

# Can information be its own signal?

# Readings for today

- Vergassola, M., Villermaux, E., & Shraiman, B. I. (2007). 'Infotaxis' as a strategy for searching without gradients. *Nature*, 445(7126), 406-409.

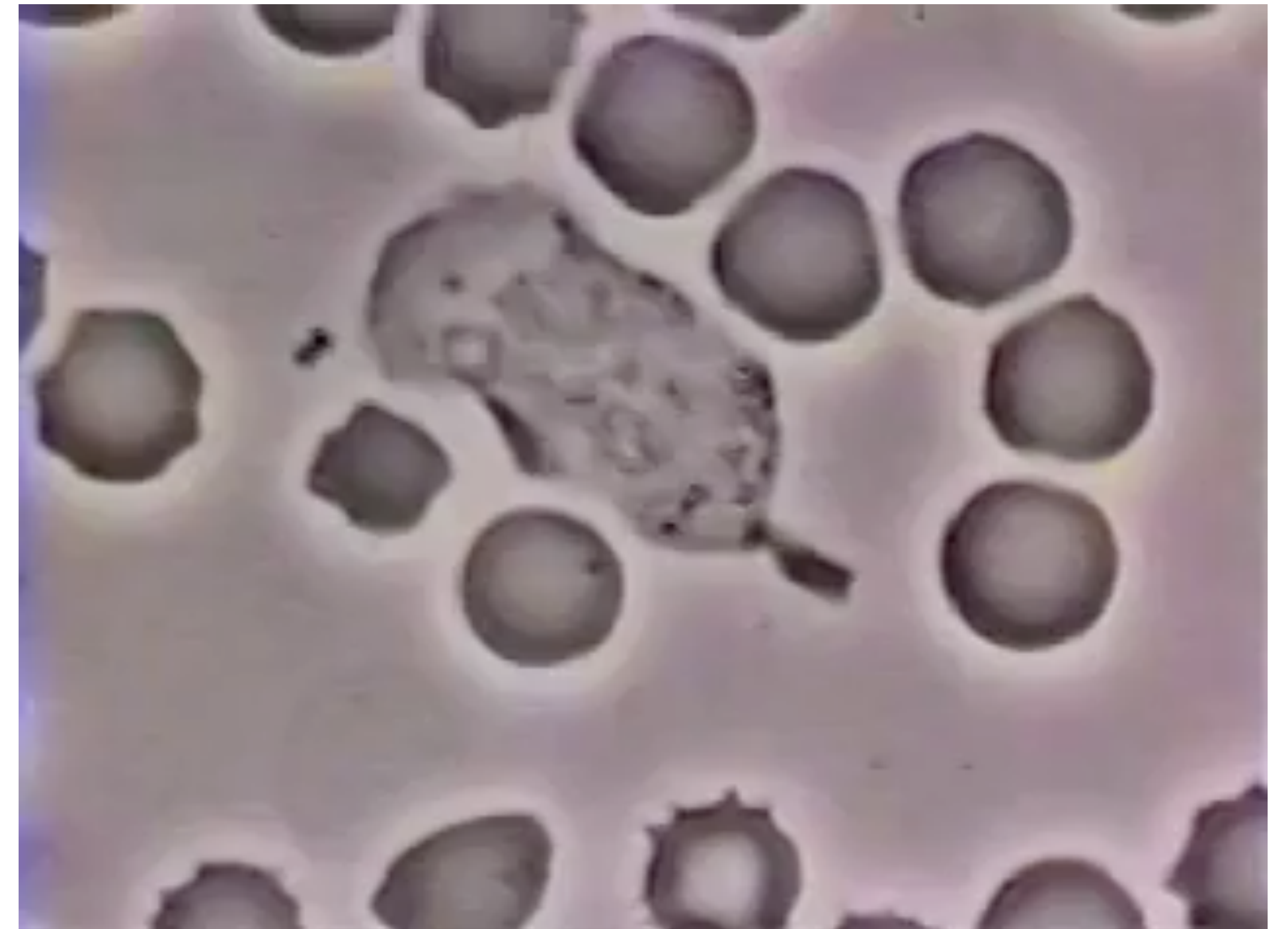
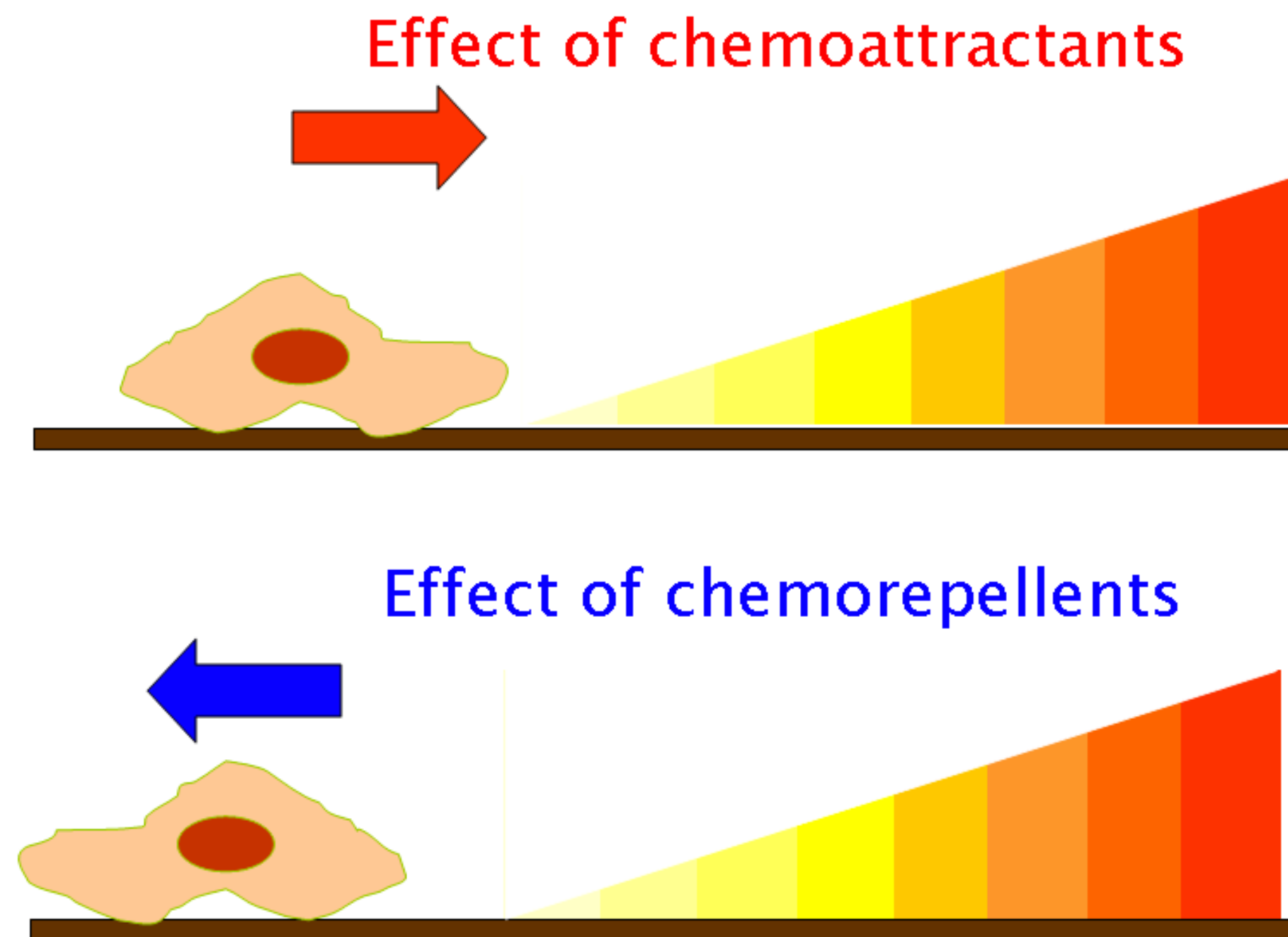
# Topics

