

Bayesian Chemotaxis

Information theory of chemotactic agents
combining spatial & temporal gradient-sensing

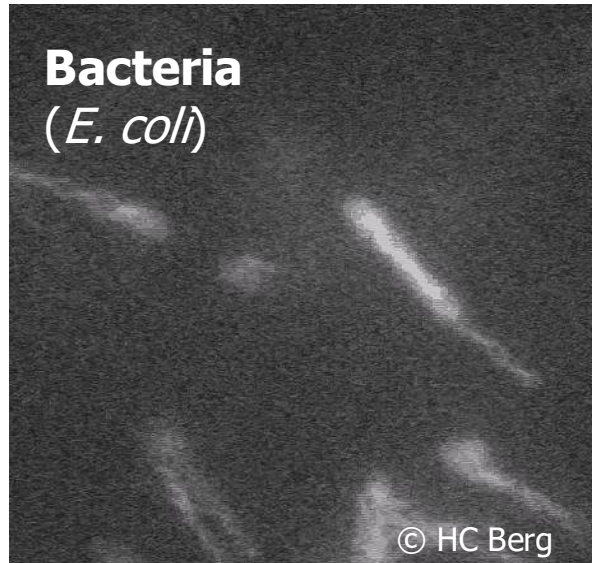
Benjamin Friedrich Biological Algorithms Group
EXC Physics of Life, TU Dresden

There is a myriad of cells and organisms

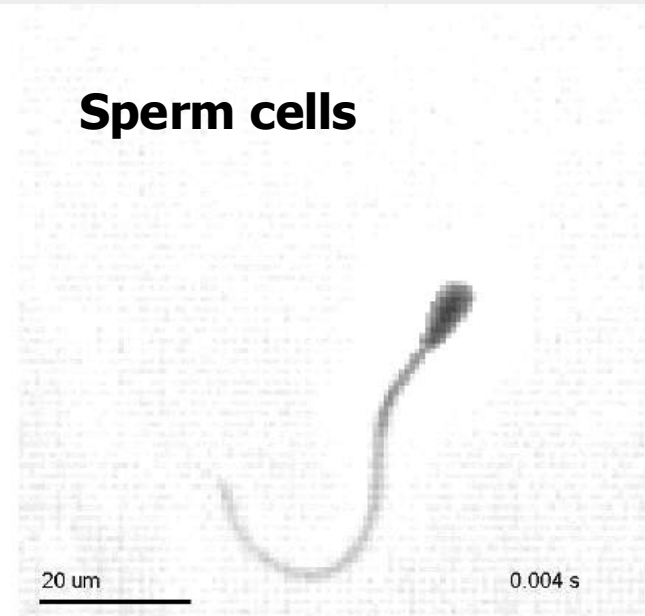
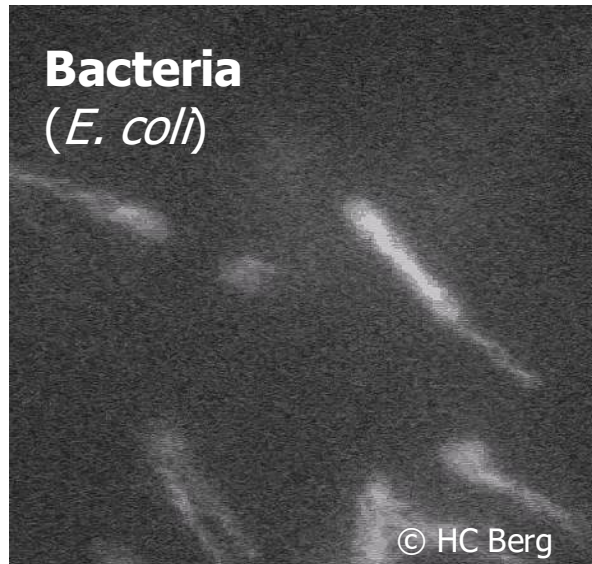


DR. RICHARD KIRBY

... that move actively

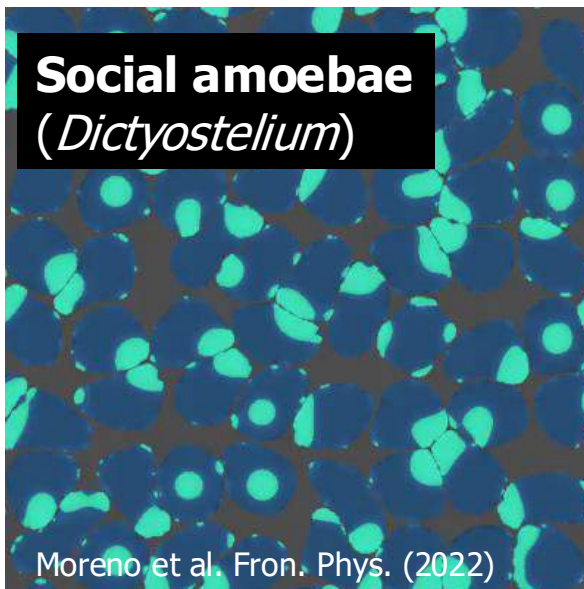
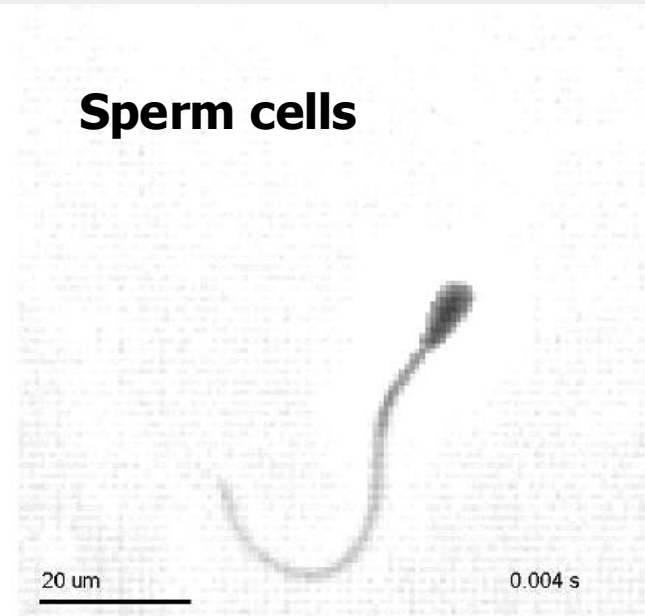
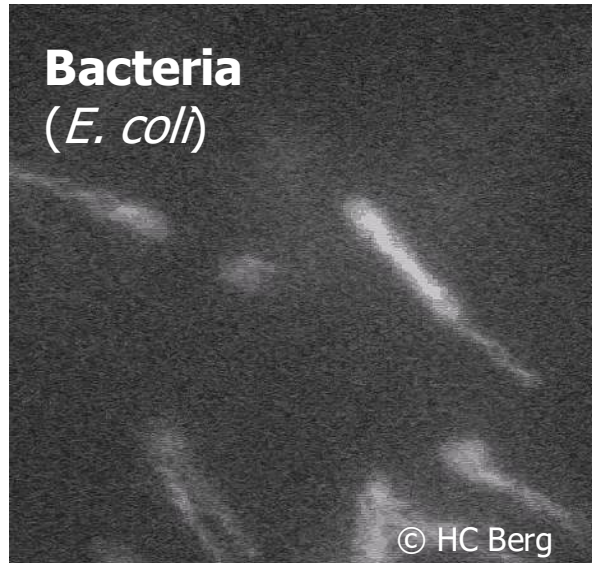


... that move actively

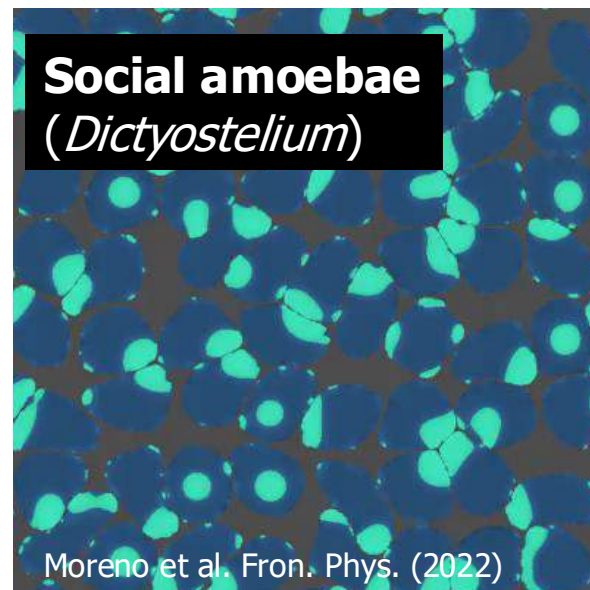
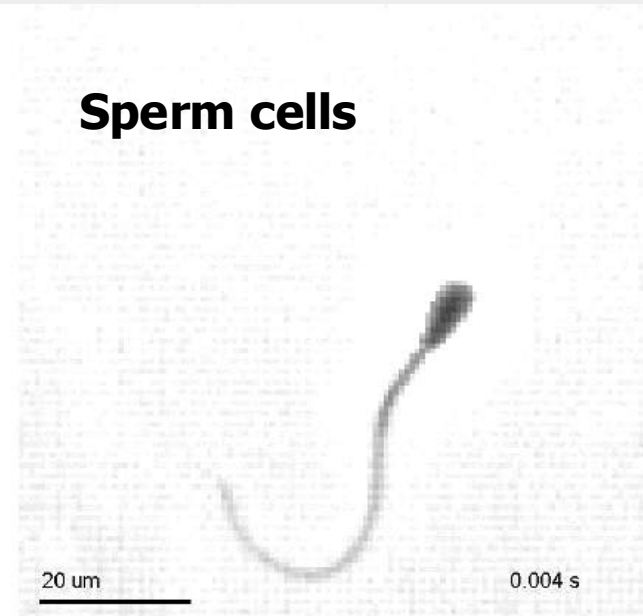
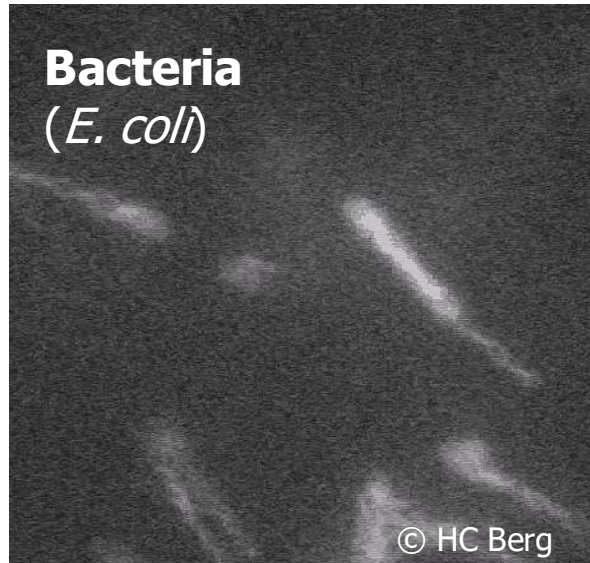


Friedrich et al. JEB (2010)

... that move actively

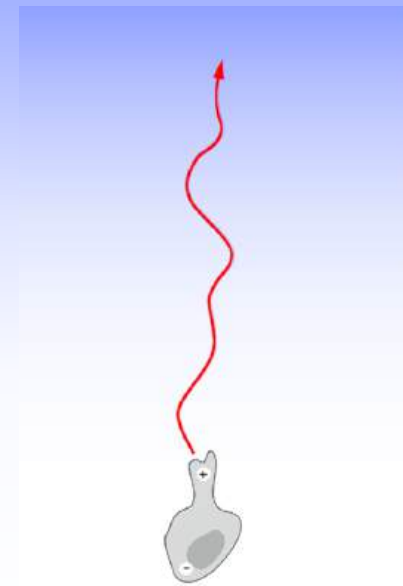


... that move actively



Cells follow **concentration gradients**

- Bacteria: food
- Sperm cells: egg
- Amoebae: social signals
- Immune cells: pathogens



