Complex Adaptive Systems

Examples from Biology with Computer Science Applications

Lecture 14

Ant Colonies

Evolution of Altruism (compare Axelrod and
The prisoners dillema)

Is Altruism a Nash Equilibrium?

Ant defection.

Ants evolved from wasps about 100 million years ago.

There are an estimated 22,000 species.

E. O. Wilson
Harvard University

Bert Hölldobler
University of Würtzburg

The Superorganism: The Beauty, Elegance, and Strangeness of Insect Societies

The Ants

Insect Societies

Deborah Gordon
Stanford University
Compares ant foraging
To TCP/IP throttling
(Desert Harvester and
Argentine Ants)

Planet of the Ants

10,000,000,000,000,000
ants

7,000,000,000
humans

10 quadrillion ants.

7 billion humans.

"Lean on a tree almost anywhere, and the first creature to crawl on you will probably be an ant."
Holldobler & Wilson, *Journey to the Ants*

QUEEN ANT

Queen ants are the founders of all colonies. Once mated, she can stay fertilized for many years laying millions of eggs. Some queens can lay thousands of eggs each day. They really are egg laying machines. In some species live up to 30 years. Some species have multiple queens.

Worker Ants

Worker ants are sterile females. Can live up to 5 years. In Pogonomyrex sp. the jobs the workers do depnd on age not caste.

Winged Princess | Alate | Virgin Queen

Mate with a drone during the nuptual flight. Stores enough sperm for the rest of her life. Her job is to find a good place
For the colony, clip her own wings off and burrow as quickly as possible. Once underground she starts producing workers.

Winged Drone | Alate | Male Ant

These are the only males in the colony. Males are haploid (only one set of chromosomes). Leave the colony during the nuptual flight and then die.

Basic Ant Biology

- All ants are eusocial
  - The colony is the unit of selection
    - Queen(s): reproducers, not masterminds
    - Reproductives: winged male and female alates
    - Workers: female, short lived compared to queens
  - Genetic sex determination
    - Haplodiploidy
    - Sociobiology
  - Division of labor:
    - All males are reproductive
    - Female caste determined by environment & larval feeding
    - Assignment to task groups is determined by colony need
    - Emergence of cooperative foraging, learning, farming, herding…
- Communication through pheromones and antennal contact
- Self organization (dumb ants, smart colonies)

Haplodiploid sex determination

- Sex is determined by the number of sets of chromosomes
  - Females are diploid: usual case in sexual reproduction: genes are inherited from mother + father
  - Males are unfertilized: all genes come from the egg (mother)
  - Males have ½ the number of chromosomes as females (haploid)
  - Males have no fathers and can only produce daughters
  - The queen determines* how many males and females to make
- Female workers could produce sons, however, females are more related to their sisters (queens produced by her colony) than to their sons

Sex	Daughter	Son	Mother	Father	Full Sister	Full Brother	
F	½	½	½	½	¾	¼	
M	1	-	1	-	½	½	

This depends on all the offspring of the queen resulting from a single mating.

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How does this relate To Nash Equilibrium?

<u>Sex</u>	Daughter	Son	Mother	Father	Full Sister	Full Brother	
F	½	½	½	½	¾	¼	
M	1	-	1	-	½	½	

This depends on all the offspring of the queen resulting from a single mating.

