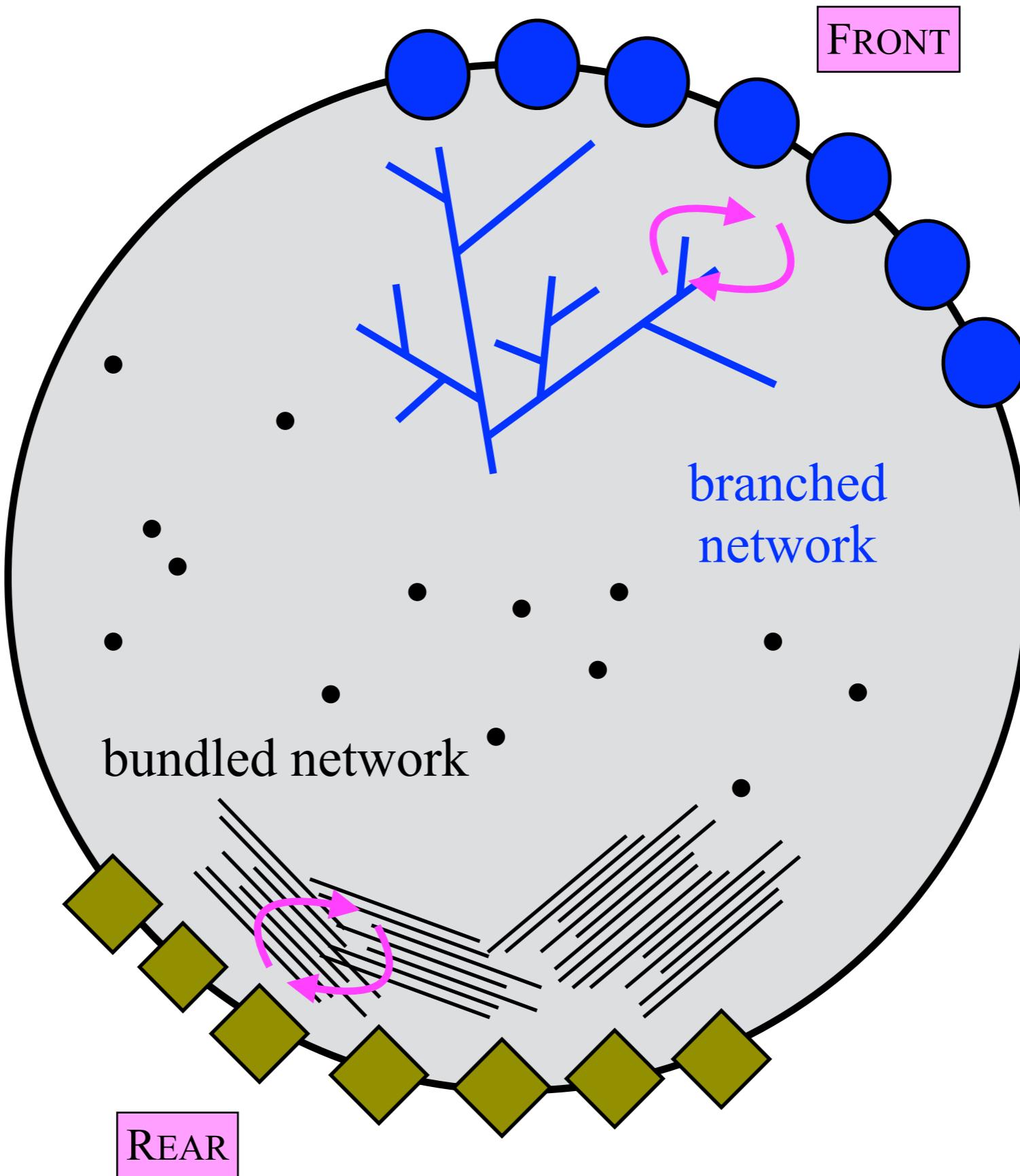
2. Actin dynamics model

The model overview

Coupling?

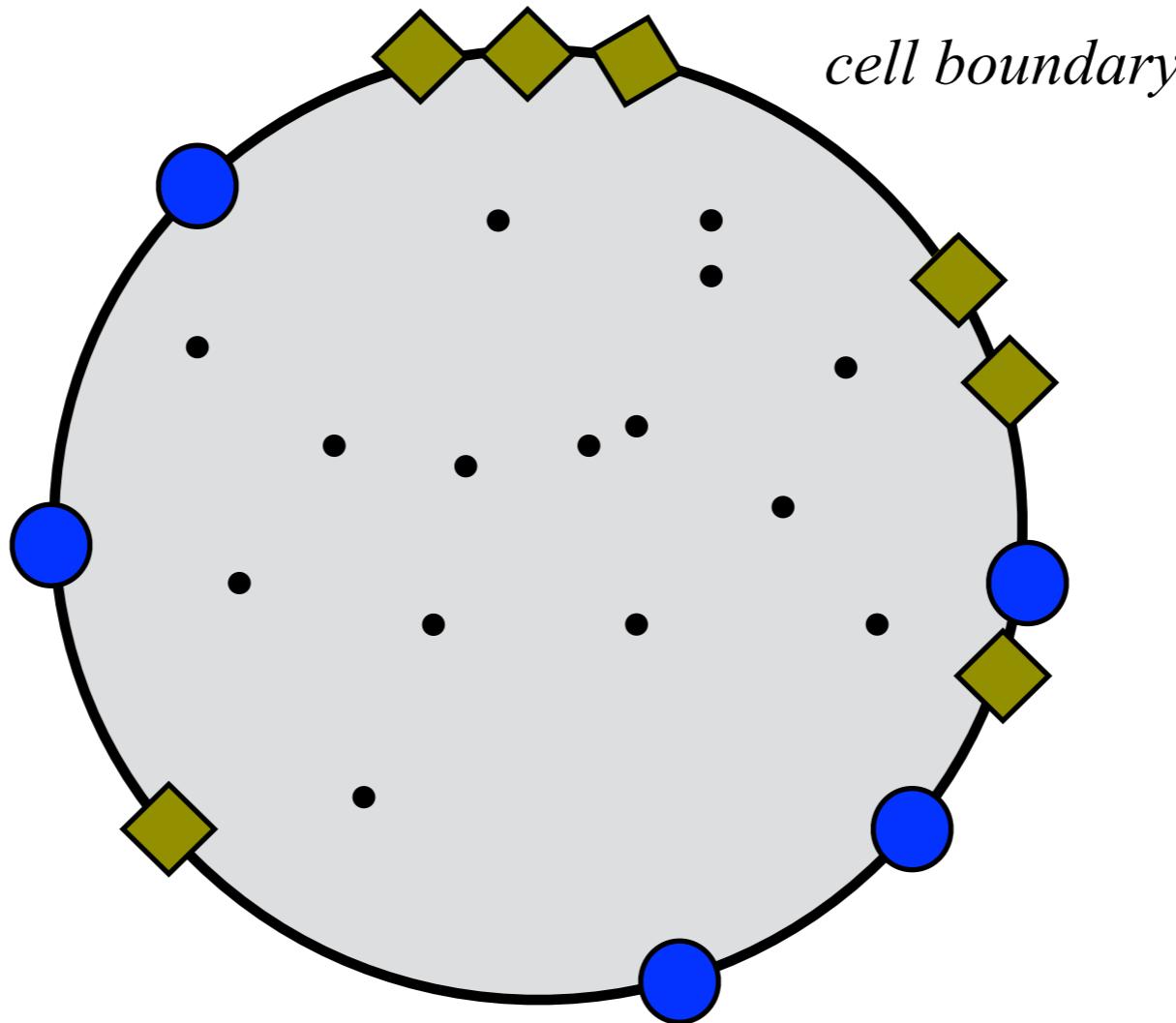
3 out of 4 directions
are well-established
biologically.

Will result in
spontaneous symmetry
breaking.



1. Biochemical module

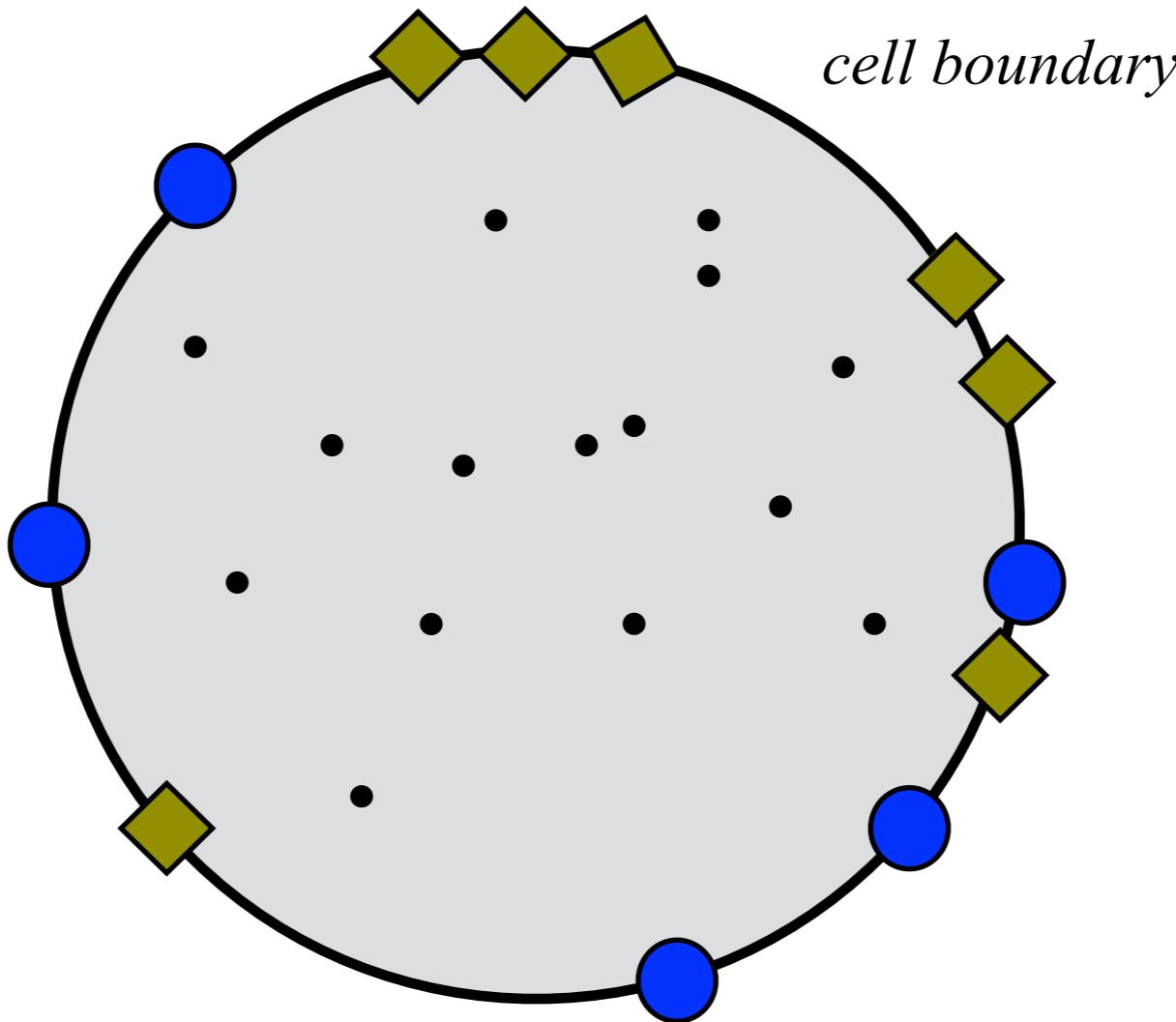
1. Biochemical module



What we know biologically:

1. *Rac/Rho signaling pathway* is a generic mechanism for breaking symmetry
2. **Actors:** **Rac (Front)** and **Rho (Rear)** with well-characterized dynamics (i.e. rates)
3. **Dynamics:** Exist in two states: (1) boundary-bound (active)
(2) cytosol (inactive)

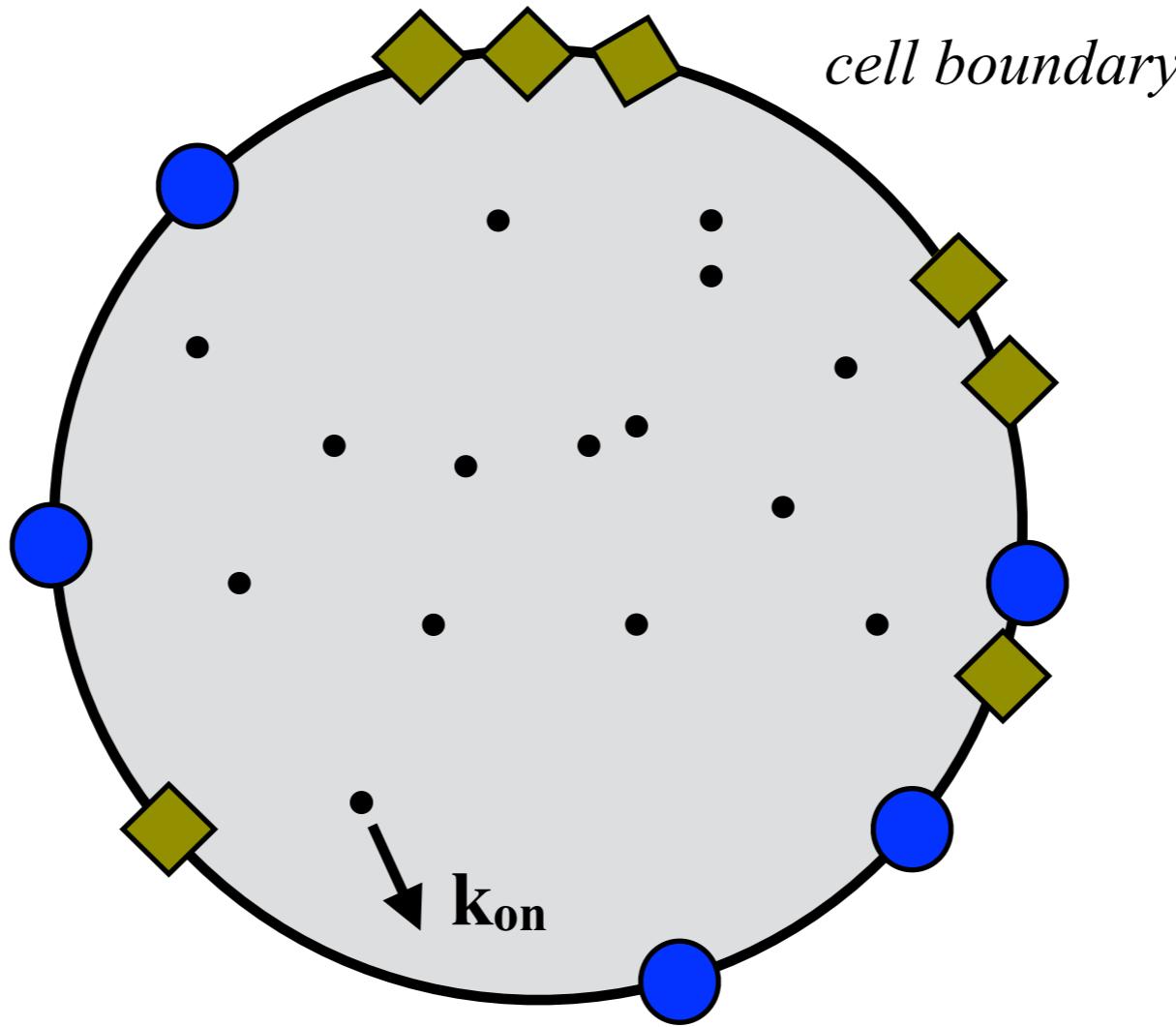
1. Biochemical module



1. Spontaneous association to the boundary (k_{on})
2. Spontaneous disassociation from the boundary (k_{off})
3. Enhanced boundary association through activators (k_{fb})
4. Brownian motion (diffusion) on the boundary (D)

Kinetic rates and diffusion have been measured experimentally.