Immune cells

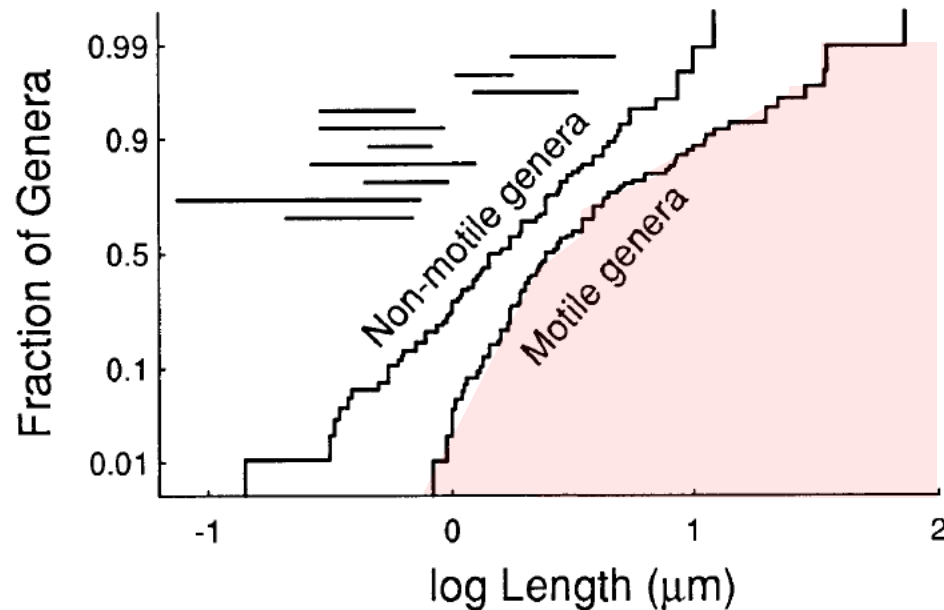
Berg, Purcell: Biophys. J. (1977)

Dusenberry: Biophys. J. (1998)

Alvarez, Friedrich, Gompper, Kaupp: Trends Cell Biol. (2014)

Wan, Jekely: Phil. Trans. R. Soc. B (2021)

Only cells larger $\frac{1}{2}$ micron are motile ...



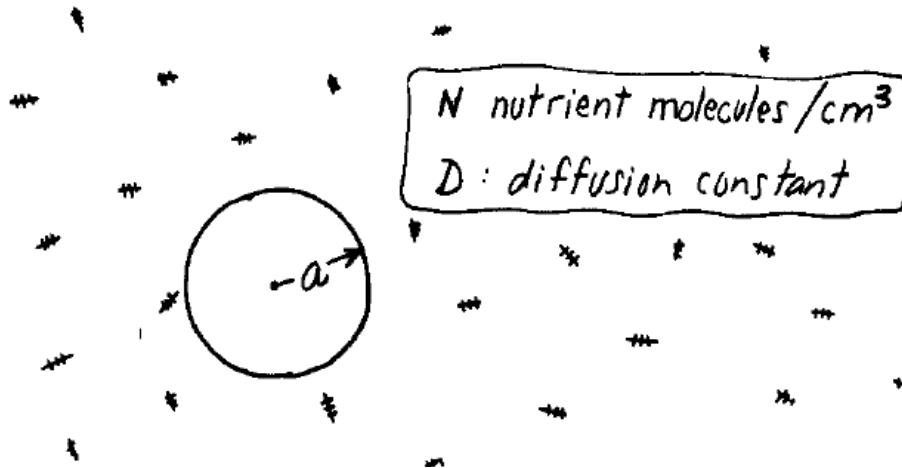
Motile fraction

Dusenberry: PNAS (1997): **Minimum size limit for useful locomotion by free-swimming microbes**

... because active motility does not help for “grazing” ...

Purcell: Am. J. Phys. (1977):

Life at low Reynolds number



Stirring vs. Diffusion

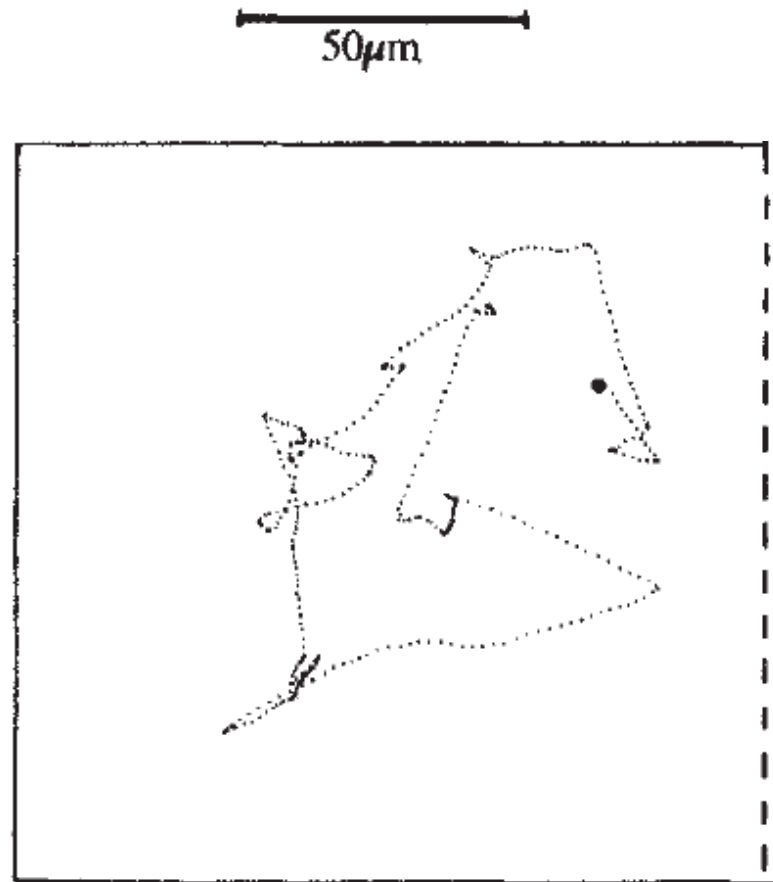
time for transport by stirring: $\frac{l}{v}$

time for transport by diffusion: $\frac{l^2}{D}$

stirring works if $\frac{lv}{D} > 1$

To enhance nutrient uptake
a bacterium would have to swim 1 mm/sec!

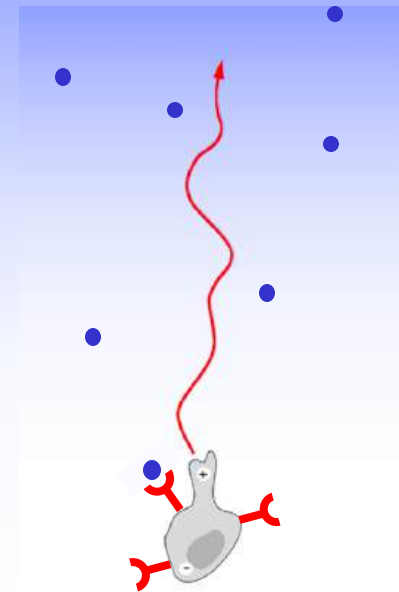
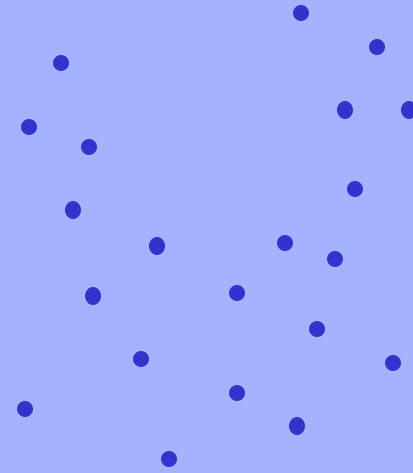
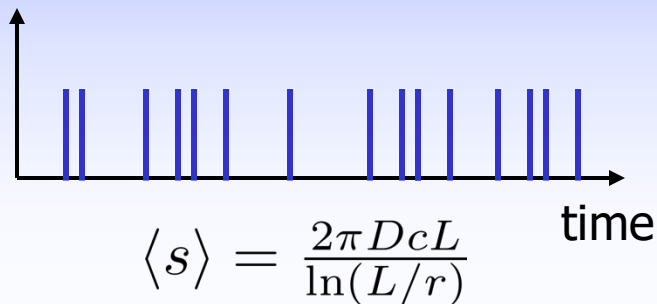
... but to find greener pastures



3D-tracking of
run-and-tumble
chemotaxis of
bacterium *E. coli*

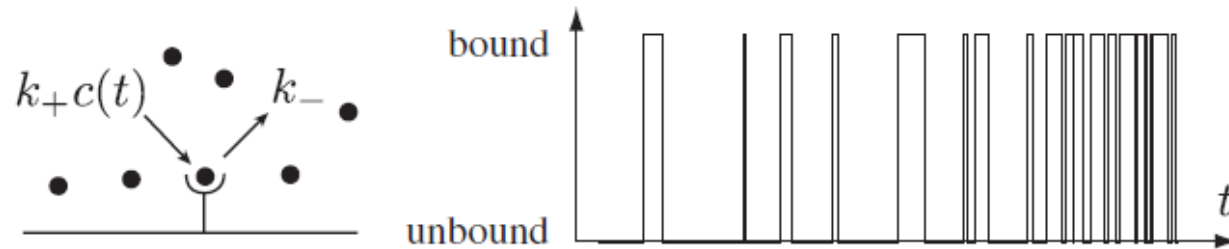
Molecule counting noise causes **sensing noise**

Detection of chemoattractant molecules



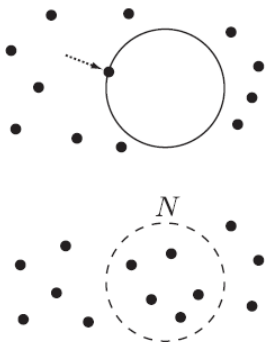
Immune cells

How to measure a concentration?



$$\frac{\delta c}{c} \sim \sqrt{D a c T}$$

diffusion agent concen- sensing
coefficient size tration time



Berg, Purcell: BPJ 1977

Bialek, Setayeshgar. PNAS 2005

Kaizu et al.: BPJ 2014

Mora, Wingreen: PRL 2010, ...

Concentration sensing as a **Bayesian decision** problem

PRL **104**, 228104 (2010)

