Complex Collective Behaviors Emerge from Simple Algorithms
in T cells, Ants & Robot Swarms

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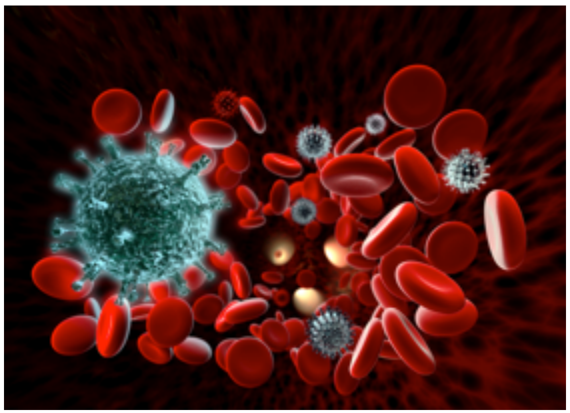
Decentralized Collective Search Strategies



http://www.wed-lock.co.za/wp-content/uploads/2013/02/3D-Render-of-the-human-immune-system.jpeg

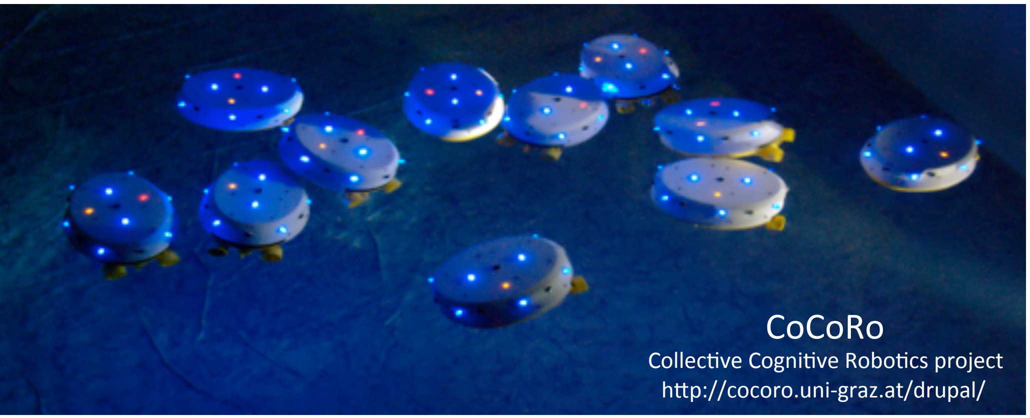
http://entnemdept.ufl.edu/creatures/urban/ants/harvester_ant03.jpg

How do effective search strategies emerge from interactions among agents and between agents and their environment?

Why Flexibility?

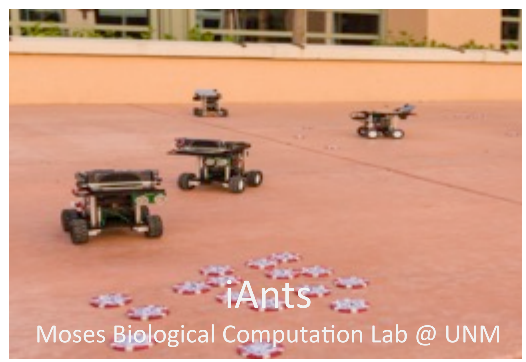
https://www.ted.com/talks/chris_urmson_how_a_driverless_car_sees_the_road?language=en

Why Swarms?

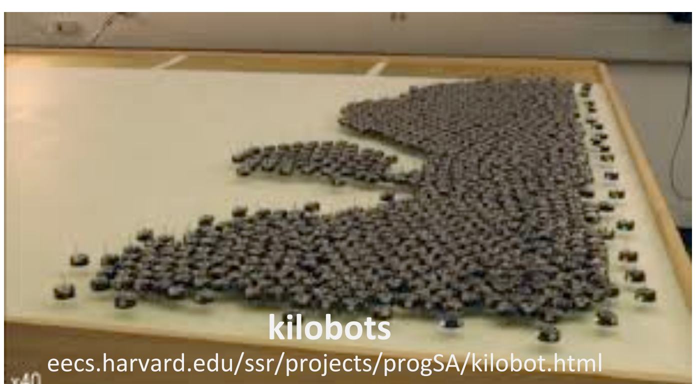


CoCoRo
Collective Cognitive Robotics project
http://cocoro.uni-graz.at/drupal/

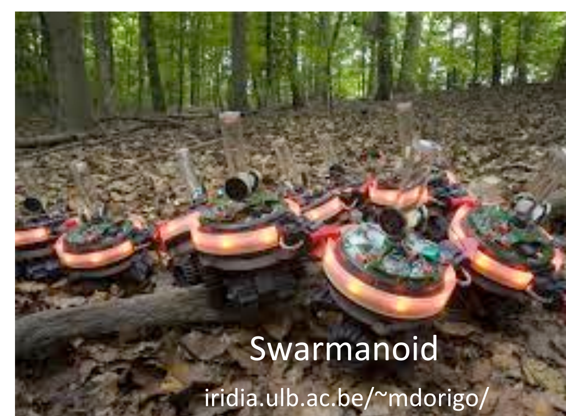
GRASP Lab
gizmag.com/grasp-nano-quadrotor-robots-swarm/21302/



iAnts
Moses Biological Computation Lab @ UNM



kilobots
eecs.harvard.edu/ssr/projects/progSA/kilobot.html



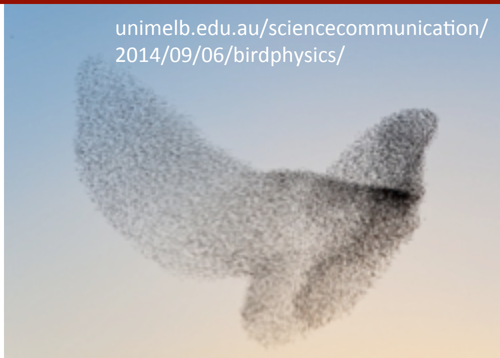
Swarmanoid
iridia.ulb.ac.be/~mdorigo/

Why Swarms?

Flexible in multiple environments

Robust to individual failure and error

Scalable to large swarm sizes



Simple Rules govern interactions among agents & with environment

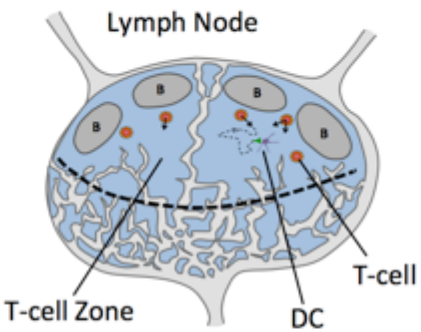
Efficient & Effective for spatially distributed tasks

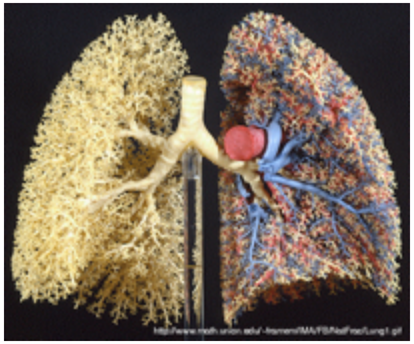
Ants: most ecologically successful foragers on earth

Focus on Collective Foraging

- Search problems are ubiquitous in biology and computer science
- Search for targets distributed in space
  - Distributed algorithms on dispersed agents increases search efficiency
  - Efficiency of search depends on target distribution
  - Requires environmental interaction
  - May require retrieval and collection to a central location
- Collective Search in robotics
  - Applications: search & rescue, waste clean up, exploration, monitoring
  - noise, stochasticity, error
  - balance spatial extent vs thoroughness
    - explore vs exploit tradeoff

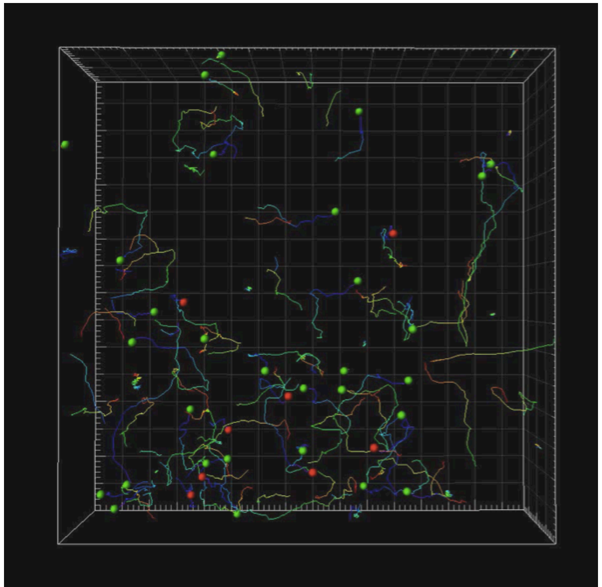
Flexibility in Multiple Environments
T cells in Lymph Nodes vs Lung

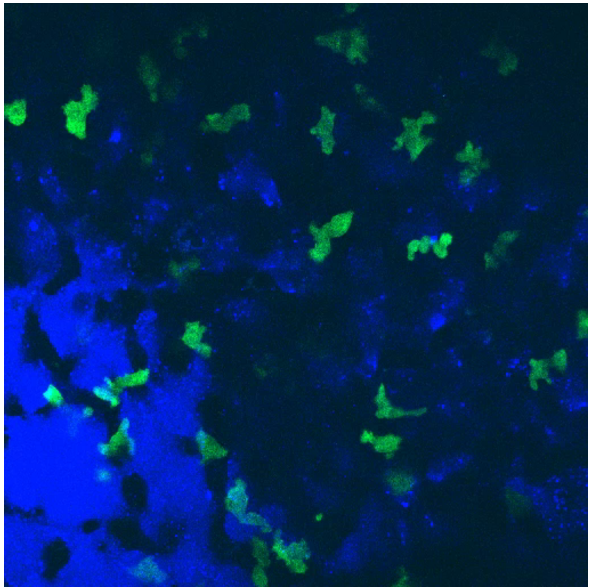




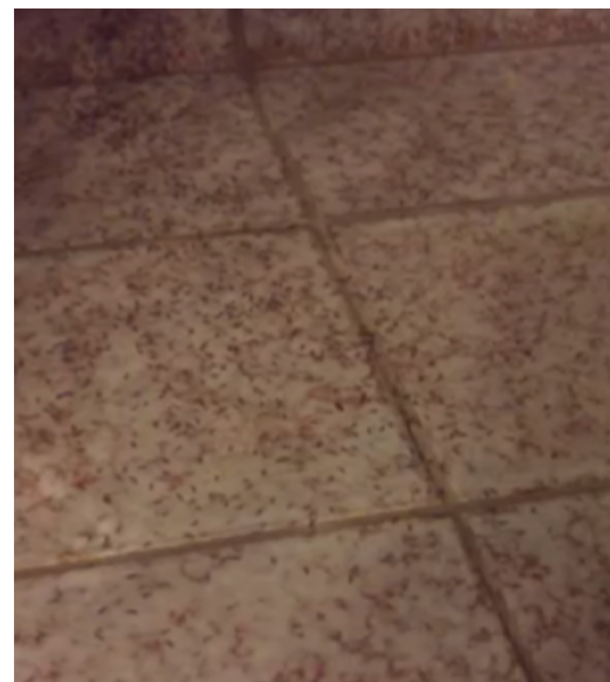
Search for Dendritic Cells in Lymph Node

Search for Infection in Lung

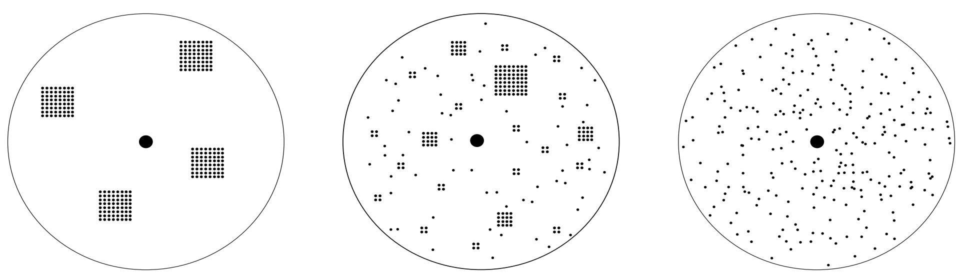




Flexibility in Multiple Environments
14,000 ant species in diverse habitats



Flexibility in Multiple Environments
Robots collect from different target distributions



Complexity Emerges from Simple Algorithms in Complex Environments

Ants interact with

- Targets
  - seeds
- Chemical Cues
  - Pheromones
- Structural Features
  - habitat
- Each other
  - signaling
  - contact rate sensing
  - fighting

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Scalable, Flexible, Robust Foraging from a simple repertoire of behaviors

