

Can information be its own signal?

Readings for today

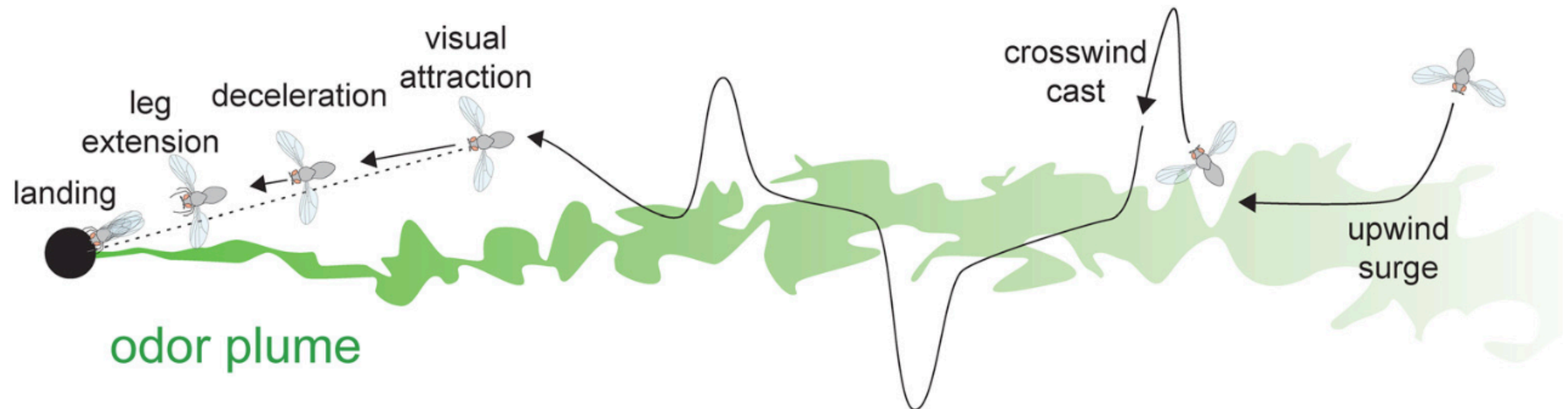
- Vergassola, M., Villermaux, E., & Shraiman, B. I. (2007). 'Infotaxis' as a strategy for searching without gradients. *Nature*, 445(7126), 406-409.