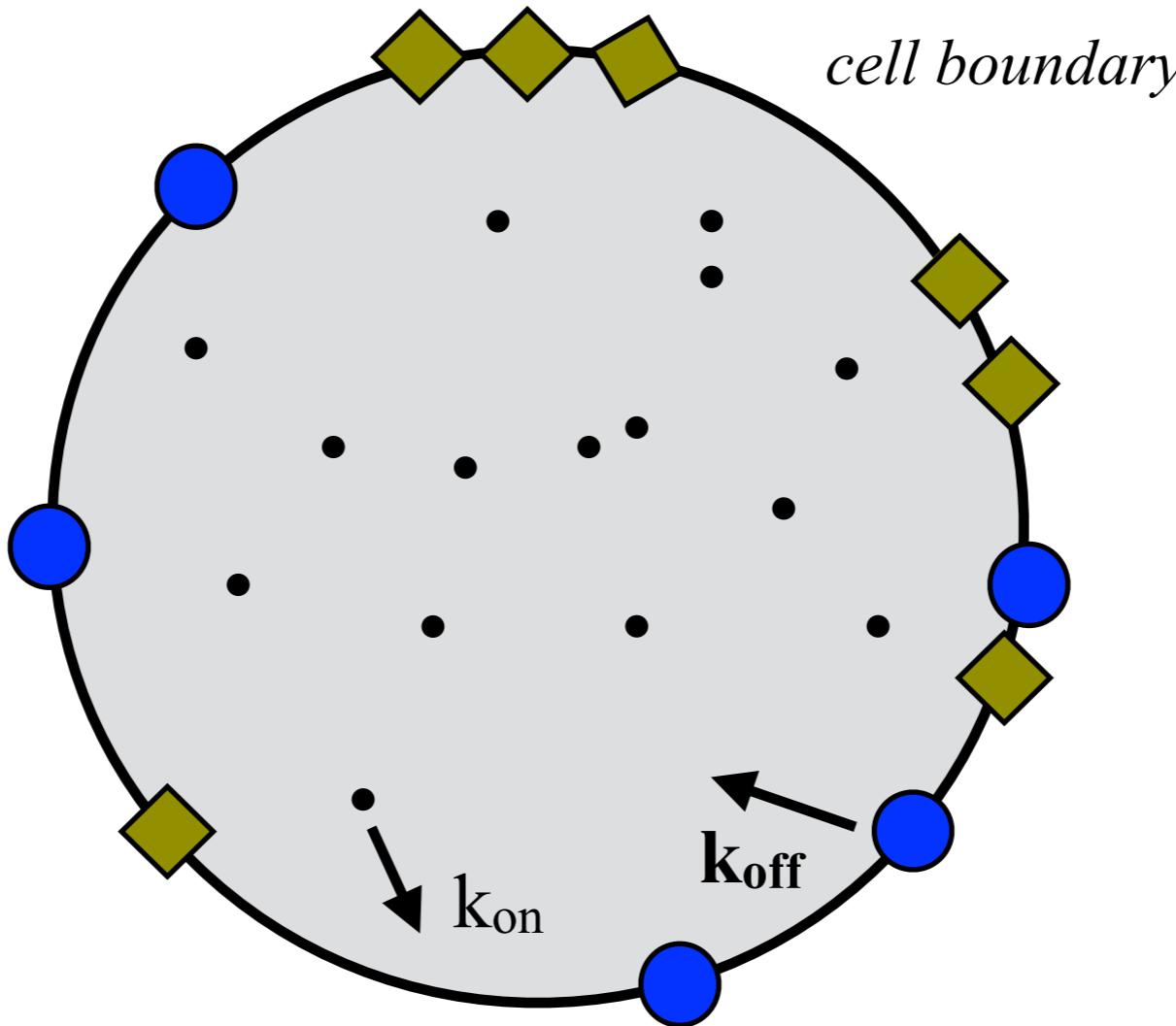
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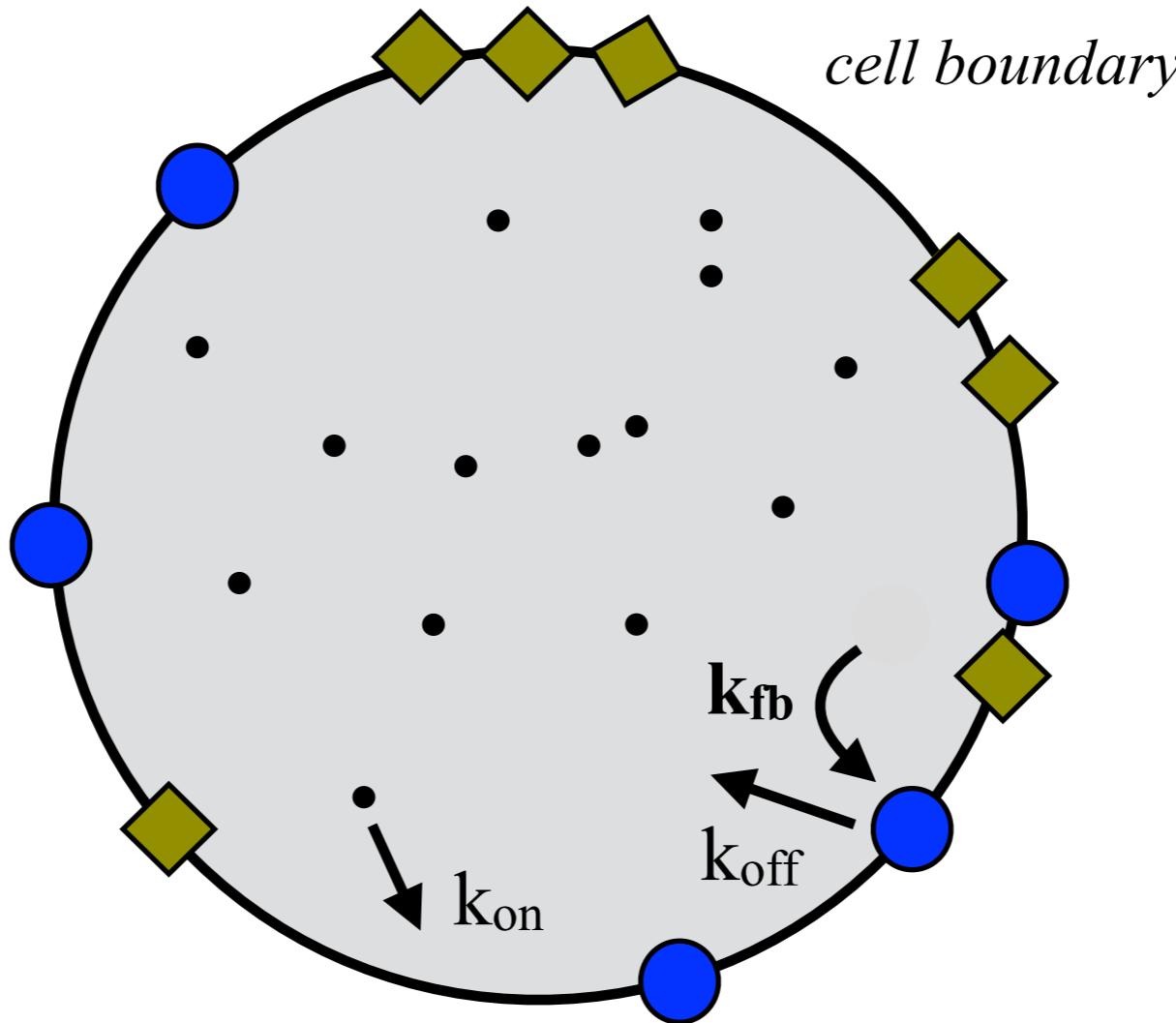
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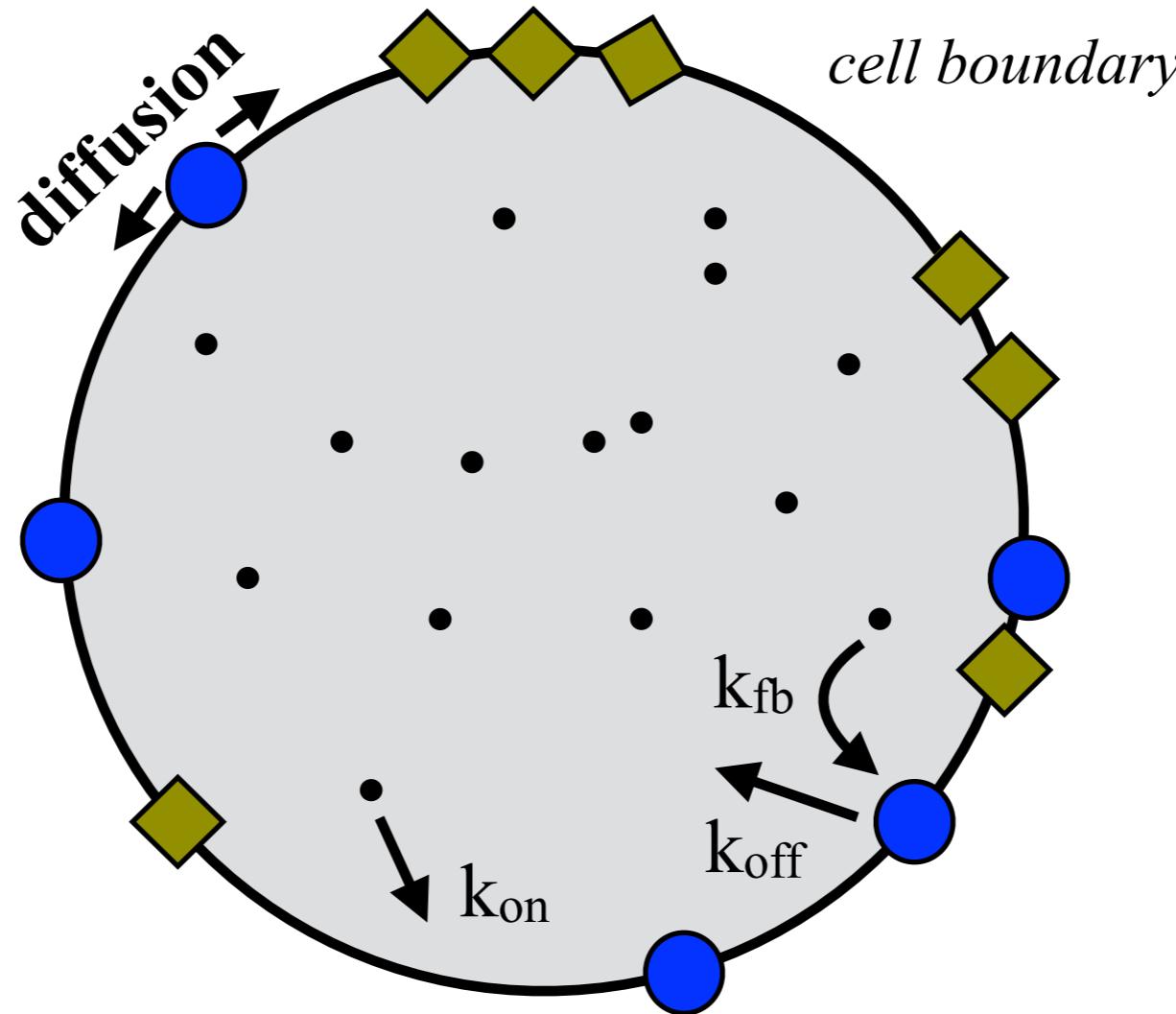
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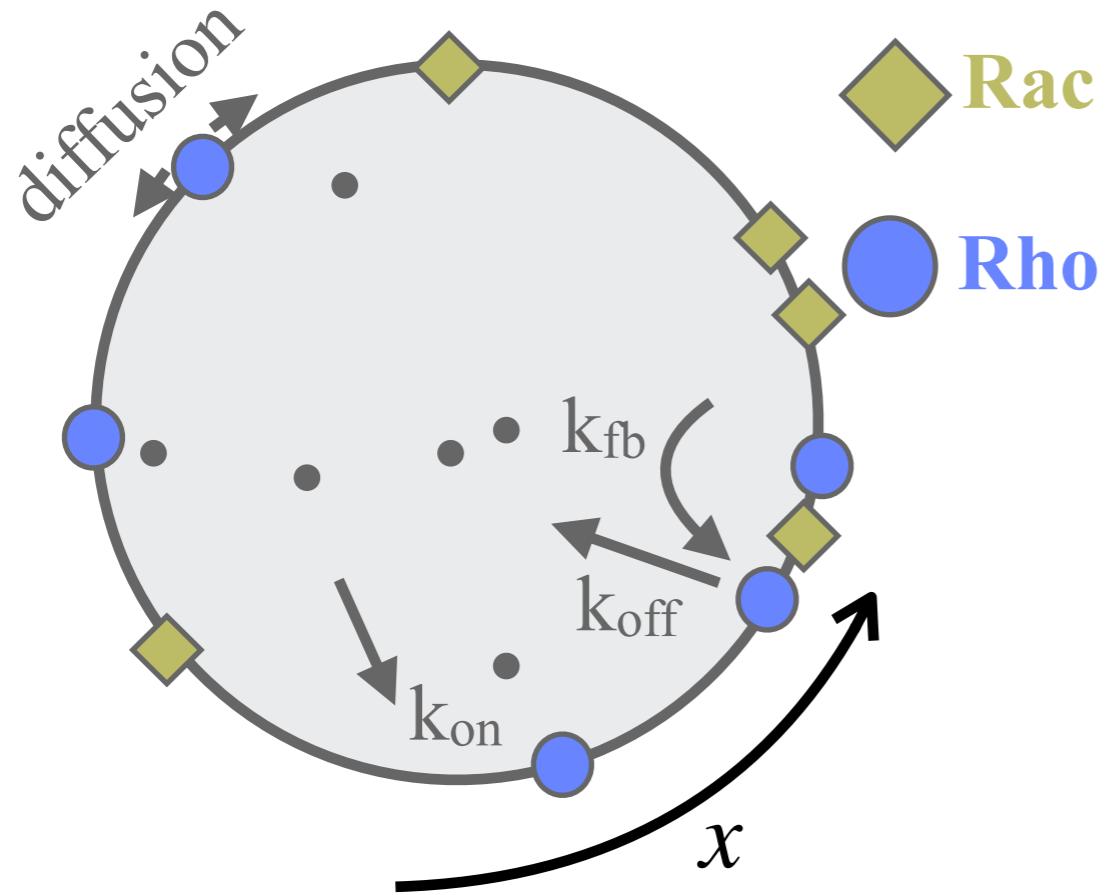
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Kinetic rates and diffusion have been measured experimentally.

1. Biochemical module - Equations



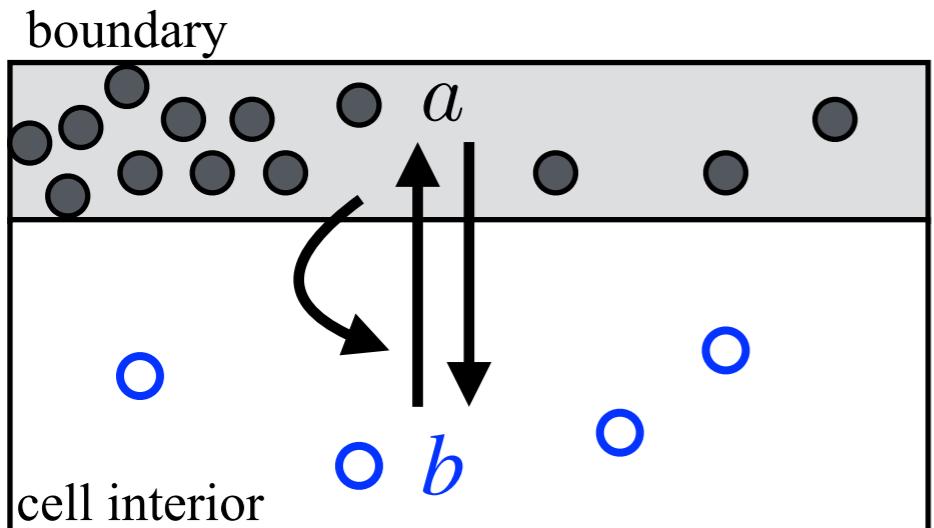
Assumptions

- (1) Interior particles are well-mixed and homogeneous
- (2) Dynamics of **only** boundary-bound (active) particles (# and locations)
- (3) Solved on a circle (thin boundary)

1. Biochemical module - Equations

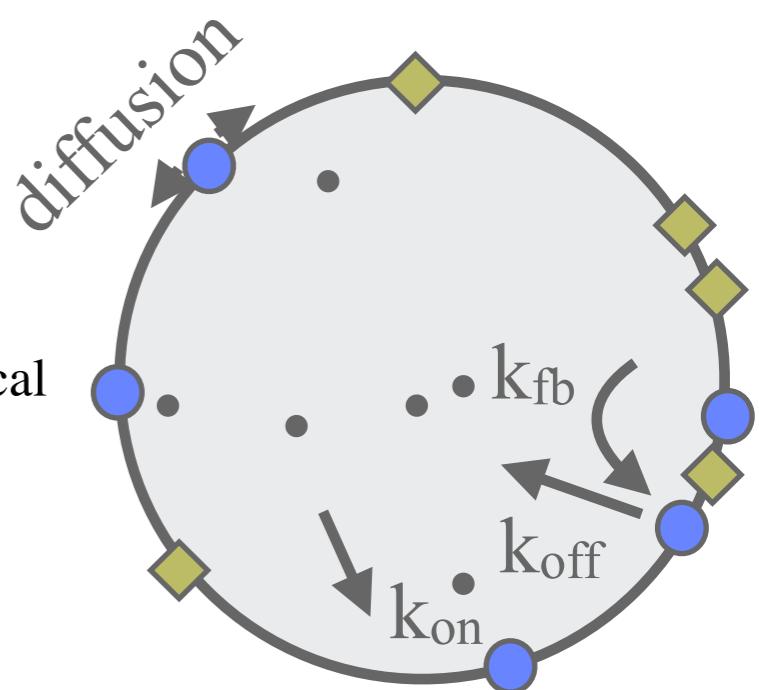
Deterministic / Continuum (averaged) / PDE system

Mori, Jilkine, Edelstein-Keshet (2008): Reaction-diffusion system for one chemical



Concentration of
active chemical

Concentration of
inactive chemical



$$\frac{\partial a}{\partial t} = D_a \frac{\partial^2 a}{\partial x^2} + f(a, b)$$

$$\frac{\partial b}{\partial t} = D_b \frac{\partial^2 b}{\partial x^2} - f(a, b)$$

$$f(a, b) = k_0 b + \frac{\gamma a^2}{K^2 + a^2} b - \delta a$$

Conservation of mass

Nonlinear term

What about other models for the biochemical system?