20 ants per colony

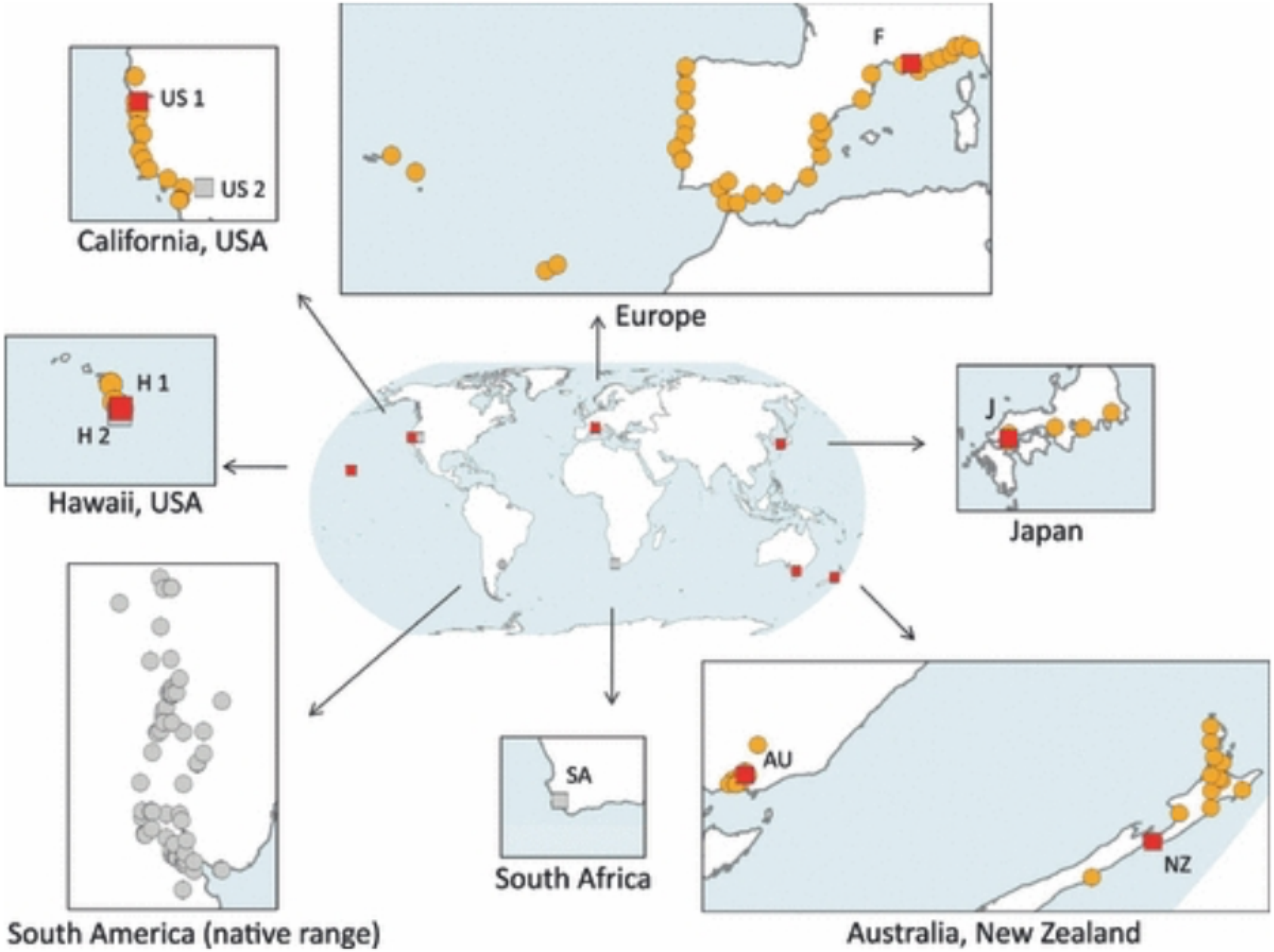
20 MILLION ants per colony


20 MILLION ants per colony
No foreman, no blueprints, no one is in charge

Cooperation

- Most ants use chemical signals to mark divisions between colonies.
- Argentine ants create multiple nests.
- Humans accidently transported colonies of ants from South America around the world
- . Since there were no other Argentine ant colonies to compete with those founder ants have expanded one giant colony in each region.
- These are called super or mega-colonies.

The largest of these Argentine ant Supercolonies is 6,000 km long (Europe).



Van Wilgenburg, Ellen, Candice W. Torres, and Neil D. Tsutsui. "The global expansion of a single ant supercolony." *Evolutionary Applications* 3.2 (2010): 136-143.