Count

Assess seed pile density

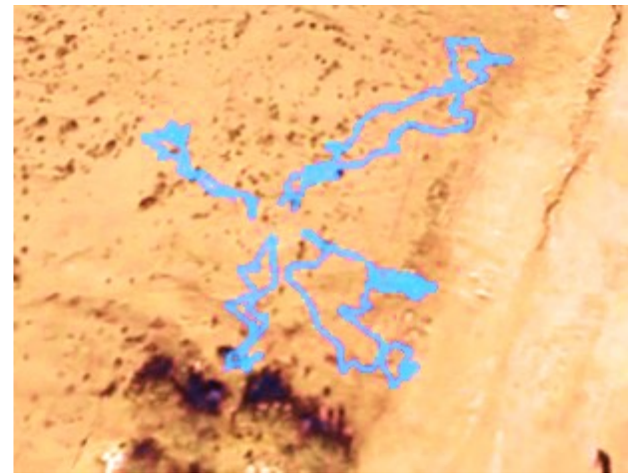
Remember & Return

Site Fidelity

Movement

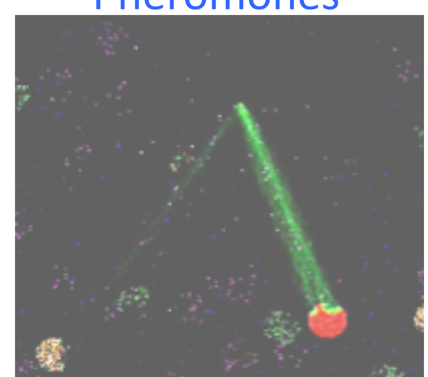
Balances search

thoroughness vs extent

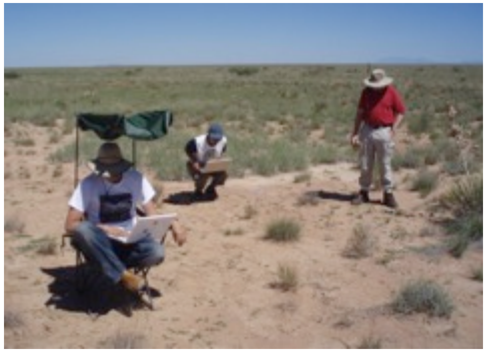


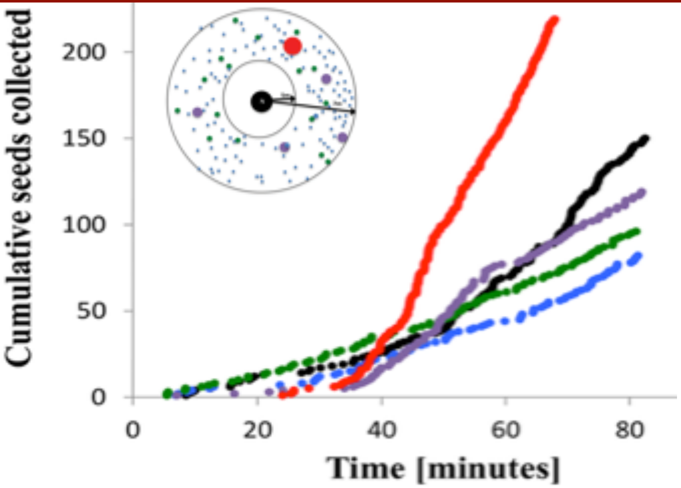
Communicate

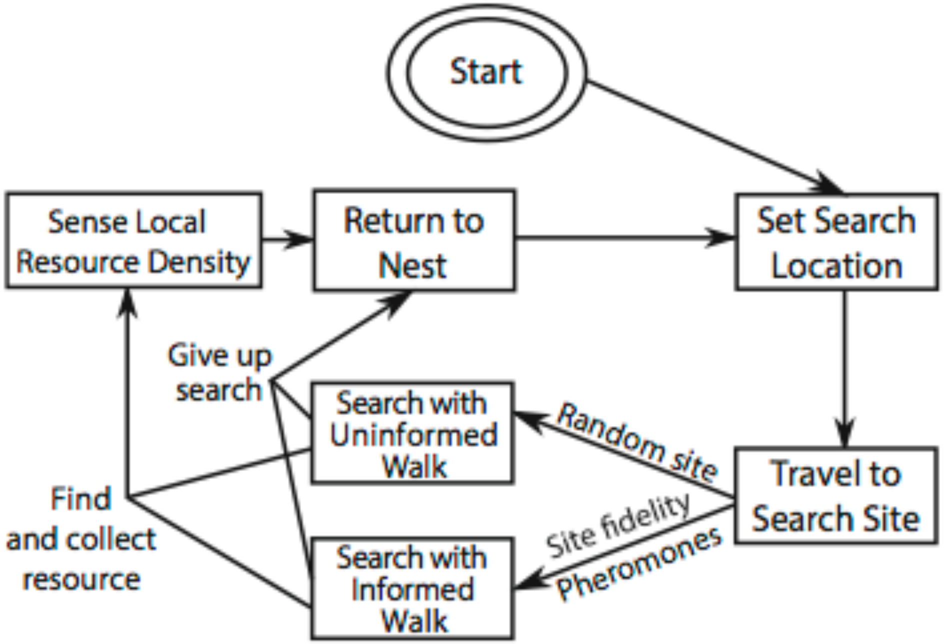
Pheromones

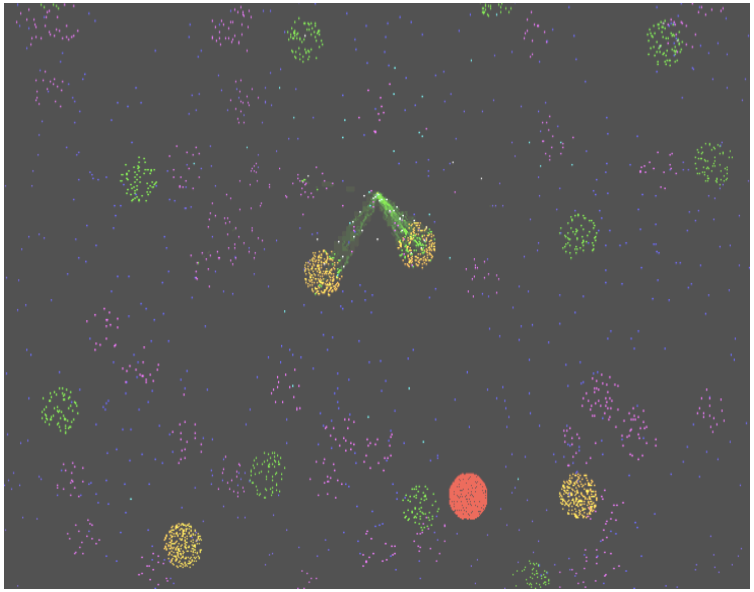


Central Place Foraging Model



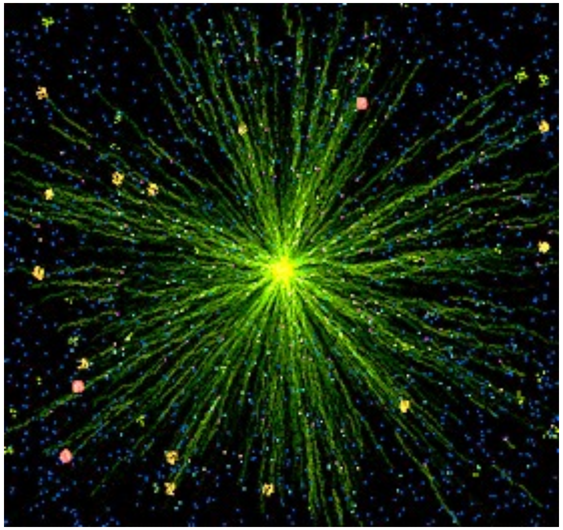




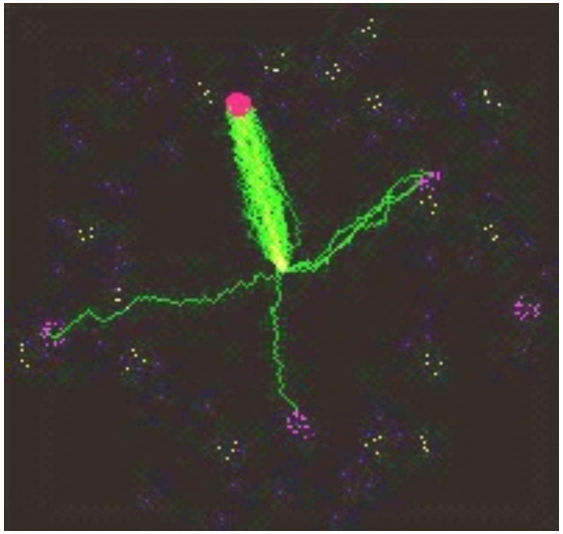


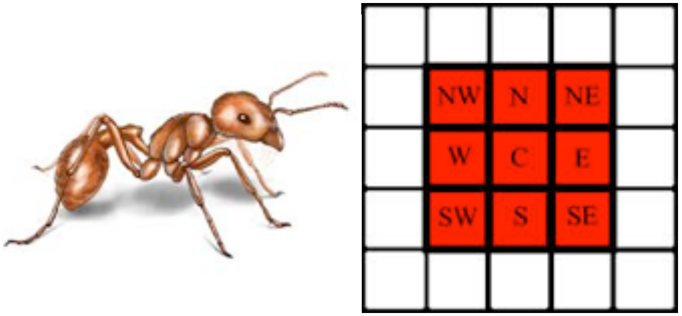
[Fla11, Fla13,Let13]

Foraging success depends on Interactions among behaviors & environment



Lay pheromone
Whenever I find a seed



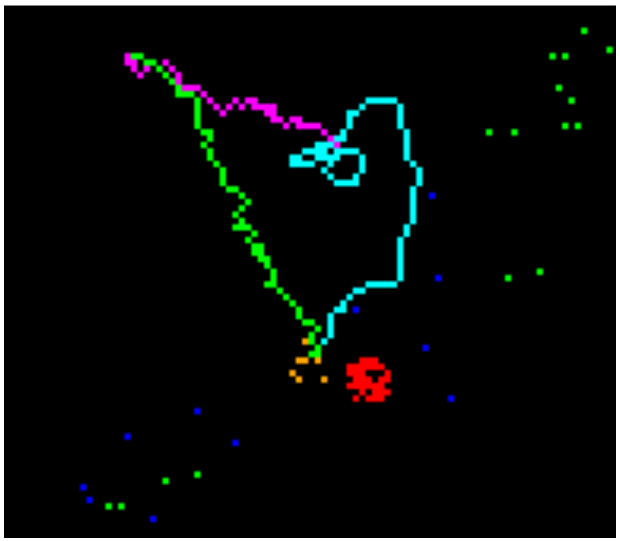


Lay pheromone
Only if count > 5

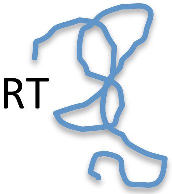
Appropriate communication depends on what is sensed in the environment

Foraging success depends on interactions among behaviors & environment

Movement balances the extensiveness and thoroughness of search



START



END

Informed Walk

After returning via site fidelity or following a pheromone trail
Turn often to search thoroughly

START

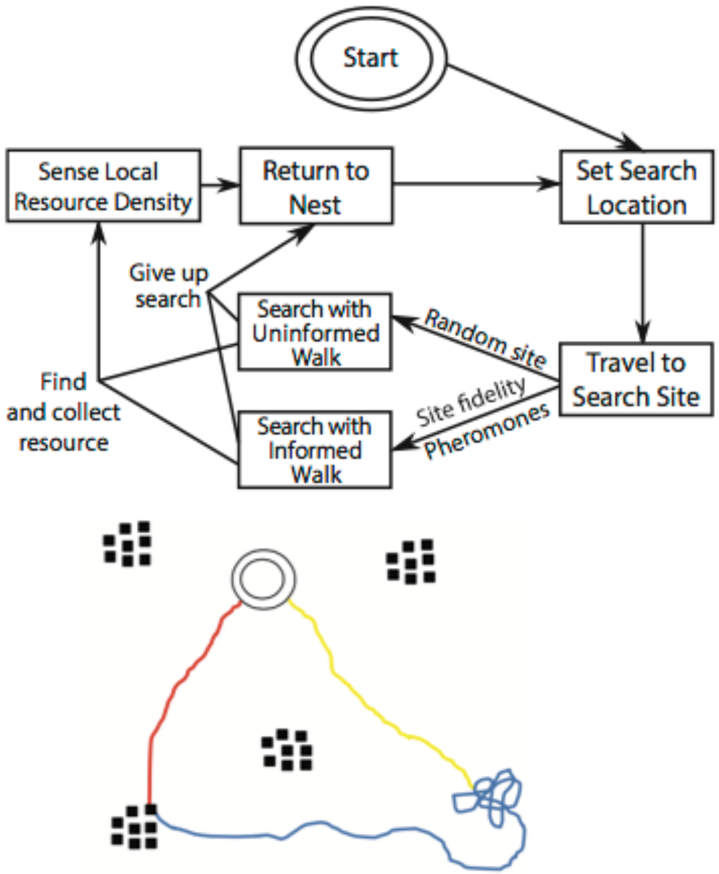
END

Uninformed Walk

When searching at random,
walk straight to search widely

Appropriate movement depends on what has been communicated & remembered

Central Place Foraging Algorithm (CPFA)