Mori et al. 2008 model:

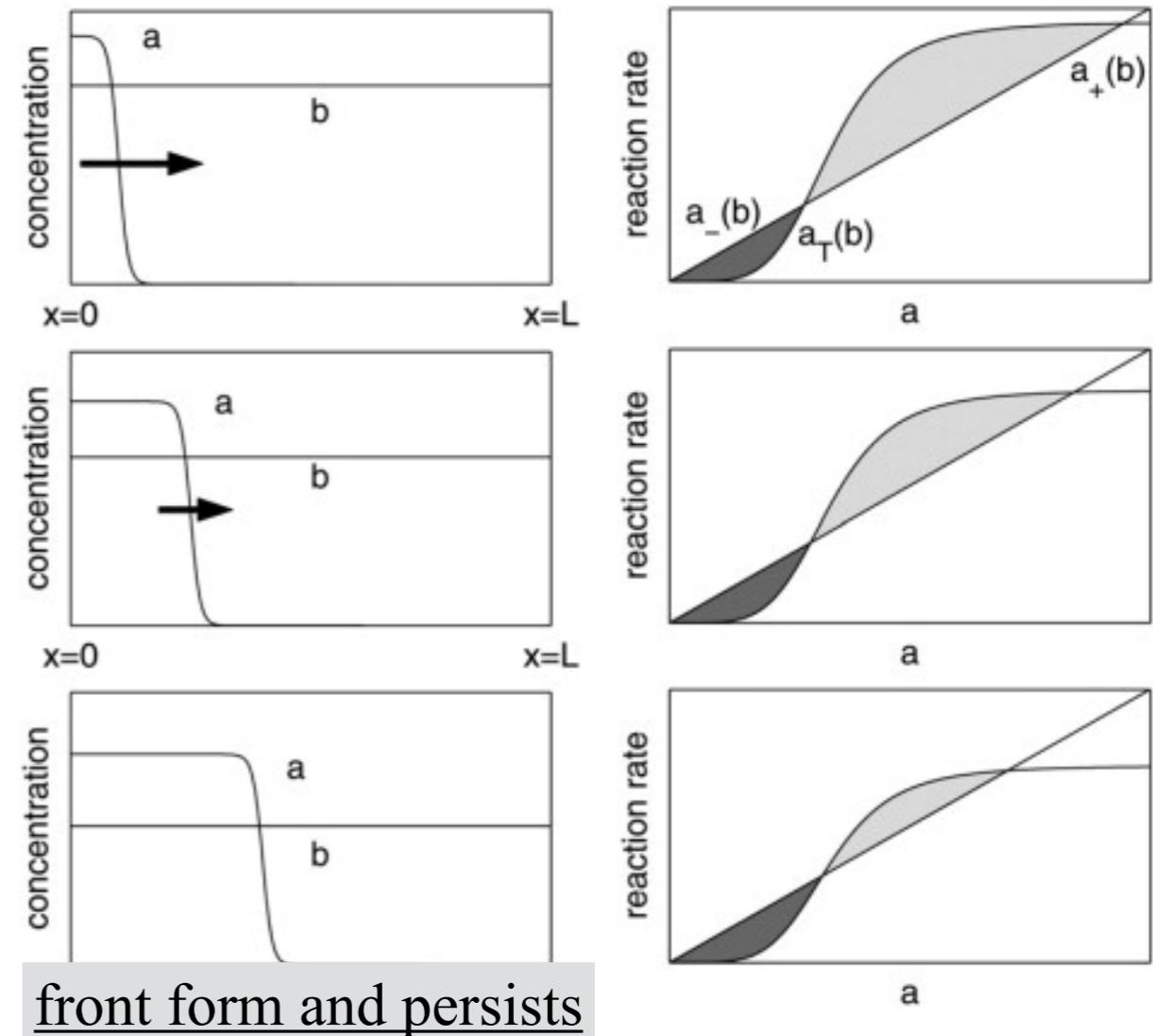
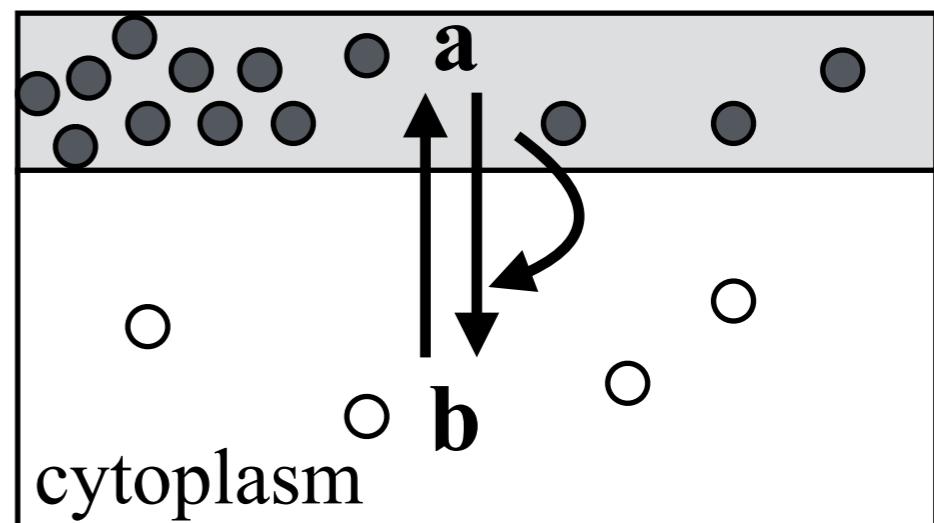
One polarity molecule in 2 states:
a (active, membrane-bound, slow)
b (inactive, cytoplasm, fast)

$$\left. \begin{aligned} \frac{\partial a}{\partial t} &= D_a \frac{\partial^2 a}{\partial x^2} + f(a, b) \\ \frac{\partial b}{\partial t} &= D_b \frac{\partial^2 b}{\partial x^2} - f(a, b) \end{aligned} \right\} \text{traveling wave solutions}$$

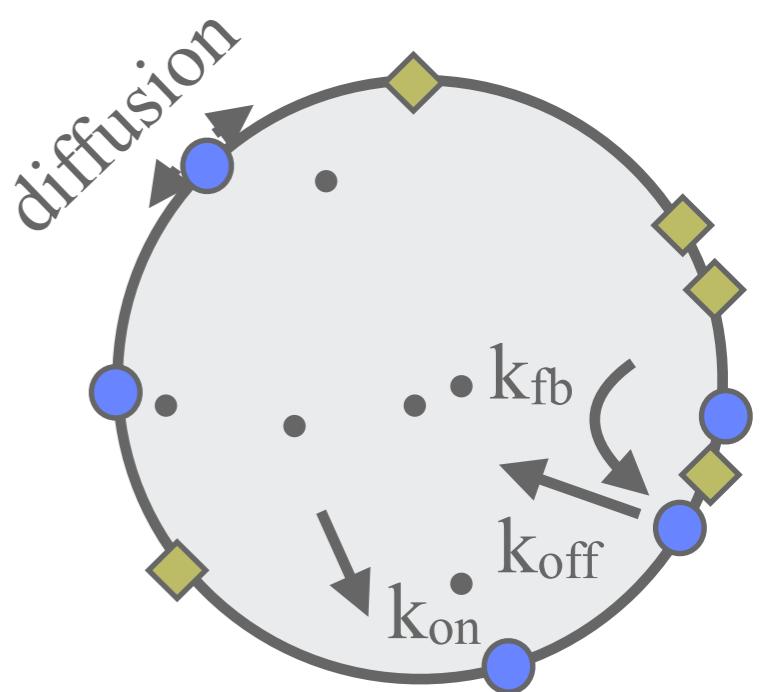
$$f(a, b) = \left(k_0 + \frac{\gamma a^2}{K^2 + a^2} \right) b - \delta a$$

No flux boundary conditions.

membrane



1. Biochemical module - Equations



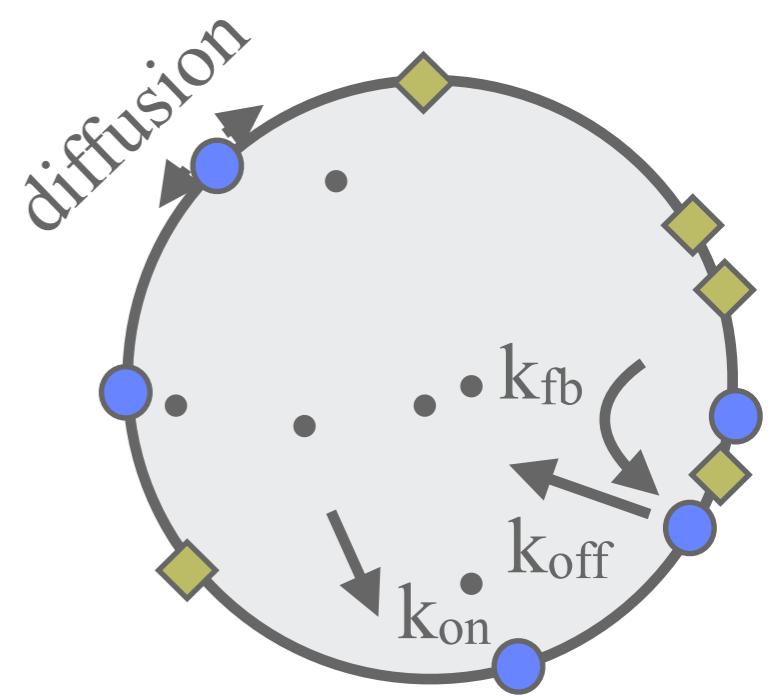
Our model is stochastic

Few molecules $O(100)$

Track chemicals with experimentally measured interaction rules

1. Biochemical module - Equations

Track number of particles and their location.



1. Biochemical module - Equations

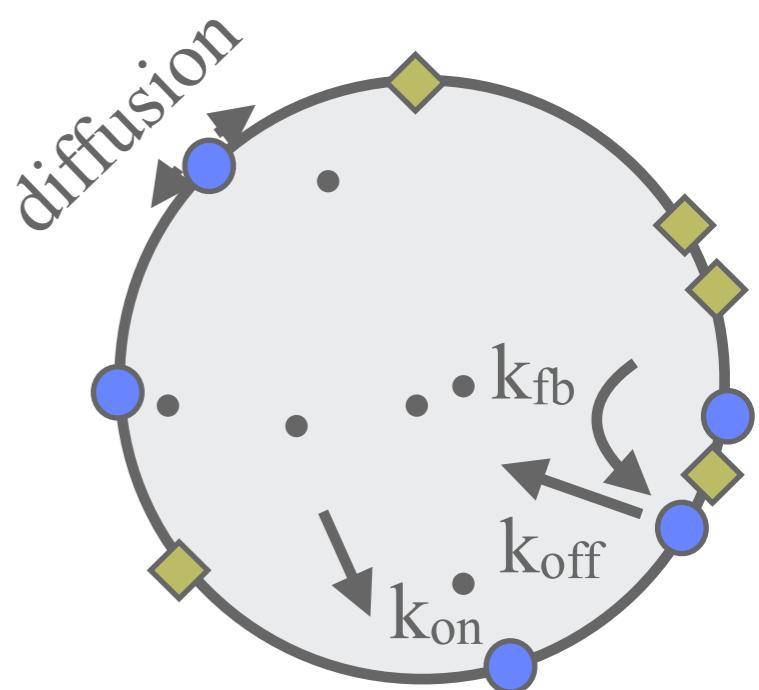
Track number of particles and their location.

(1) Number of active particles at a given time:

- Modeled by a continuous time Markov chain process (+/- 1 jumps)
- Time between events: independent, RV exponentially distributed with rate:

rate:
$$\lambda(n) = \underbrace{k_{\text{off}} n}_{\text{unbinding}} + \underbrace{\left(k_{\text{on}} + k_{\text{fb}} \frac{n}{N} \right) (N - n)}_{\text{binding}}$$

$$\begin{array}{c|c} n(t) & \text{Number of membrane-bound / active molecules} \\ \hline N & \text{Total number of molecules} \end{array}$$



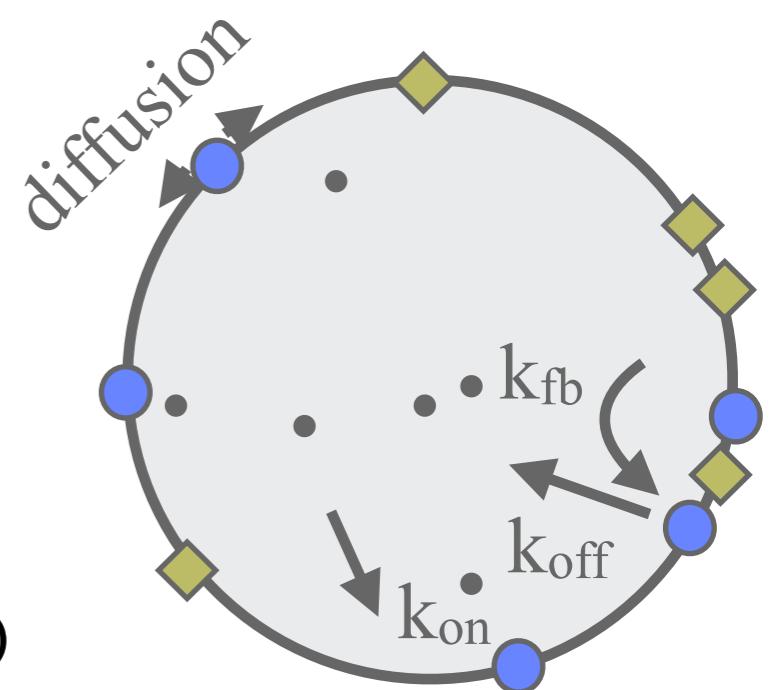
1. Biochemical module - Equations

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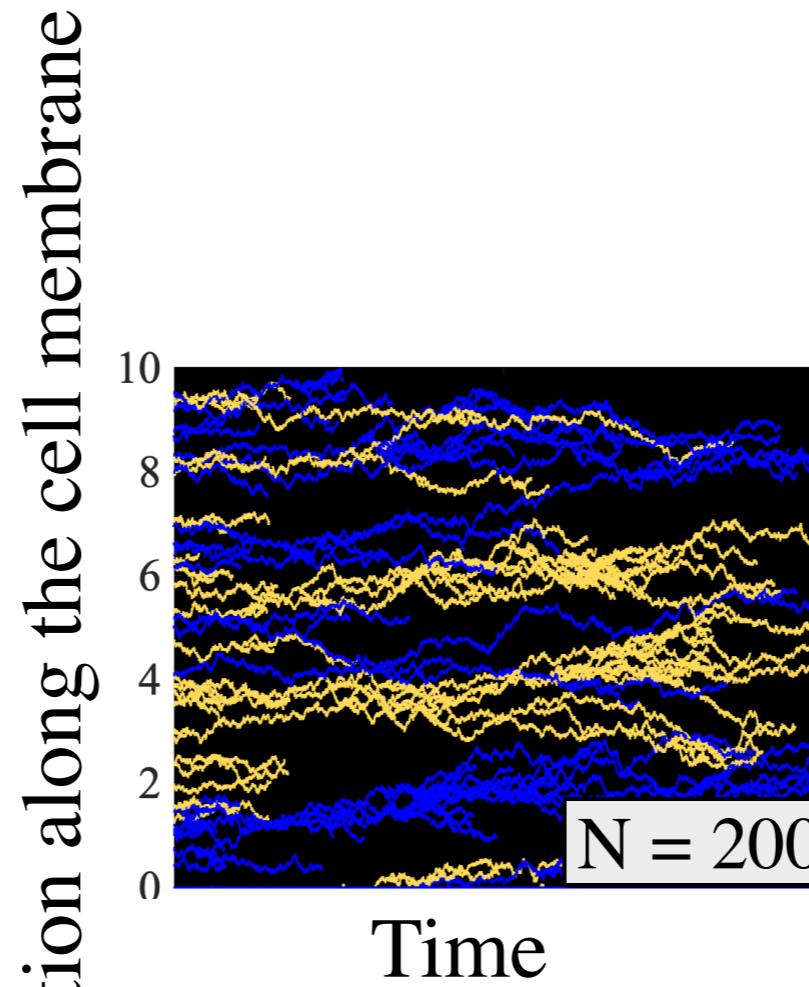
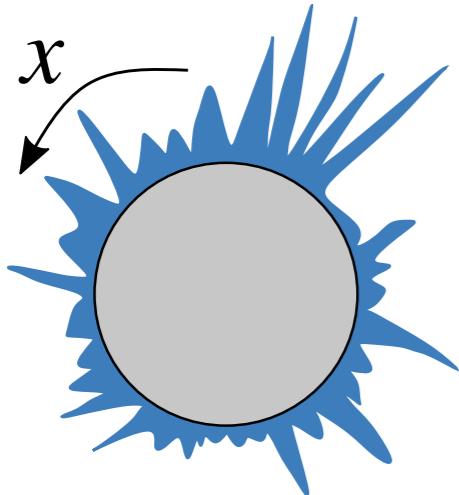