Cooperation in Superorganisms

4 simple behaviors → cooperative foraging

- **Count**
- Remember
- Communicate
- Move

Steps

Seeds

Interactions

4 simple behaviors → cooperative foraging

- Count
- **Remember**
- Communicate
- Move

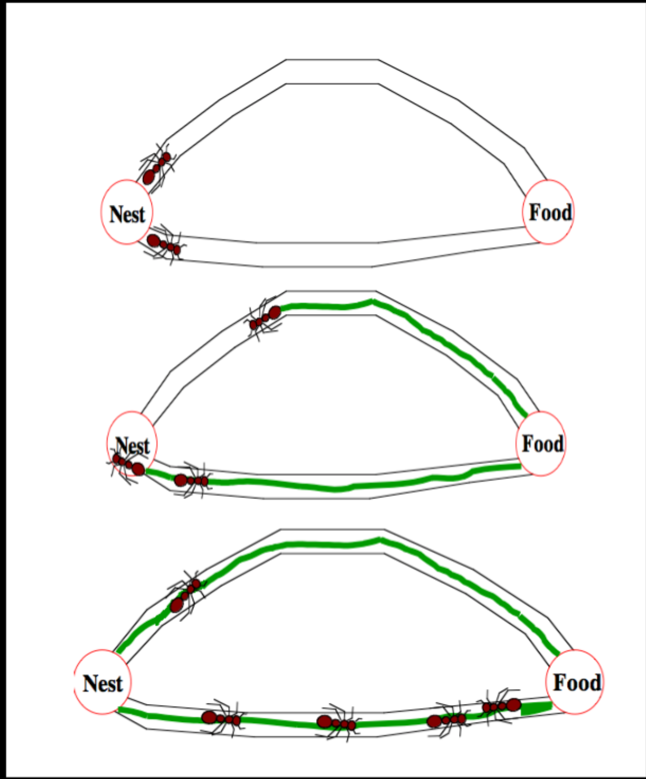
Site Fidelity

There and back again…and again

4 simple behaviors → cooperative foraging

- Count
- Remember
- **Communicate**
- Move

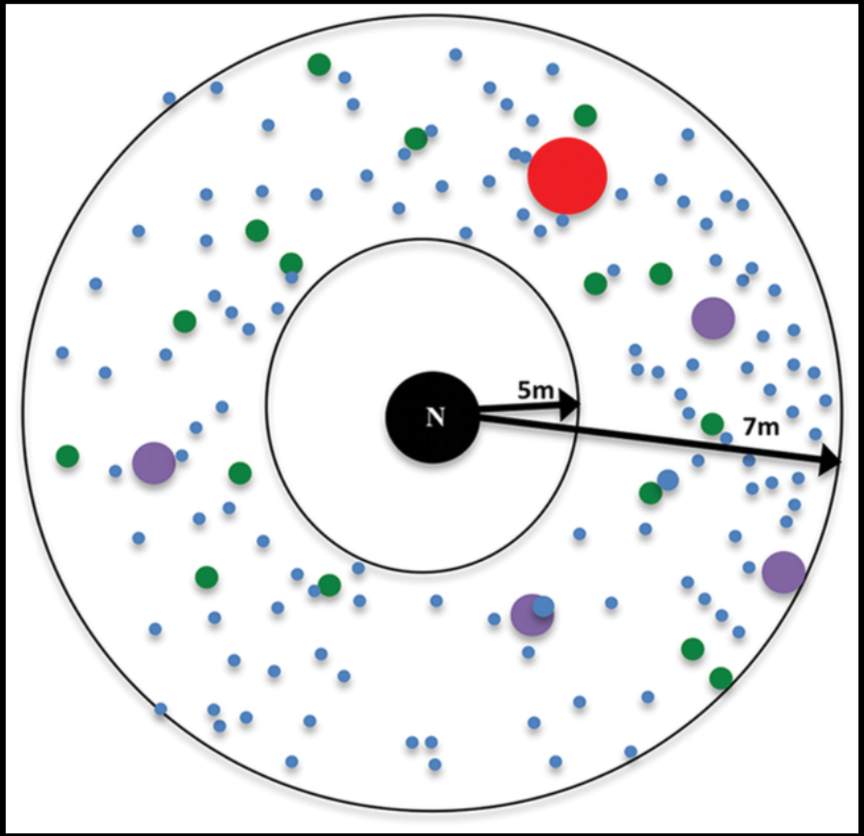
Pheromones

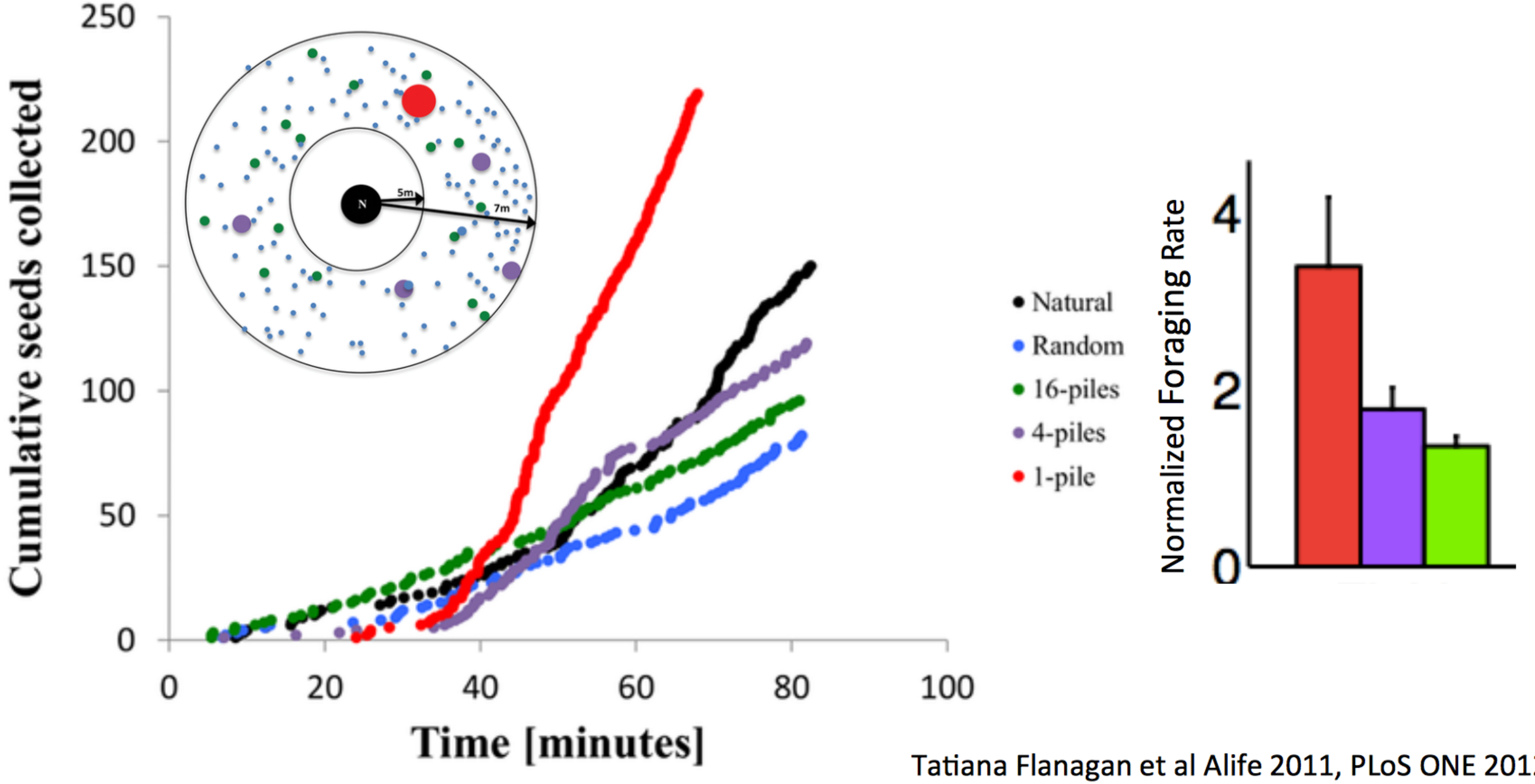


4 simple behaviors → cooperative foraging

- Count
- Remember
- Communicate
- **Move**
  - Travel
  - Search
    - Thoroughly
    - Broadly

How does complex foraging emerge from interactions among these 4 behaviors?

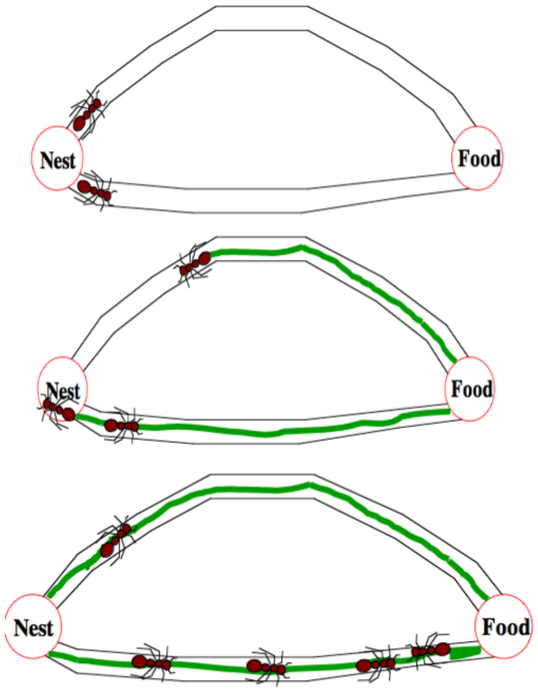


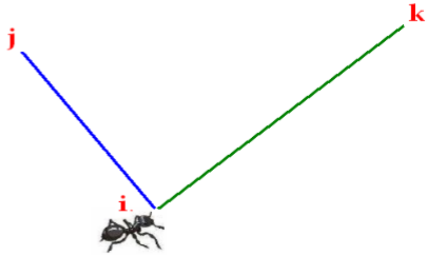


Tatiana Flanagan et al Alife 2011, PLoS ONE 2012

How should ants behave to collect seeds as fast as possible?