Algorithm 1 Central-Place Foraging Algorithm

Disperse from nest to random location
while experiment running **do**
  Conduct uninformed correlated random walk
  if resource found **then**
    Collect resource
    Count number of resources c near current location l_f
    Return to nest with resource
    if $\textsc{Pois}(c, \lambda_{lp}) > U(0, 1)$ **then**
      Lay pheromone to l_f
    end if
    if $\textsc{Pois}(c, \lambda_{sf}) > U(0, 1)$ **then**
      Return to l_f
      Conduct informed correlated random walk
    else if pheromone found **then**
      Travel to pheromone location l_p
      Conduct informed correlated random walk
    else
      Choose new random location
    end if
  end if
end while

GA tunes CPFA parameters to specific environments:

Behavioral strategies are evolved from a repertoire of behavioral primitives

[HecSI15]

GA-evolved CPFA
7 CPFA parameters (**real-valued, interact**)

Parameter	Description	Initialization Function
p_s	Probability of switching to searching	$\mathcal{U}(0,1)$
p_r	Probability of returning to nest	$\mathcal{U}(0,1)$
ω	Uninformed search variation	$\mathcal{U}(0,4\pi)$
λ_{id}	Rate of informed search decay	$exp(5)$
λ_{sf}	Rate of site fidelity	$\mathcal{U}(0,20)$
λ_{lp}	Rate of laying pheromone	$\mathcal{U}(0,20)$
λ_{pd}	Rate of pheromone decay	$exp(10)$

- Uninformed robots use a Correlated Random Walk: $\theta_t = \mathcal{N}(\theta_{t-1}, \omega)$
- Informed robots use a less correlated CRW: $\sigma = \omega + (4\pi - \omega)e^{-\lambda_{\mathrm{id}} t}$
- Information decisions governed by a Poisson CDF: $\textsc{Pois}(c,\lambda) = e^{-\lambda} \sum_{i=0}^{\lfloor c \rfloor} \frac{\lambda^i}{i!}$
  - Robots return to location of discovered resource if the count of nearby resources *c* is large
  - Robots can use memory (site fidelity, $\lambda = \lambda_{sf}$) or communication (pheromone-like waypoints, $\lambda = \lambda_{lp}$)
- Pheromone waypoints decay exponentially over time: $\gamma = e^{-\lambda_{pd} t}$

GA selects parameters to maximize seeds collected in fixed time

Each model run requires a set of input parameters $[p_t, p_s, \omega, \lambda_{id}, \lambda_{lp}, \lambda_{sf}, \lambda_{fp}]$
Each individual in a colony is identical

Cross over and mutation on parameters

G0: $[p_t, p_s, \omega, \lambda_{id}, \lambda_{lp}, \lambda_{sf}, \lambda_{fp}]$ x $[p_t, p_s, \omega, \lambda_{id}, \lambda_{lp}, \lambda_{sf}, \lambda_{fp}]$
G1: $[p_t, p_s, \omega, \lambda_{id}, \lambda_{lp}, \lambda_{sf}, \lambda_{fp}]$

- 100 runs with different parameter sets (colonies) for 100 Generations
- Each colony, each generation, evaluated on 8 different target placements for 1 simulated hour
- Colonies with highest 'fitness' (seeds collected) replicate into next generation

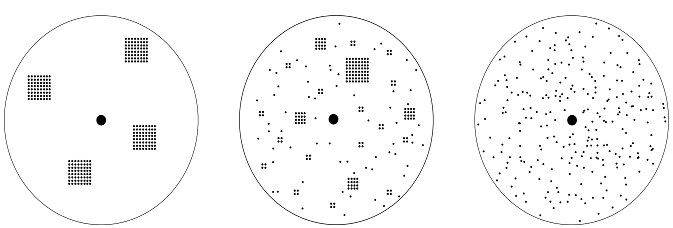
Group Selection Experiments *in silico* evolve colonies to maximize foraging rate

Complexity Emerges from Simple Algorithms in Complex Environments

Robots interact with

- Targets
  - April Tags
- Virtual Pheromones
  - wifi waypoints
- Structural Features
  - Tag distribution
- Each other
  - obstacle avoidance
  - contact rate sensing

https://youtu.be/Cs6PlInKYH8

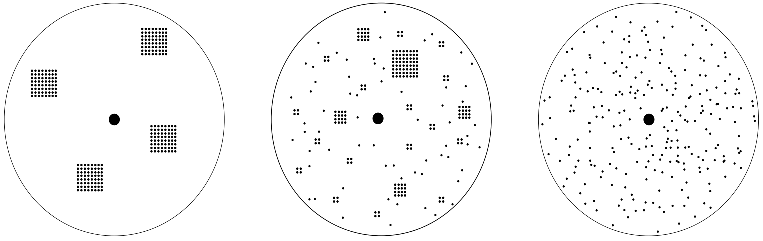


- Explore with correlated random walk
- Estimate number of resources by rotating 360°
- Return via memory or communication
- Search thoroughly; gradually give up
- Parameters governing movement, memory & communication tuned *in silico* by GA

Complexity Emerges from Simple Algorithms in Complex Environments

Robots interact with

- Targets
  - April Tags
- Virtual Pheromones
  - error-prone waypoints over wifi or BT
- Structural Features
  - Tag distribution
- Each other
  - obstacle avoidance
  - contact rate sensing



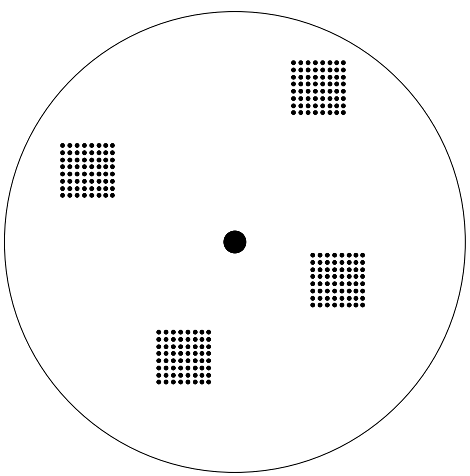
Experimental Setup

Simulated foraging:

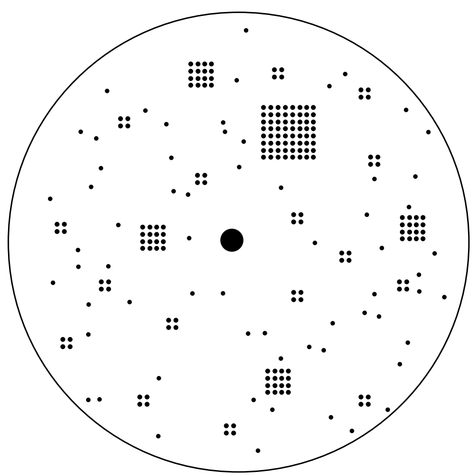
- 1 (simulated) hour
- 1 to 768 robots per swarm
- 125 x 125 grid (1323 x 1323)
- 256 resources (28,672)
- Error model emulates sensor noise:
  - 50% detection error
  - 50 – 100 cm positional error
- Constitutes fitness function for GA

Physical foraging:

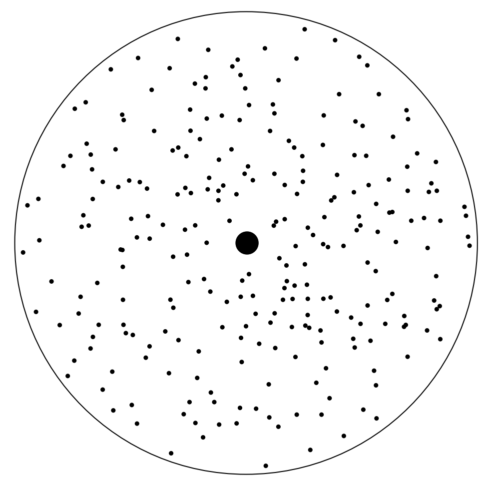
- 1 hour
- 1, 3, and 6 robots per swarm
- 100 m^2 arena
- 256 QR barcode tags
- WiFi communication
- Simulated retrieval via unique tag
- Evolved behaviors transferred from simulated to physical robots