- Review of chemotaxis
- Infotaxis by entropy reduction

# Review of chemotaxis

# Chemotaxis

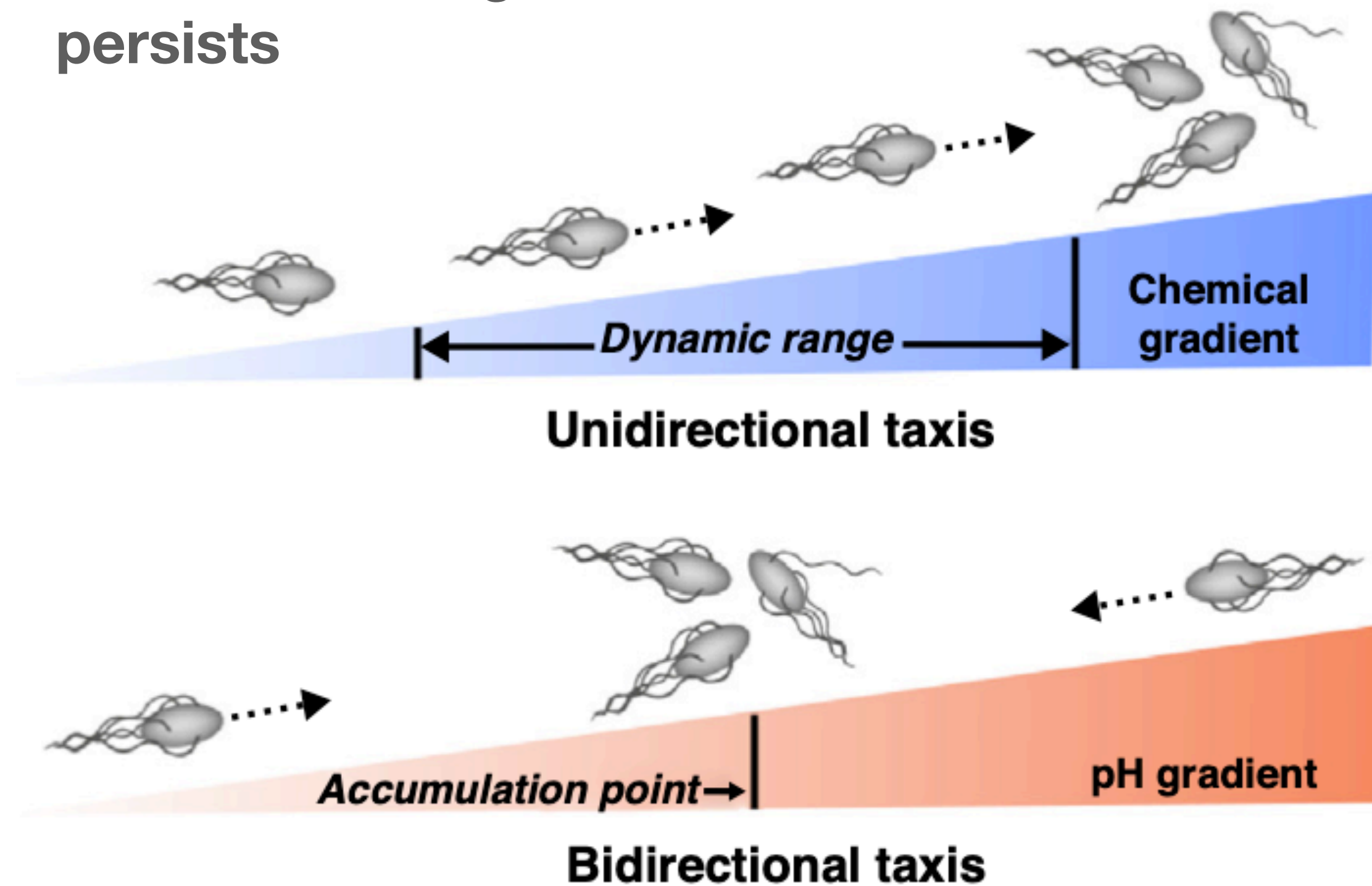
Movement in response to a chemical stimulus.



<https://routledgetextbooks.com/textbooks/9780815344506/videos.php>

# The chemosensing algorithm

Keep moving in the same direction if the gradients persists



**Calculate gradient**

$$\nabla o = o_t - o_{t-1}$$

olfactory scent magnitude

**Accumulate evidence**

$$e_t = \gamma * \nabla o + \eta$$

accumulation noise

accumulation rate

**Make decision**

$$\theta_t = \begin{cases} \theta_{t-1}, & \text{if } e_t < a \\ U(-\pi, \pi), & \text{if } e_t \geq a \end{cases}$$

movement angle

random turn



# The limitations of chemotaxis

## The problem of dilution

In many natural environments, the dispersal of a chemical will lead to a fast reduction in the signal-to-noise and loss of the gradient altogether.