Pheromone recruitment:
a well-studied emergent behavior





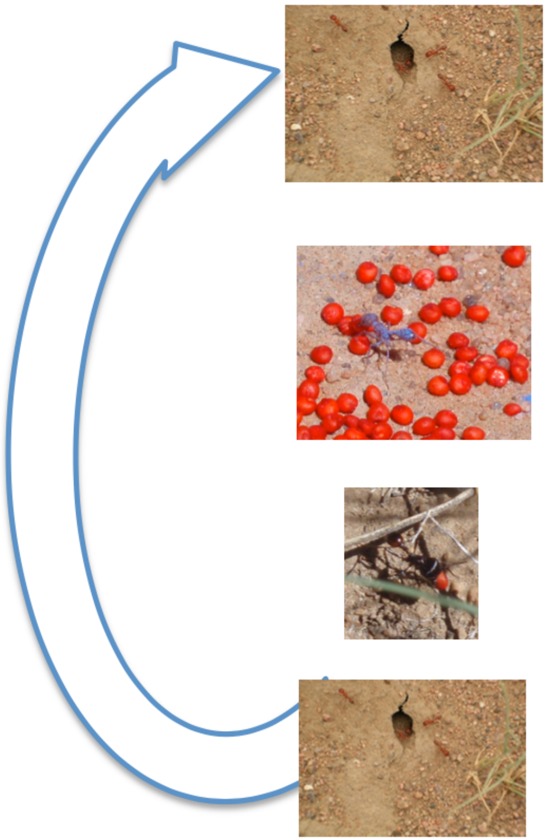
$$p_{ij}^{k}(t)=\frac{[\tau_{ij}(t)]^{\alpha}\cdot[\eta_{ij}]^{\beta}}{\sum_{l\in N_i^k}[\tau_{ij}(t)]^{\alpha}\cdot[\eta_{ij}]^{\beta}} \quad if\ j\in N_i^k$$

Ant colony optimization

Memory vs. Communication

<u>Site Fidelity</u>

There and back again

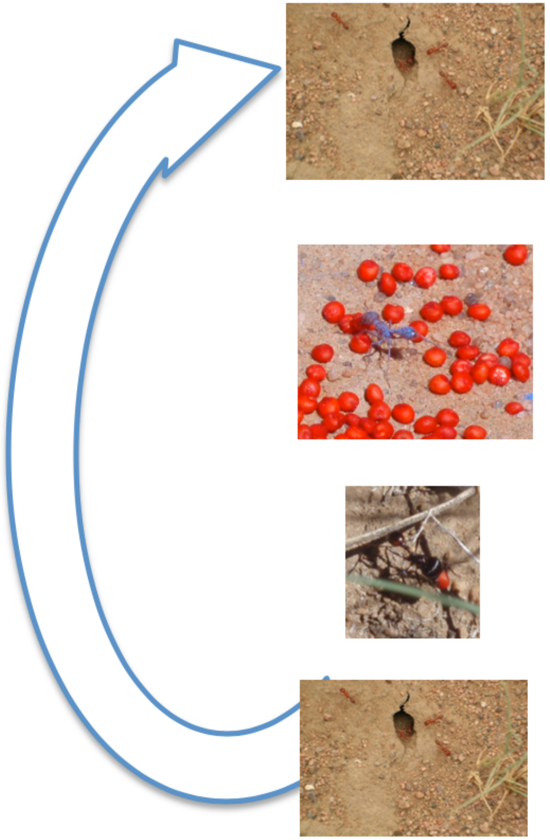


Memory vs. Communication

private vs. public information

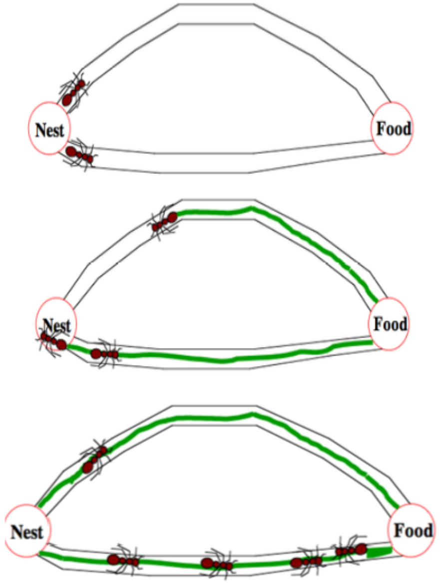
Site Fidelity

There and back again



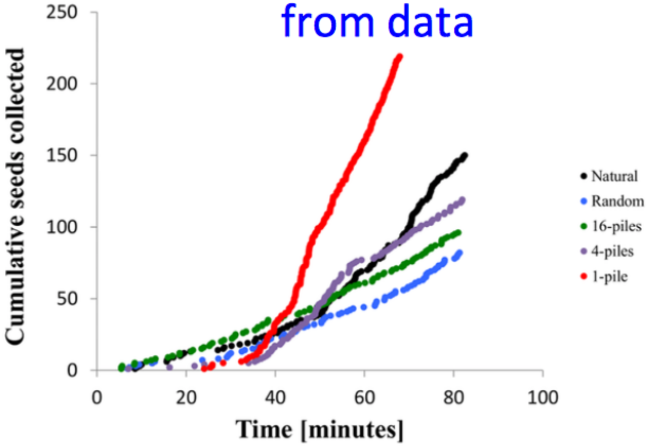
Pheromone Communication

Recruit nestmates



$$p_{ij}^{k}(t) = \frac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}]^{\beta}}{\sum_{l \in N_i^k} [\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}]^{\beta}} \quad if \;\; j \in N_i^k$$

Both processes are indistinguishable from data



Agent Based Model

How important is remembered vs. communicated information?