Clustered



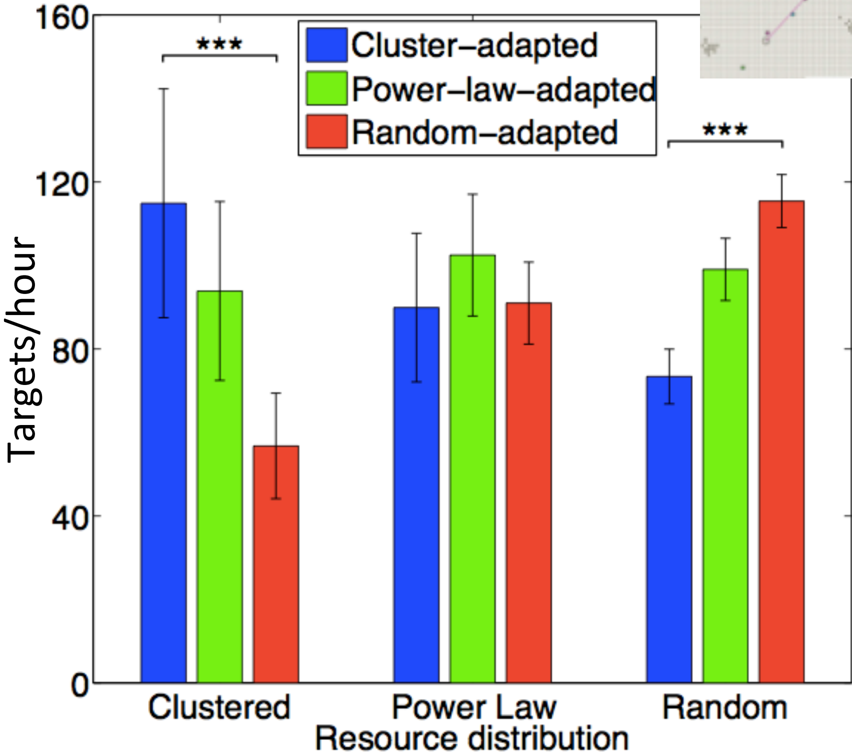
Powerlaw-distributed

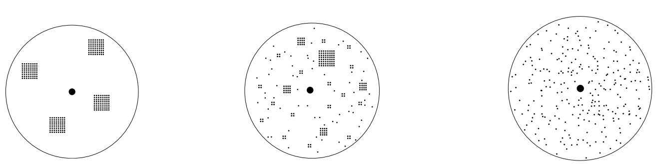


Random

iAnts adapt to their environment

In simulation



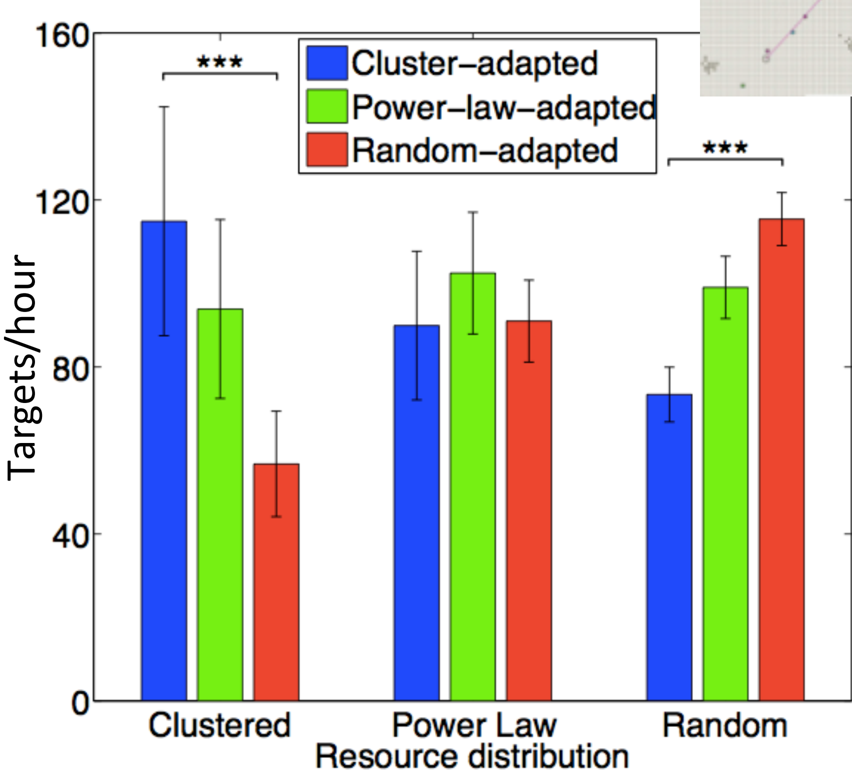


Behaviors evolve that increase foraging rate in each environment

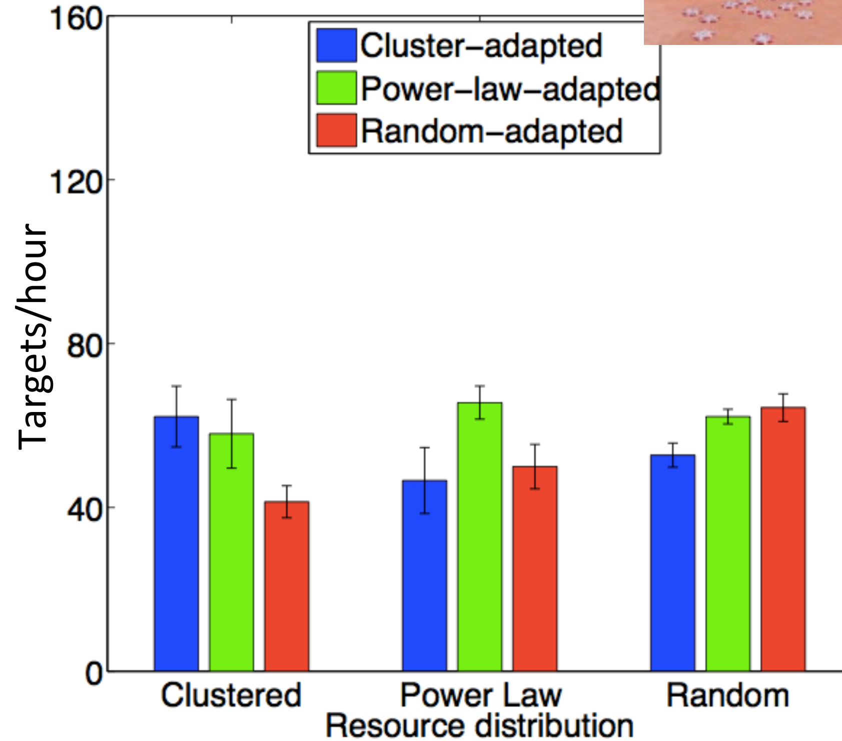
[HecSI15]

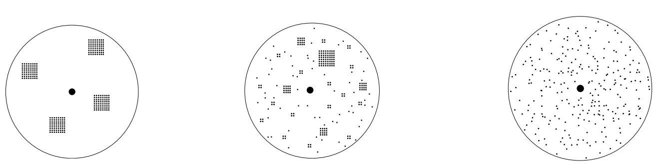
iAnts adapt to their environment

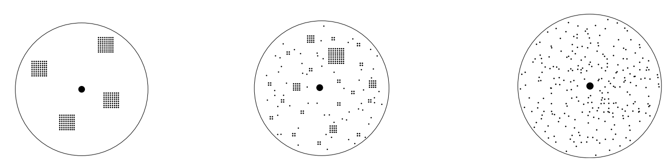
In simulation



In iAnts



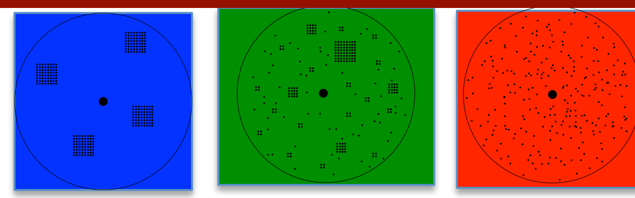


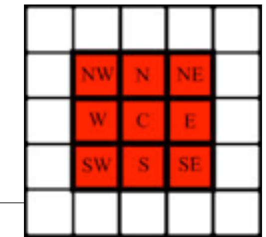


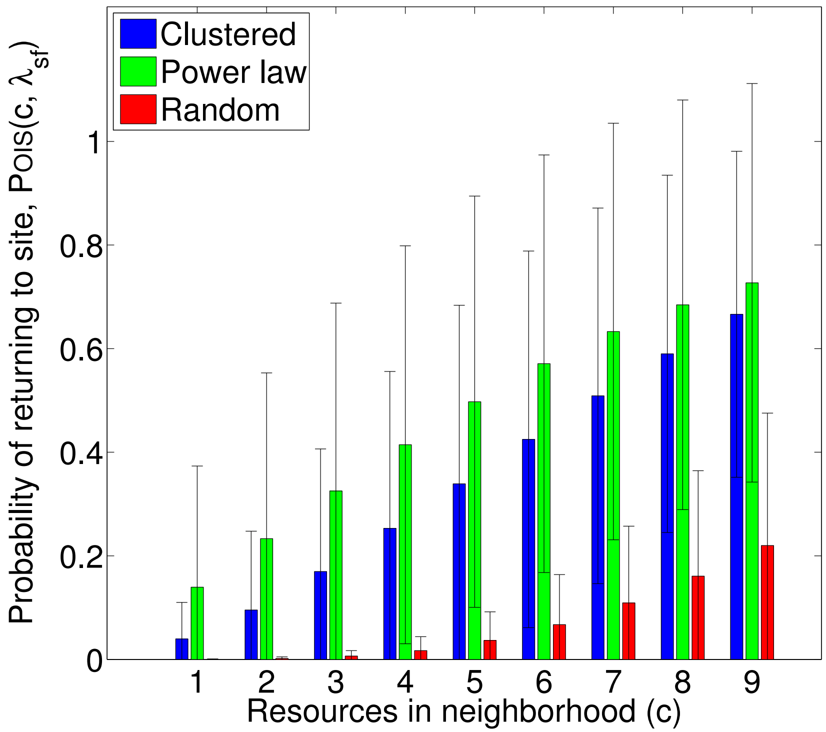
Behaviors evolve that increase foraging rate in each environment

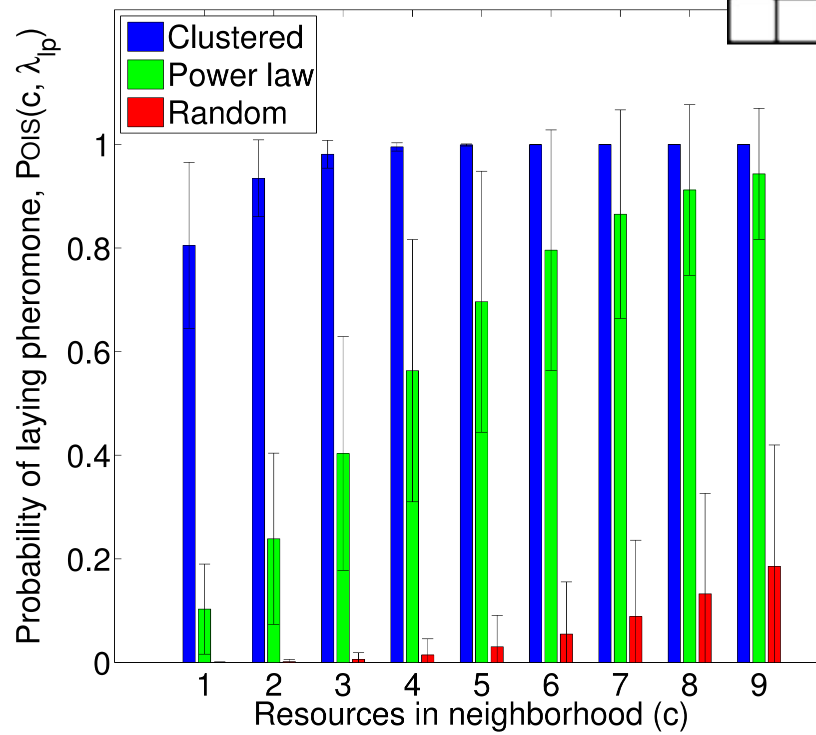
[HecSI15]

Flexibility: different behaviors for different target distributions



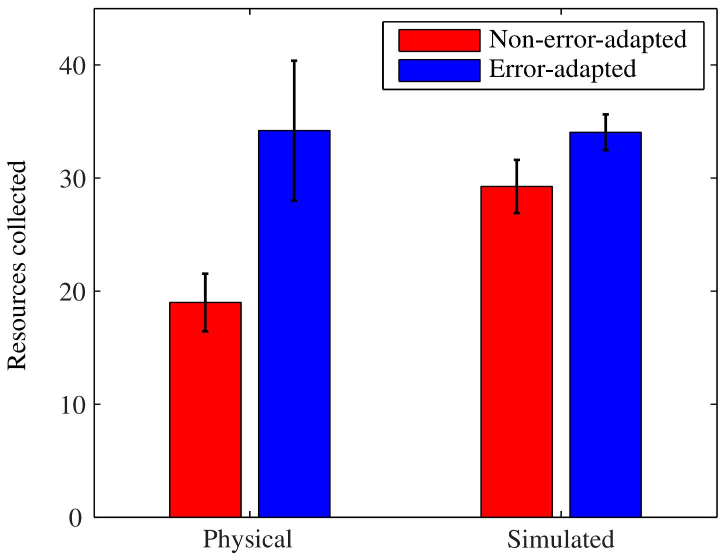


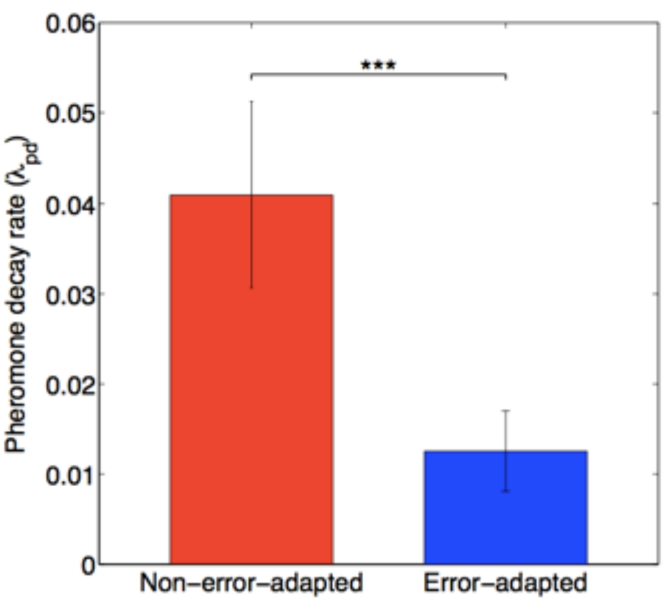




- Cluster-adapted swarms use less site fidelity (memory) and more pheromone (communication) than power-law-adapted swarms
- Random-adapted swarms rarely use either memory or communication

Flexible response to error





Tag detection error: ~50%
Localization error up to 50 cm

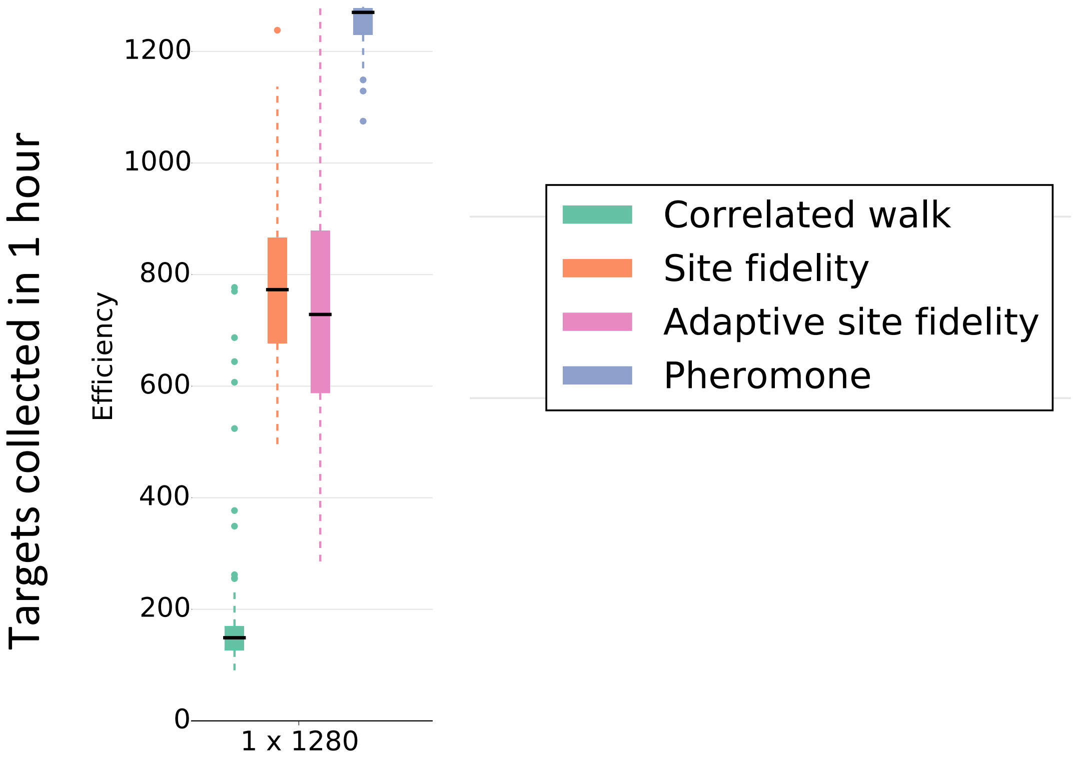
Error causes robots in <u>clustered</u> world to lay more pheromone that evaporates slowly