PHYSICAL REVIEW LETTERS

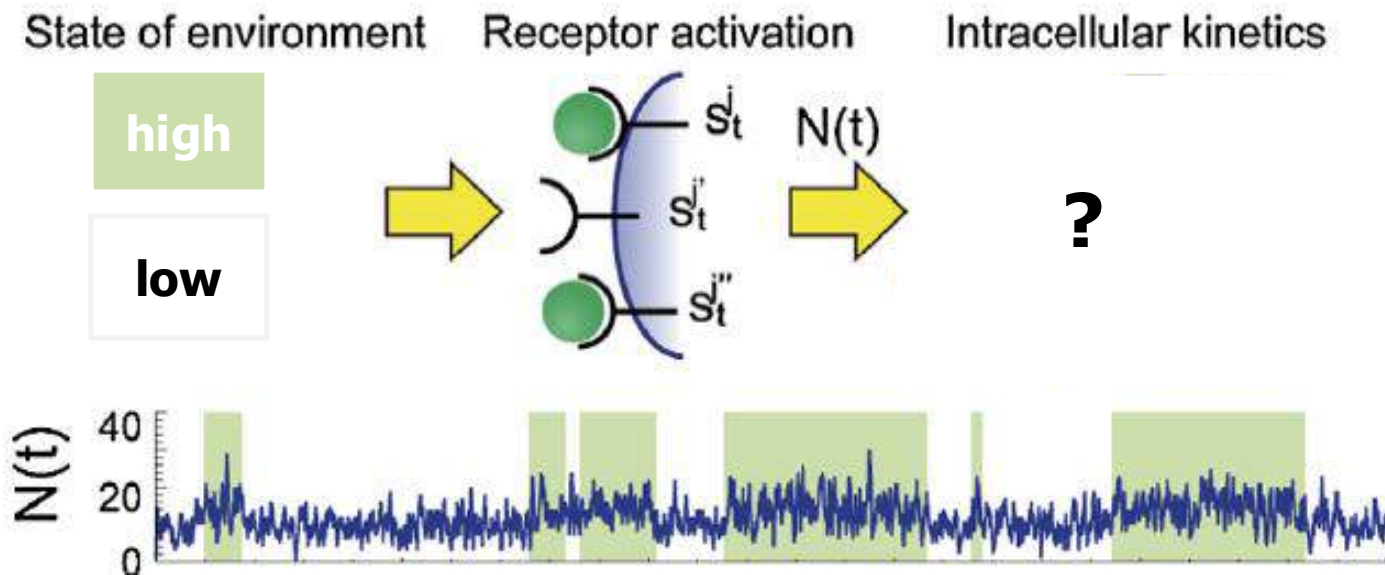
week ending
4 JUNE 2010

Implementation of Dynamic Bayesian Decision Making by Intracellular Kinetics

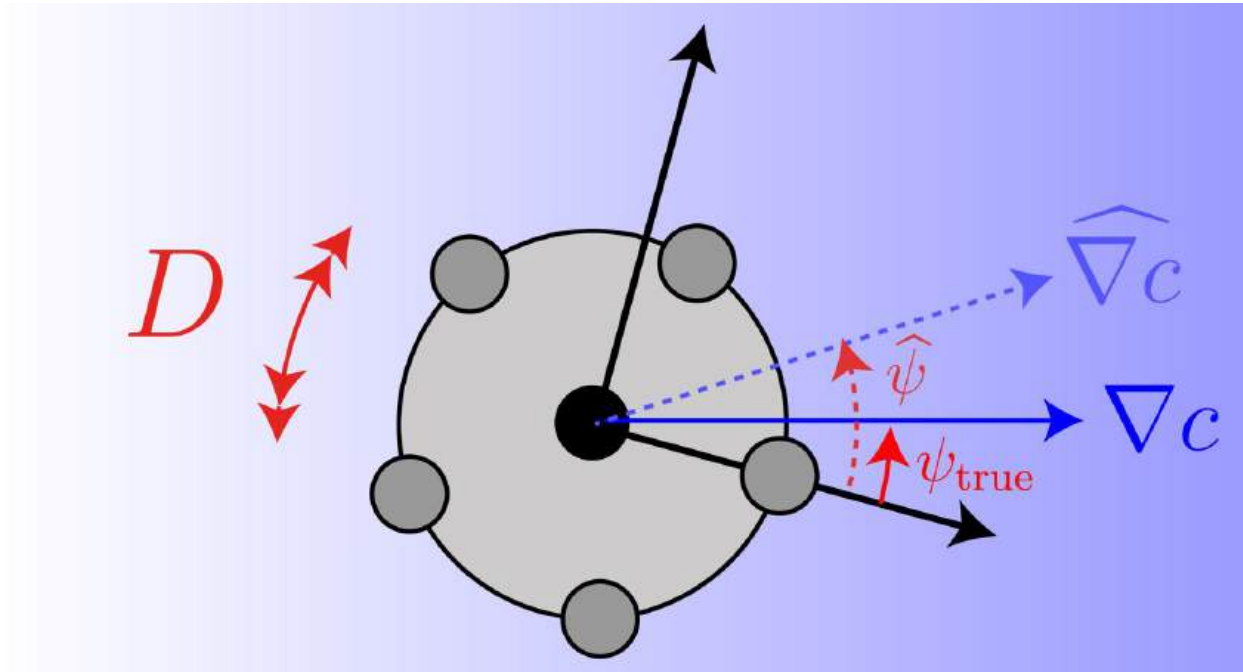
Tetsuya J. Kobayashi*

Institute of Industrial Science, The University of Tokyo, 4-6-1 Komaba Meguro-ku, Tokyo 153-8505, Japan

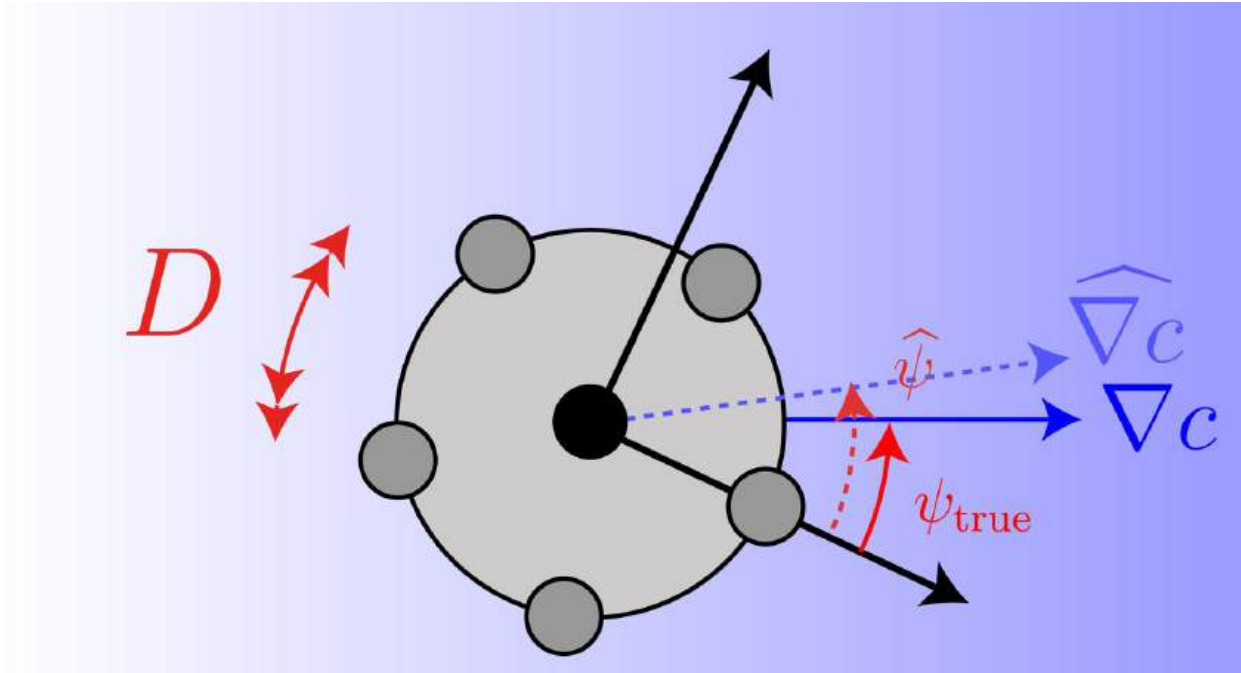
(Received 20 January 2010; published 3 June 2010)



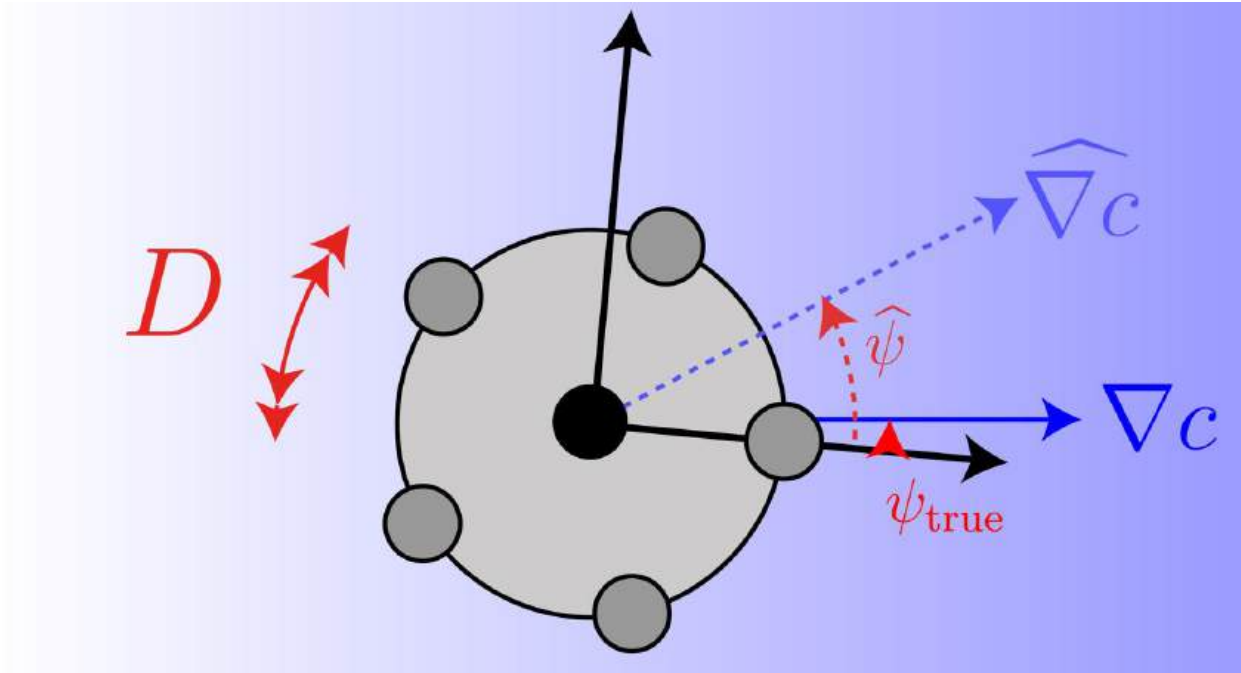
But how to estimate a concentration **gradient**?



... in the presence of **sensing** and **motility noise**?



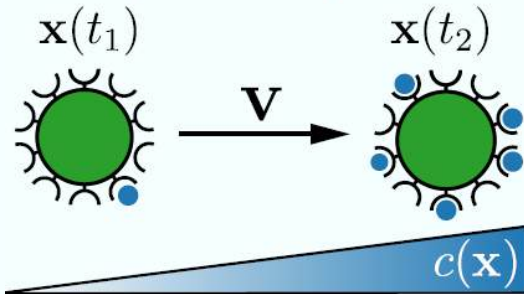
... in the presence of **sensing** and **motility noise**?



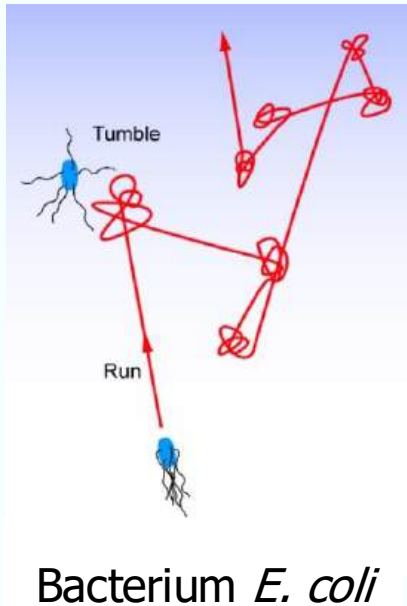
Two fundamental **gradient-sensing** strategies