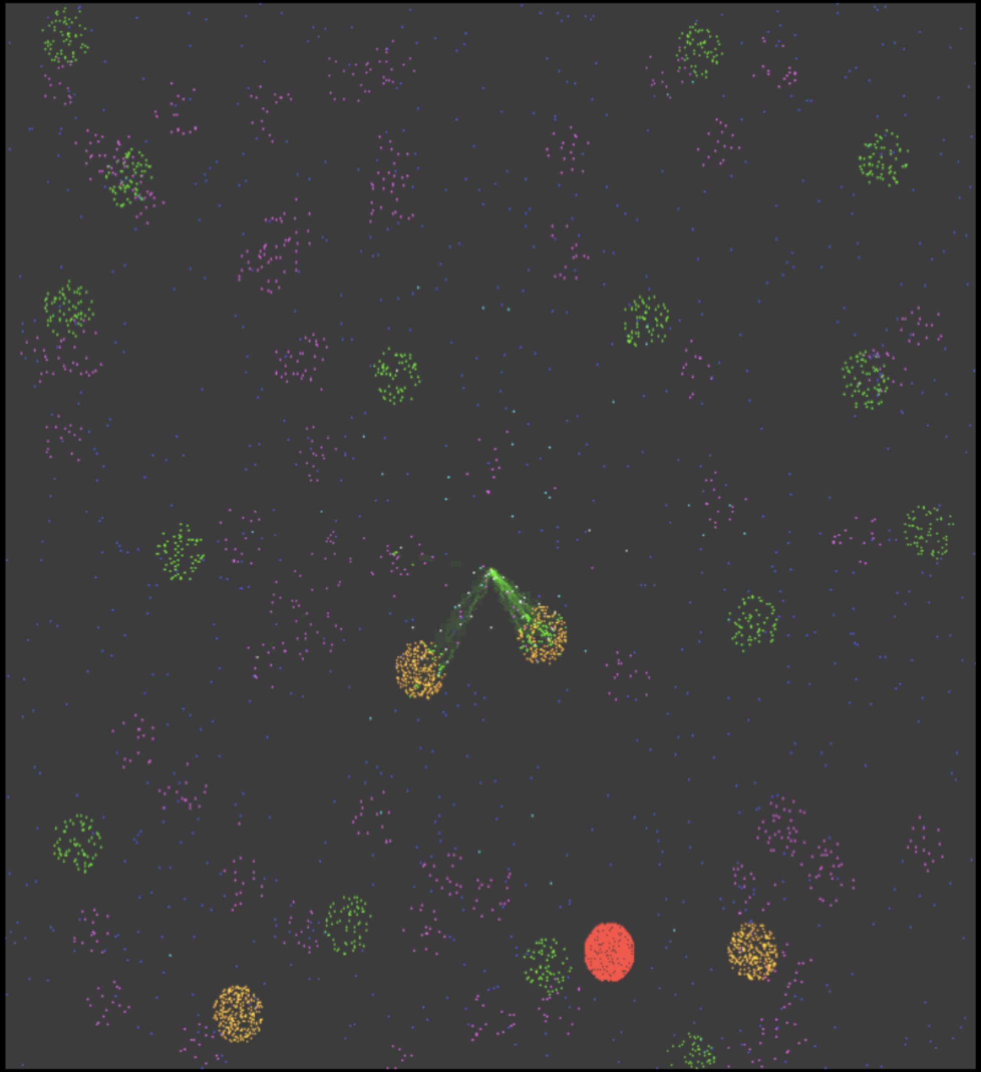
Ants search for food on a grid

Travel from the nest
Move with directed & random walks

Upon finding food, ants
Count the seeds nearby

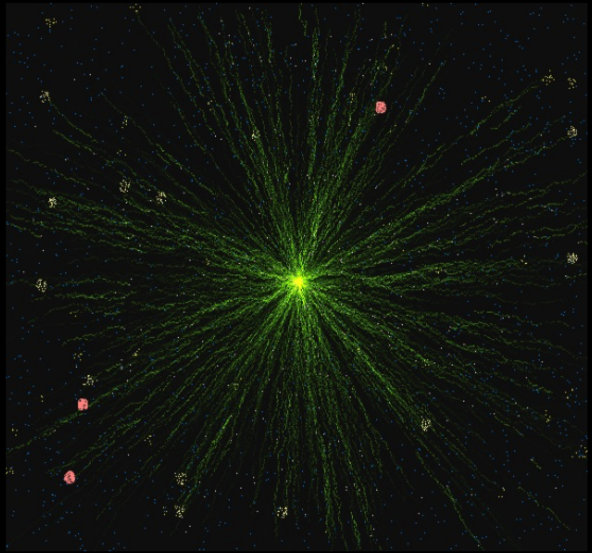
Decide whether to use
- memory (site fidelity) or
- communication (pheromones)

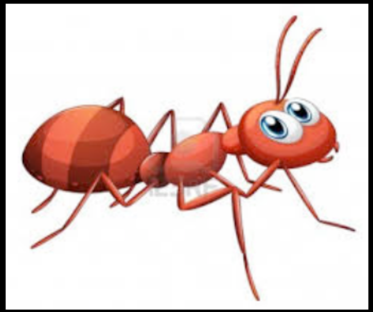
GOAL: Combine behaviors in individuals to maximize seeds collected by colony



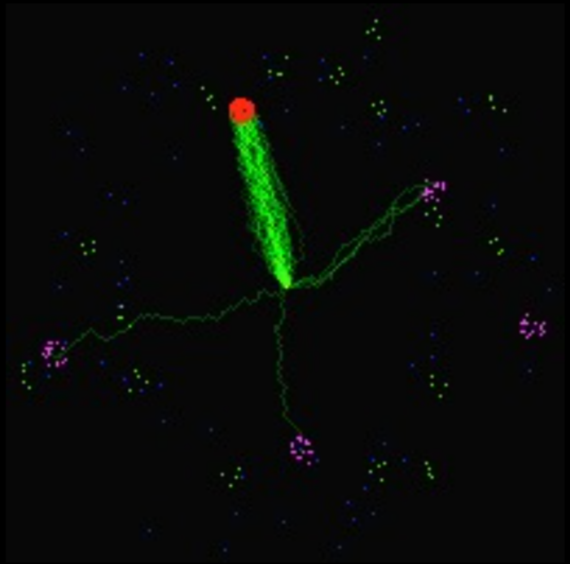
Dr. Kenneth Letendre, UNM CS & Biology

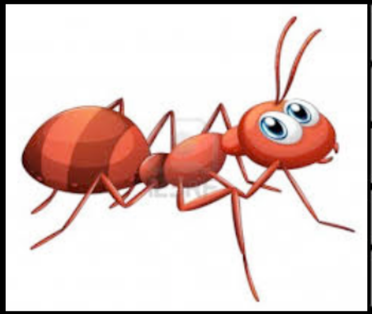
Foraging success depends on interactions among behaviors