Topics

- Infotaxis by entropy reduction
- Curiosity-driven search

Infotaxis by entropy reduction

Recall the problem of the plume

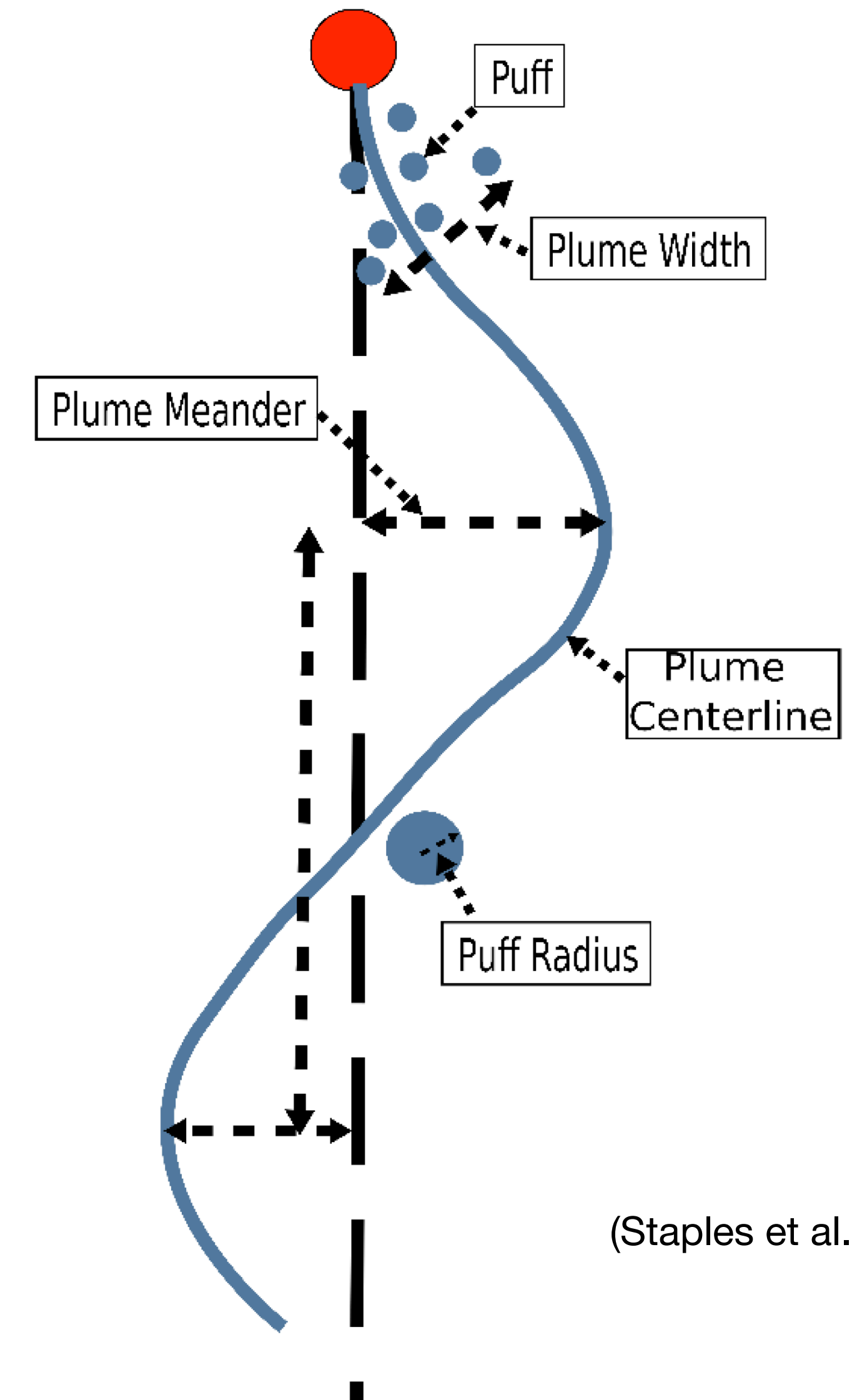


Search for information

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

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

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

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

Maximizing information gain

Information gain is entropy reduction

The diagram illustrates the concept of information gain as entropy reduction. It features two equations with labels and arrows indicating the flow of information.

The first equation is:

$$G(s, a) = \underbrace{H(s)}_{\text{overall entropy}} - \underbrace{H(s | a)}_{\text{entropy after action } a}$$

Below this equation, it states: $H(s | a) < H(s)$

The second equation is:

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

A curved arrow labeled "search trajectory" points from the first equation to the second equation.

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

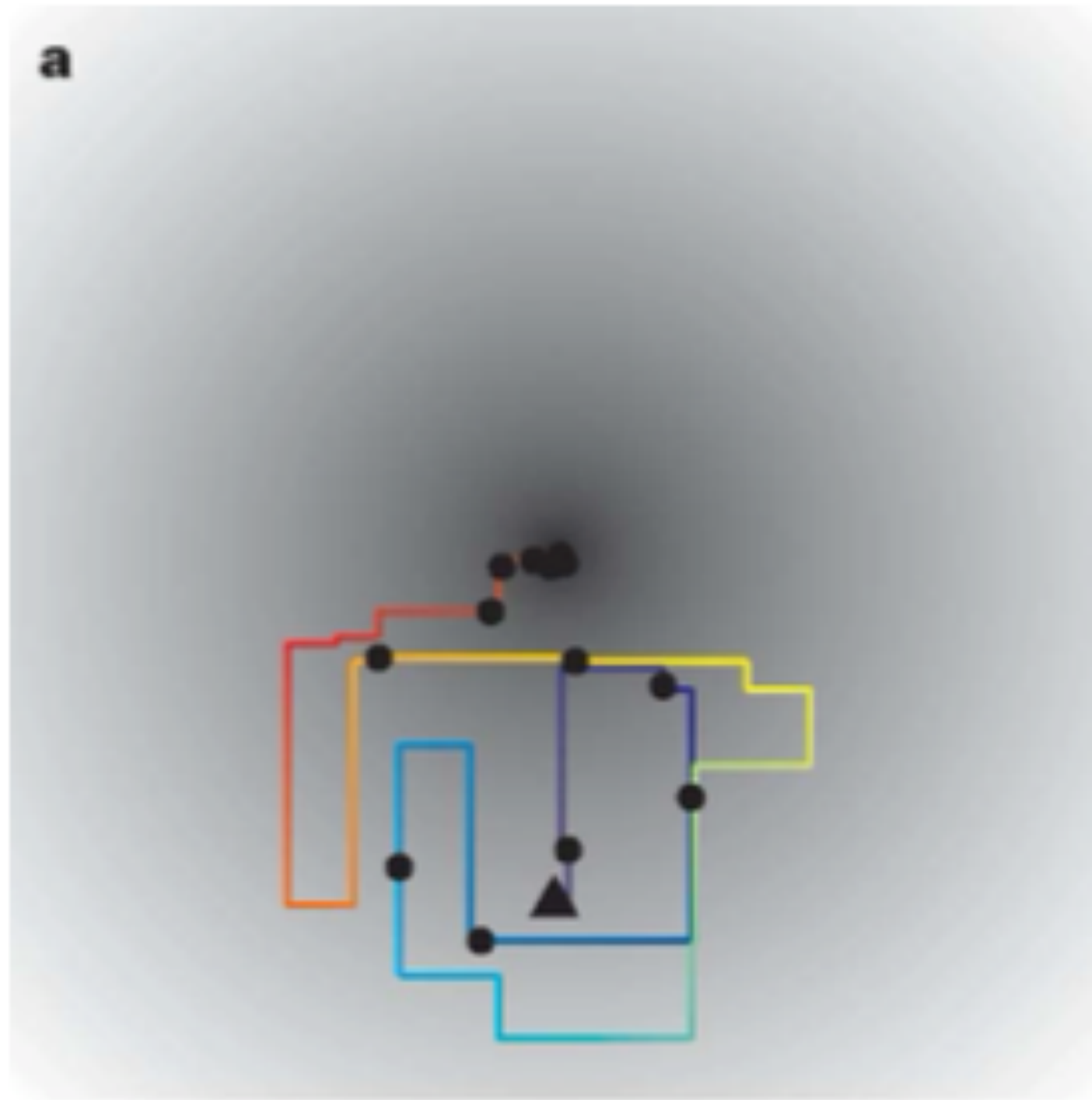
$$\begin{aligned}\pi^*(s) &= \arg \min_{\pi} \mathbb{E}_{p_0, \pi}[T] \longrightarrow T = \text{search duration} \\ &= \arg \min_a \sum_{s'} \Pr(s' | s, a) [1 + \boxed{v^*(s')}] \\ &\quad \text{Optimal value} \quad \curvearrowright\end{aligned}$$