TC

Temporal comparison

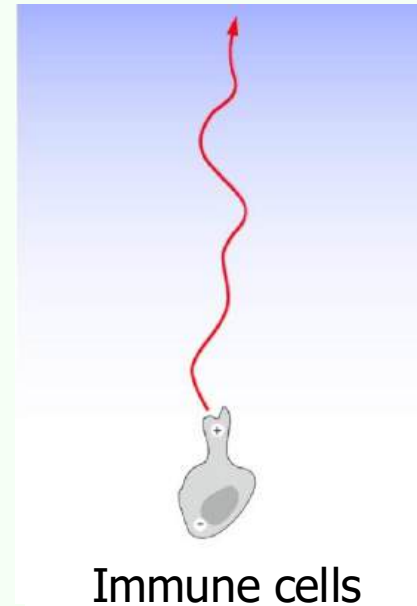
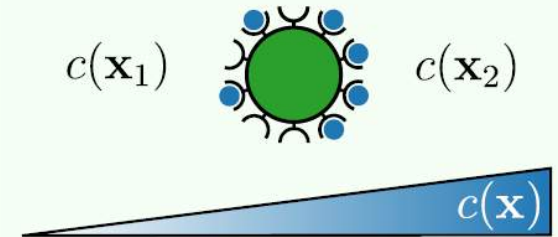


run & tumble



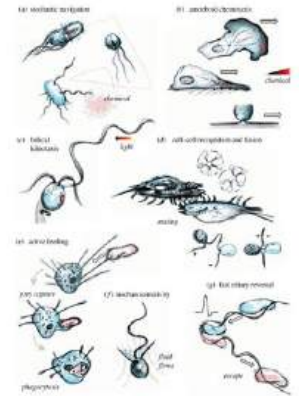
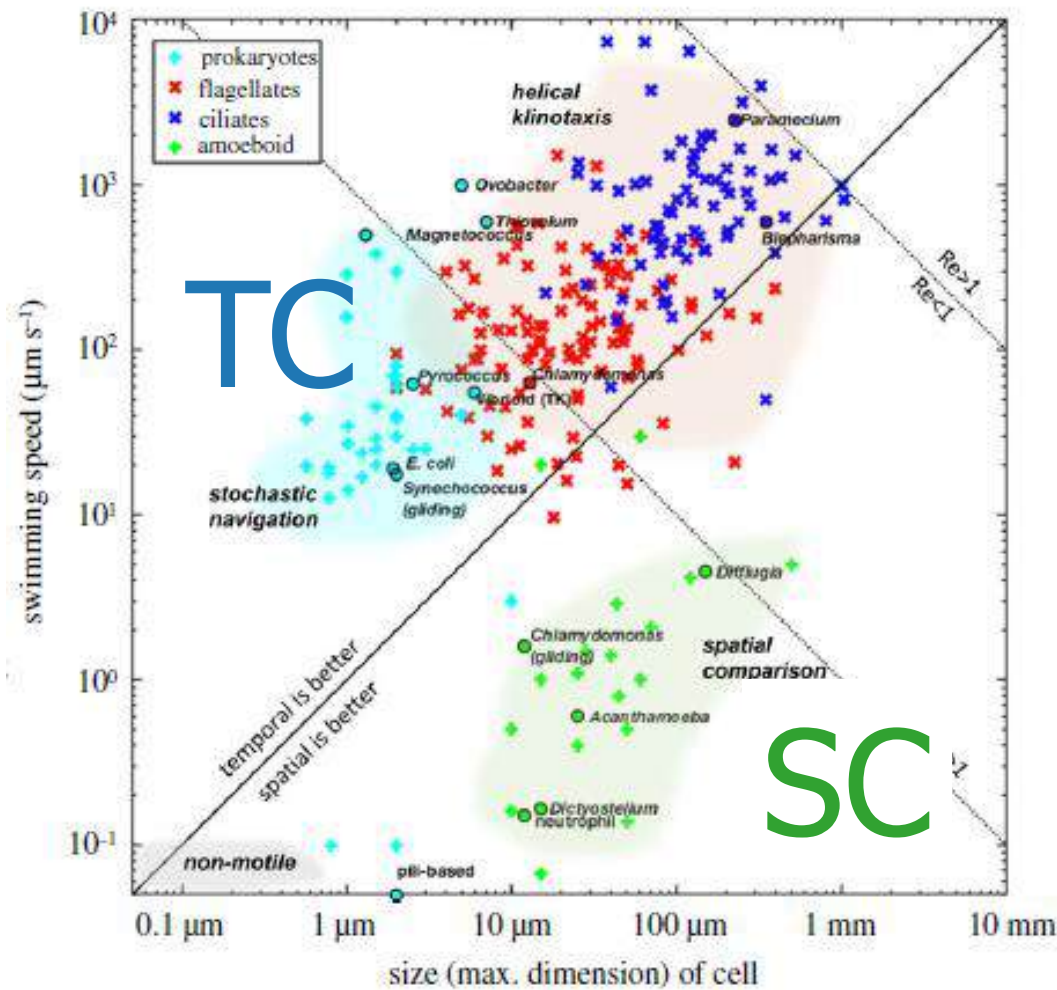
SC

Spatial comparison



Gradient-sensing strategy depends on **size** & **speed**

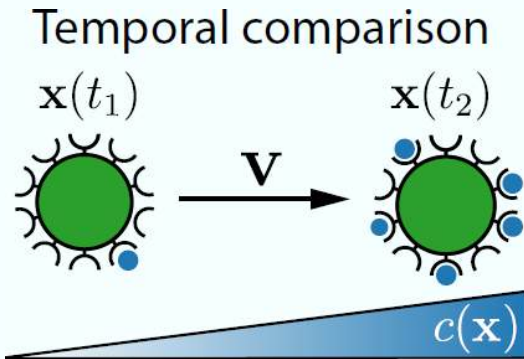
speed



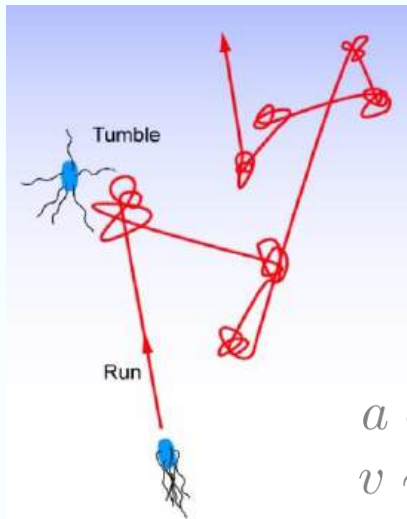
size

Gradient-sensing by **Temporal Comparison**

TC



run & tumble



$$a \sim 3 \mu\text{m}$$
$$v \sim 10 \mu\text{m/s}$$

Bacterium *E. coli*

$$\text{SNR}^{\text{TC}} = \frac{v^2 t^3 \lambda |\nabla c|^2}{c}$$

Gradient-sensing by temporal comparison
information-limited for shallow gradients:

- Brumley et al. PNAS 2019
- Mattingly et al. Nat. Phys. 2021
- Thornton et al. Nat. Commun. 2020
- Nakamura et al. Phys. Rev. Res. 2022

Gradient-sensing by **Spatial Comparison**

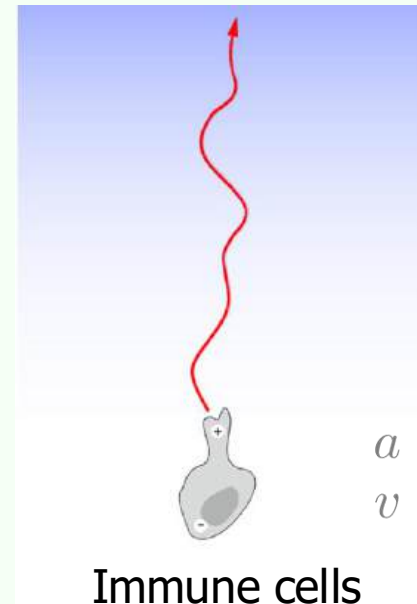
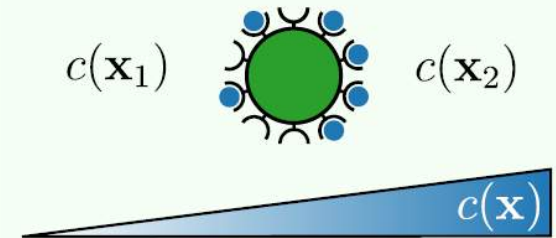
$$\text{SNR}^{\text{SC}} = \frac{a^2 t \lambda |\nabla c|^2}{c}$$

Gradient-sensing by spatial comparison is **information-limited** for shallow gradients:

- Van Haastert et al. BPJ 2007
- Amselem et al. PRL 2012
- Fuller et al. PNAS 2010

SC

Spatial comparison



$$a \sim 100 \mu\text{m}$$

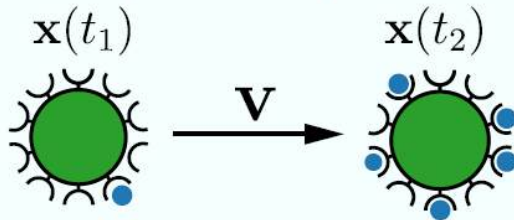
$$v \sim 1 \mu\text{m}/\text{min}$$

Immune cells

Two fundamental **gradient-sensing** strategies

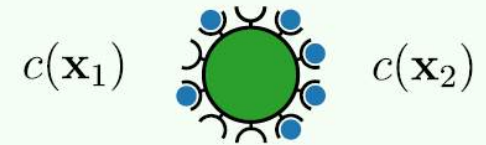
TC

Temporal comparison

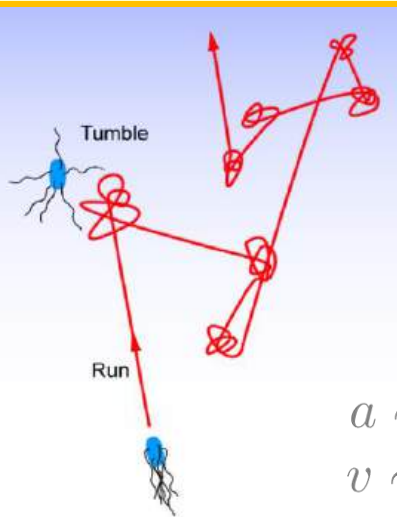


SC

Spatial comparison



Which strategy works best when?



$$a \sim 3 \mu\text{m}$$
$$v \sim 10 \mu\text{m/s}$$

Bacterium *E. coli*



$$a \sim 100 \mu\text{m}$$
$$v \sim 1 \mu\text{m/min}$$

Immune cells

Infotaxis: Update likelihood map of source position

Vergassola et al. Nature 2007:

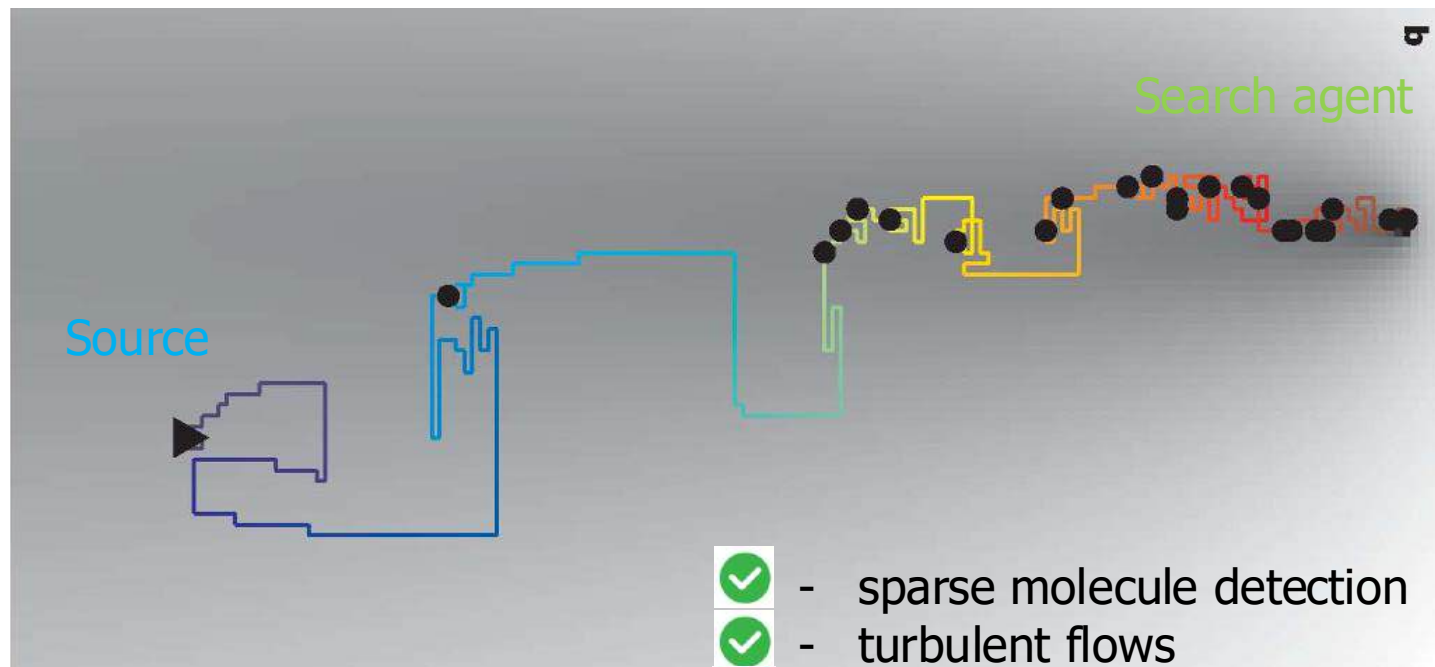
'Infotaxis' as a strategy for searching without gradients