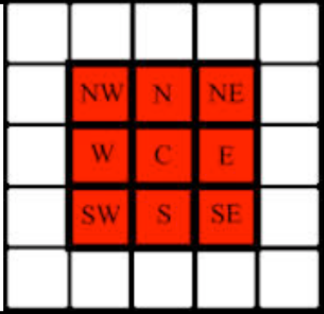




Lay pheromone
Whenever I find a seed

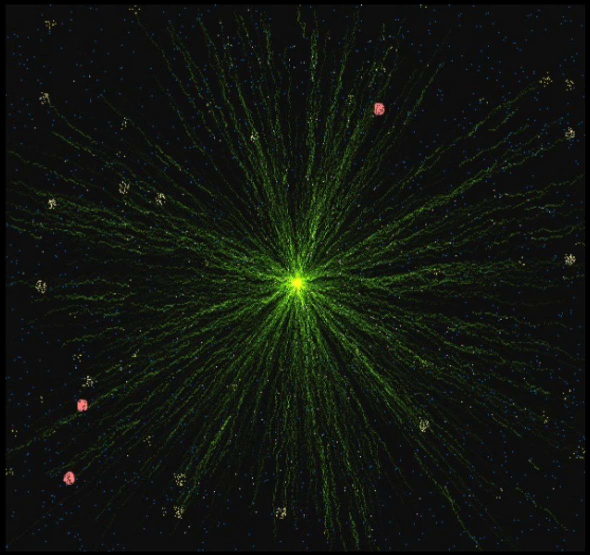


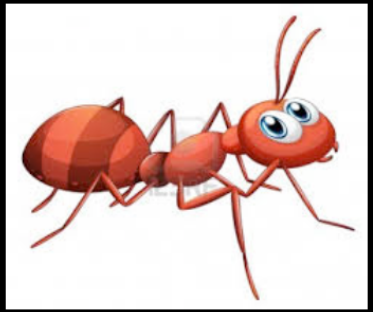




Lay pheromone
Only if count > 5

Foraging success depends on interactions among behaviors

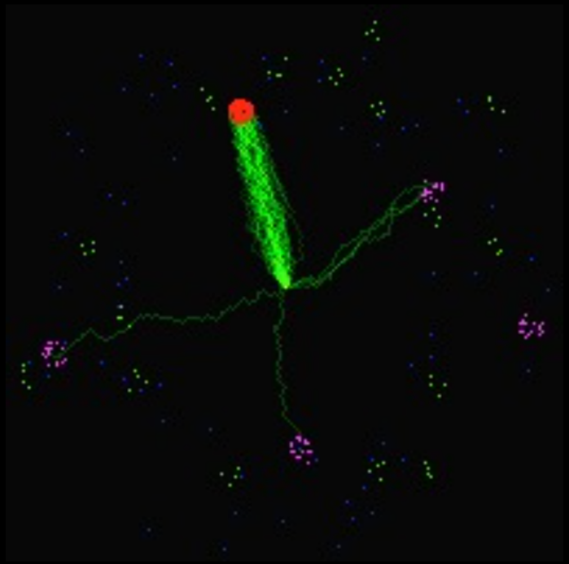


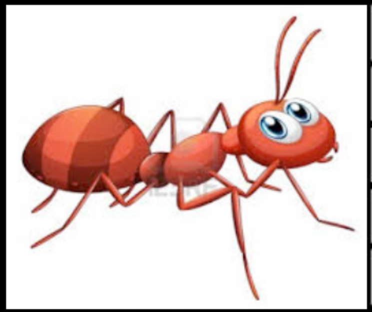


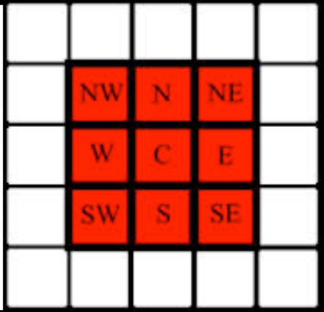
Lay pheromone
Whenever I find a seed

Decision to lay pheromones or use site fidelity depends on seed density in the current pile

Communication & memory interact with counting



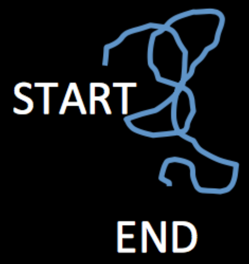




Lay pheromone
Only if count > 5

Foraging success depends on interactions among behaviors

Movement interacts with communication & memory

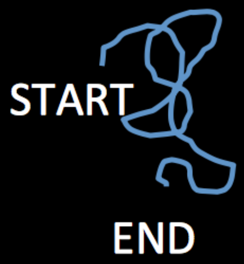


Informed Walk

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

Foraging success depends on interactions among behaviors

Movement interacts with communication & memory



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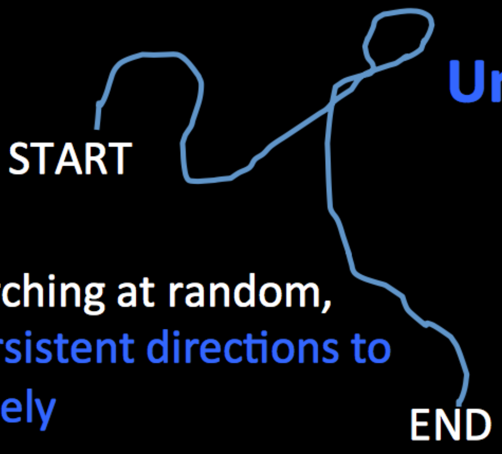
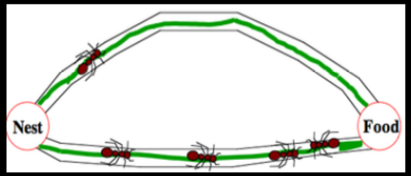