Optimal Infotaxis policy

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

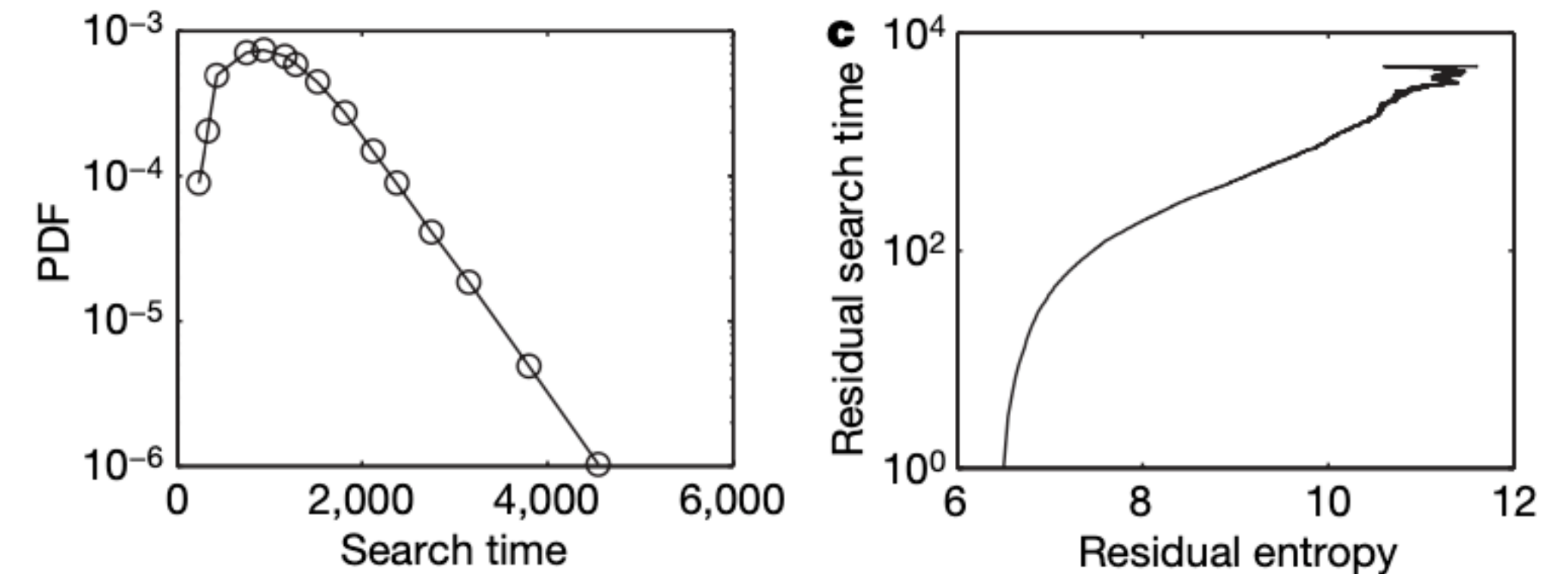
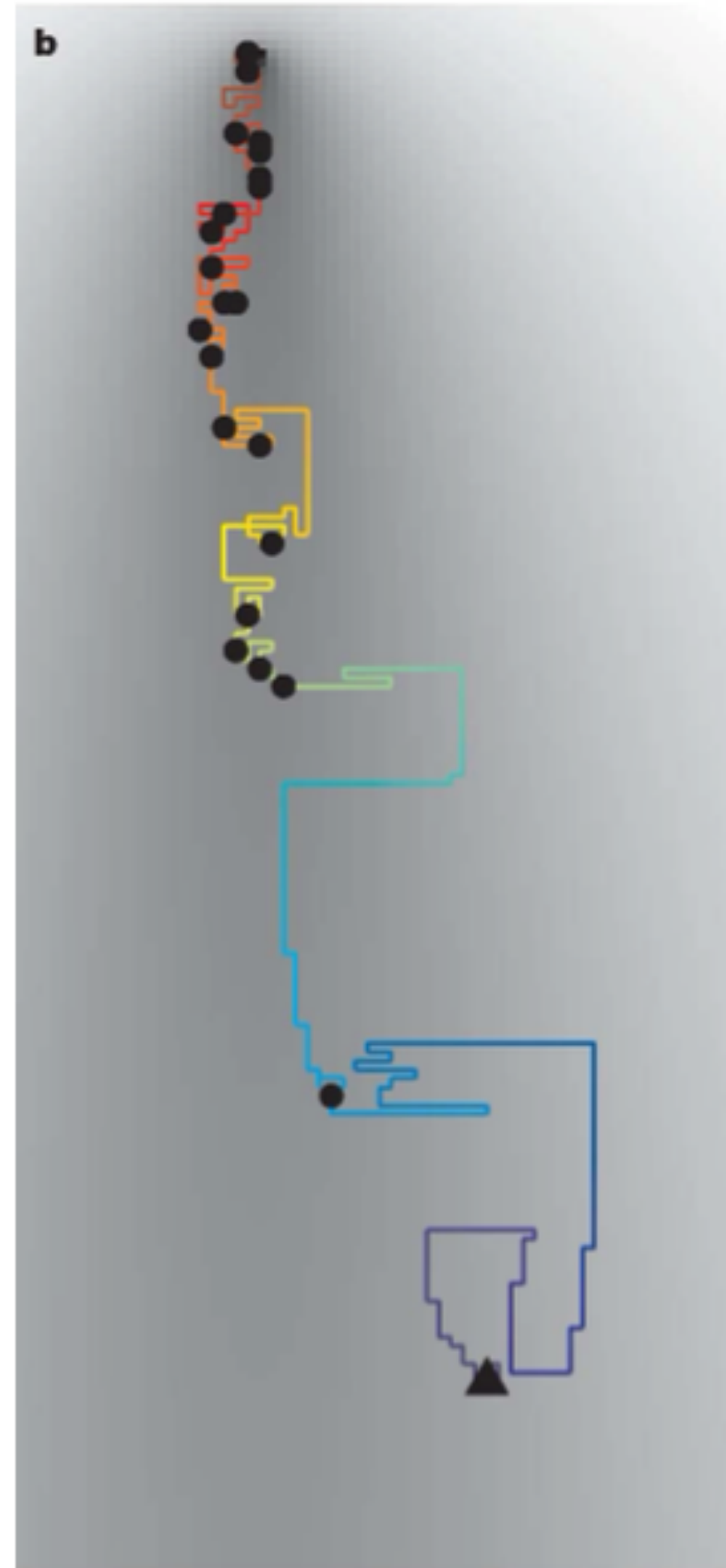
Efficiency of infotaxis