↖ The dilute limit



# Infotaxis by entropy reduction

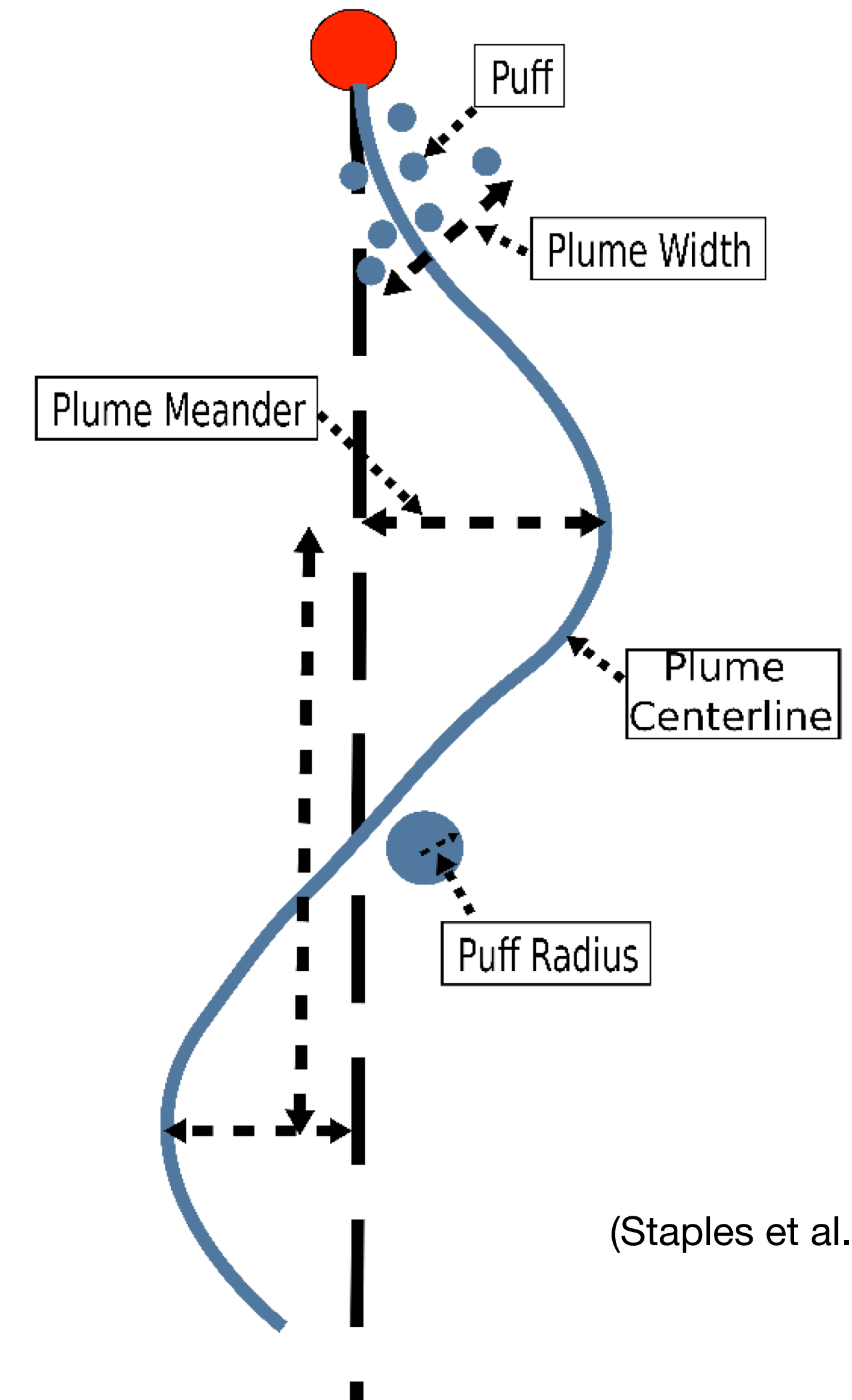


# Search for information

# Infotaxis

A search strategy that organisms or algorithms use to find a source of interest by optimizing the acquisition of information from the environment, often in situations where the source is intermittently detectable or has a sparse distribution.

A balance between exploring areas of uncertainty and exploiting areas where the source has been previously detected.



(Staples et al. 2023)

# Infotaxis algorithm

## Shannon entropy

$$H(s) = - \sum_{\mathbf{x}} p(\mathbf{x}) \log_2 p(\mathbf{x})$$

belief state  $s = [\mathbf{x}^a, p(\mathbf{x})]$

detection probability

## Expected entropy

upon taking action  $a$  in belief state  $s$

$$H(s \mid a) = \sum_{s'} \Pr(s' \mid s, a) H(s')$$

successor state

## Information gain

with action  $a$  in belief state  $s$

$$G(s, a) = H(s) - H(s \mid a)$$

How much uncertainty is reduced by taking action  $a$

## Infotaxis policy

Select the action  $a$  that maximizes the expected information gain in belief  $s$

$$\pi^{info}(s) = \arg \min_a \sum_{s'} \Pr(s' \mid s, a) H(s'),$$

# Maximizing information gain

## Information gain is entropy reduction

$$G(s, a) = \underbrace{H(s)}_{\text{overall entropy}} - \underbrace{H(s \mid a)}_{\text{entropy after action } a} \rightarrow H(s \mid a) < H(s)$$
  
$$\underbrace{\Delta H(r_i \rightarrow r_j)}_{\text{change in entropy}} = \underbrace{P_t(r_j)[-H]}_{\text{finding the source}} + \underbrace{[1 - P_t(r_j)][\rho_0(r_j)\Delta H_0 + \rho_1(r_j)\Delta H_1 + \dots]}_{\text{alternative case when source is not found}}$$