Likelihood of source position

$$P_t(\mathbf{r}_0) = \frac{\mathcal{L}_{\mathbf{r}_0}(\mathcal{T}_t)}{\int \mathcal{L}_{\mathbf{x}}(\mathcal{T}_t) d\mathbf{x}}$$

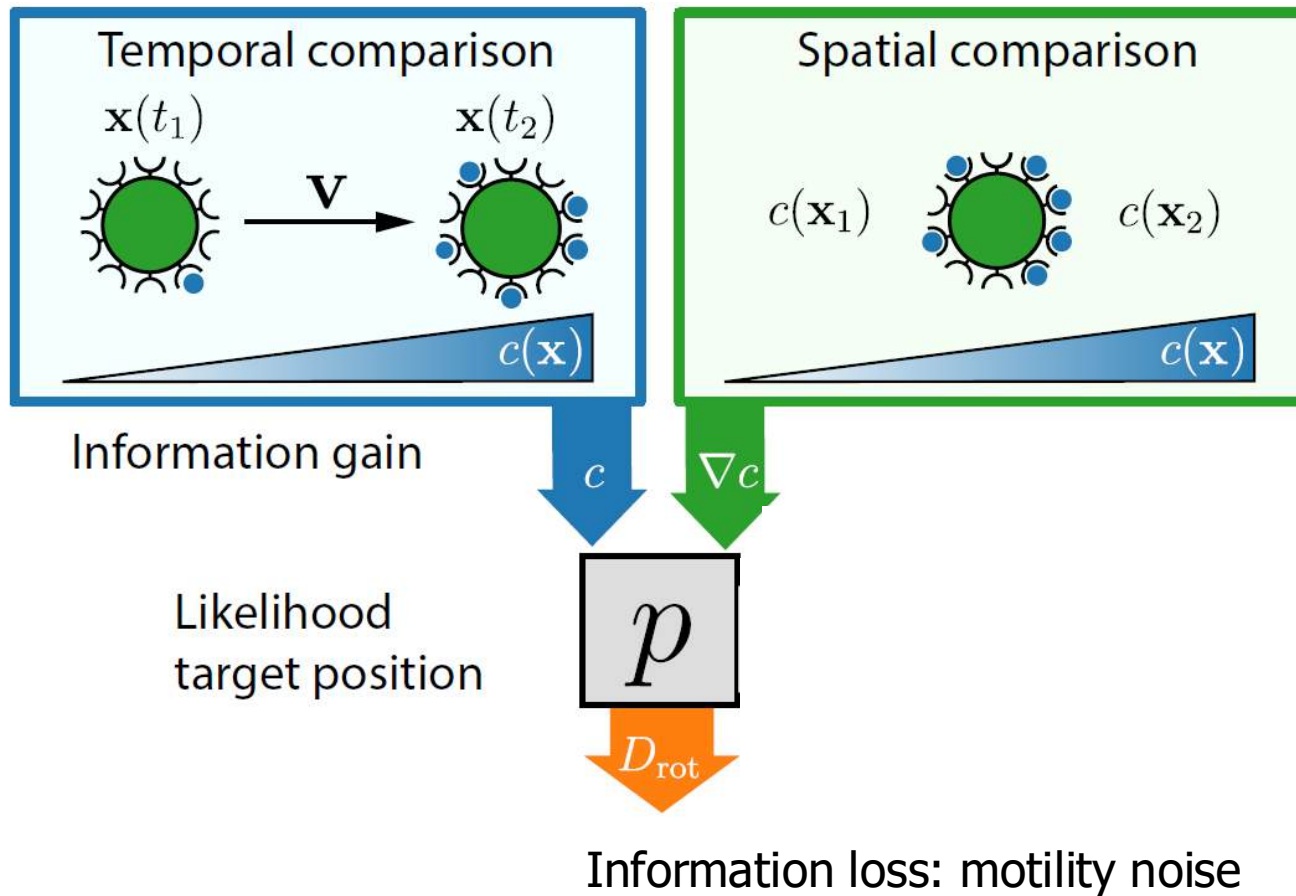
Likelihood of past molecule detections

Unlimited information processing capabilities



- ✓ - sparse molecule detection
- ✓ - turbulent flows
- ✗ - no spatial sensing
- ✗ - no motility noise: allocentric map

An ideal chemotactic agent capable of both **TC** and **SC**



The agent detects both **time** and **position** of molecules

$$s(t) =$$

Vector-valued

= time & position of molecule detections

Bayesian updating of a likelihood map of target position

Bayes' rule:

new measurement



$$p(\mathbf{x}, t + \Delta t) \sim p(\int_{\Delta t} s(t) | \mathbf{x}) p(\mathbf{x}, t)$$

new likelihood map
of target position

cond. prob.
of measurement

old likelihood map
of target position

Bayesian updating of a likelihood map of target position

Bayes' rule:

$$p(\mathbf{x}, t + \Delta t) \sim p(\overset{\text{new measurement}}{\int_{\Delta t} s(t)} | \mathbf{x}) \underset{\substack{\text{cond. prob.} \\ \text{of measurement}}}{p(\mathbf{x}, t)} \underset{\text{old likelihood map of target position}}{p(\mathbf{x}, t)}$$

new likelihood map of target position



Time-continuous limit:

TC

SC

$$\frac{\partial}{\partial t} p(\mathbf{x}, t) = \underbrace{\left(s - \mathbb{E} s \right) \left(\frac{J}{\langle J \rangle} - 1 \right) p}_{\text{TC}} + \underbrace{\left(\mathbf{s} - \mathbb{E}(\mathbf{s} | s > 0) \right) \cdot \left(\frac{a \nabla c}{c} - \frac{\langle a \nabla c \rangle}{\langle c \rangle} \right) \frac{J p}{\langle J \rangle}}_{\text{SC}} + \underbrace{D_{\text{rot}} \frac{\partial^2 p}{\partial \varphi^2}}_{\text{motility noise}} + \underbrace{\mathbf{v} \cdot \nabla p}_{\text{co-advection}} + \mathcal{O}(a^2),$$

$J \dots$ current of hits

Only TC: Barbieri et al. EPL 2011

TC+SC: Auconi et al. EPL 2022

Expected information gain

Bayes' rule:

$$p(\mathbf{x}, t + \Delta t) \sim p(\underbrace{\int_{\Delta t} s(t)}_{\text{cond. prob. of measurement}} | \mathbf{x}) \underbrace{p(\mathbf{x}, t)}_{\text{old likelihood map of target position}}$$

new measurement
↓

new likelihood map of target position

old likelihood map of target position

Expected information gain:

TC

SC

$$\mathbb{E} \frac{d}{dt} I = \underbrace{\left\langle J \ln \left(\frac{J}{\langle J \rangle} \right) \right\rangle}_{\text{TC}} + \underbrace{\frac{1}{4} \left\langle J \left| \frac{a \nabla c}{c} - \frac{\langle a \nabla c \rangle}{\langle c \rangle} \right|^2 \right\rangle}_{\text{SC}} + \underbrace{D_{\text{rot}} \left\langle \frac{\partial^2}{\partial \varphi^2} \ln p \right\rangle}_{\text{motility noise}} + \mathcal{O}(a^3)$$

> 0 > 0 < 0

Expected information gain

Two decision strategies

Exploration

Maximize expected
information gain

Vergassola et al. Nature 2007

Exploitation

Maximum-likelihood



Expected
information gain:

TC

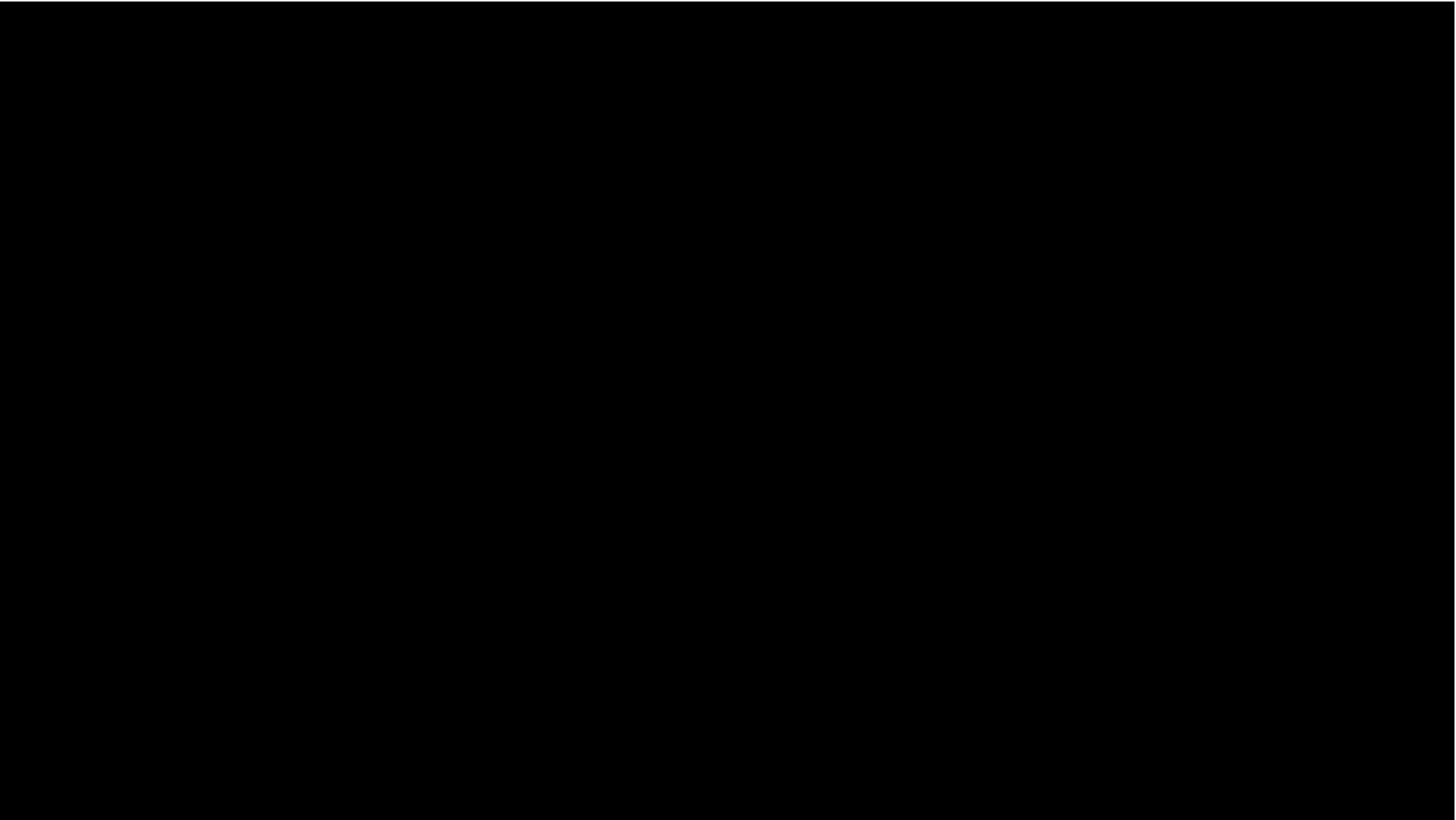
SC

$$\mathbb{E} \frac{d}{dt} I = \underbrace{\left\langle J \ln \left(\frac{J}{\langle J \rangle} \right) \right\rangle}_{\text{TC}} + \underbrace{\frac{1}{4} \left\langle J \left| \frac{a \nabla c}{c} - \frac{\langle a \nabla c \rangle}{\langle c \rangle} \right|^2 \right\rangle}_{\text{SC}} + \underbrace{D_{\text{rot}} \left\langle \frac{\partial^2}{\partial \varphi^2} \ln p \right\rangle}_{\text{motility noise}} + \mathcal{O}(a^3)$$