Without wind



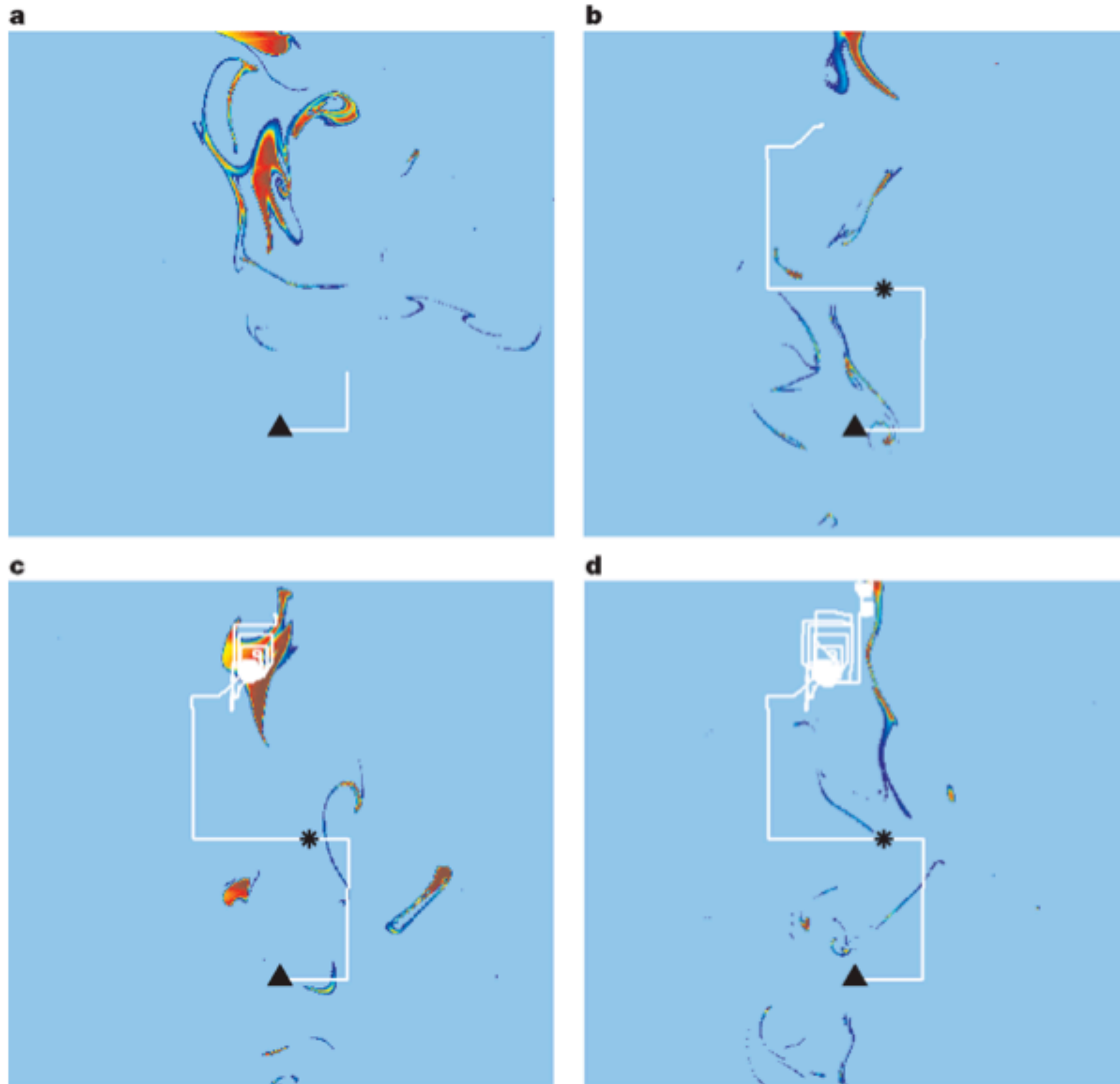
● Scent detection (hit)

With wind



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

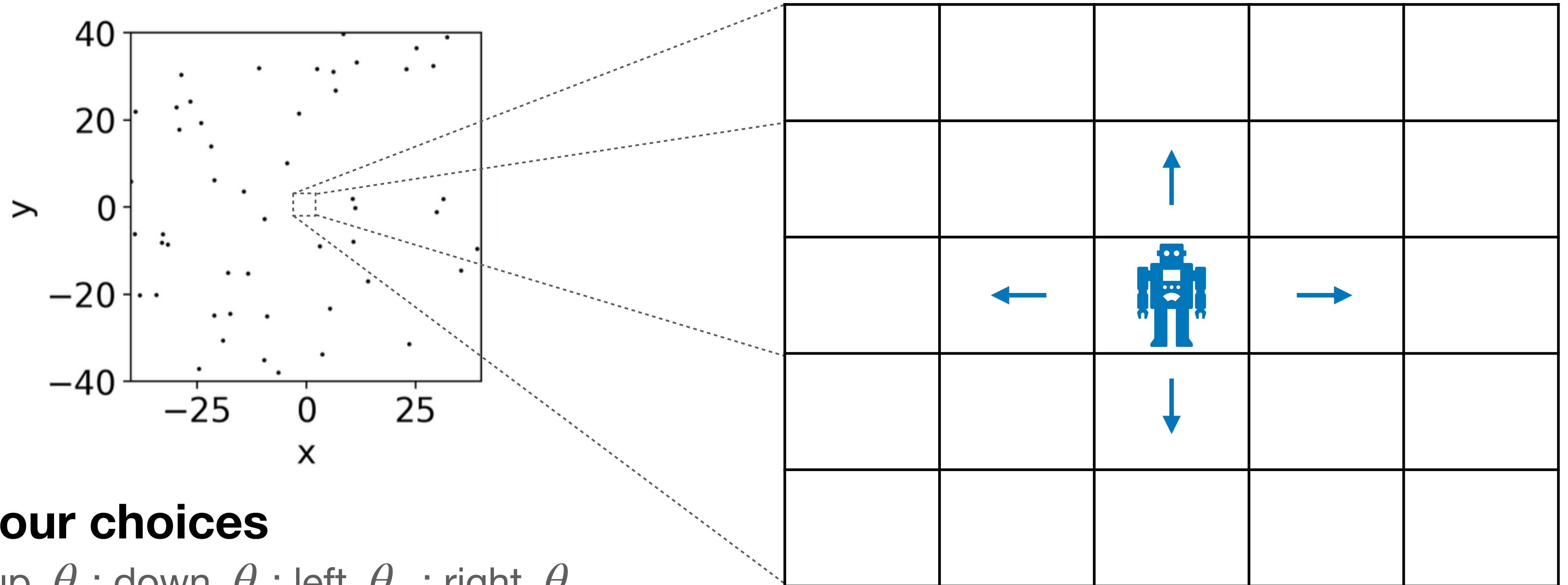
Robustness of infotaxis



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

Curiosity-driven search

Information seeking valentino (Info)