Uninformed Walk

When searching at random, walk in persistent directions to search widely

Collective Foraging success depends on **interactions**

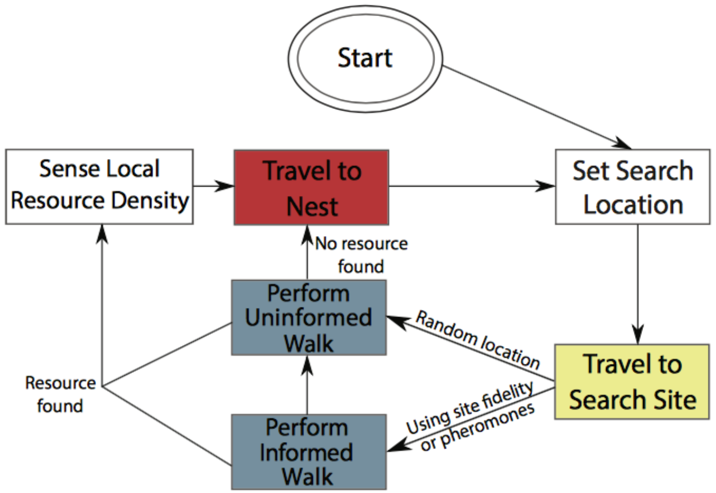
among ants

and

between ants & their environment

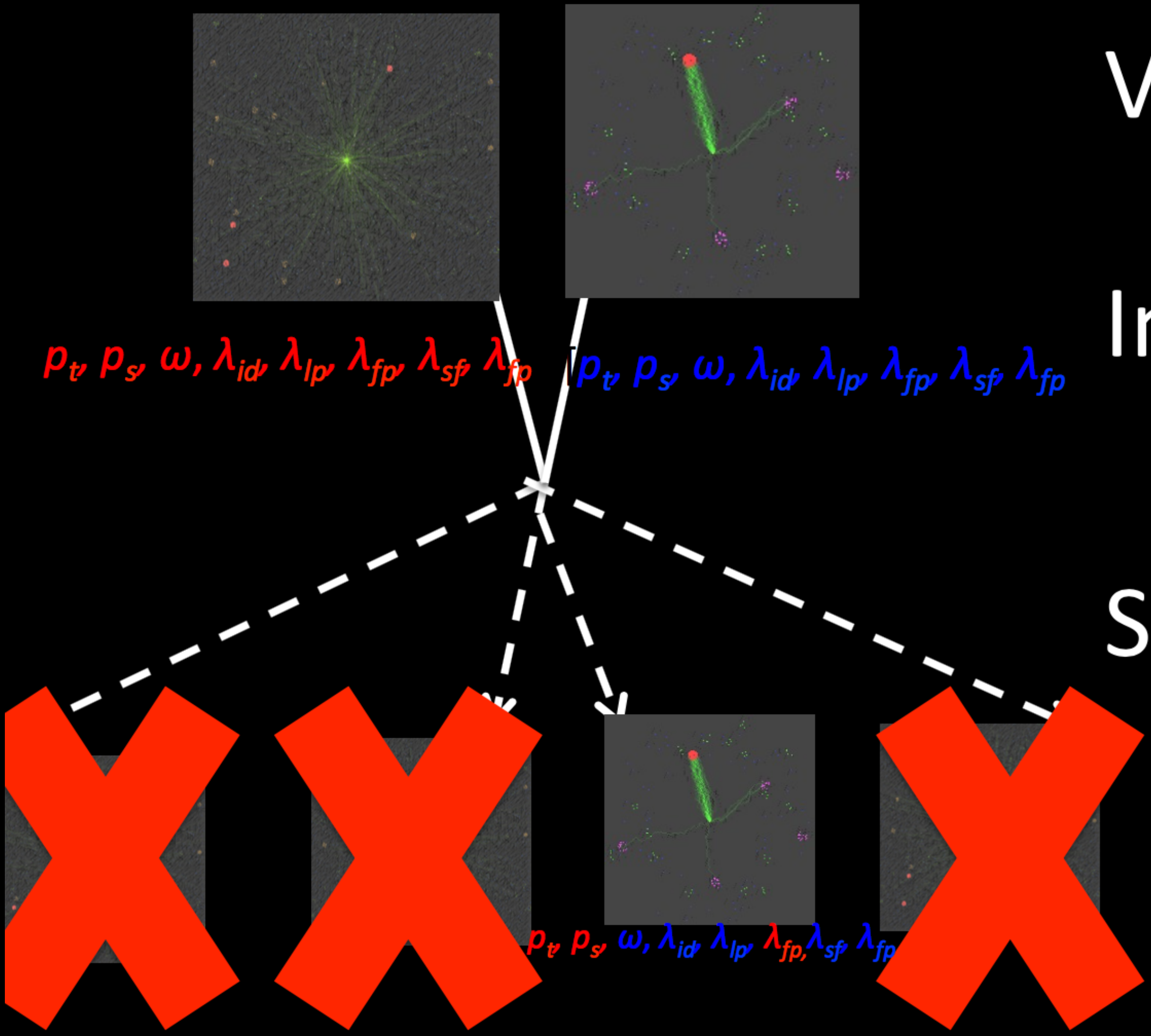
Computer algorithms "evolve" ant behaviors

to maximize seed collection in fixed time



Parameter	Description	Function
p_t	Probability of switching to traveling	–
p_s	Probability of switching to searching	–
ω	Uninformed search correlation	$\sigma = \omega$
λ_{id}	Informed search decay	$\sigma = \omega + (4\pi - \omega) * e^{-\lambda_{id} * t}$
λ_{lp}	Rate of laying pheromone	$F_{lp}(x) = 1 - e^{-\lambda_{lp} * (x+1)}$
λ_{fp}	Rate of following pheromone	$F_{fp}(x) = 1 - e^{-\lambda_{fp} * (9-x)}$
λ_{sf}	Rate of site fidelity	$F_{sf}(x) = 1 - e^{-\lambda_{sf} * (x+1)}$
λ_{pd}	Rate of pheromone decay	$e^{-\lambda_{pd} * t}$