For partially clustered targets, the opposite

For random targets, irrelevant

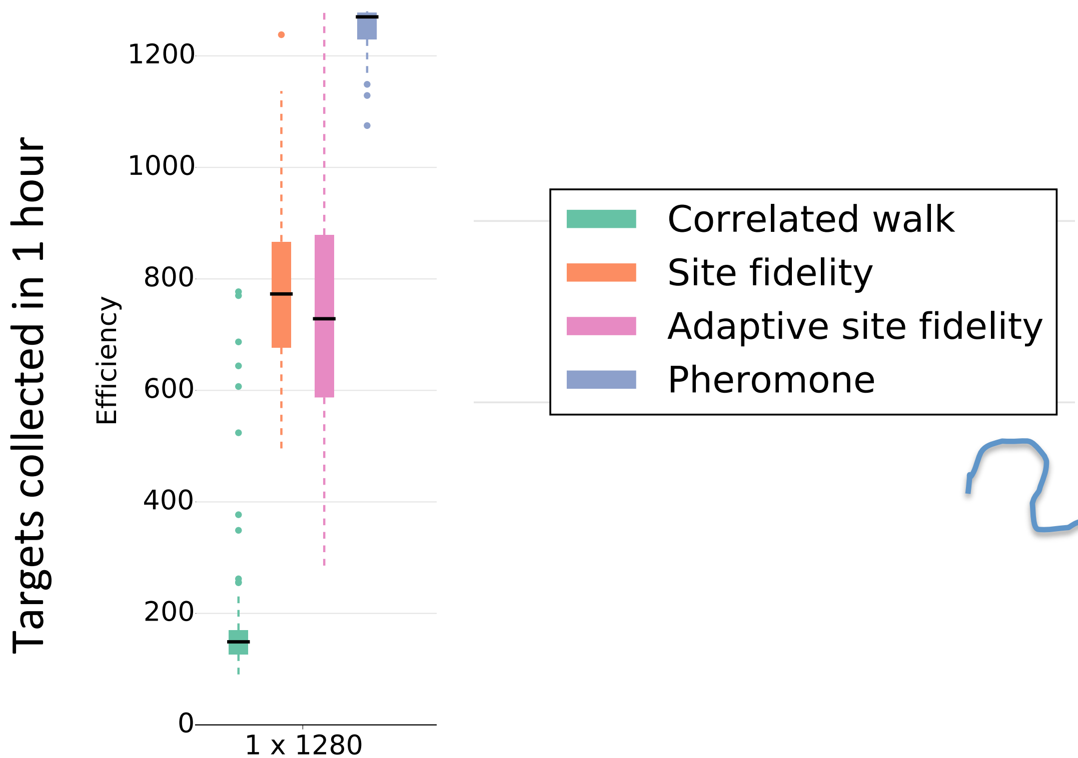
[Hec13, HecSI15]

Communication improves foraging given clustered targets

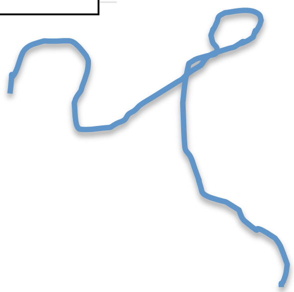


single large pile

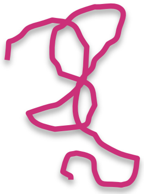
Communication improves foraging given clustered targets



single large pile

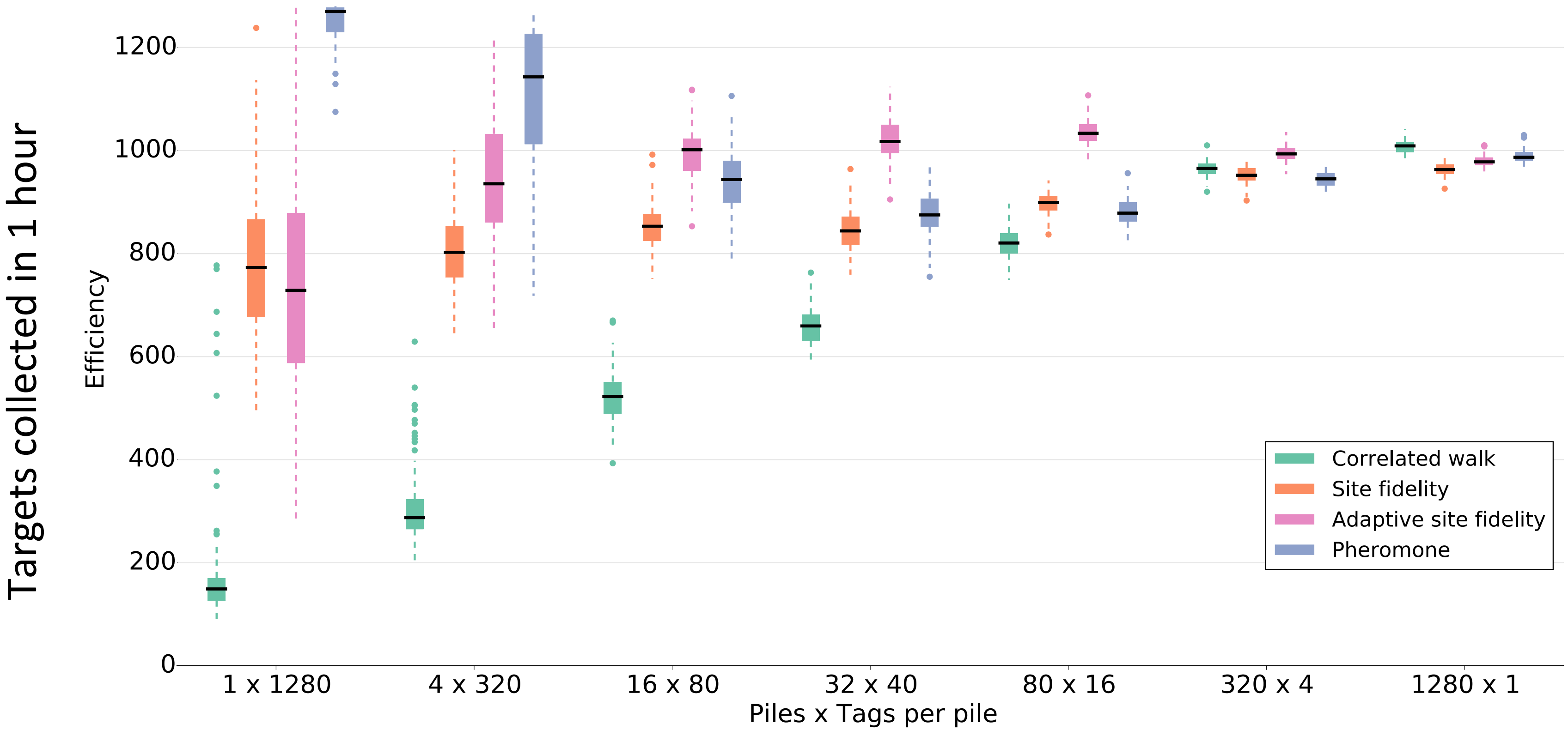


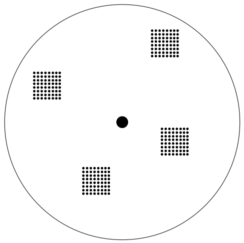
Uninformed walk increases search extent

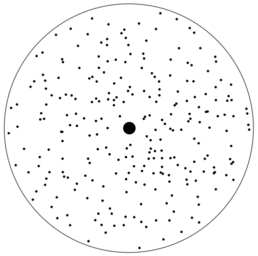


Informed walk increases search thoroughness

Adapting movement to sensed resource density improves search given small clusters

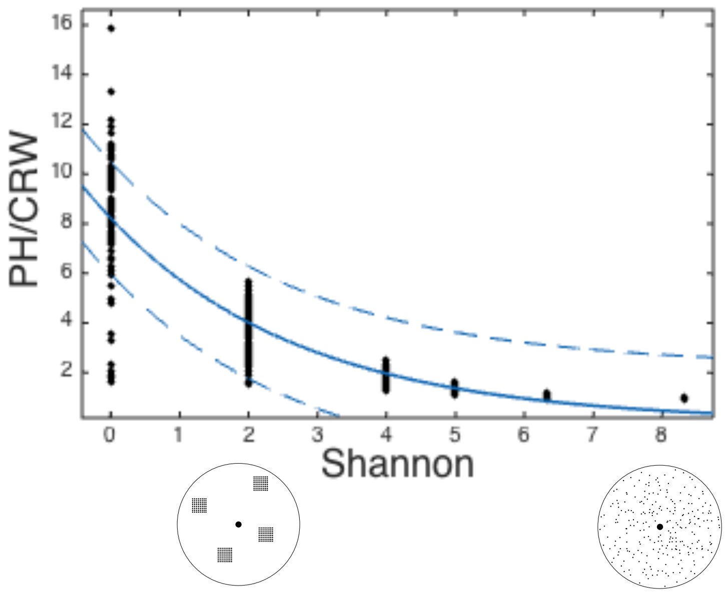






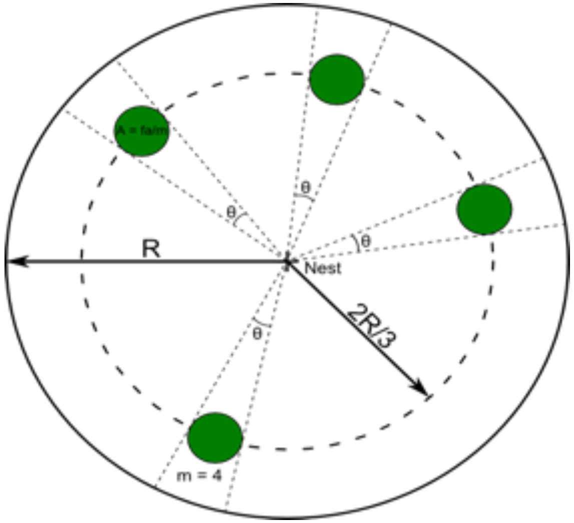
Value of Communication depends on information in the environment

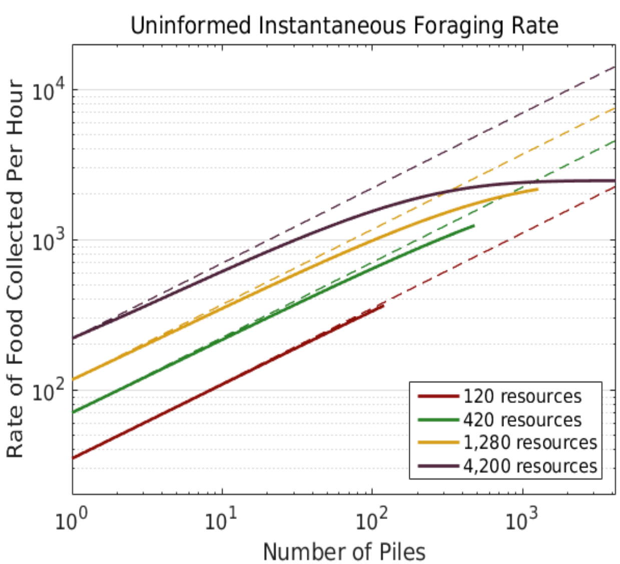
- For a single cluster
  - pheromones: 8 times better than random search
  - site fidelity: 4 times better than random search
  - Value of information declines exponentially with the log of the number of resources
- For many small clusters
  - adaptive site fidelity is 4 times better than random
- For randomly distributed resources
  - information is useless



[Fla15]