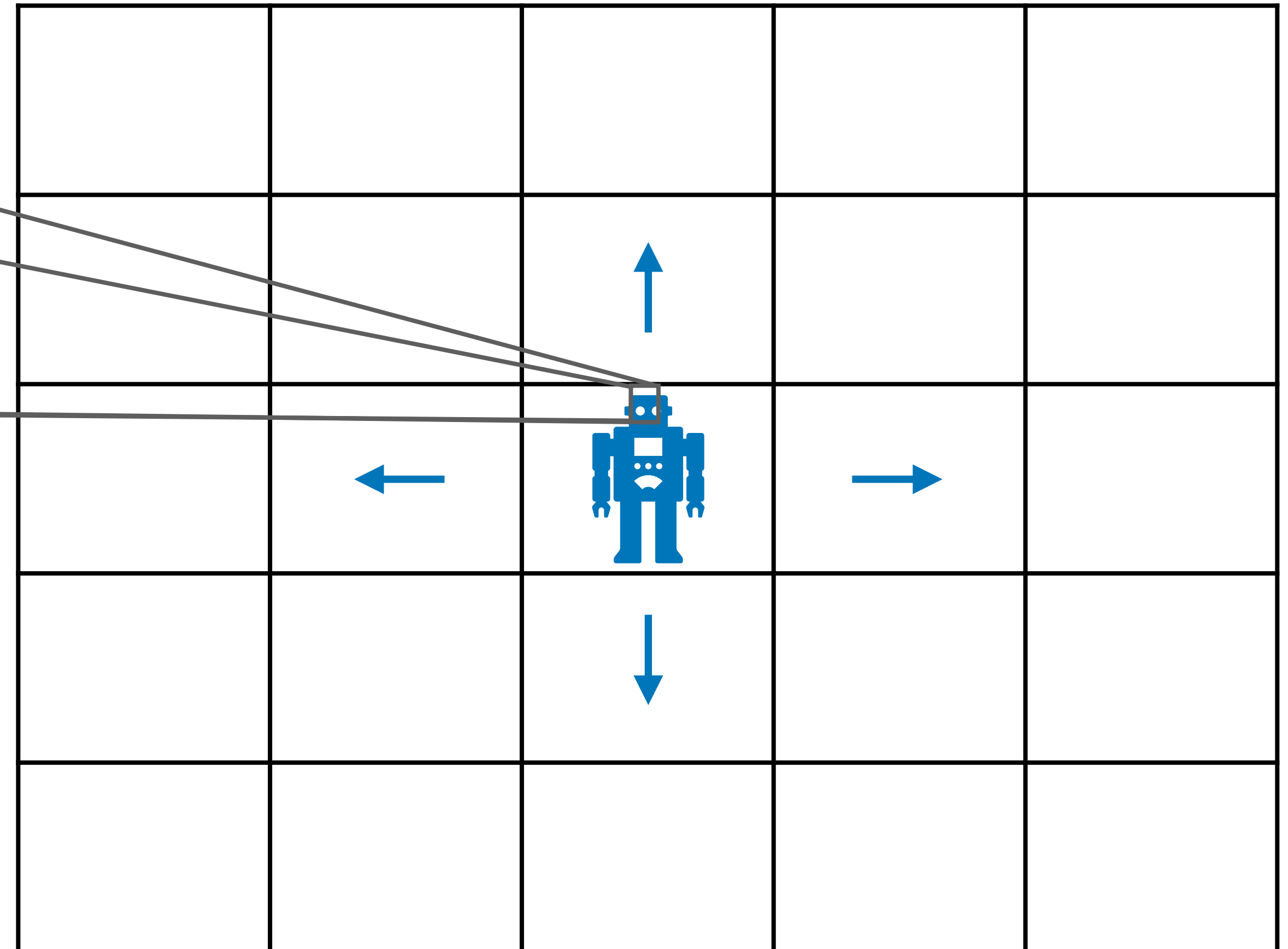
Four choices

up, θ_{\uparrow} ; down, θ_{\downarrow} ; left, θ_{\leftarrow} ; right, θ_{\rightarrow}

Information seeking valentino (Info)