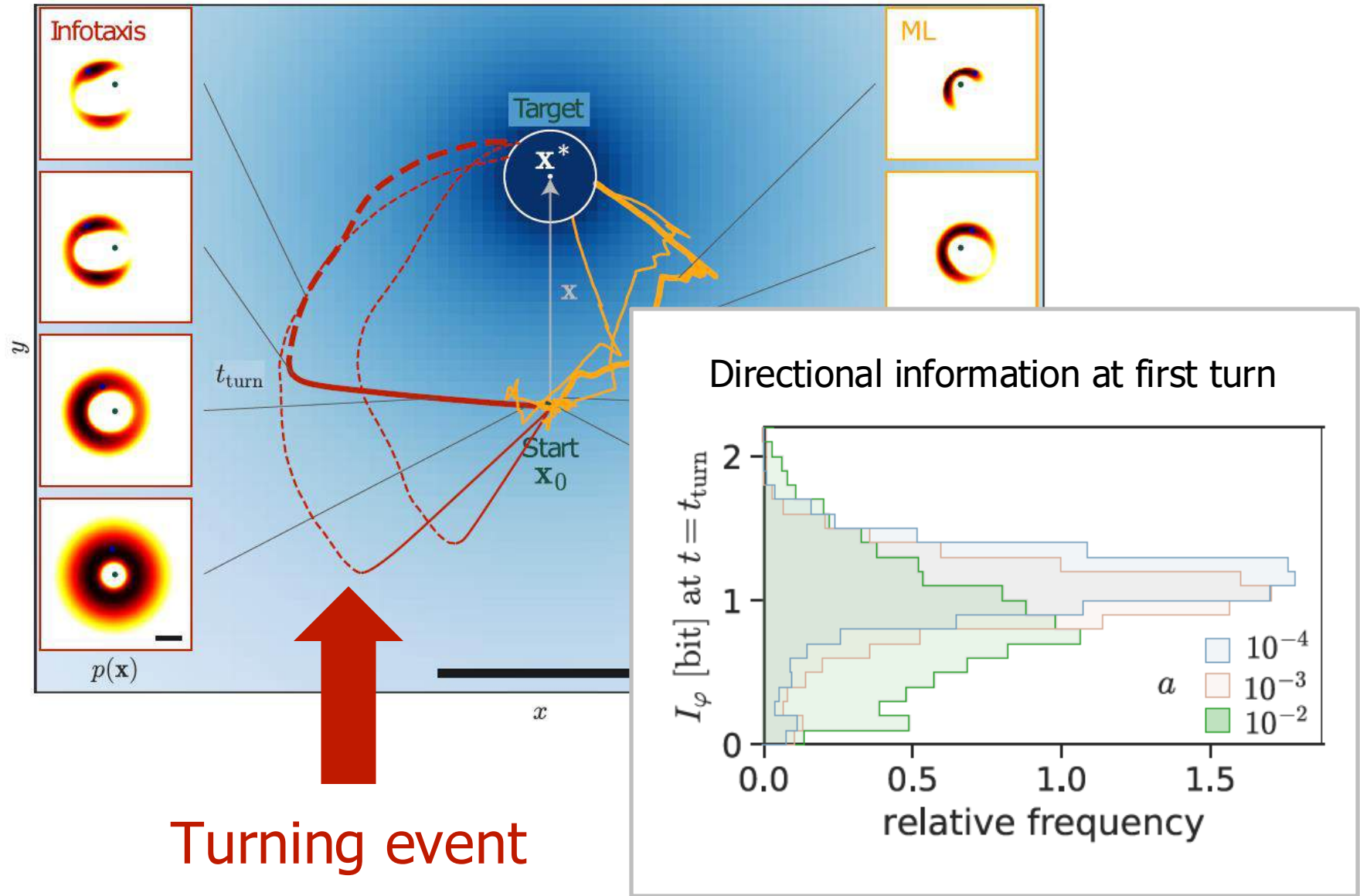
> 0
> 0
< 0

Auconi et al. EPL 2022
Rode et al. PRX Life 2024

Stereotypic navigation in the absence of motility noise



Fun fact: infotaxis agents turn first when they got **1 bit**

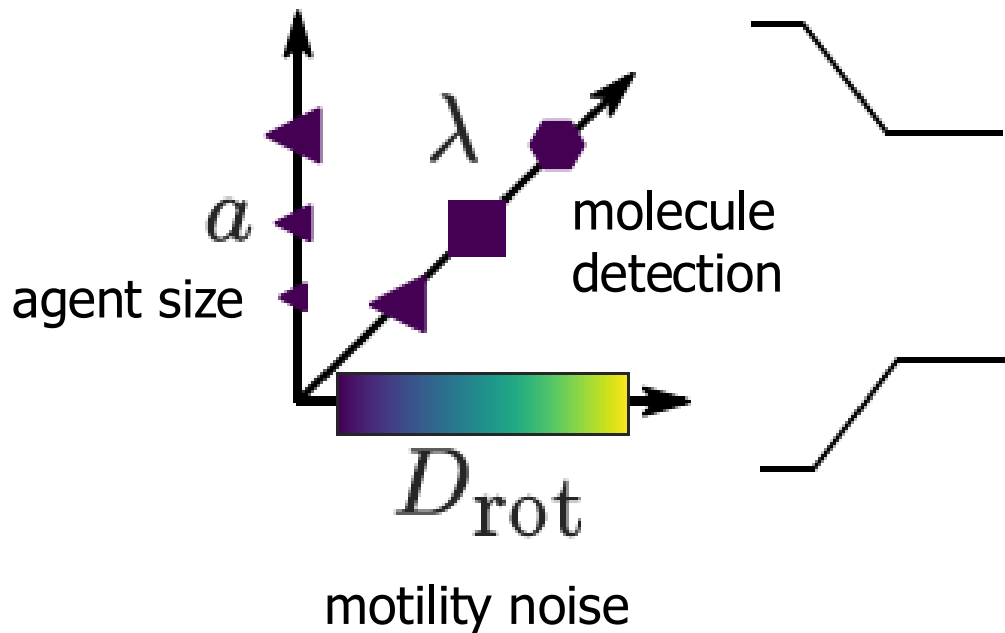


Biased random walk with **motility noise**

Information decomposition as function of noise and size



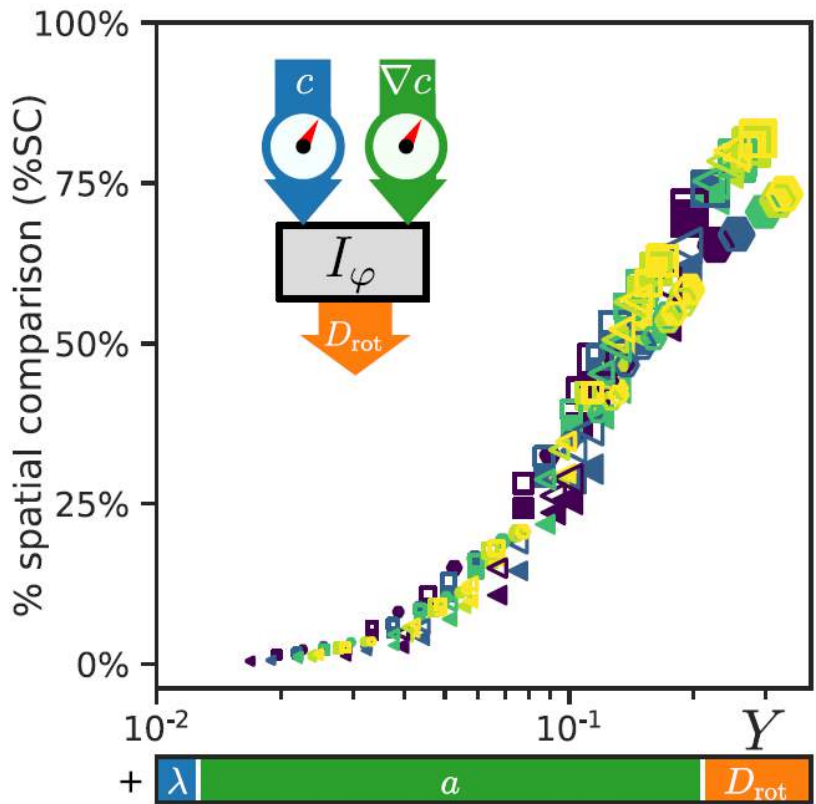
Three fundamental parameters
(speed can be eliminated)



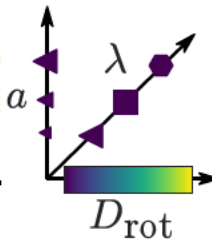
Empirical power-law for
"master" parameter

$$Y \sim \lambda^{\alpha} a^{\beta} D_{\text{rot}}^{\gamma}$$

Information decomposition as function of noise and size

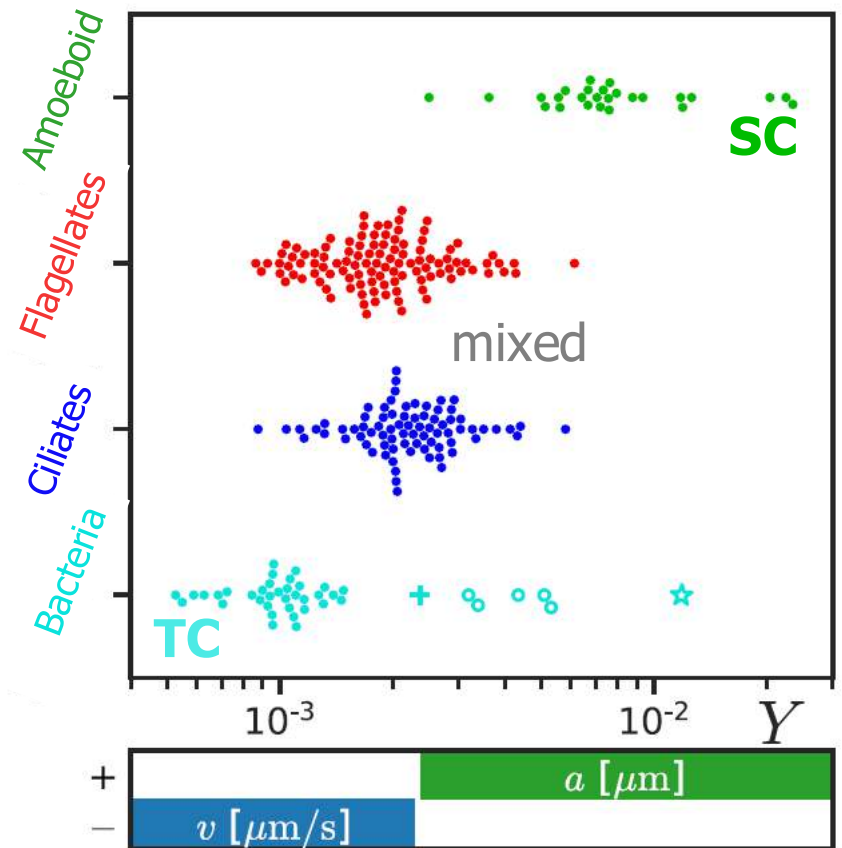
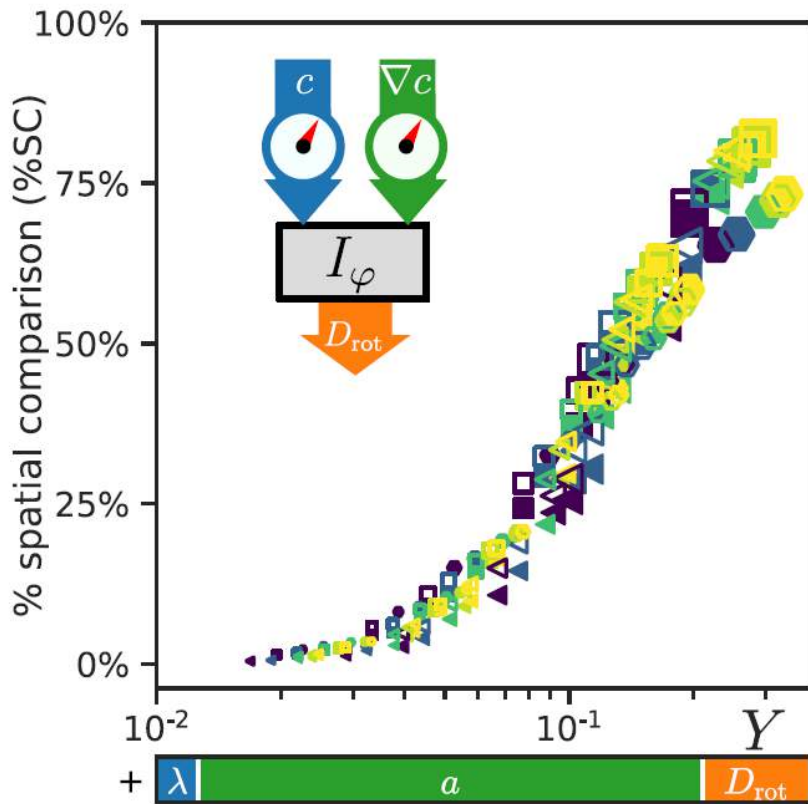