Analytical Model of Random Foraging





Diameter of a Pile

$$d = 2\sqrt{\frac{fa}{m\pi}}$$

Angle of a Pile

$$\theta = 2sin^{-1}\left(\frac{3d}{4R}\right)$$

Probability of Hitting *At Least* One Pile

$$p = 1 - \left(\frac{2\pi - \theta}{2\pi}\right)^m$$

Expected Foraging Rate of *n* Ants

$$n \cdot \frac{df}{dt} = \frac{3nsp}{2R(3-p)}$$

Analytical Model of Nest Recruitment

Optimal Scout Population (x)

$$\frac{2k}{n-x} = \frac{2+q^x}{1-q^x}$$

Value of a Discovery:
Amount Able to be Collected

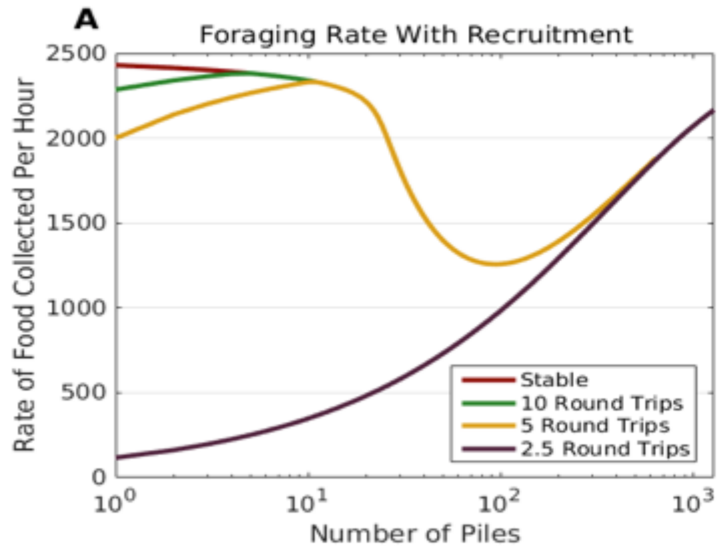
$$k = min\left(f/m - 1, \frac{(v-1)(n-x)}{2}\right)$$

Expected Foraging Rate of *n* Ants

$$n \cdot \frac{df}{dt} = \frac{3s[(n-x)(3-p)+2xp]}{4R(3-p)}$$

Value of nest recruitment

$$\frac{[(n-x)(3-p)+2xp]}{2np}$$

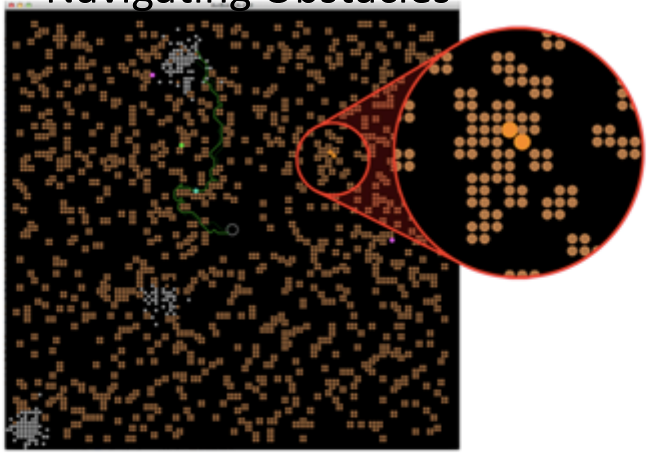


- Assumptions eliminate interesting environmental features
- Results are sensitive to
  - optimal scout number
  - timing
- Identifies a decrease in foraging rate for recruitment given many small piles—where adaptive sf is most useful

[Lev16]

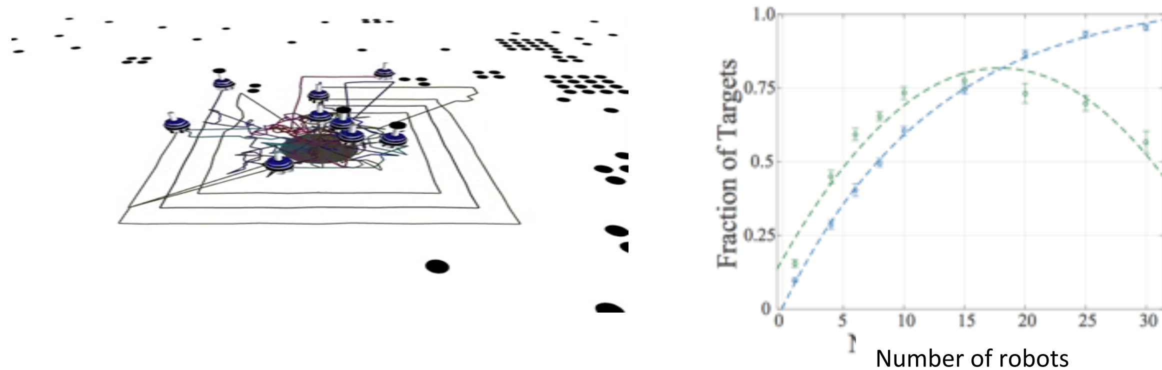
CPFA Extensions

Navigating Obstacles



[Sto16]

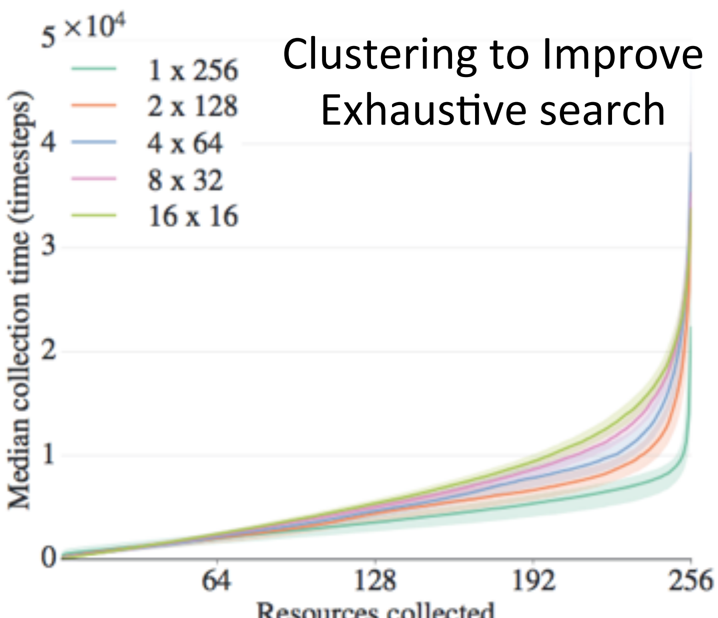
Comparison to Deterministic Search



Surprisingly efficient, error-tolerant,
but not scalable

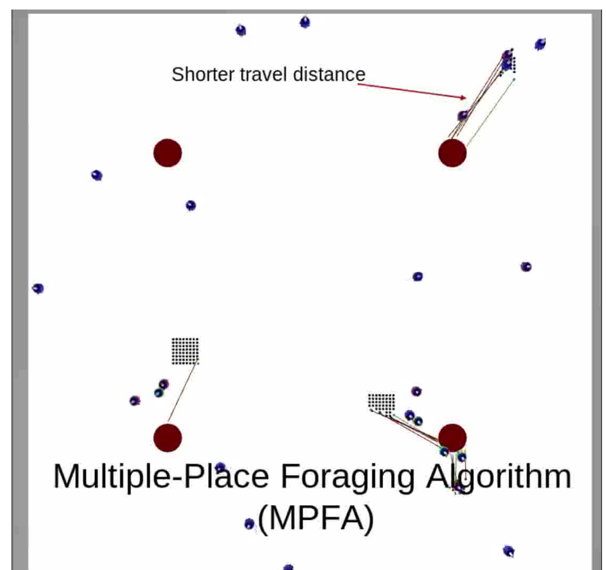
[Fri16]

Clustering to Improve Exhaustive search



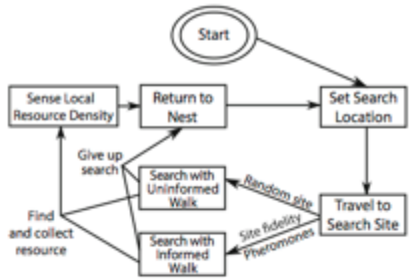
[Hec15]

[Qi16]



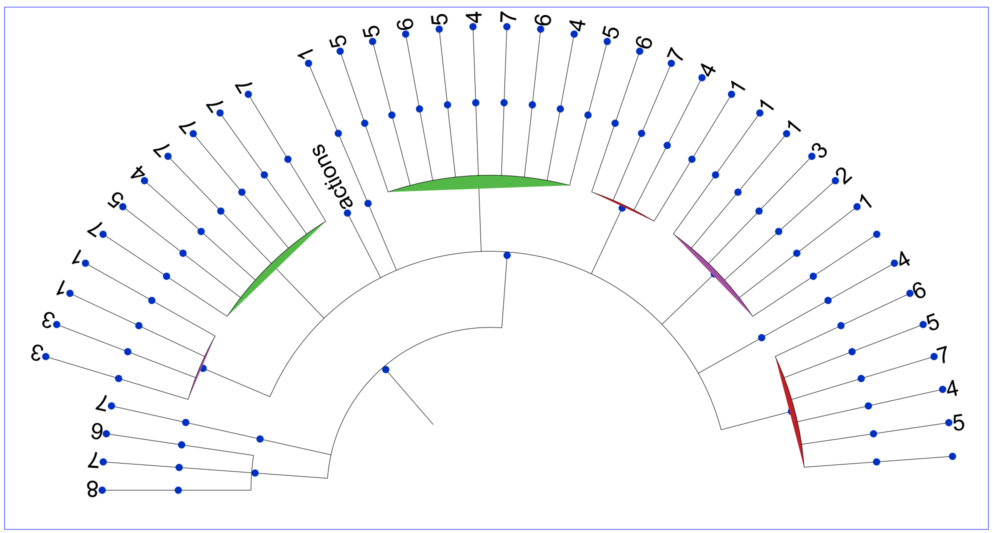
Multiple-Place Foraging Algorithm (MPFA)

Grammatical Evolution to increase CPFA flexibility



$$\mathcal{R} = \{R_i\}, i \in \{1, \ldots, n_R\}.$$

$$R_i = \mathcal{P}_i \times \mathcal{B}_i \times \mathcal{A}_i,$$



preconditions
behaviors
actions

If not-holding food & not-on-food
Random walk
If on-food & not-holding-food
Pick-up-hold-food
If holding-food
Return-to-nest

Following GESwarm*, foraging strategies are rule sets in Extended Backus Naur form with preconditions, behaviors & actions.

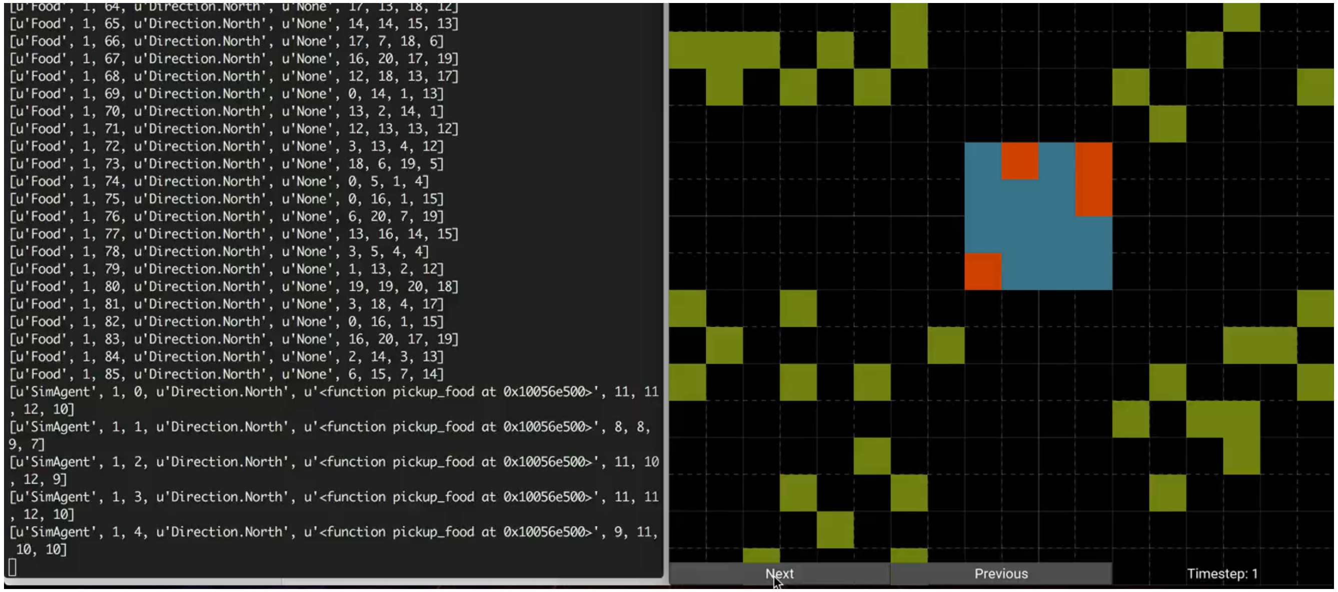
A genotype is a string representing a set of rules; GA performs mutation & cross-over.