Information Memory E

1/n	1/n	1/n	1/n	1/n
1/n	1/n	1/n	1/n	1/n
1/n	1/n	1/n	1/n	1/n
1/n	1/n	1/n	1/n	1/n
1/n	1/n	1/n	1/n	1/n

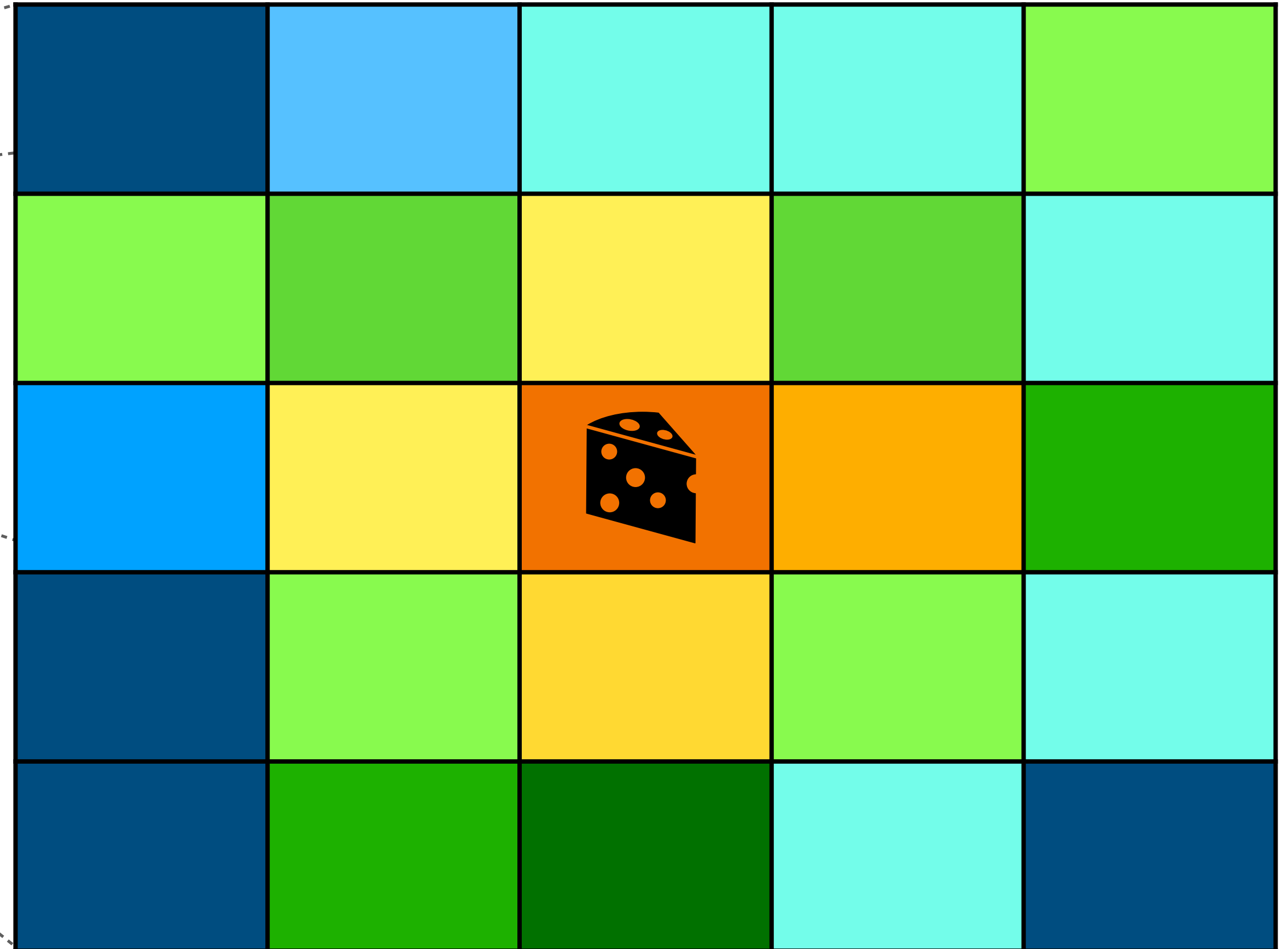


- Give Info a spatial memory, E , of the information contained at each position of the grid
- Initialize E as a uniform distribution at first, giving each position equal amounts of information.
- Update the information at each point in the grid.