(2) Location of active particles:

- Between Markov events: Random diffusion on circle
- Within a Markov event: Location depends on type of event
 - (a) Association: random location
 - (b) Association via recruitment: random BUT from already bound particles
 - (c) Disassociation: random bound particle

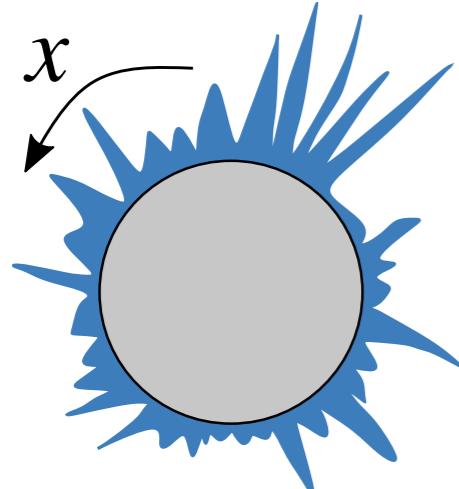
Numerical simulations: (1) Spatial Gillespie algorithm (2) Brownian motion between events.

1. Biochemical module

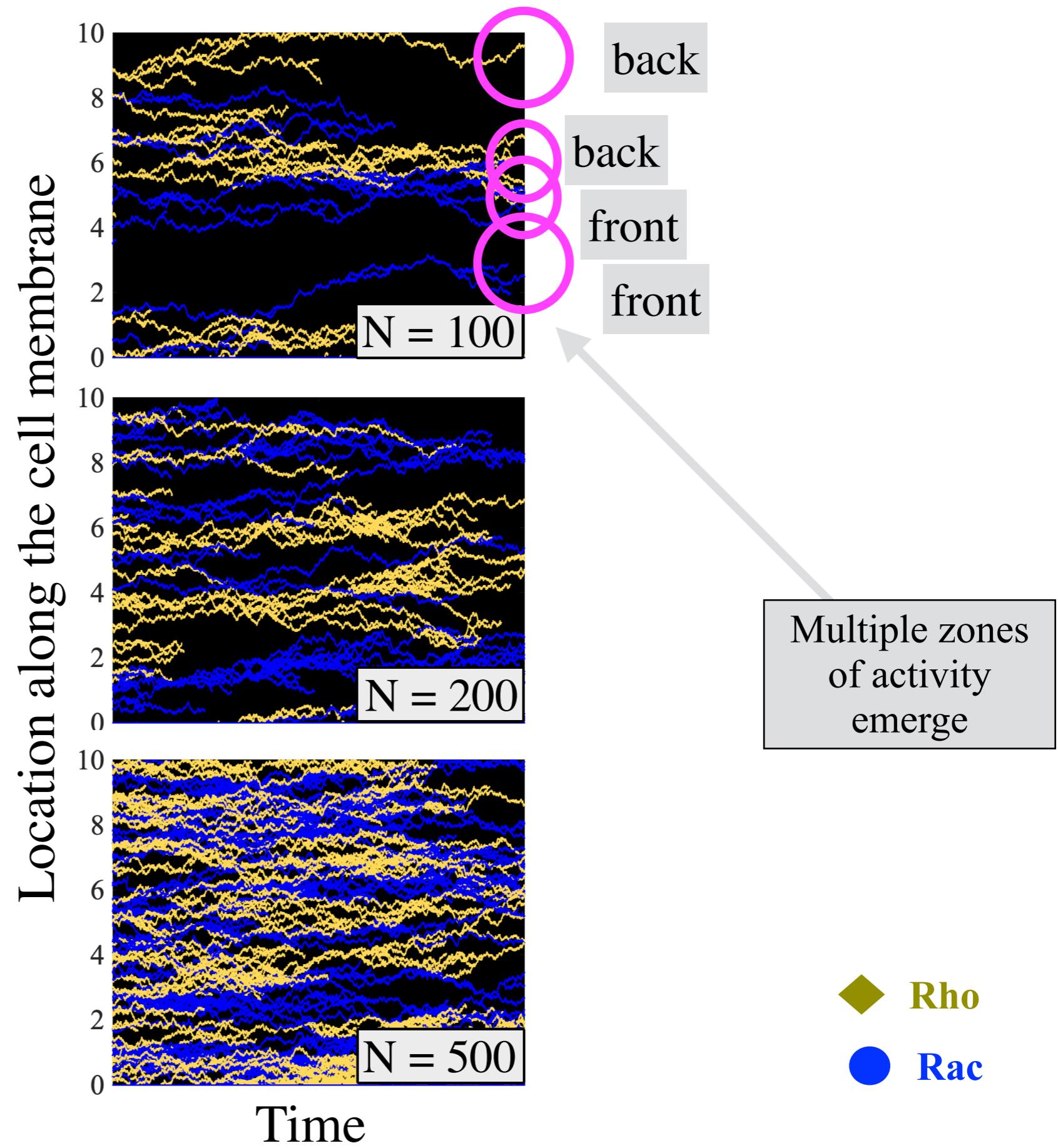
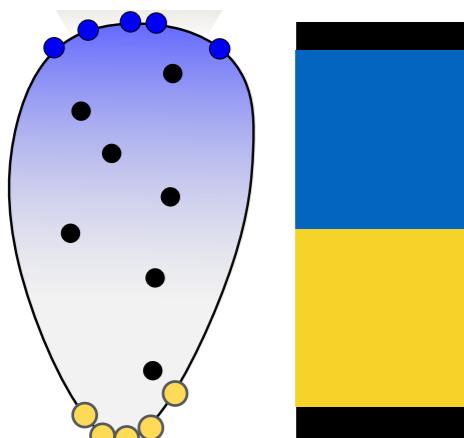


- ◆ Rho
- Rac

1. Biochemical module

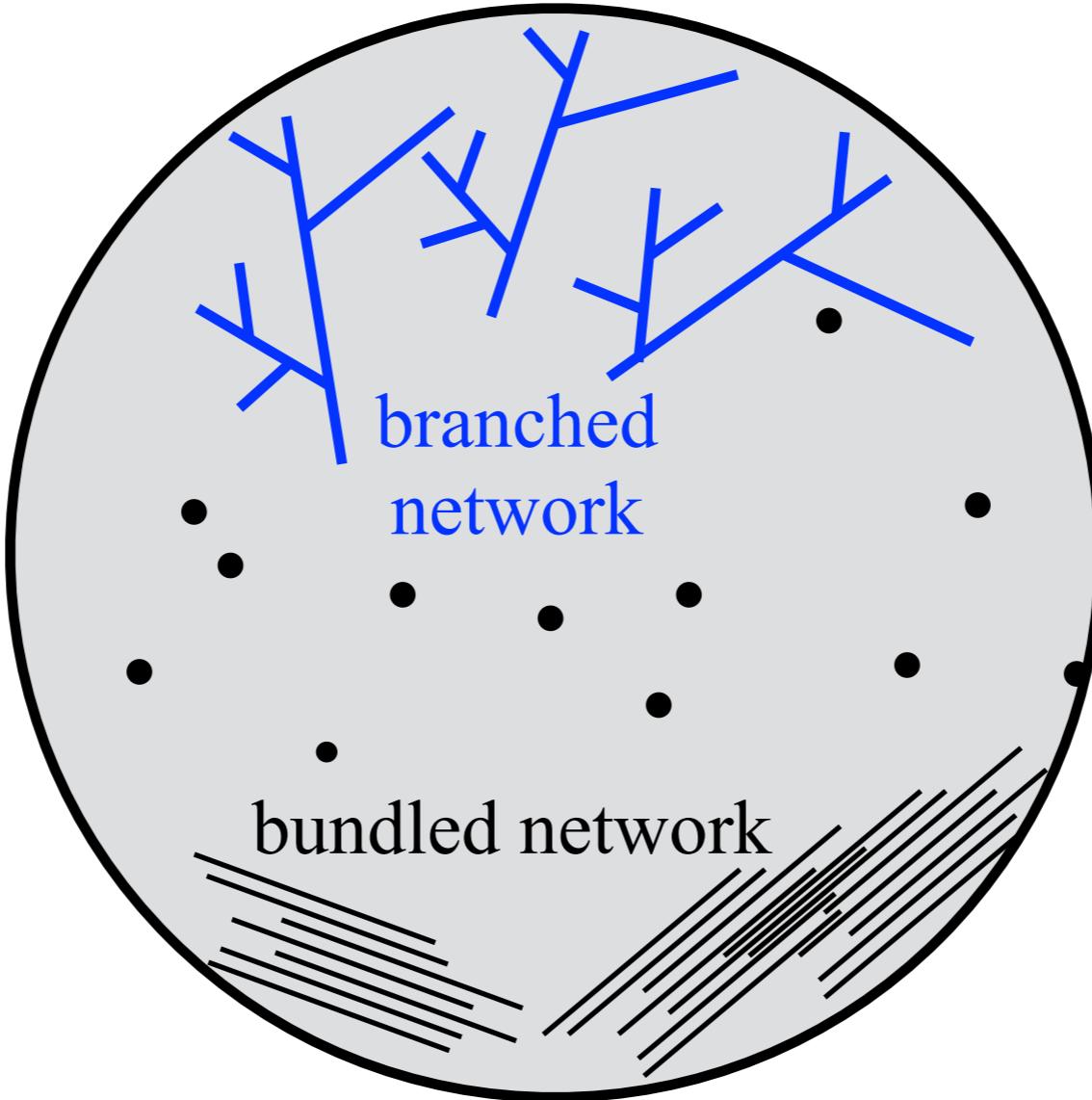


The desired result:



2. Actin module

2. Actin module - Assumptions



What we know biologically:

1. **Actors:** Free actin monomers, **branched actin**, and **bundled actin**
2. **Dynamics:** Two major actin networks assembled & maintained while competing for a limited resource

2. Actin module - Equations

$$\frac{\partial A(x, t)}{\partial t} = A - A^2 - m_0 AB + D \frac{\partial^2 A}{\partial x^2}$$

$$\frac{\partial B(x, t)}{\partial t} = B - B^2 - m_0 AB + D \frac{\partial^2 B}{\partial x^2}$$

$A(x, t)$	Branched actin concentration
$B(x, t)$	Bundled actin concentration

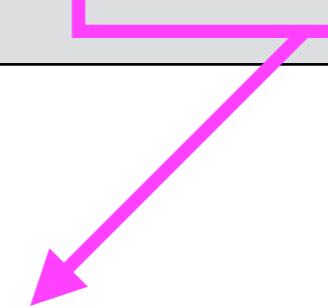
Equations: Lotka-Volterra with diffusion

- Limited resource: free actin monomers
- Continuum/deterministic: Larger number in concentration

2. Actin module - Equations

$$\frac{\partial A(x, t)}{\partial t} = A - A^2 - m_0 AB + D \frac{\partial^2 A}{\partial x^2}$$

$$\frac{\partial B(x, t)}{\partial t} = B - B^2 - m_0 AB + D \frac{\partial^2 B}{\partial x^2}$$



Saturated growth term but limited at high density

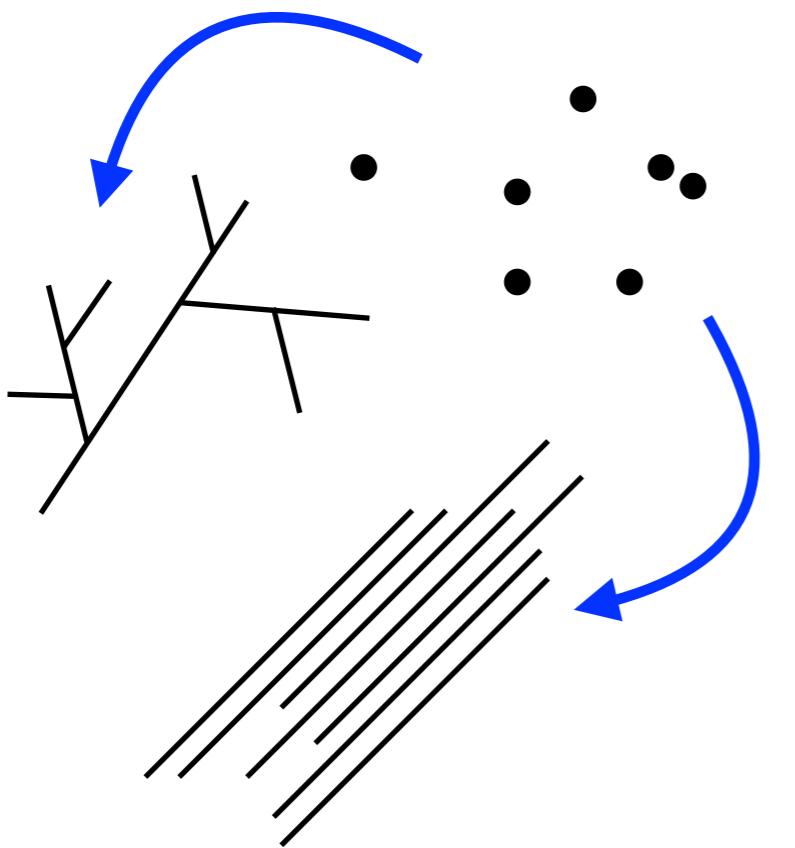
2. Actin module - Equations

$$\frac{\partial A(x, t)}{\partial t} = A - A^2 - m_0AB + D\frac{\partial^2 A}{\partial x^2}$$

$$\frac{\partial B(x, t)}{\partial t} = B - B^2 - m_0AB + D\frac{\partial^2 B}{\partial x^2}$$