The diagram illustrates the concept of information gain as entropy reduction. It consists of two main equations. The first equation,  $G(s, a) = H(s) - H(s \mid a)$ , defines information gain as the difference between overall entropy  $H(s)$  and the entropy after an action  $a$ ,  $H(s \mid a)$ . A curved arrow labeled "search trajectory" points from this equation to the second equation. The second equation,  $\Delta H(r_i \rightarrow r_j) = P_t(r_j)[-H] + [1 - P_t(r_j)][\rho_0(r_j)\Delta H_0 + \rho_1(r_j)\Delta H_1 + \dots]$ , breaks down the change in entropy  $\Delta H(r_i \rightarrow r_j)$  into two parts: the probability  $P_t(r_j)$  of finding the source  $r_j$  (which results in a decrease in entropy  $-H$ ), and the probability  $1 - P_t(r_j)$  of not finding the source, which leads to a weighted sum of alternative entropy changes  $\Delta H_0, \Delta H_1, \dots$  based on probabilities  $\rho_0, \rho_1, \dots$ .

**Note:** In Vergassola et al. 2007,  $S$  is used as the symbol for entropy. Here we use the traditional  $H$

# Infotaxis policy in more detail

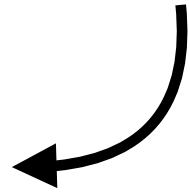
## Infotaxis policy

$$\begin{aligned}\pi^{info}(s) &= \arg \min_a \sum_{s'} \Pr(s' | s, a) H(s') \\ &= \arg \max_a G(s, a) \\ &= \arg \min_a H(s | a)\end{aligned}$$

At each time step, the searcher chooses the direction that **locally maximizes the expected rate of information acquisition**. Entropy decreases faster closer to the source because cues arrive at a faster rate.

## Optimal source-tracking policy

$$\begin{aligned}\pi^*(s) &= \arg \min_{\pi} \mathbb{E}_{p_0, \pi}[T] \rightarrow T = \text{search duration} \\ &= \arg \min_a \sum_{s'} \Pr(s' | s, a) [1 + v^*(s')]\end{aligned}$$