Rules are instantiated and run in an environment to evaluate fitness (targets collected)

*[Fer15]

Grammatical Evolution to increase CPFA flexibility

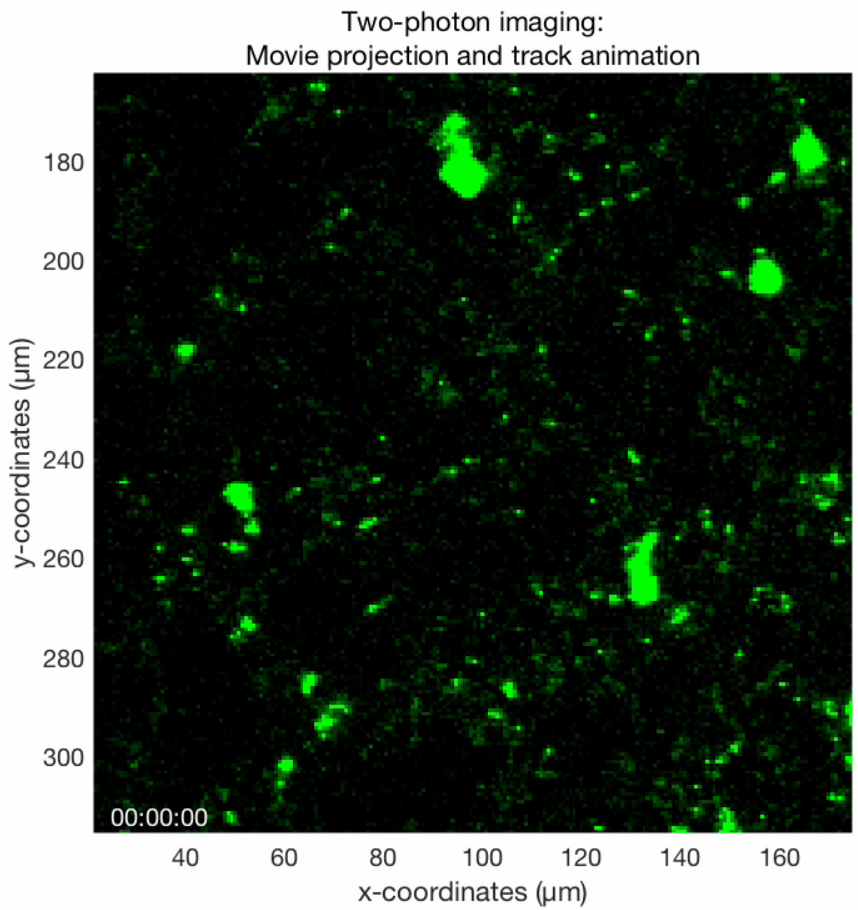
- Increased flexibility
- Phylogenetic relationships among successful strategies
  - constraints of evolutionary history?
- Generate new strategies:
  - Add behavioral primitives
  - Increasing environmental or task complexity



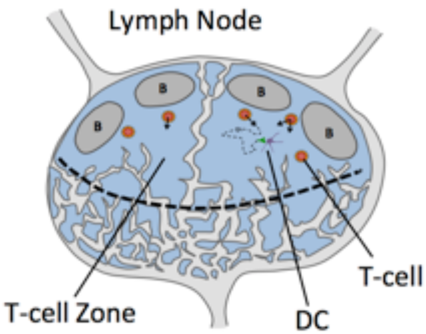
Complexity Emerges from Simple Algorithms in Complex Environments

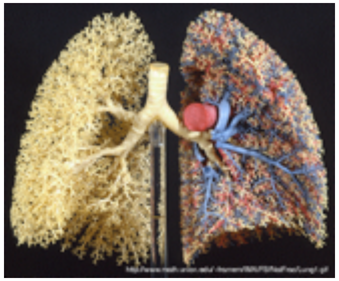
T cells interact with

- Targets
  - Dendritic Cells in LN
  - Infected cells in lung
- Chemical Cues
  - Chemokines
  - Inflammation
- Structural Features
  - FRCs in LN
  - Vasculature in lung
- Each other (?)

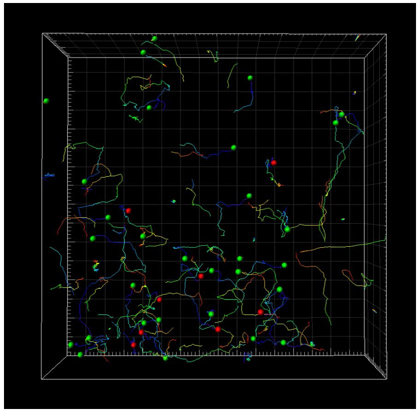


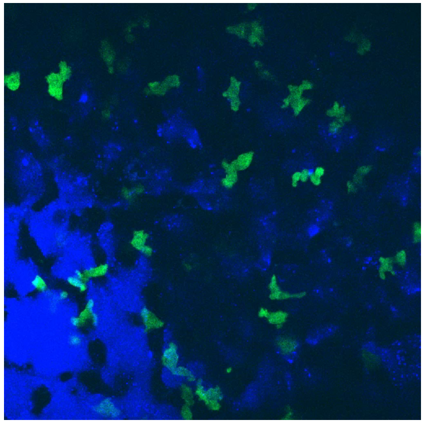
Flexibility in Multiple Environments
T cells in Lung vs. Lymph Nodes





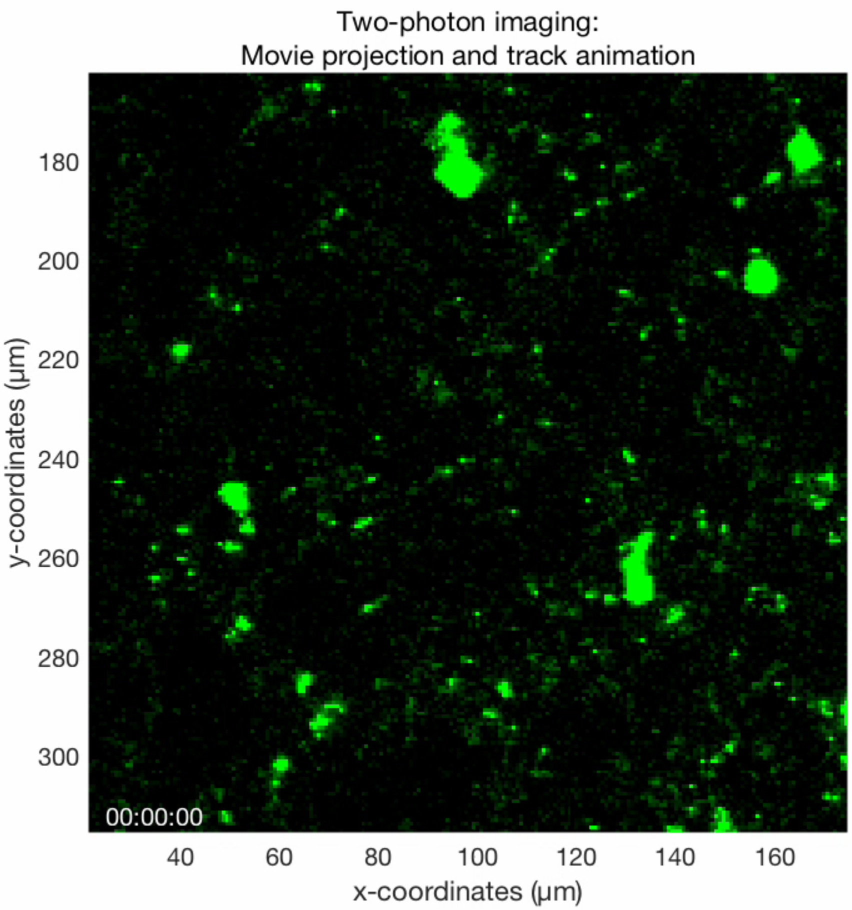
How do T cells balance
search thoroughness vs extent?

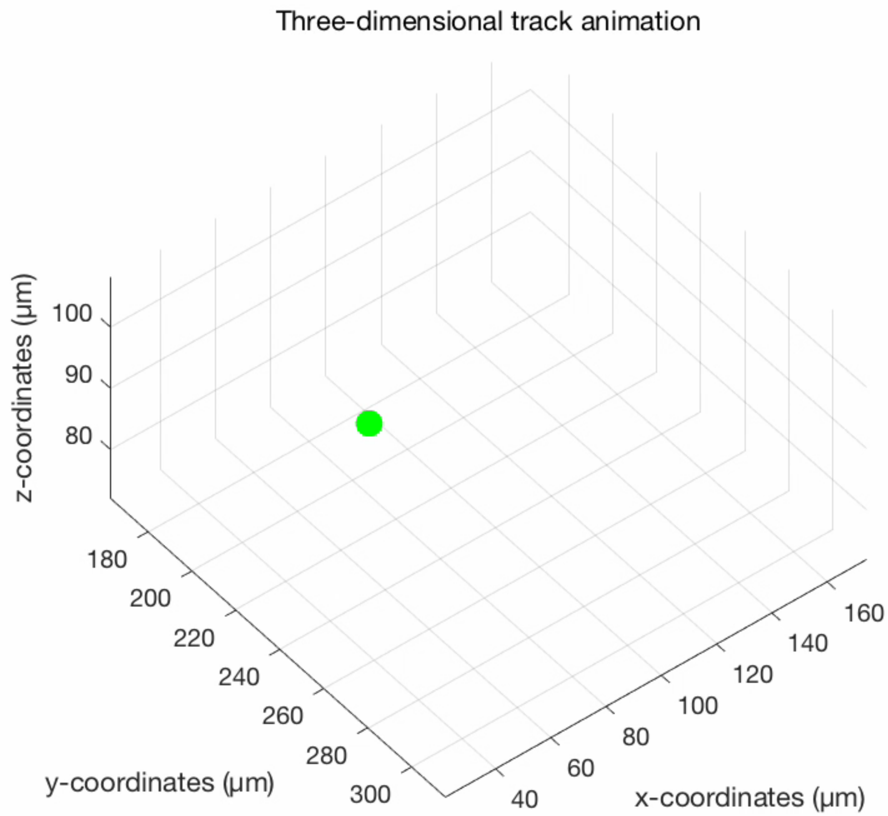




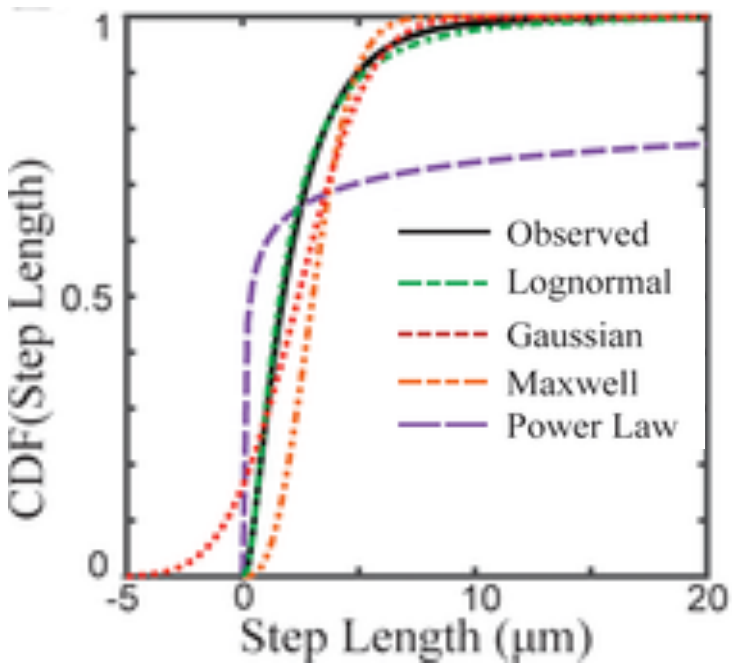
What changes to produce different
behaviors in different environments?