Empirical power-law for
"master parameter" Y

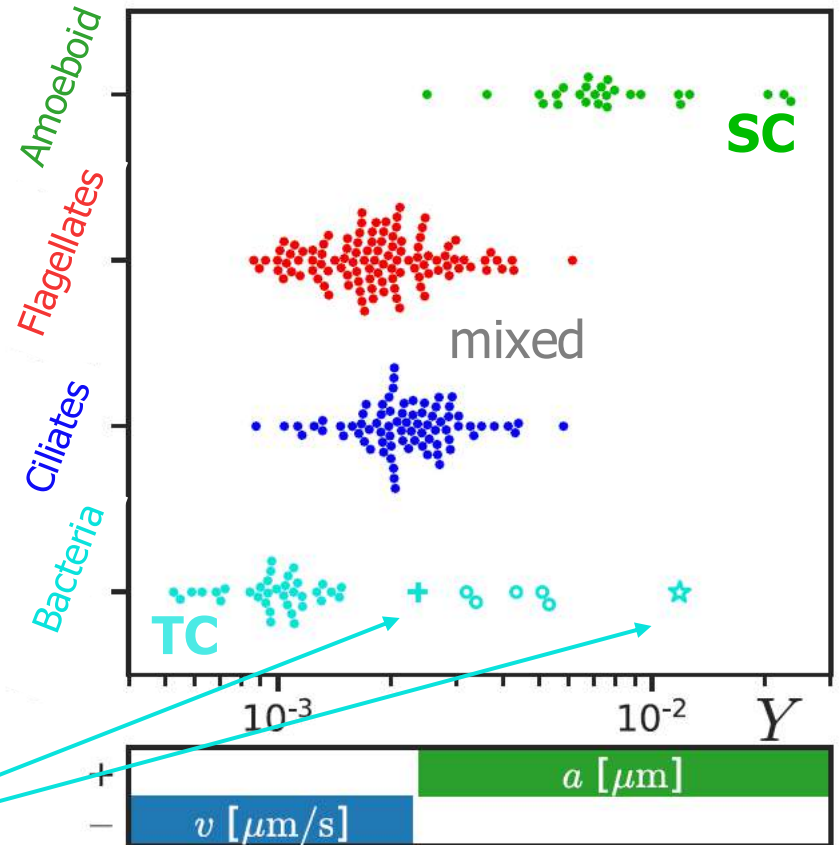
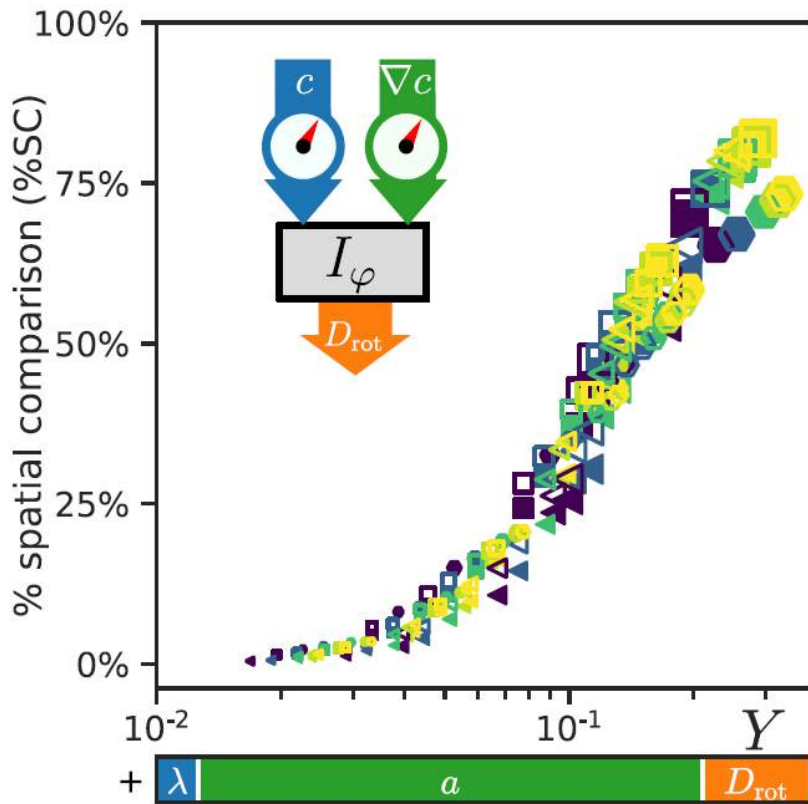


$$Y \sim \lambda^\alpha a^\beta D_{\text{rot}}^\gamma$$

Information decomposition explains strategy of 250 cells



Information decomposition explains strategy of 250 cells



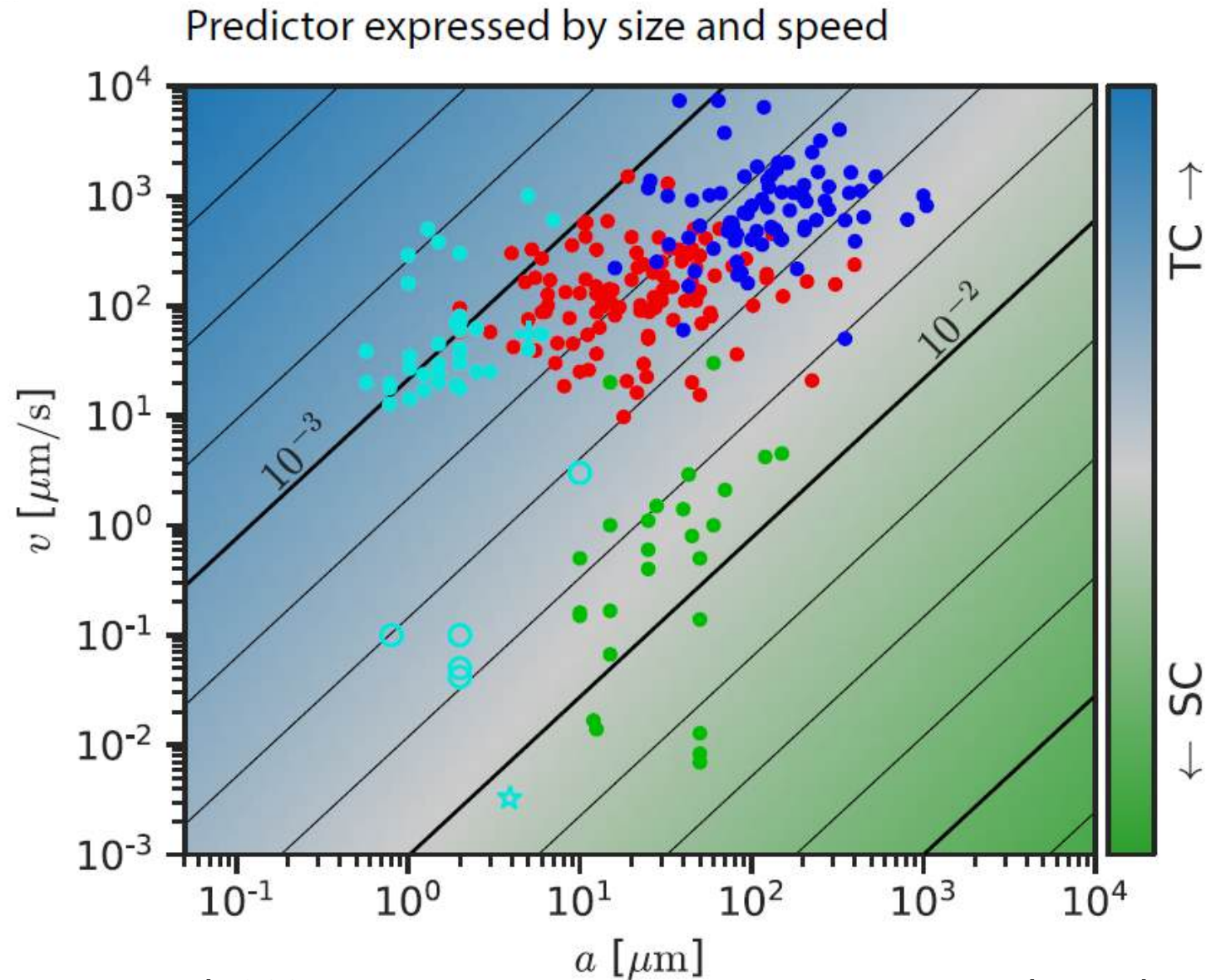
Bacteria using SC

Thar et al. PNAS 2003

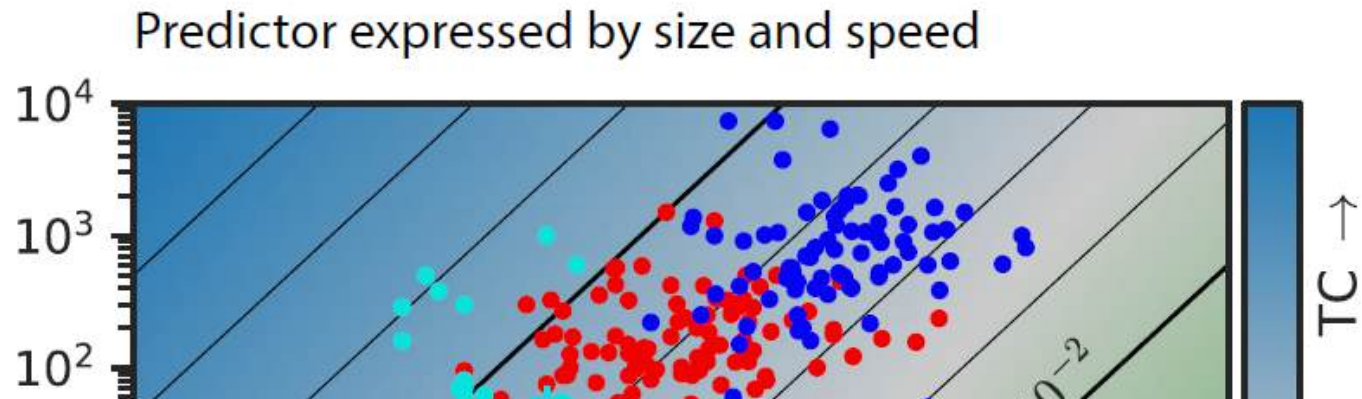
Wheeler et al. Nat. Microbiol. 2024

Rode et al. PRX Life 2024

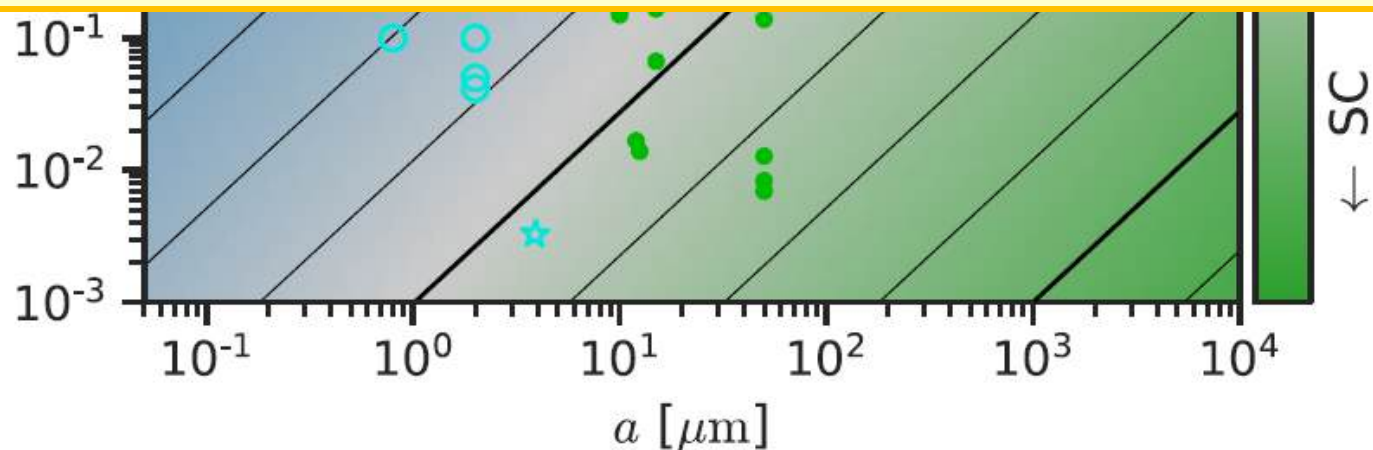
We can rephrase our result in **size a & speed v**