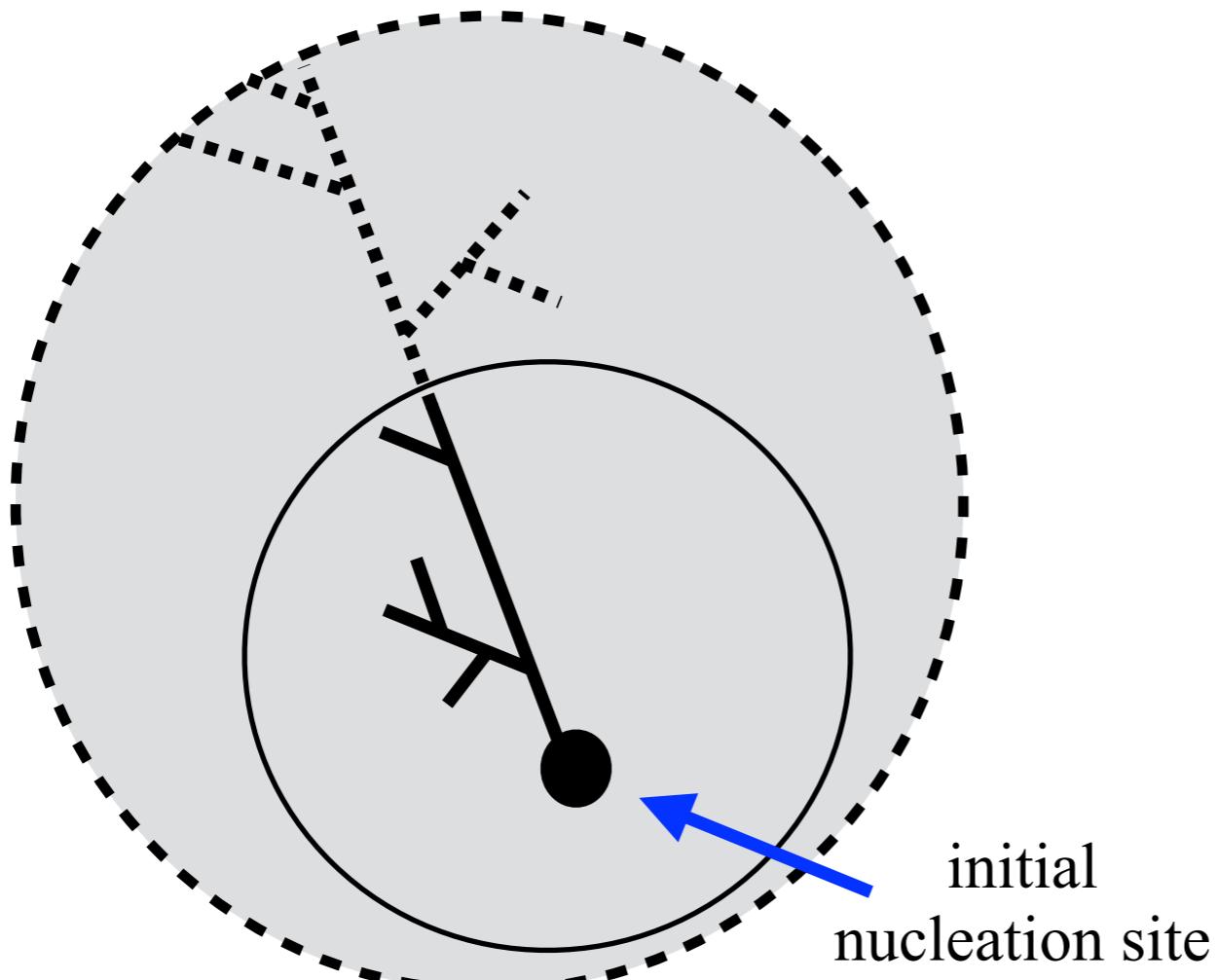
Mechanics of competition

Limited pool of
actin monomers



2. Actin module - Equations

$$\frac{\partial A(x, t)}{\partial t} = A - A^2 - m_0 AB + D \frac{\partial^2 A}{\partial x^2}$$
$$\frac{\partial B(x, t)}{\partial t} = B - B^2 - m_0 AB + D \frac{\partial^2 B}{\partial x^2}$$



Diffusion

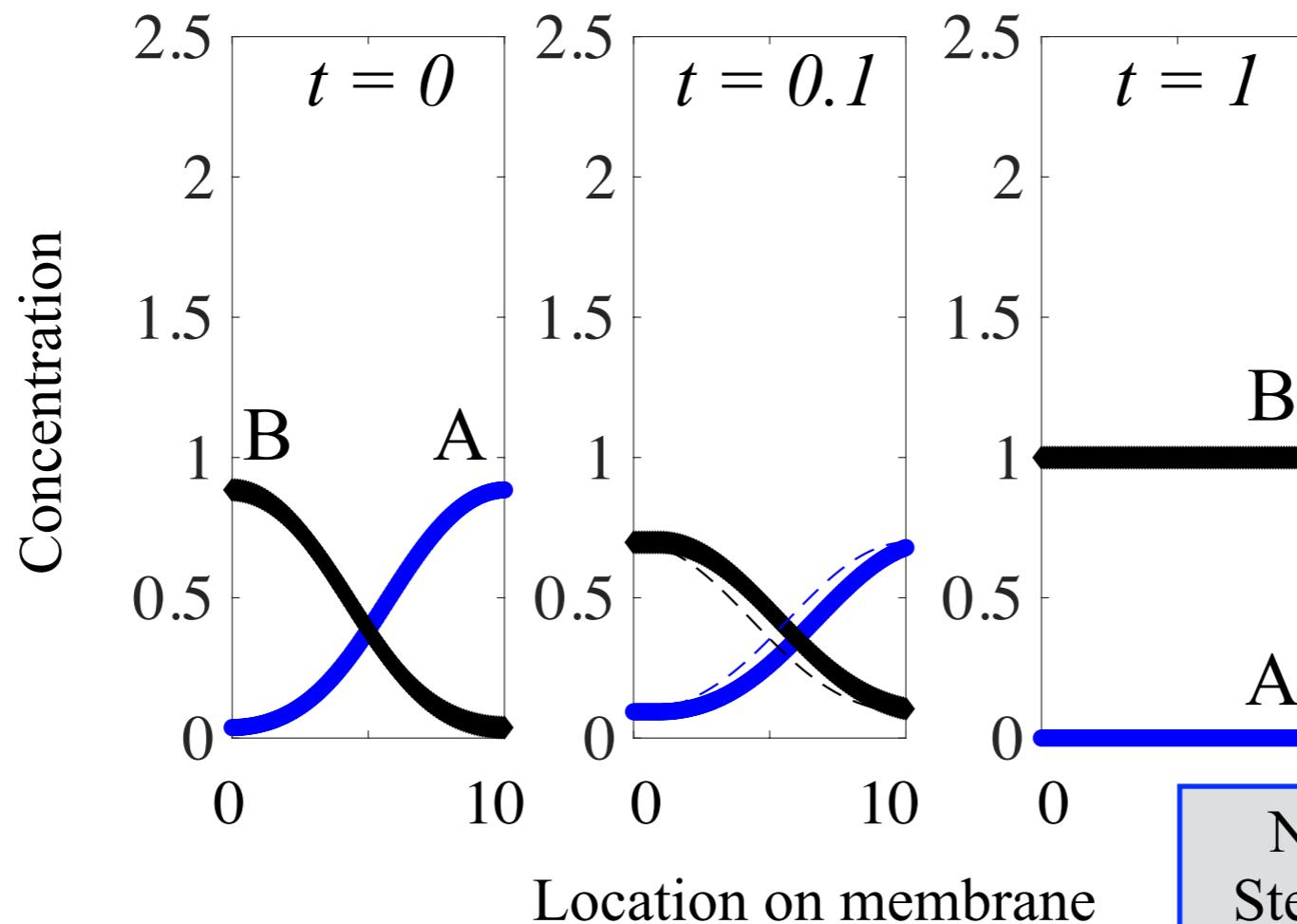
+ sliding/shuffling of
actin filaments
due to molecular motors

2. Actin module - Solutions

Equations: Competition of two species for a limited resource with diffusion

- Limited resource: free actin monomers
- Continuum/deterministic: Larger number in concentration

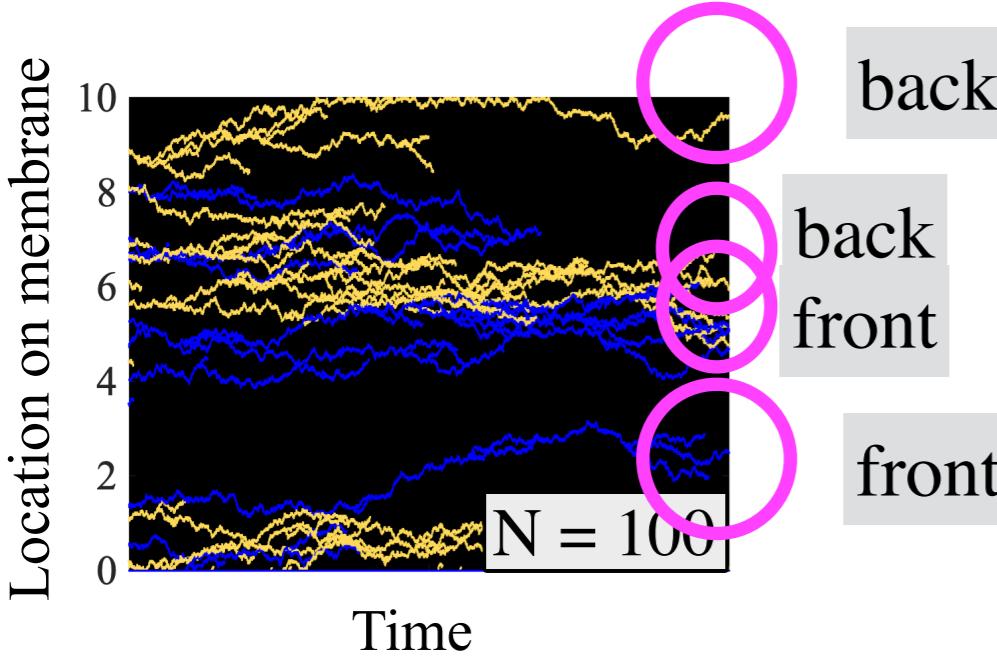
Computational simulation:



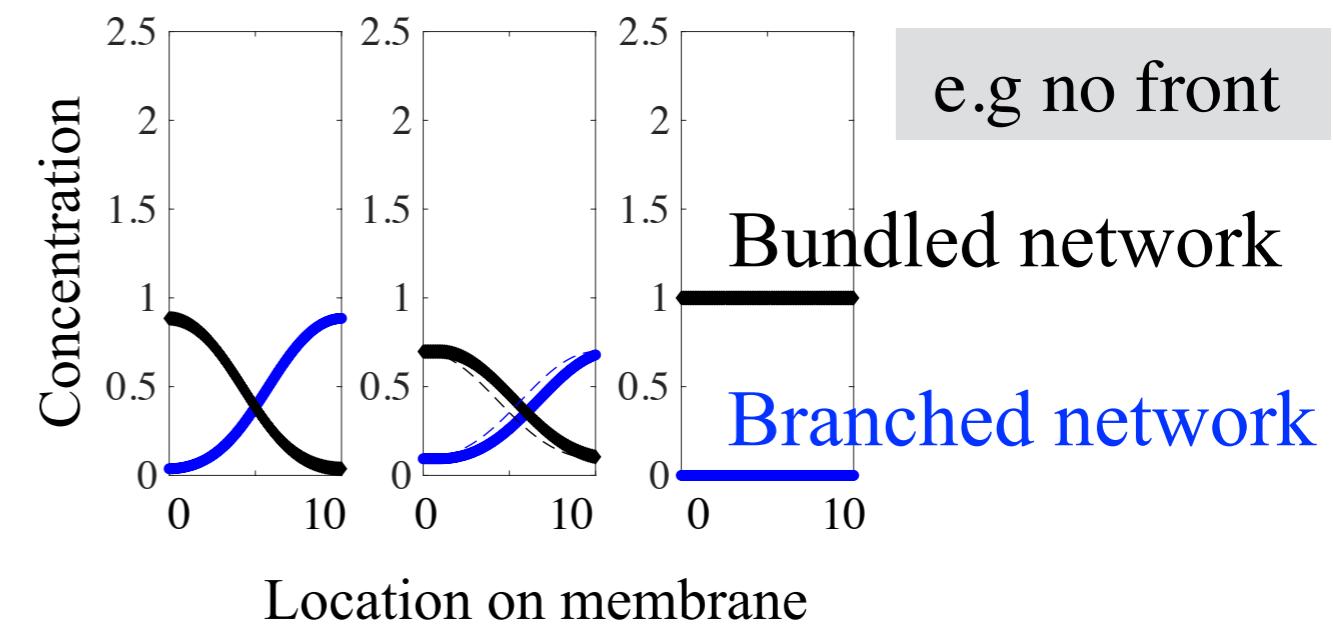
No stable polarized solutions
Steady state depends on relative concentrations

Is it possible for two minimal, non-polarizing models to work together to break cell symmetry and achieve polar distributions?

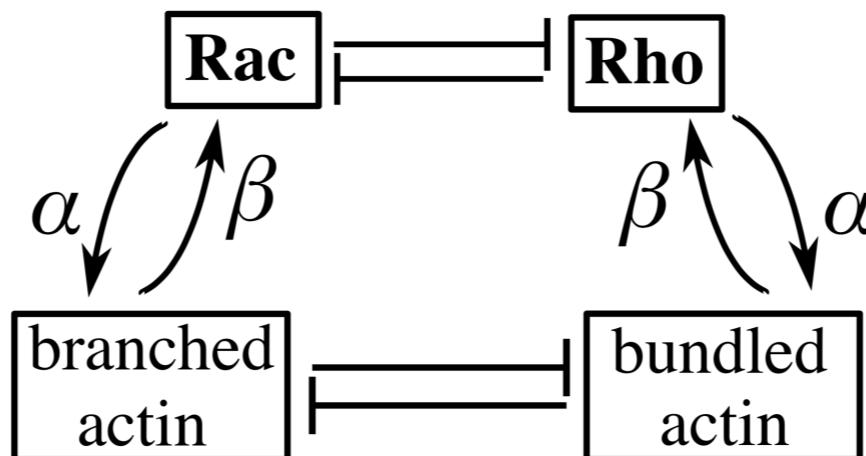
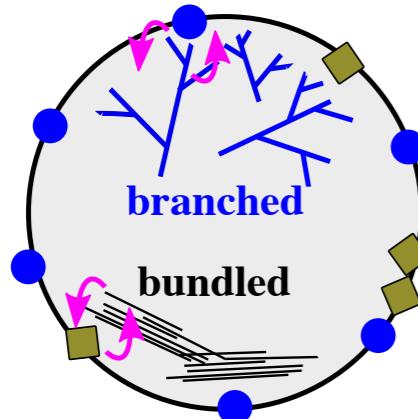
A number of Rac and Rho activity zones emerge



Depending on initial conditions, either one of the two actin networks can persist while the other becomes extinct



Couple the signaling module to the cytoskeleton module



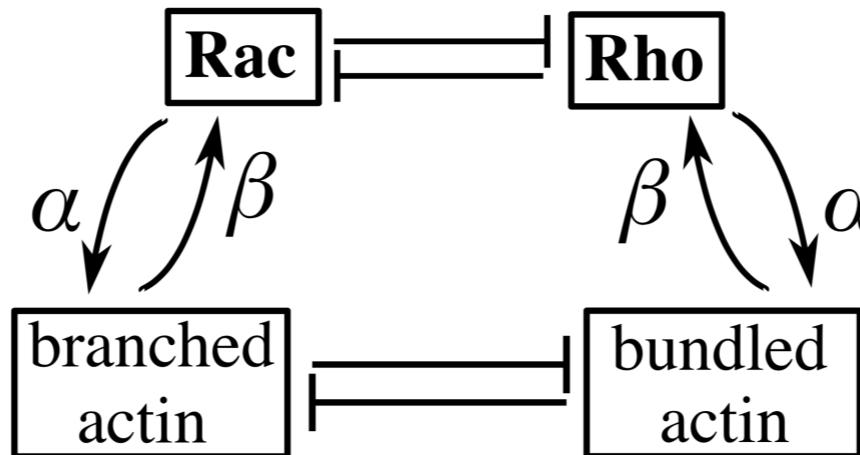
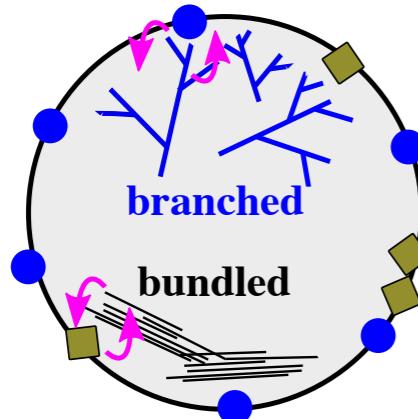
*local, linear
coupling*

At any given time, reaction rates depend on local actin concentrations:

Rac/Rho dynamics $\left\{ \begin{array}{l} k_{\text{on,fb}} = k_{\text{on,fb}} (1 + \beta C(x, t)) \\ k_{\text{off}} = k_{\text{off}} \end{array} \right. \quad C(s, t) = A(s, t) \text{ or } B(s, t)$