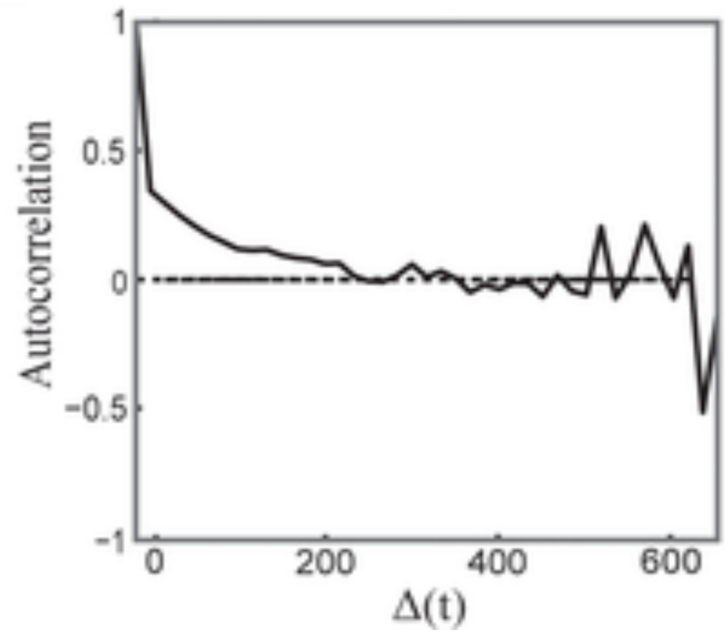
Mrass et al., Movie S3





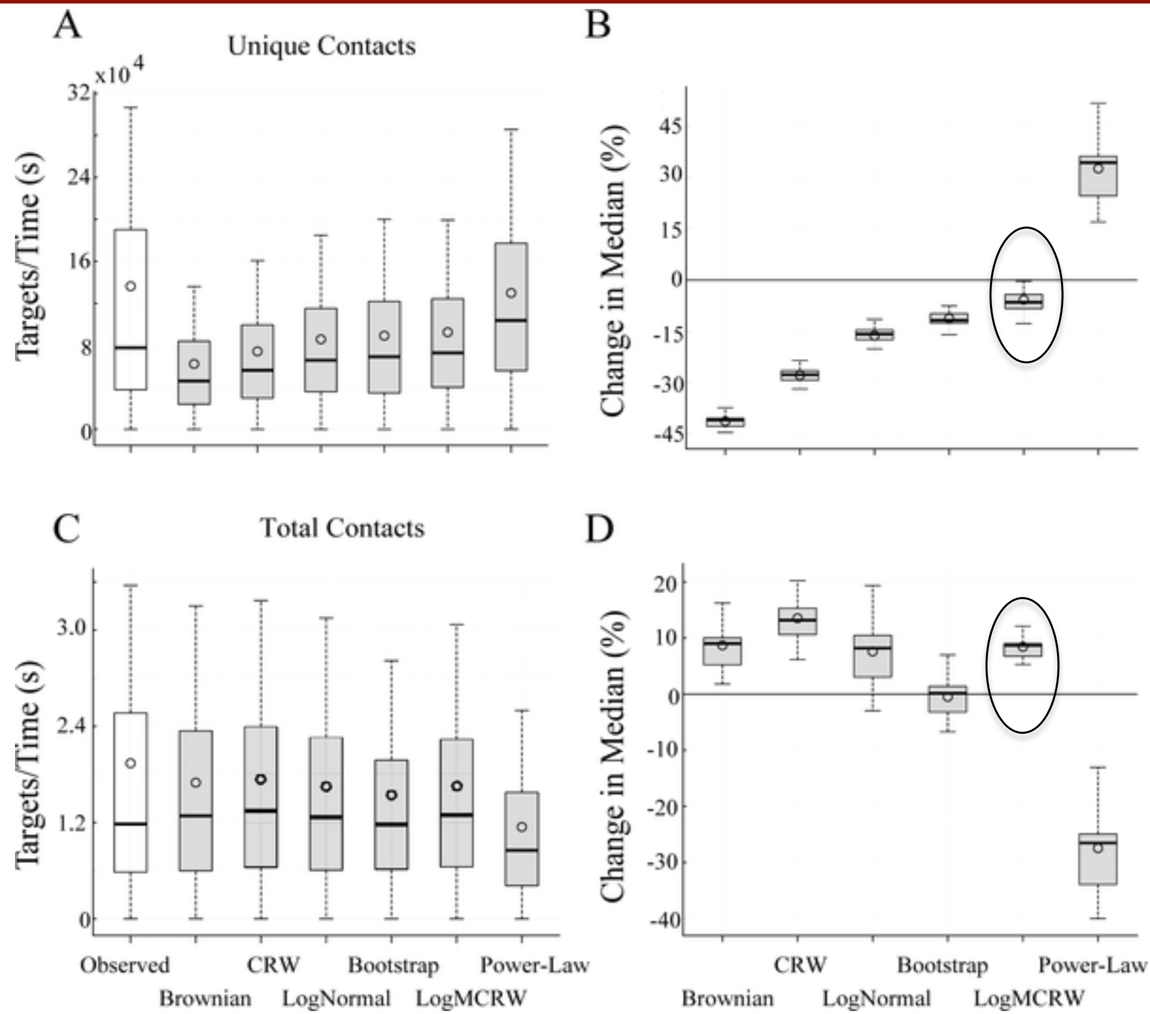
T Cell movement neither Levy nor Brownian Lung & LN
Correlated Random Walk with lognormal step sizes

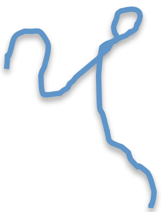




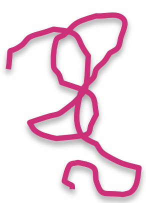
[Fri16]

T Cell search balances unique & total contacts with targets





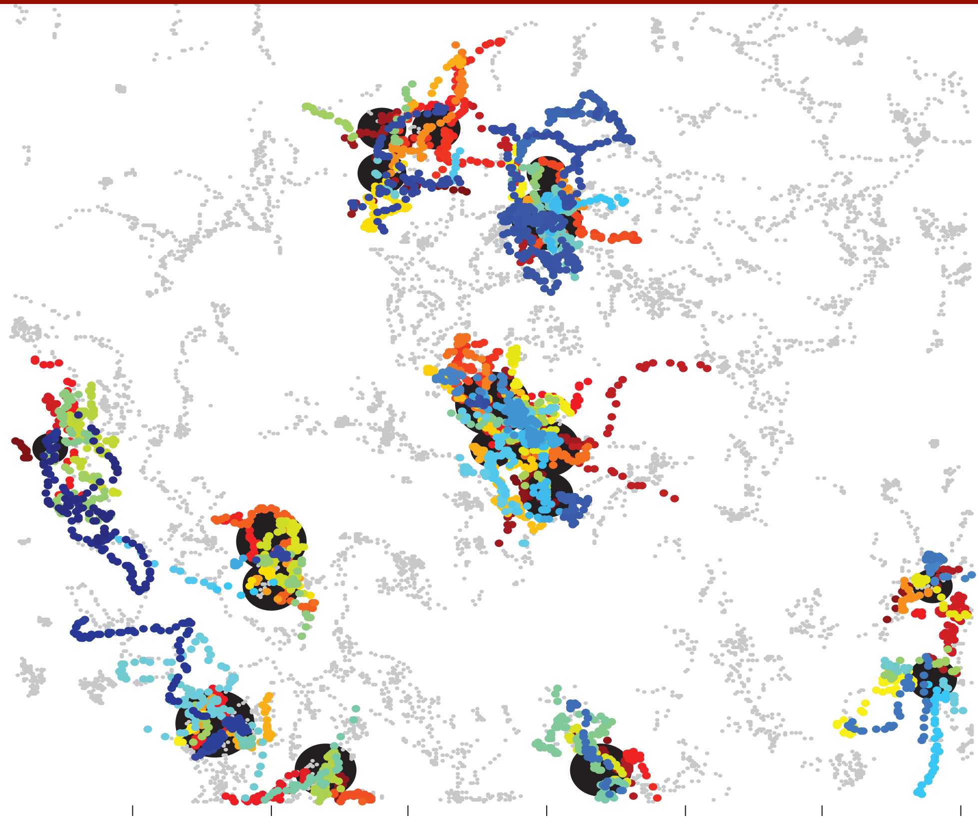
Extensive

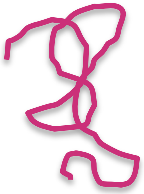


Thorough

[Fri16]

T cells visit "hotspots" in LN more frequently than expected by chance

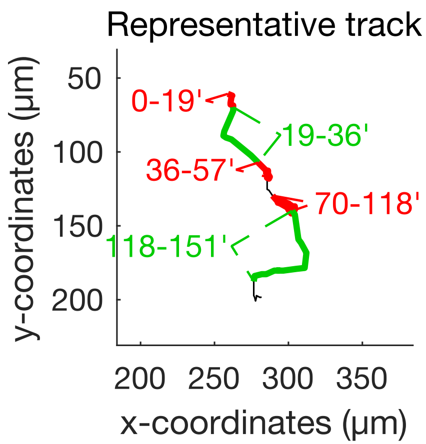


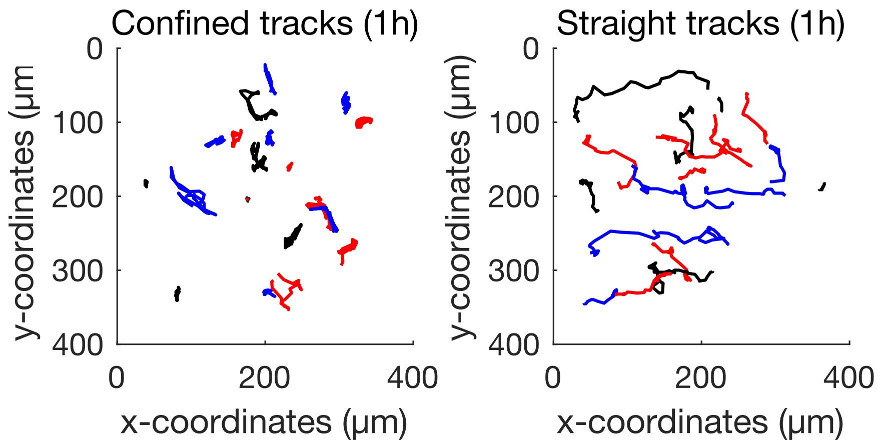


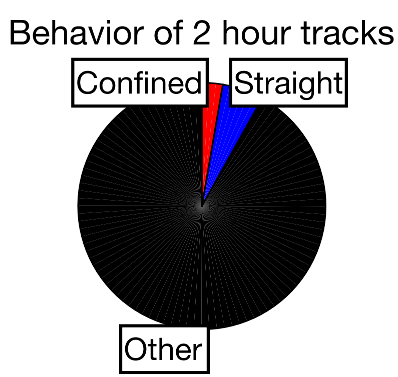
T cells that visit hotspots search more thoroughly than other T cells
Hypothesis: T cells alter movement in response to environmental cues

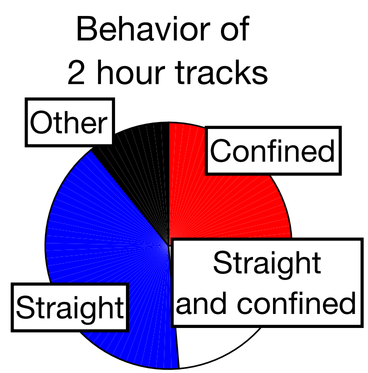
[Fri15,Fri16]

T cells use mixed movement patterns in the lung









15 min segments

Complexity Emerges from Simple Algorithms in Complex Environments

T cells interact with

- Targets
  - Dendritic Cells in LN
  - Infected cells in lung
- Chemical Cues
  - Chemokines
  - Inflammation
- Structural Features
  - FRCs in LN
  - Vasculature in lung
  - hotspots
- Other immune cells

Ants interact with

- Targets
  - seeds
  - ephemeral food, prey
- Chemical Cues
  - Pheromones
  - alarm signals
- Structural Features
  - Habitat
- Each other
  - signaling
  - contact rate sensing
  - fighting

Complexity Emerges from Simple Algorithms in Complex Environments

- Simple behaviors
  - movement patterns balances thoroughness/extent
  - sense signals & density/contact rates
  - recruitment & communication
  - memory
- Environment influences behavior

- Evolutionary process evaluates behaviors in environments– behavior exists in interaction between agents and environment
- Robot swarms embed algorithms in the real world, requiring an ecological perspective
- Open questions:
  - What behavioral primitives to use?
  - What process for turning rules into strategies? GEswarm?
  - What features of rules generate flexibility?

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A challenge to engage students to develop collective robots to to revolutionize space exploration

- 24 teams from MSIs
- 475 undergraduates, hundreds of HS students
- 60 Robots
- Competition April 2016 at NASA KSC
- Virtual competition in Gazeebo
- 40 teams from MSIs in 2017

Swarm robots for ISRU:
In Situ Resource Utilization or
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