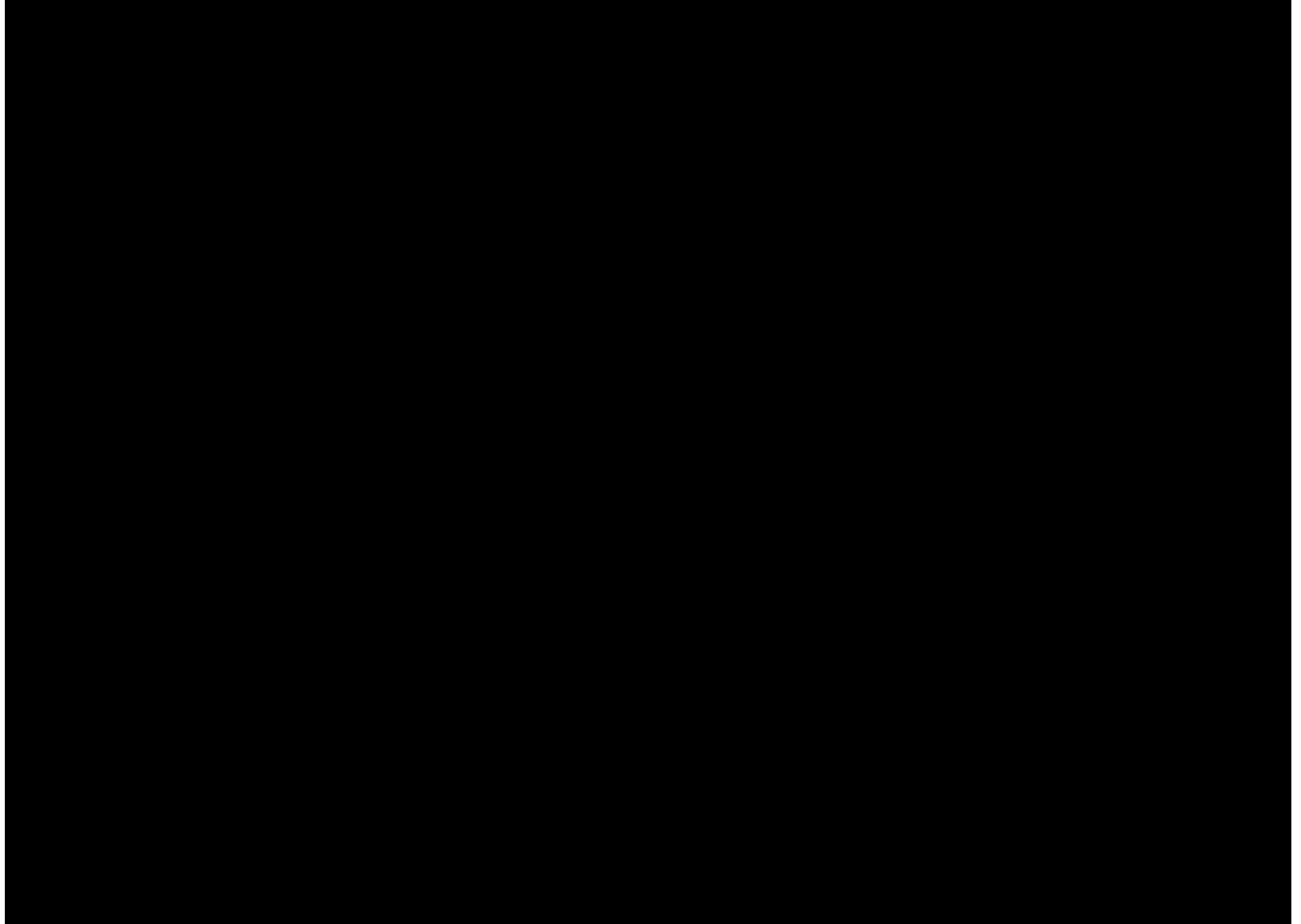
We can rephrase our result in **size a & speed v**



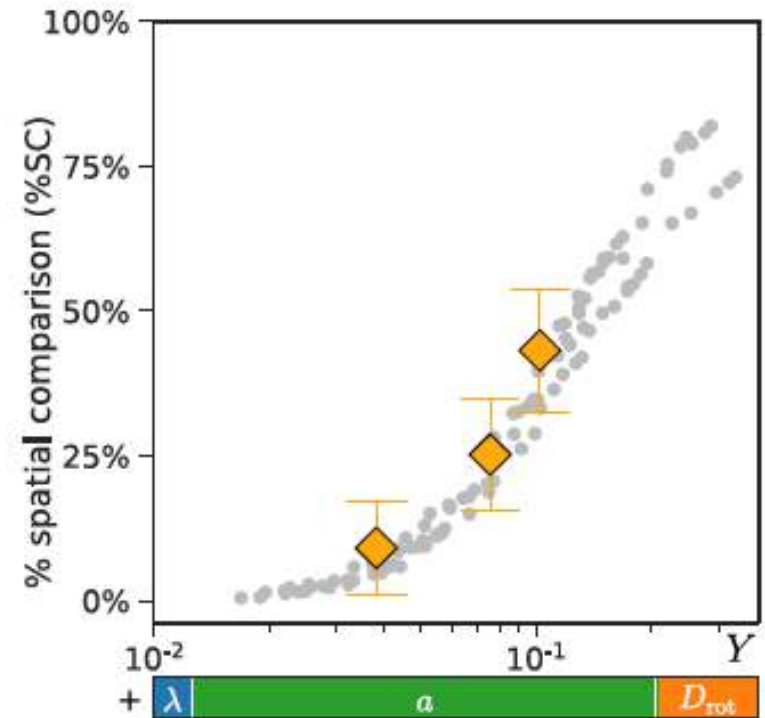
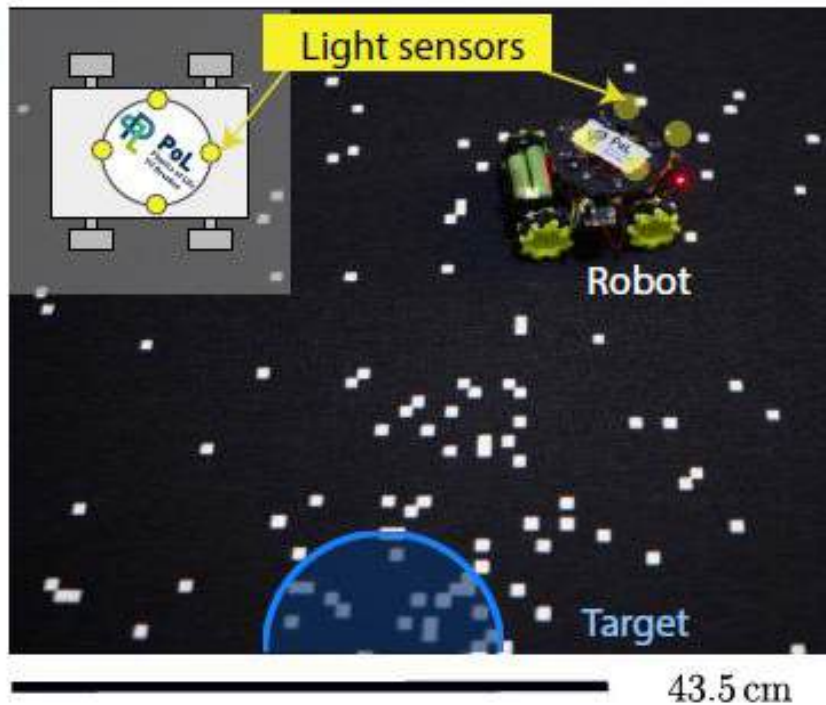
Large and slow cells use SC,
small and fast cells use TC
(but motility noise and concentration matter too)



A robotic demonstrator



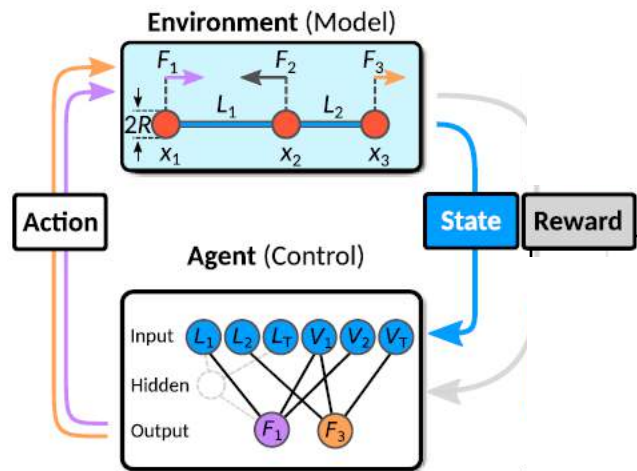
Robot experiments and simulations agree



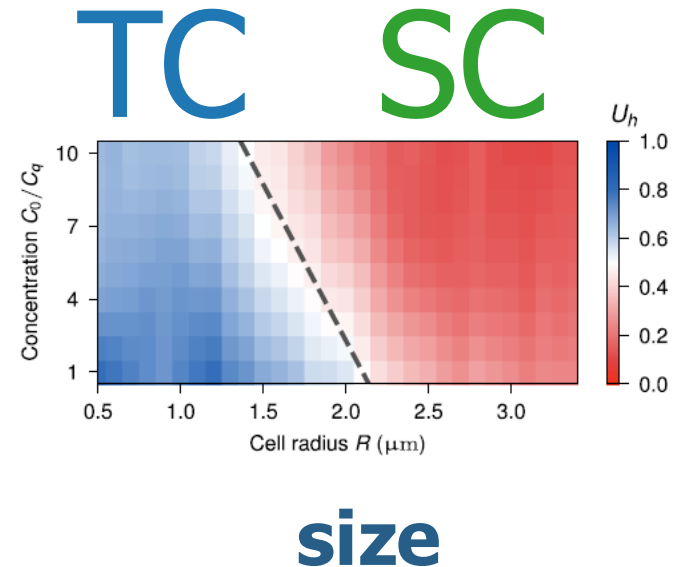
Other: **Limited information processing** capabilities



Learning chemotaxis with **small-scale neuronal networks**:



Hartl et al. PNAS (2021)



Alonso et al. PNAS Nexus (2024)
→ similar finding for **agent size**



CLUSTER OF EXCELLENCE



PHYSICS OF LIFE

The Dynamic Organization of Living Matter

Master of Science in Physics of Life



Dresden International Graduate School for Biomedicine and Bioengineering



© 2016 Sven Döring / Agentur Focus

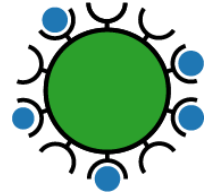


Postdoctoral Fellows



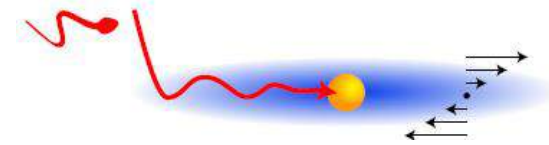
Conclusions & Thank you!

- **Spatial comparison** outweighs **temporal comparison** for ideal agents that are large, slow & persistent



Rode et al. PRX Life (2024)

- **Sperm surf along concentration filaments** in small-scale turbulence



Lange et al. PLoS Comp. Biol. (2021)

Thanks to all members of the
Biological Algorithms Group



Funding:



PoL
Physics of Life
TU Dresden