Kinetic rates are spatially-dependent

Couple the signaling module to the cytoskeleton module



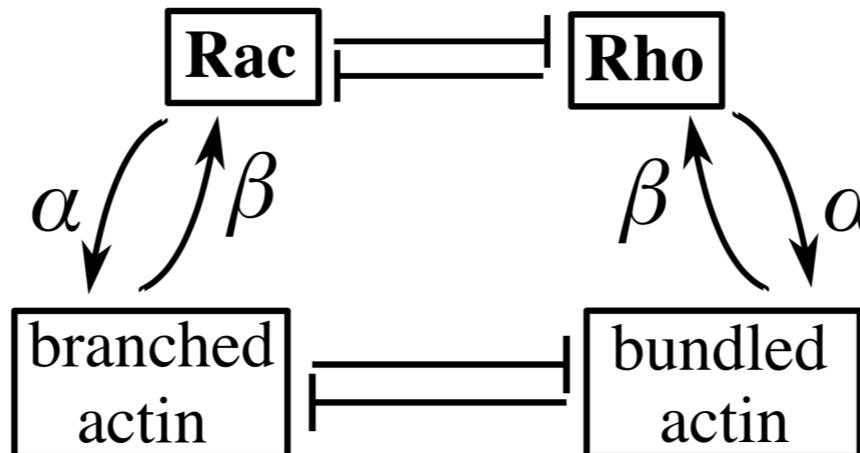
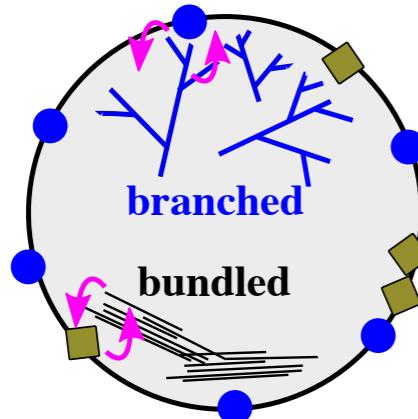
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$$\text{Cytoskeleton dynamics} \quad \left\{ \begin{array}{l} \frac{\partial A(x, t)}{\partial t} = A(1 + \alpha n^{\text{Rac}}(x, t)) - A^2 - m_0 AB + D \frac{\partial^2 A}{\partial x^2} \\ \frac{\partial B(x, t)}{\partial t} = B(1 + \alpha n^{\text{Rho}}(x, t)) - B^2 - m_0 AB + D \frac{\partial^2 B}{\partial x^2} \end{array} \right.$$

Couple the signaling module to the cytoskeleton module



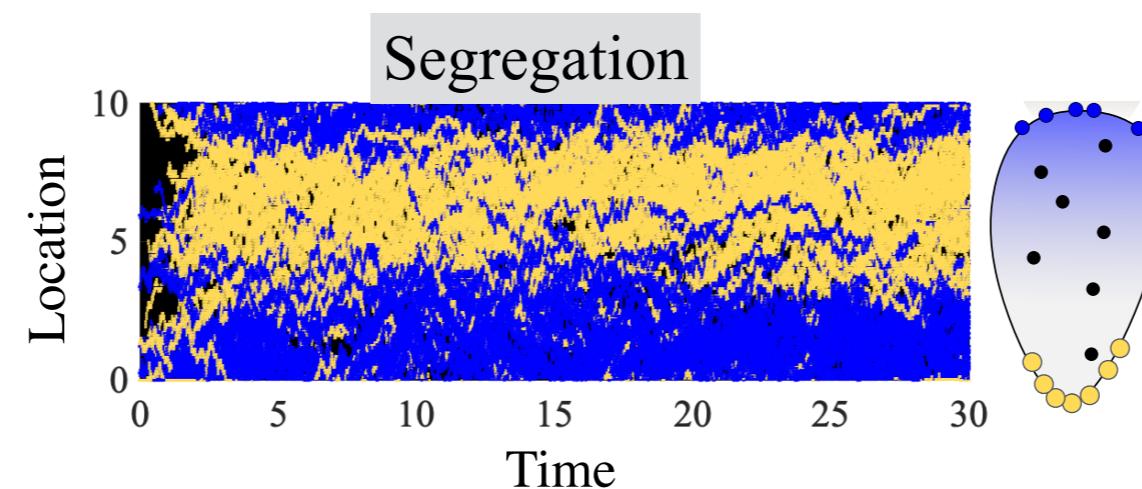
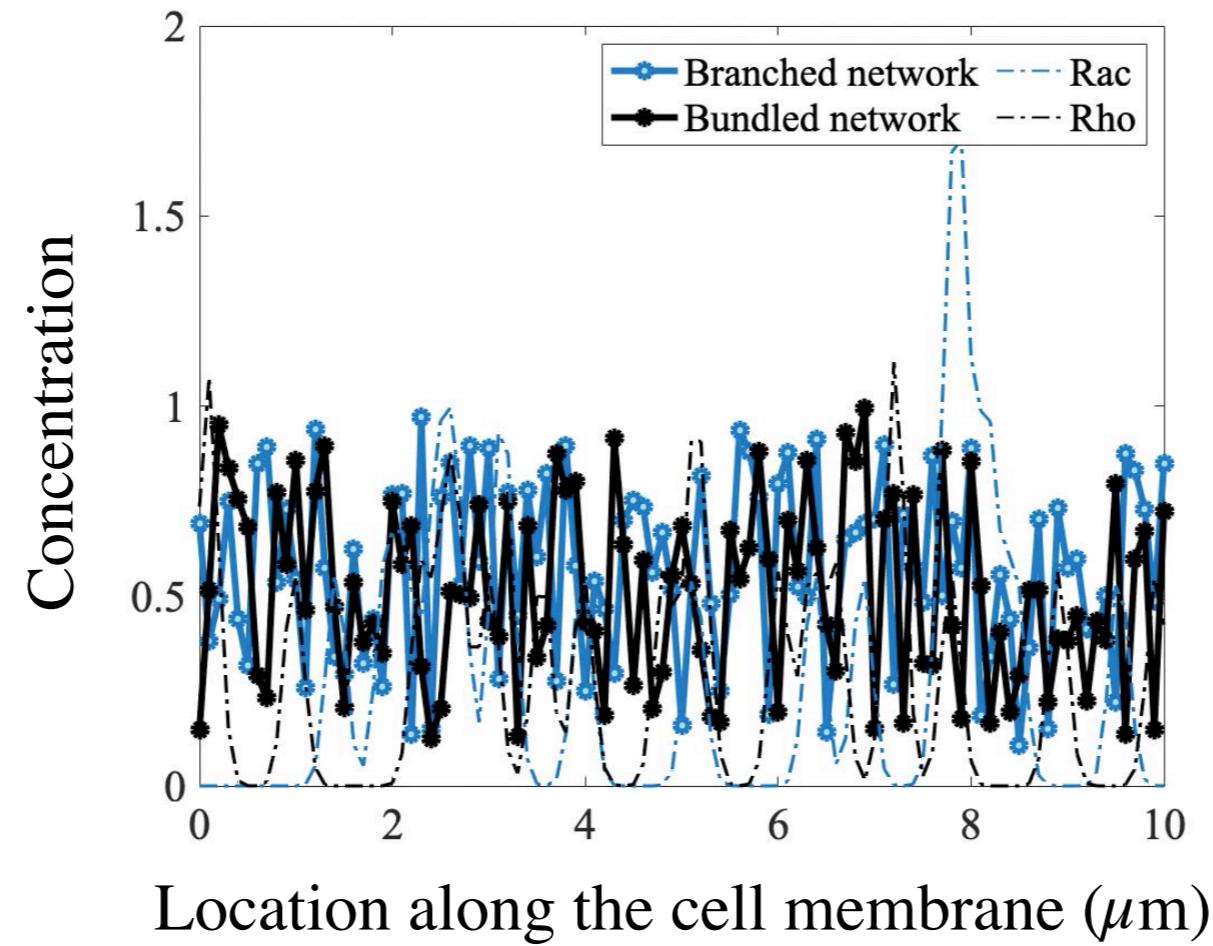
*local, linear
coupling*

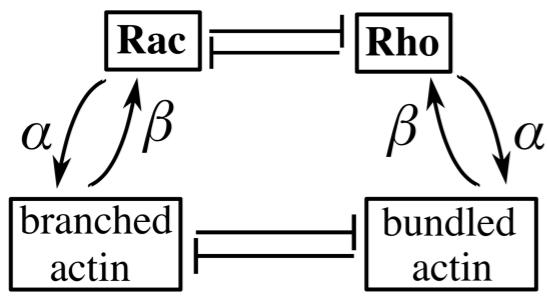
At any given time, reaction rates depend on local actin concentrations:

$$\text{Rac/Rho dynamics} \quad \left\{ \begin{array}{l} k_{\text{on,fb}} = k_{\text{on,fb}} (1 + \cancel{\beta C(x,t)}) \\ k_{\text{off}} = k_{\text{off}} \end{array} \right. \quad C(x,t) : A(x,t) \text{ or } B(x,t)$$

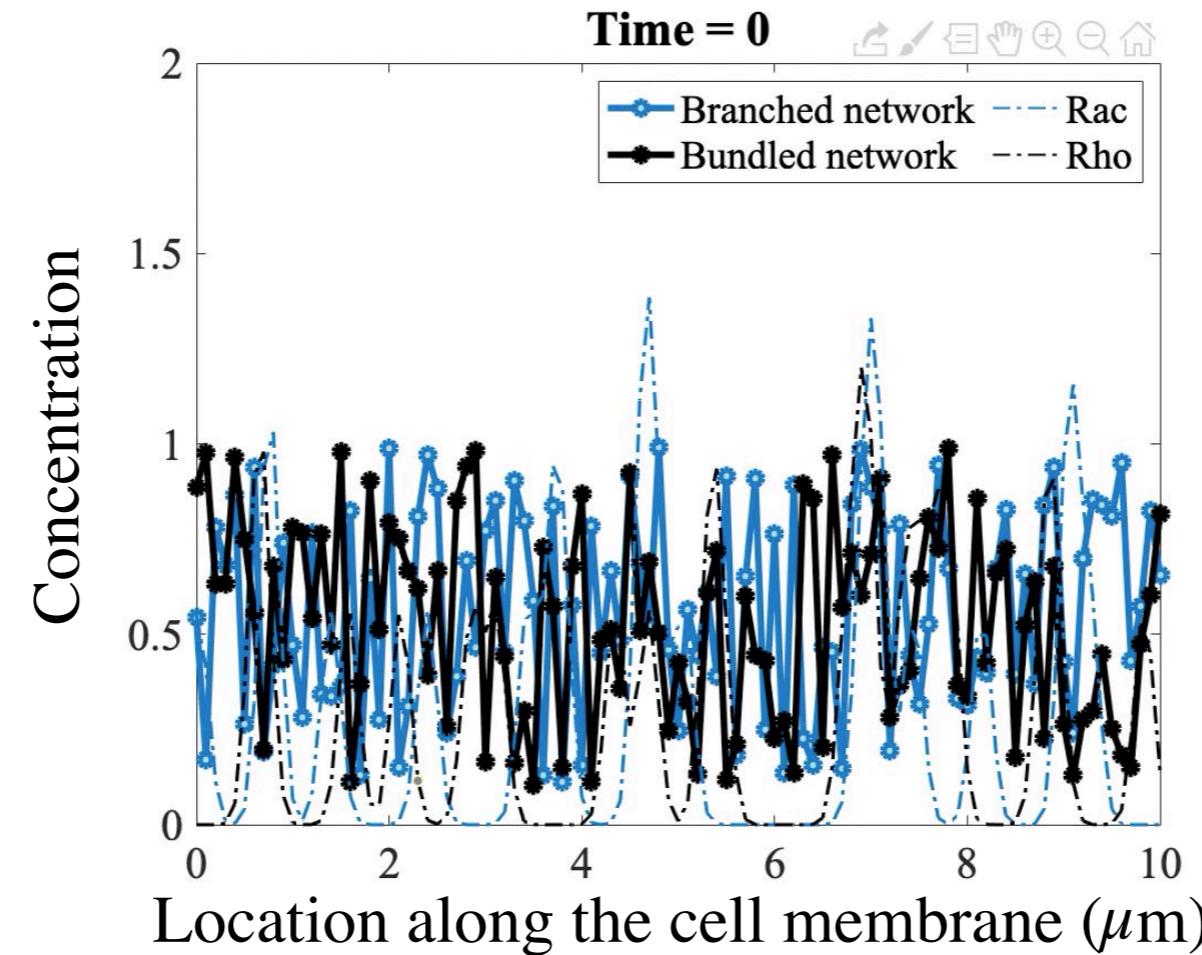
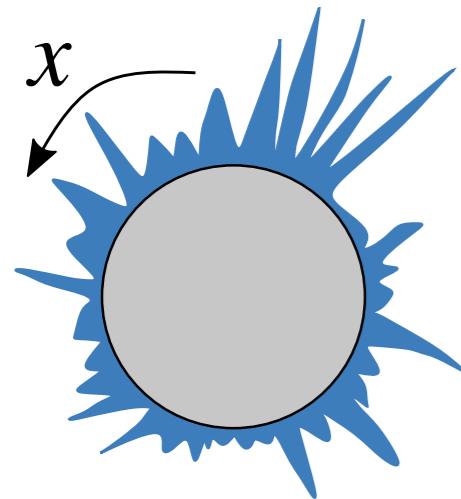
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A strongly coupled system yields spontaneous symmetry breaking α, β large



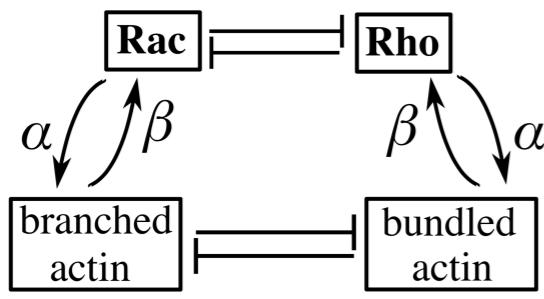


A weakly coupled system
 α, β small

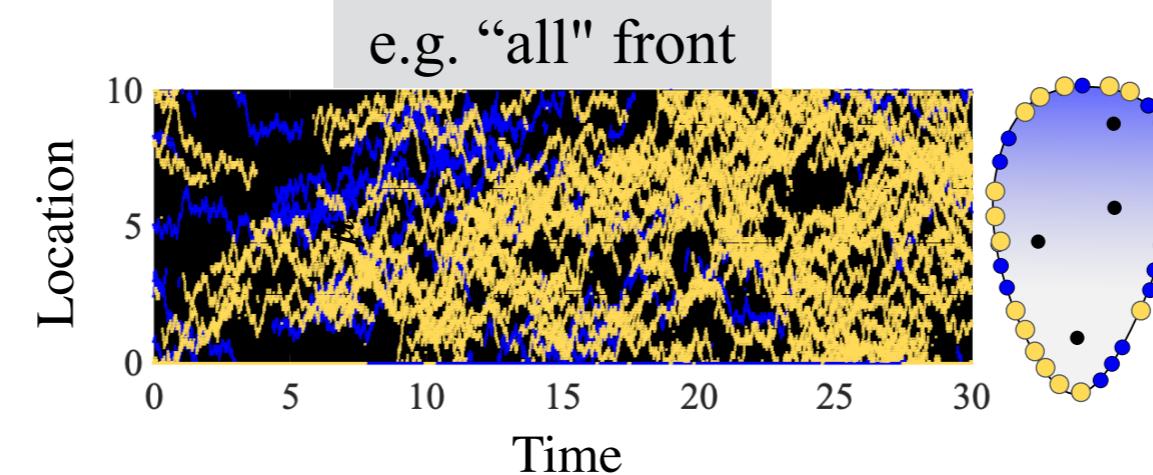
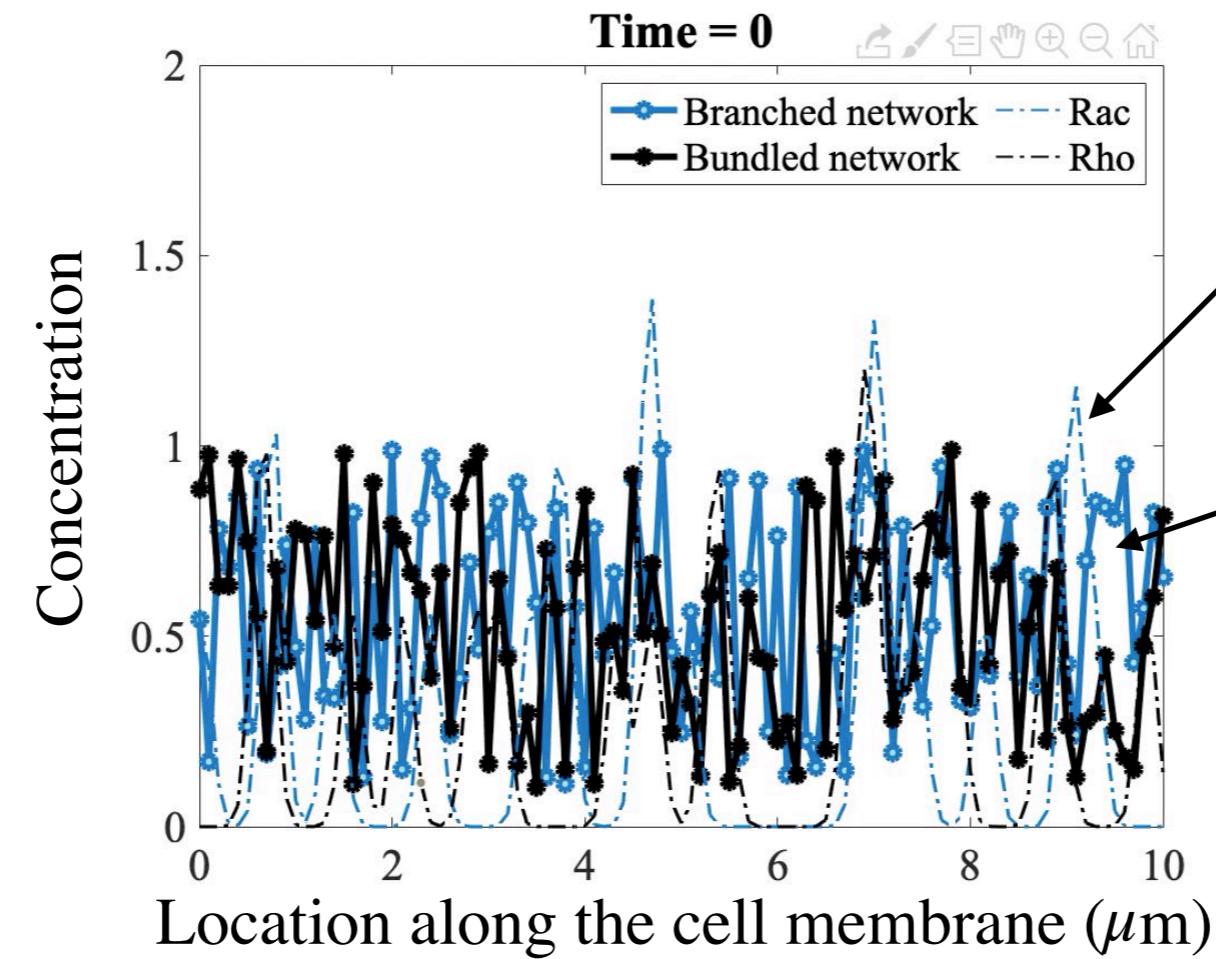
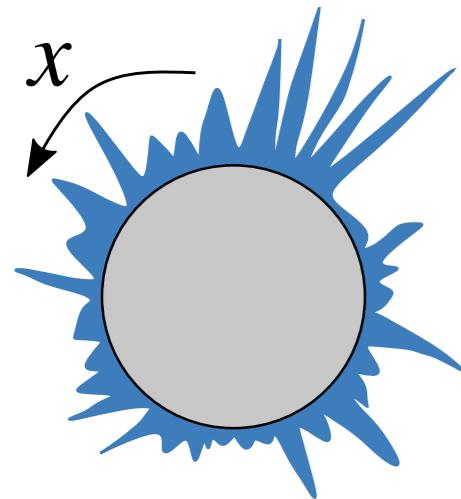