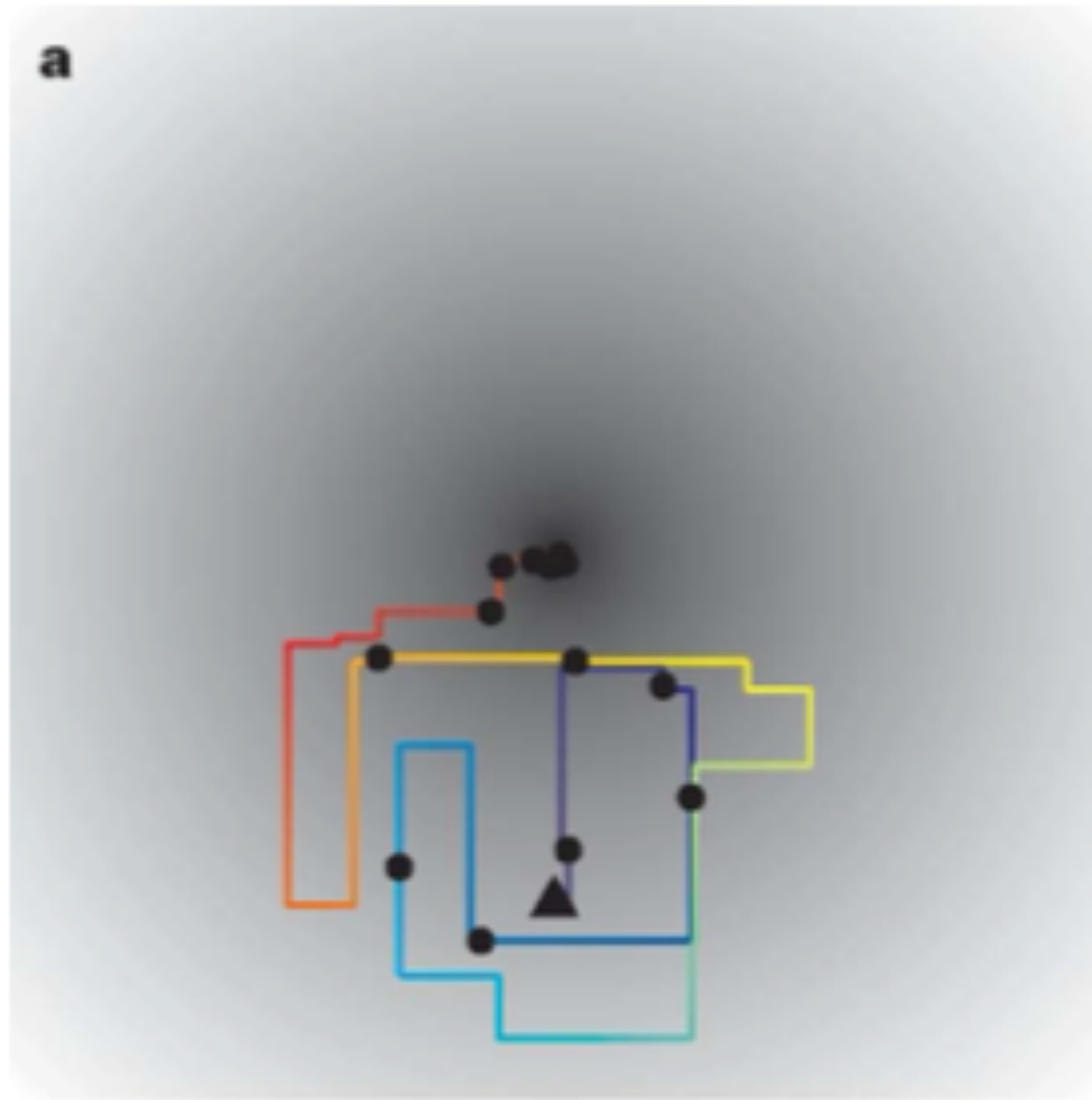
Bellman optimality 

## Optimal Infotaxis policy

$$\pi^*(s) = 1 + \arg \min_a \sum_{s'} \Pr(s' | s, a) v^*(s')$$