The “info” algorithm

Algorithm 4 Info

```
1: Set  $n_{max}$  number steps
2: Set  $a$  information threshold
3: Determine  $n_{pos}$  number of positions on the grid
4: Initialize grid memory  $\forall i, j E(i, j) = 1/n_{pos}$ 
5: Set probability of tumble when  $\Delta o > 0$  as  $\rho_+$ 
6: Set probability of tumble when  $\Delta o \leq 0$  as  $\rho_-$ 
7: for  $step = 1, \dots, n_{max}$  do
8:   Sample gradient:  $\Delta o = o_s - o_{s-1}$ 
9:   Sample state:  $\eta_t \sim U(0, 1)$ 
10:
11:   if  $\Delta o > 0$  then
12:      $hit = 1$ 
13:   else
14:      $hit = 0$ 
15:   end if
16:
17:   Get old info state:  $p(i, j) = E(i, j)$ 
18:   Determine info gain:  $\Delta E = D_{KL}(p(i, j), hit)$ 
19:
20:   if  $(\Delta E > a \text{ and } \eta_s > \rho_+) \text{ or } (\Delta E \leq a \text{ and } \eta_s > \rho_-)$  then
21:     Select direction:  $\theta_s \sim U(1, 4)$ 
22:   else
23:     Select direction:  $\theta_s = \theta_{s-1}$ 
24:   end if
25:
26:   Change memory:  $E(i, j) = hit$ 
27:   Move 1 step in  $\theta_s$  direction
28: end for
```

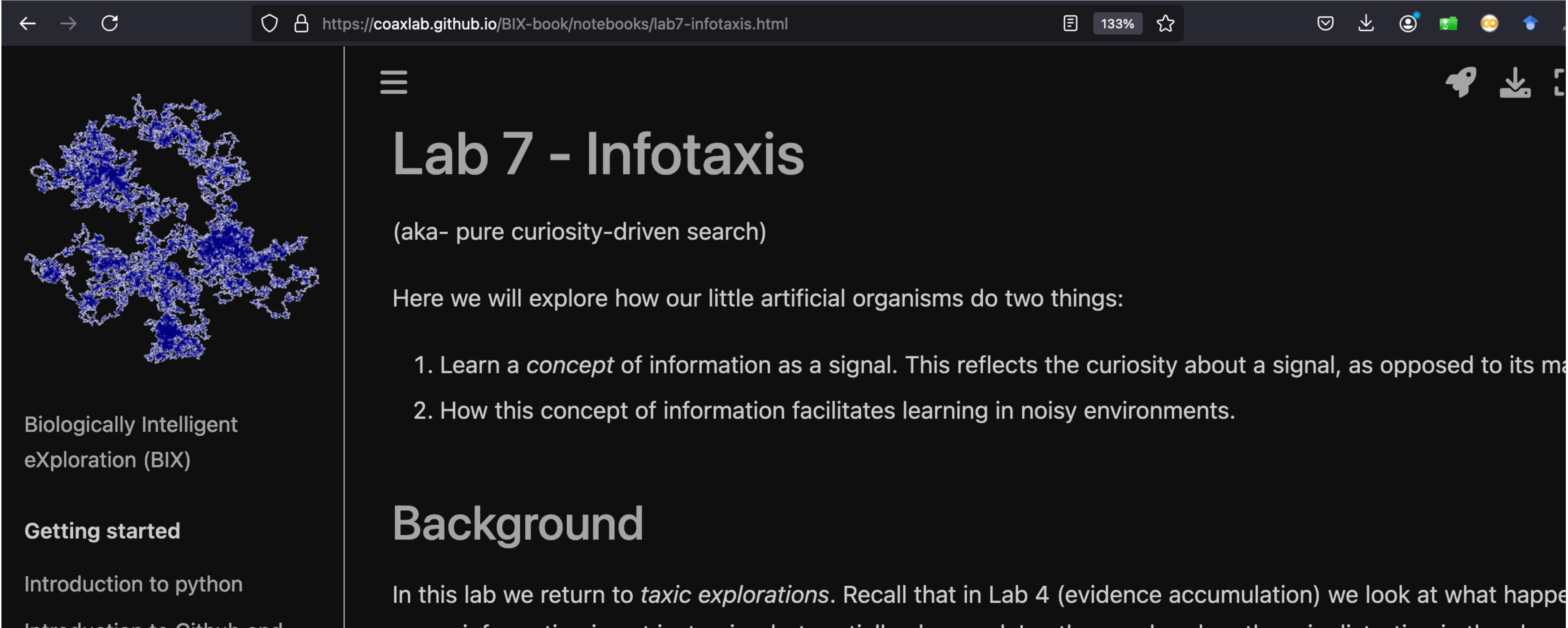


Take home message

- 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/lab7-infotaxis.html>



← → ↺ <https://coaxlab.github.io/BIX-book/notebooks/lab7-infotaxis.html> 133% ☆

☰

Lab 7 - Infotaxis

(aka- pure curiosity-driven search)

Here we will explore how our little artificial organisms do two things:

1. Learn a *concept* of information as a signal. This reflects the curiosity about a signal, as opposed to its ma
2. How this concept of information facilitates learning in noisy environments.

Background

In this lab we return to *toxic explorations*. Recall that in Lab 4 (evidence accumulation) we look at what happens when information is not just noisy, but partially observed. In other words, when there is distortion in the observations