Dotted lines (chemicals)

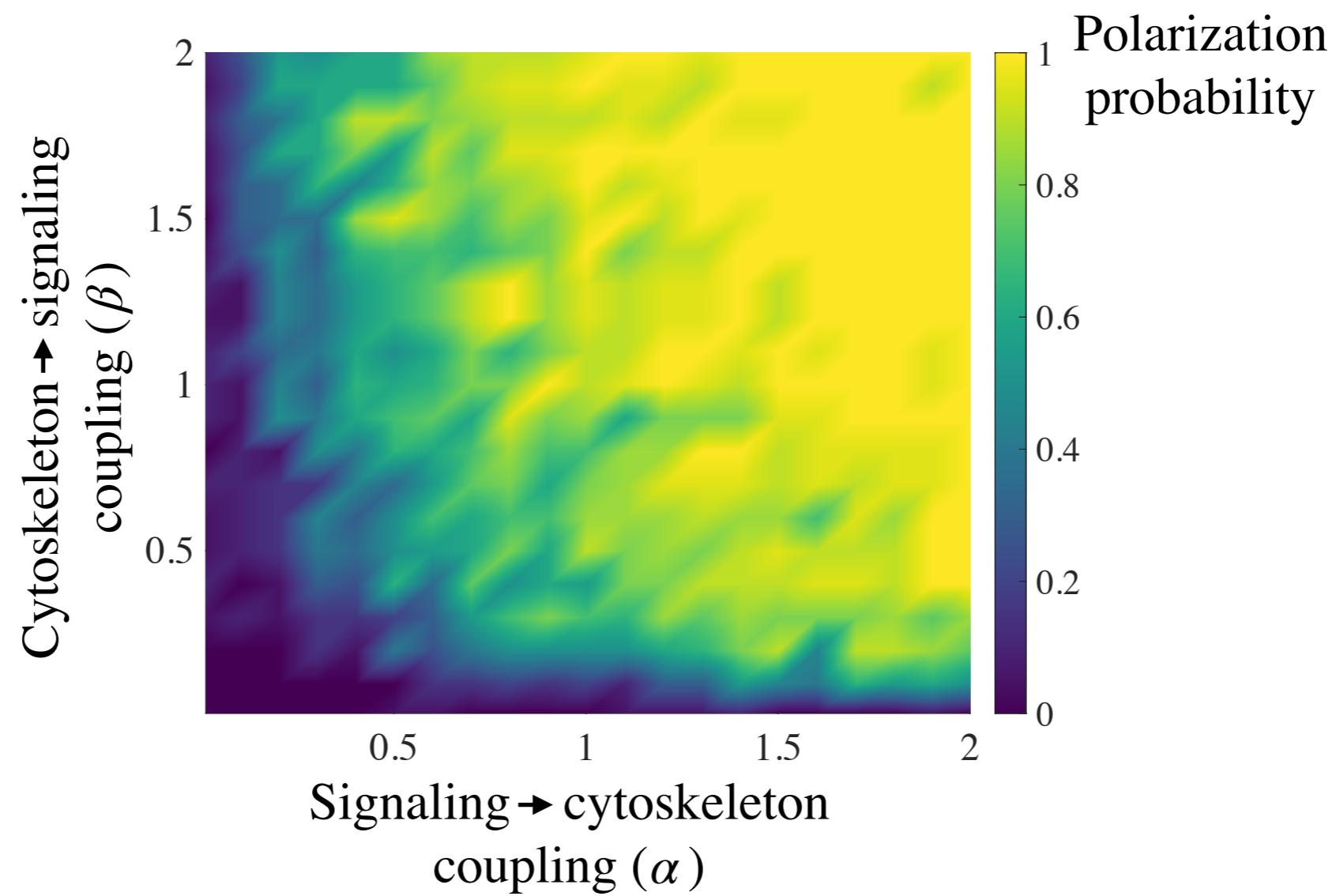
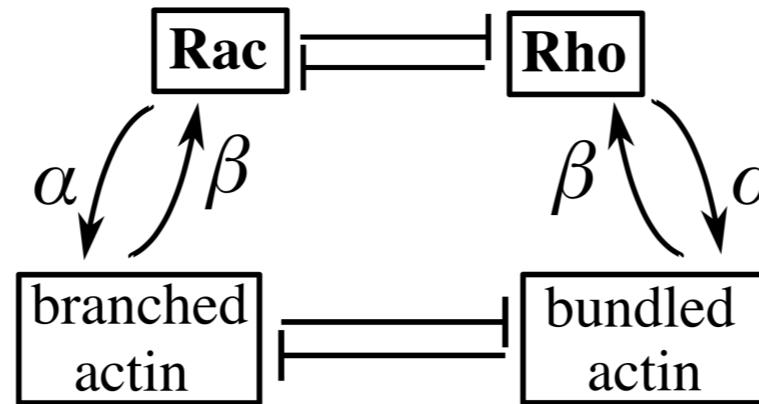
Solid lines (networks)



A weakly coupled system
 α, β small



Self-polarization requires mutual reinforcement/coupling

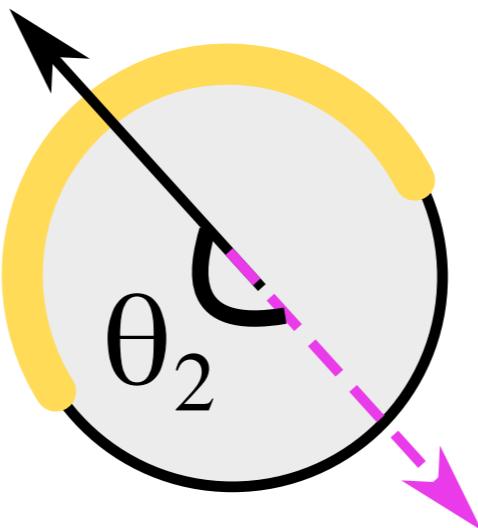


Can the model capture re-orientation?

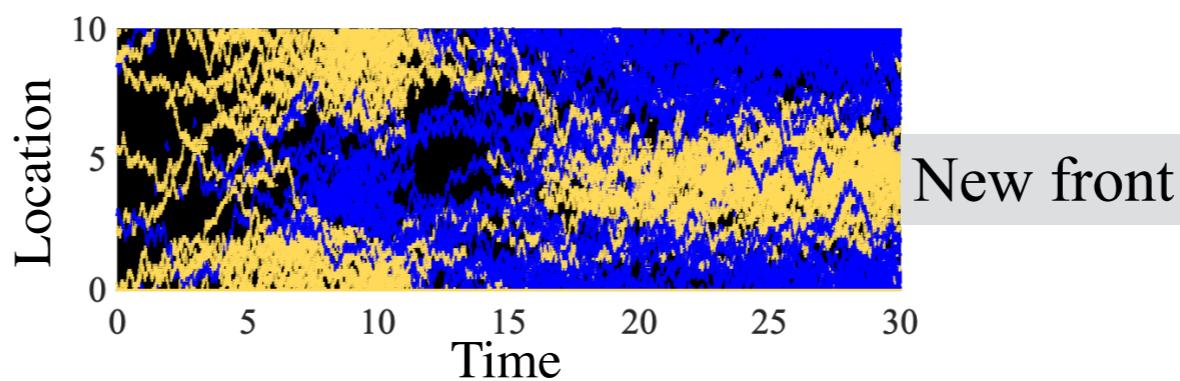
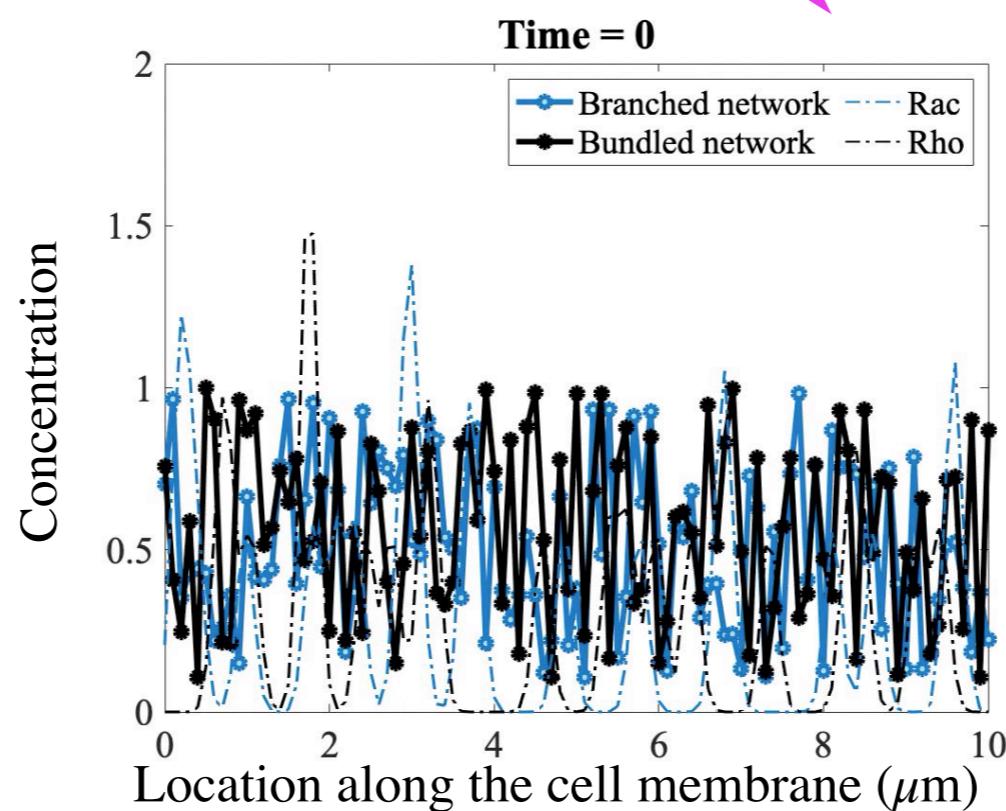
Motivation: Cells frequently change direction of locomotion in the presence of external cues.

Can the model capture re-orientation?

Initial:
External cue A



Later:
External cue B



WHAT MECHANISM IS RESPONSIBLE FOR THE FORMATION OF CELL “FRONT” AND “REAR”?

I. BIOCHEMICAL SIGNALING PATHWAYS

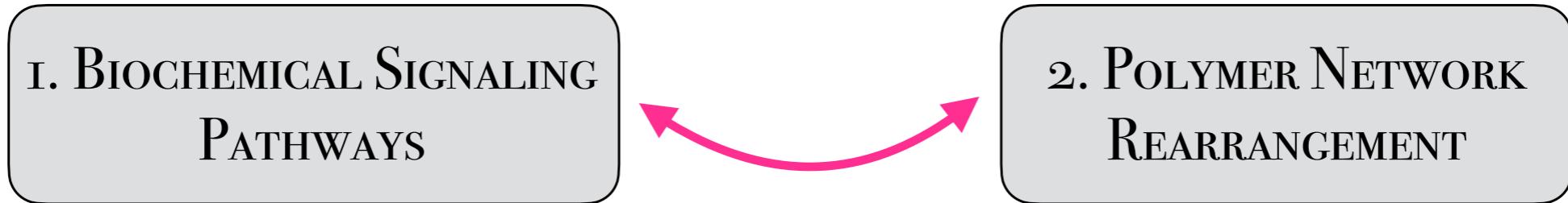
Meinhardt and Gierer 1974
Levchenko and Iglesias 2002
Mori, Jilkine, Edelstein-Keshet 2008
Maree, Jilkine, Dawes, Grieneisen, Edelstein-Keshet, and Dawes 2007
Altschuler, Angenent, Wang, Wu 2008
Pablo, Ramirez, Elston 2018
and many more

2. POLYMER NETWORK REARRANGEMENT

Lomakin, Lee, Han, Bui, Davidson, Mogilner, Danuser 2015

A minimal mechano-chemical model captures spontaneous symmetry breaking

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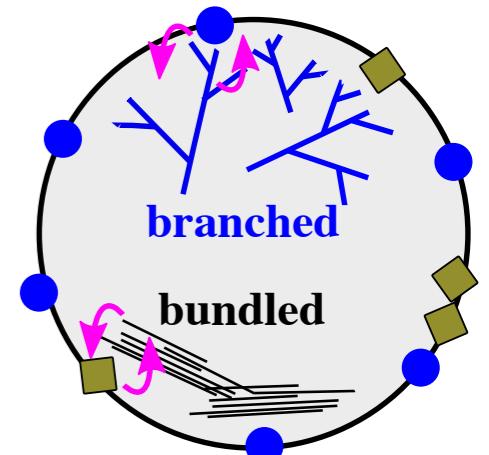
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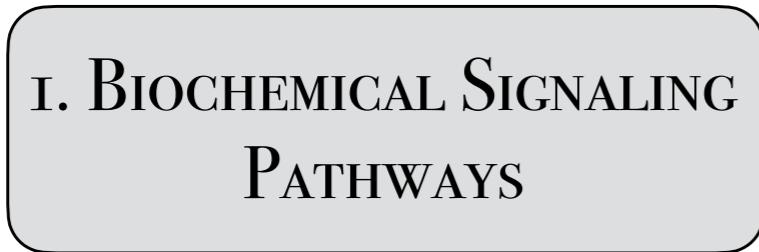
Lomakin, Lee, Han, Bui, Davidson, Mogilner, Danuser 2015

- **Minimally nonlinear**
- **Introduced feedback/coupling (local, linear)**
 - Biologically “speculated” (3 out of 4 directions are established)
 - **Novel testable component:** Positive feedback loop between Rho and formation of actomyosin bundles