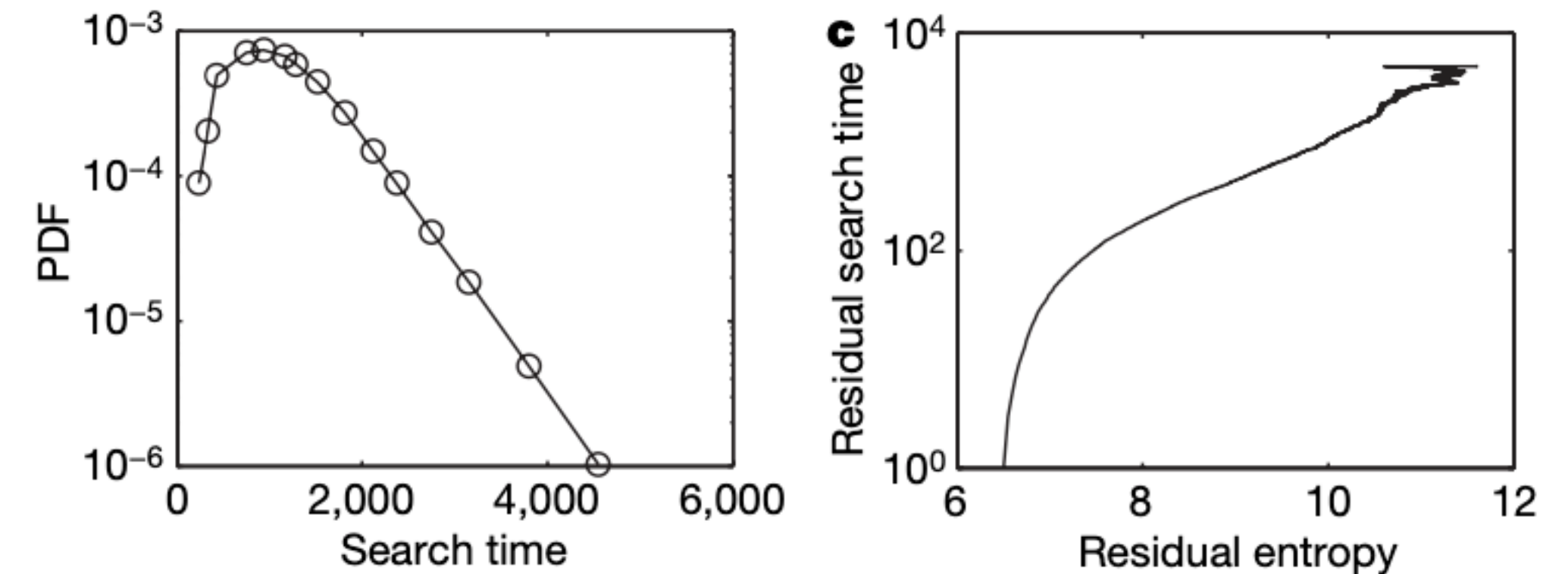
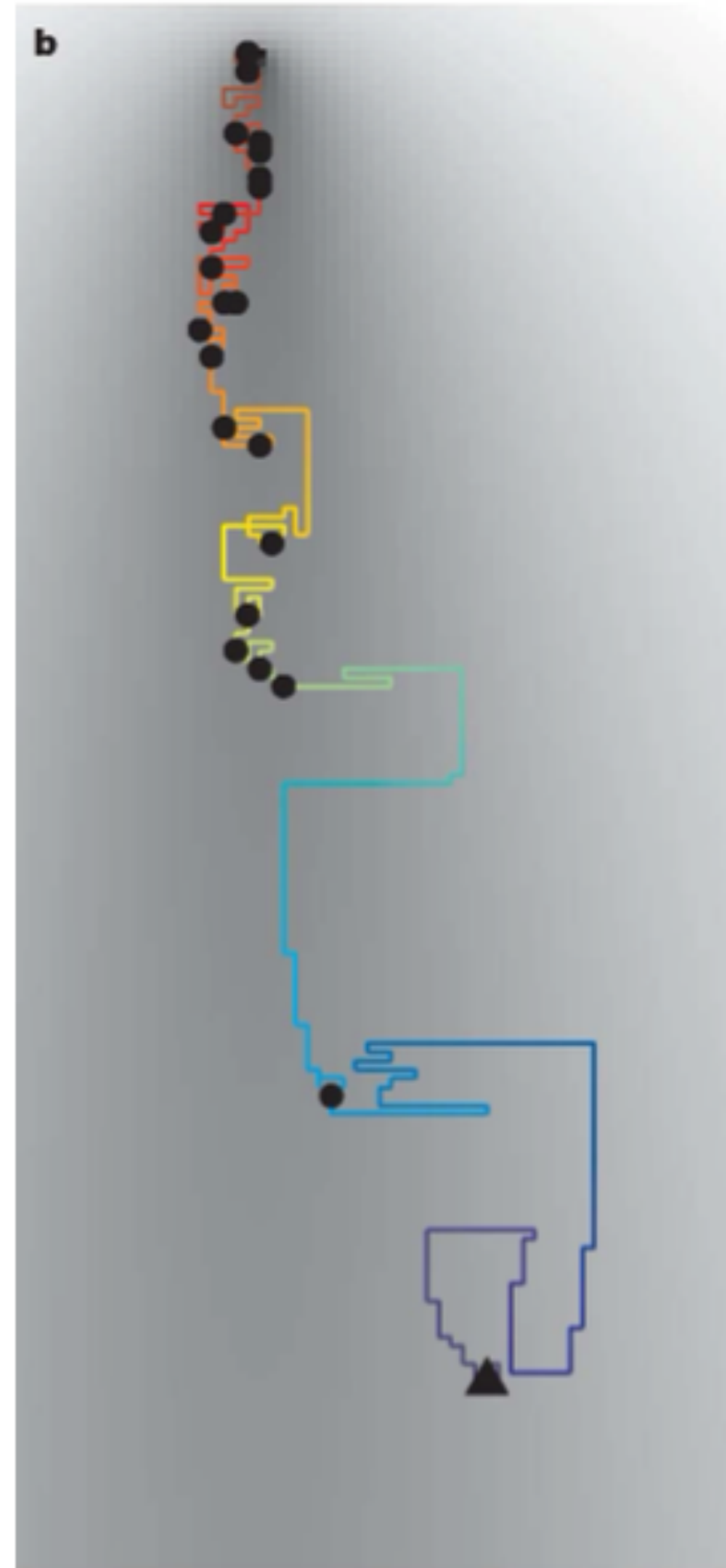
# Efficiency of infotaxis

Without wind



● Scent detection (hit)