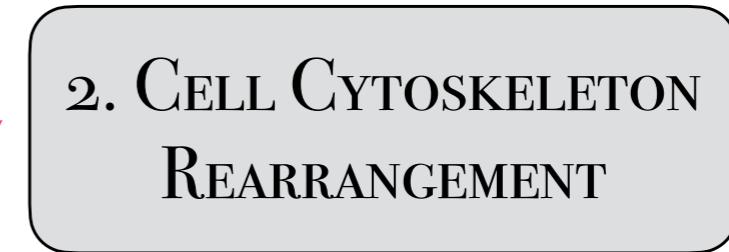


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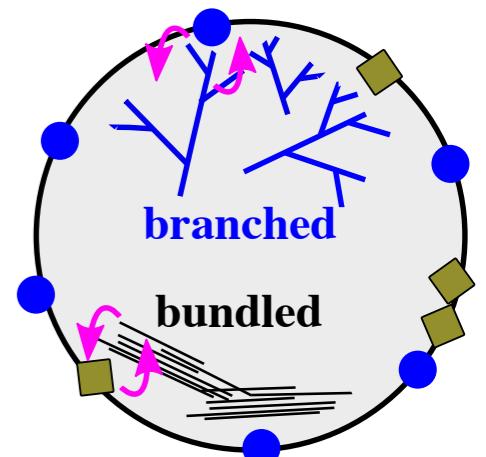
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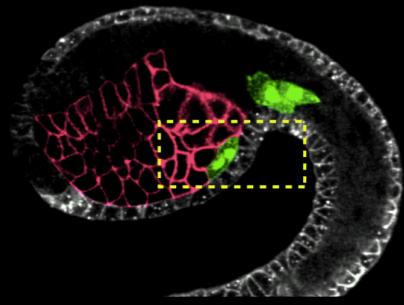


Lomakin, Lee, Han, Bui, Davidson, Mogilner, Danuser 2015

• Mathematical challenges

- Coupling stochastic-deterministic systems
- Time to establish cell polarity?
Continuum description? Not feasible
Peak detection? Statistical learning approach
- 3D (Multiple zones? Any additional complexity?)
- Resolved across multiple cells





Moving as a pair is “better” than alone

Hypothesis #1: There is a **mechanical advantage** to move as a two-cell system

Hypothesis #2: It is easier to **initiate locomotion** as a pair

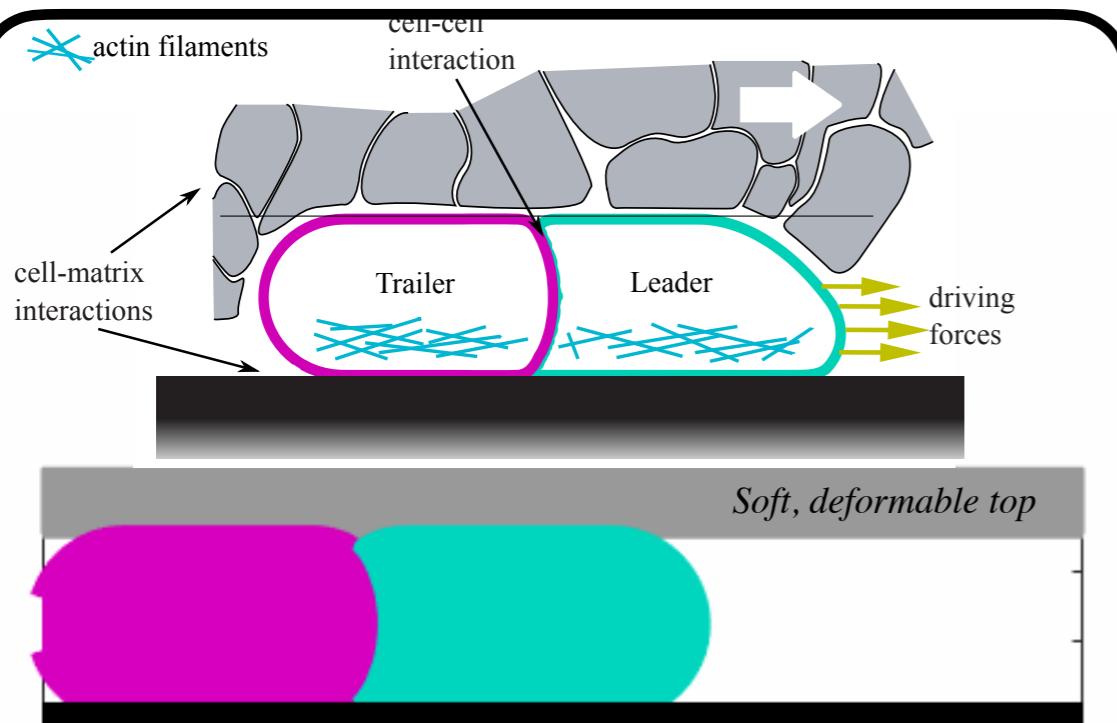
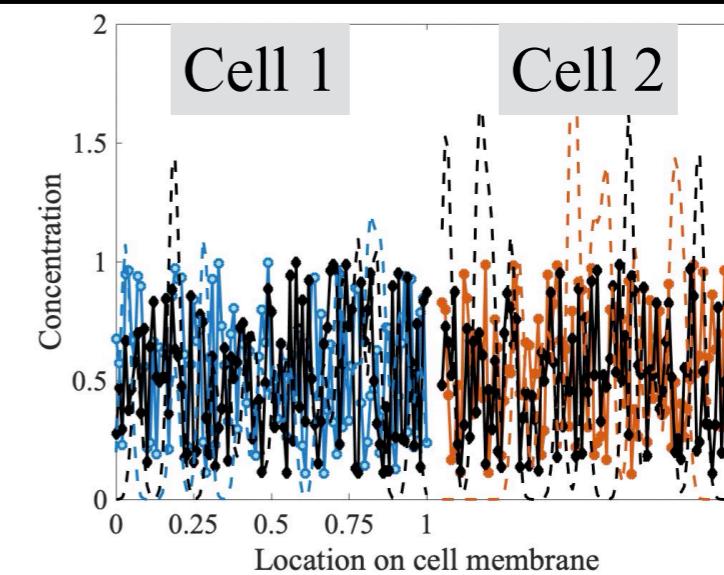


Image analysis (morphometrics)
Mechanical models (force balance)
Traction forces



Hybrid stochastic-deterministic model
Modeling of cell-cell junction behavior
Peak detection algorithms
Eventually, coupled to moving domains

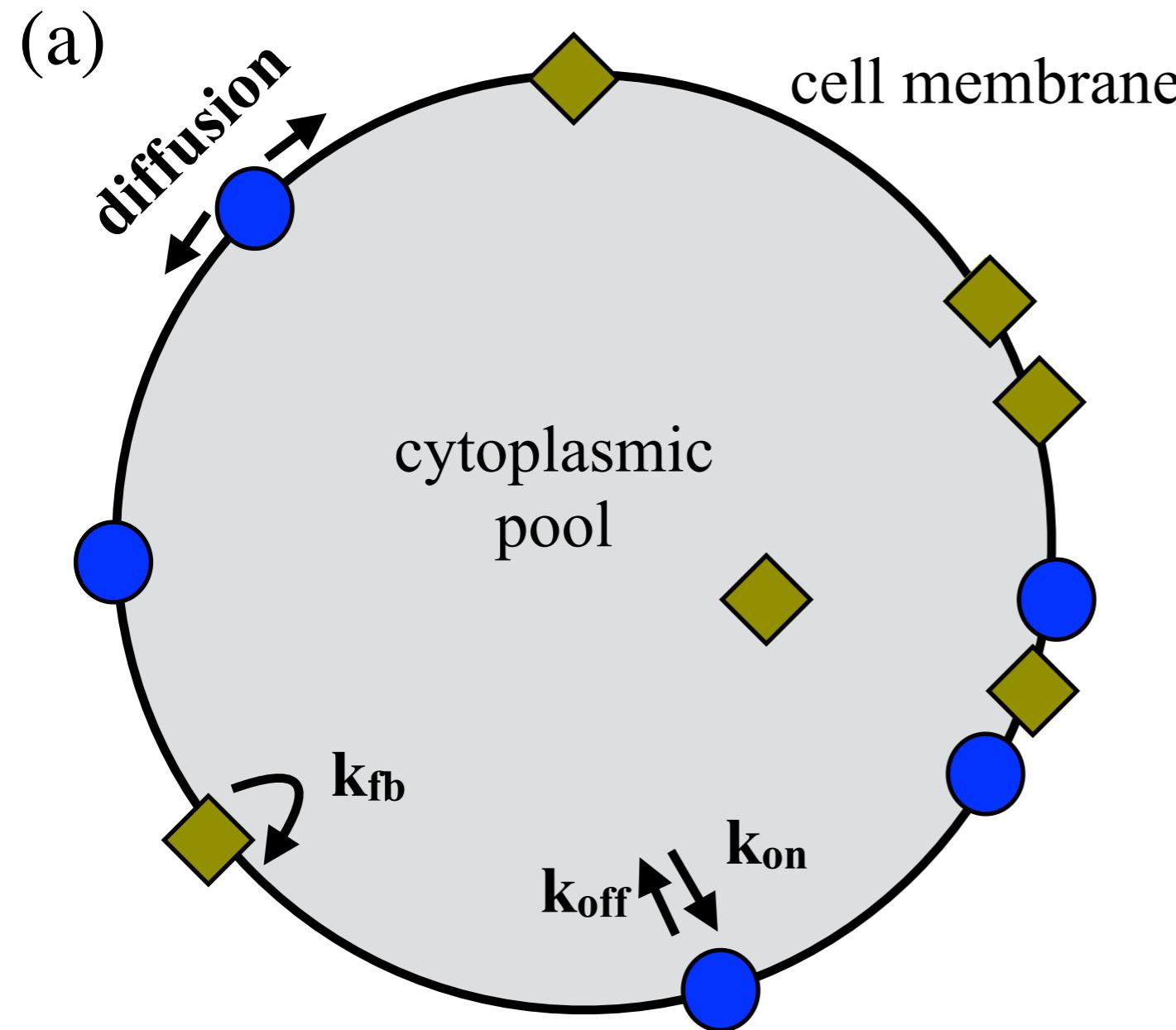
THANK YOU FOR LISTENING!

More info:

- Y. Bernadskaya, H. Yue, **C. Copos**, L. Christiaen, A. Mogilner. (2021) *Supracellular organization confers directionality and mechanical potency to migrating pairs of cardiopharyngeal progenitor cells.* Accepted at eLife.
- T. Vignaud, **C. Copos**, Q. Tseng, L. Blanchoin, A. Mogilner, M. Thery, L. Kurzawa. (2020) *Stress fibers are embedded in a contractile cytoplasmic meshwork.* Nature Materials, Vol. 20, 410-420.
- Y.-H. Sun, H. Yue, **C. Copos**, Y. Sun, K. Zhu, B. Reid, B.W. Draper, M. Zhao, A. Mogilner. (2020) *PI3K inhibition reverses migratory direction of single cells but not cell groups in electric fields.* In review at Biophysical Journal.
- **C. Copos**, A. Mogilner. (2020) *A hybrid stochastic-deterministic mechanochemical model of cell polarization.* Molecular Biology of the Cell, Vol. 31, 1637-1649.
- **C. Copos**, B. Bannish, K. Glasior, R. Pinals, M. Rostami, A. Dawes. (2020) *Connecting actin polymer dynamics across multiple scales.* R.Segal et al. (eds), Using Mathematics to Understand Biological Complexity, Series 22, Springer.
- **C. Copos**, R.D. Guy. (2018) *A porous viscoelastic model for the cell cytoskeleton.* ANZIAM Journal, Vol. 59, 472-498.
- **C. Copos**, S. Walcott, J.C. del Alamo, E. Bastounis, A. Mogilner, R.D. Guy. (2017) *Mechanosensitive adhesion explain stepping motility in amoeboid cells.* Biophysical Journal, Vol. 112, 2672-2682.
- W. Strychalski, **C. Copos**, O.L. Lewis, R.D. Guy. (2015) *A poroelastic immersed boundary method with applications to cell biology.* Journal of Computational Physics, Vol. 282, 77-97.
- C. Bodea, **C. Copos**, M.F. Der, D. O'Neal, J.A. Davis. (2011) *Shared autocorrelation property of sequences.* IEEE: Transactions on Information Theory, Vol. 57, 3805-3809.

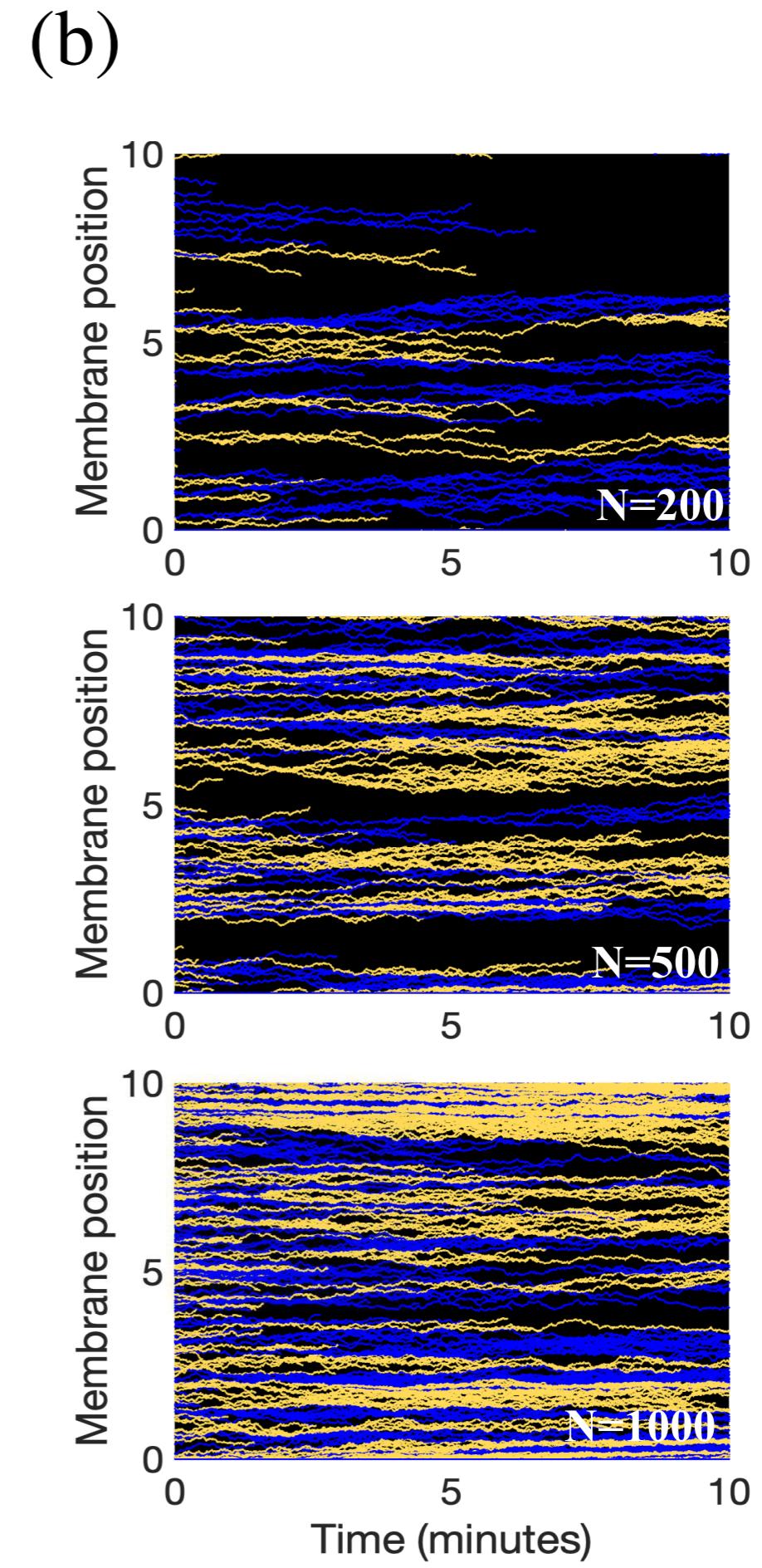


Figure 2



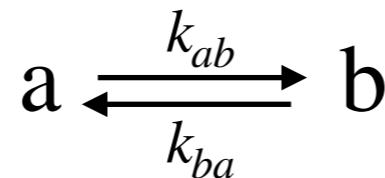
2 polarity
protein species:

Rac
 Rho



Wave pinning model - why this reaction term

$$\begin{aligned}\frac{\partial a}{\partial t} &= D_a \frac{\partial^2 a}{\partial x^2} + f(a, b) \\ \frac{\partial b}{\partial t} &= D_b \frac{\partial^2 b}{\partial x^2} - f(a, b) \\ f(a, b) &= \left(k_0 + \frac{\gamma a^2}{K^2 + a^2} \right) b - \delta a\end{aligned}$$



$$\begin{aligned}\frac{da}{dt} &= \text{Rate of activation} - \text{Rate of inactivation} \\ &= k_{ba} b - k_{ab} a = f(a, b)\end{aligned}$$

Bistability requires either rate to be nonlinear. Here, authors assume cooperative positive feedback:

$$k_{ba} = k_0 + \frac{\gamma a^2}{K^2 + a^2}, k_{ab} = \delta$$

Lower diffusion scenario

(A) Wave pinning with
 $D = 0.01 \text{ } \mu\text{m}^2/\text{sec}$

(B) Our hybrid model
with $D = 0.01 \text{ } \mu\text{m}^2/\text{sec}$