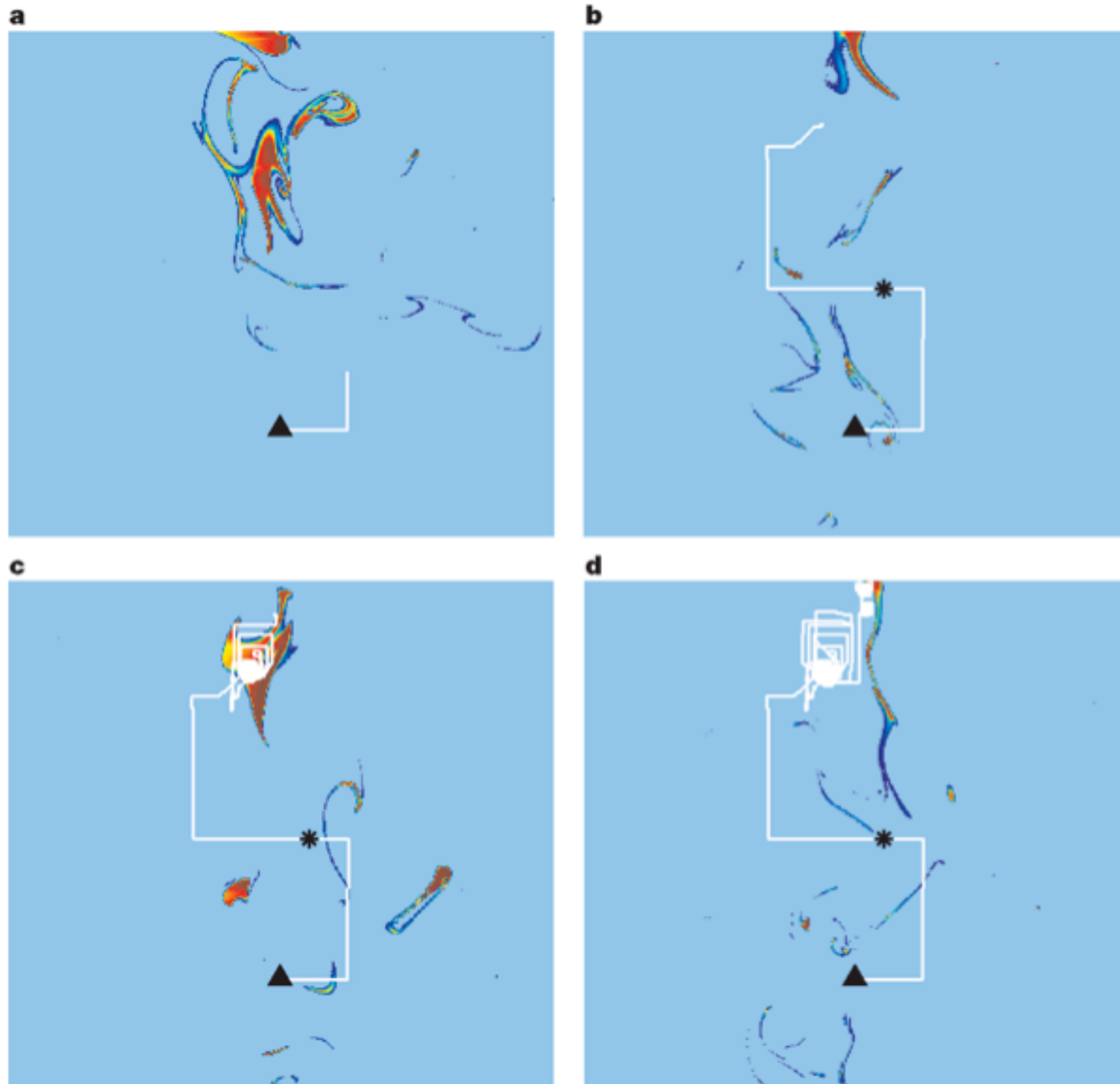
With wind



Infotaxis allows for a fast and efficient search in high entropy environments by tracking the information obtained from sparse signal detection events.



# Robustness of infotaxis



Infotaxis allows is effective even in dynamic environments where the spatial distribution of signal varies with time.

# Take home message

- Chemotaxis can fail when the signal becomes so sparse that the gradient disappears.
- Infotaxis uses the information gained from sparsely occurring events as a policy to determine search.
- Infotaxis allow for fast and efficient search behaviors in dynamic, low-signal environments.

# Lab 8: Infotaxis

URL: <https://coaxlab.github.io/BIX-book/notebooks/lab8-infotaxis.html>