Genetic Algorithms



Variation

Diversity

Inheritance

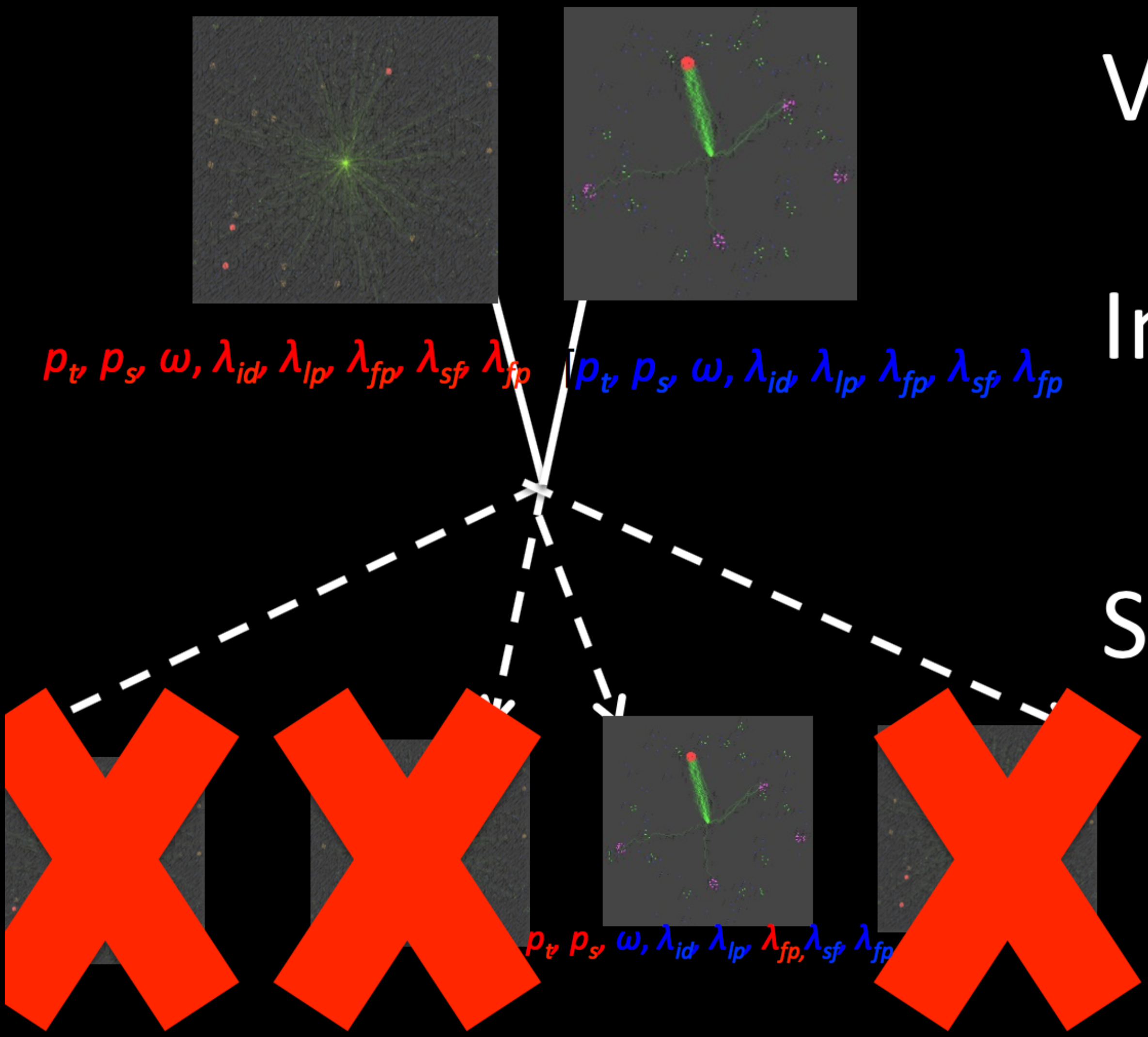
Mutation & Recombinatio

Selection

Environment

FITNESS = # Seeds Collecte

Genetic Algorithms



Variation

Diversity

Inheritance

Mutation & Recombinatior

Selection

Environment

FITNESS = # Seeds Collecte

GA selects parameters to maximize seeds collected in fixed time

Group Selection Experiments *in silico*

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

Each individual in a colony is identical

Cross over and mutation on parameters

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

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

100 runs with different parameter sets (colonies) for 100 Generations

Each colony, each generation, evaluated on 8 grids for 20,000 time steps

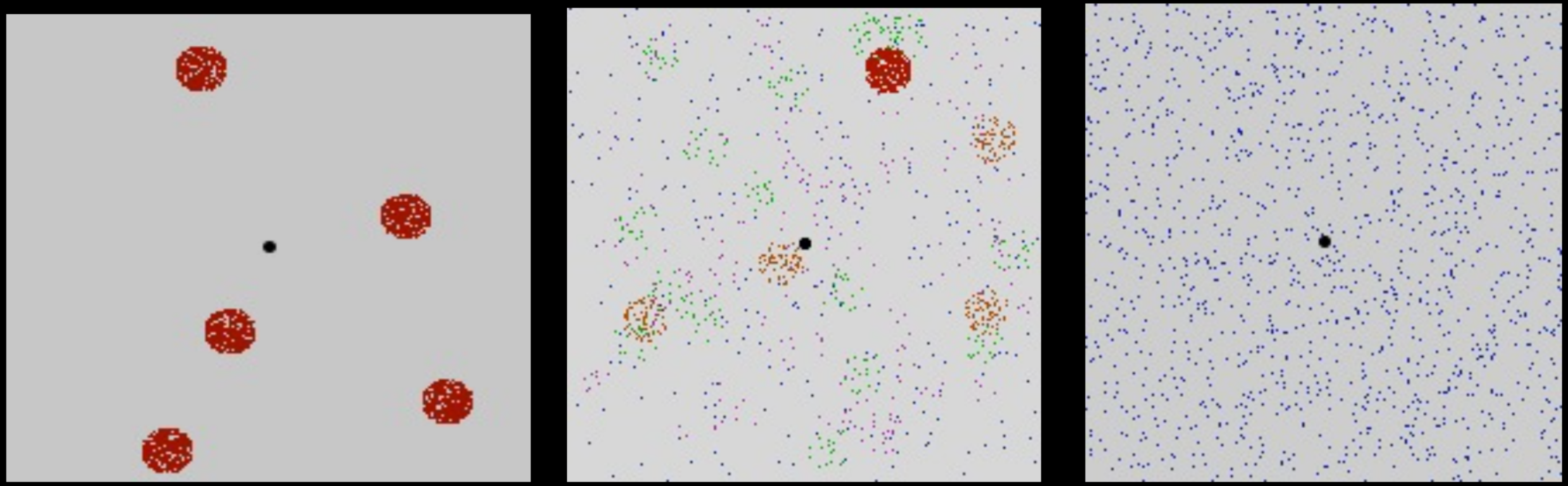
Colonies with highest 'fitness' (seeds collected) replicate into next generation

Run for colony sizes 10, **100**, 1000, 10,000 foragers

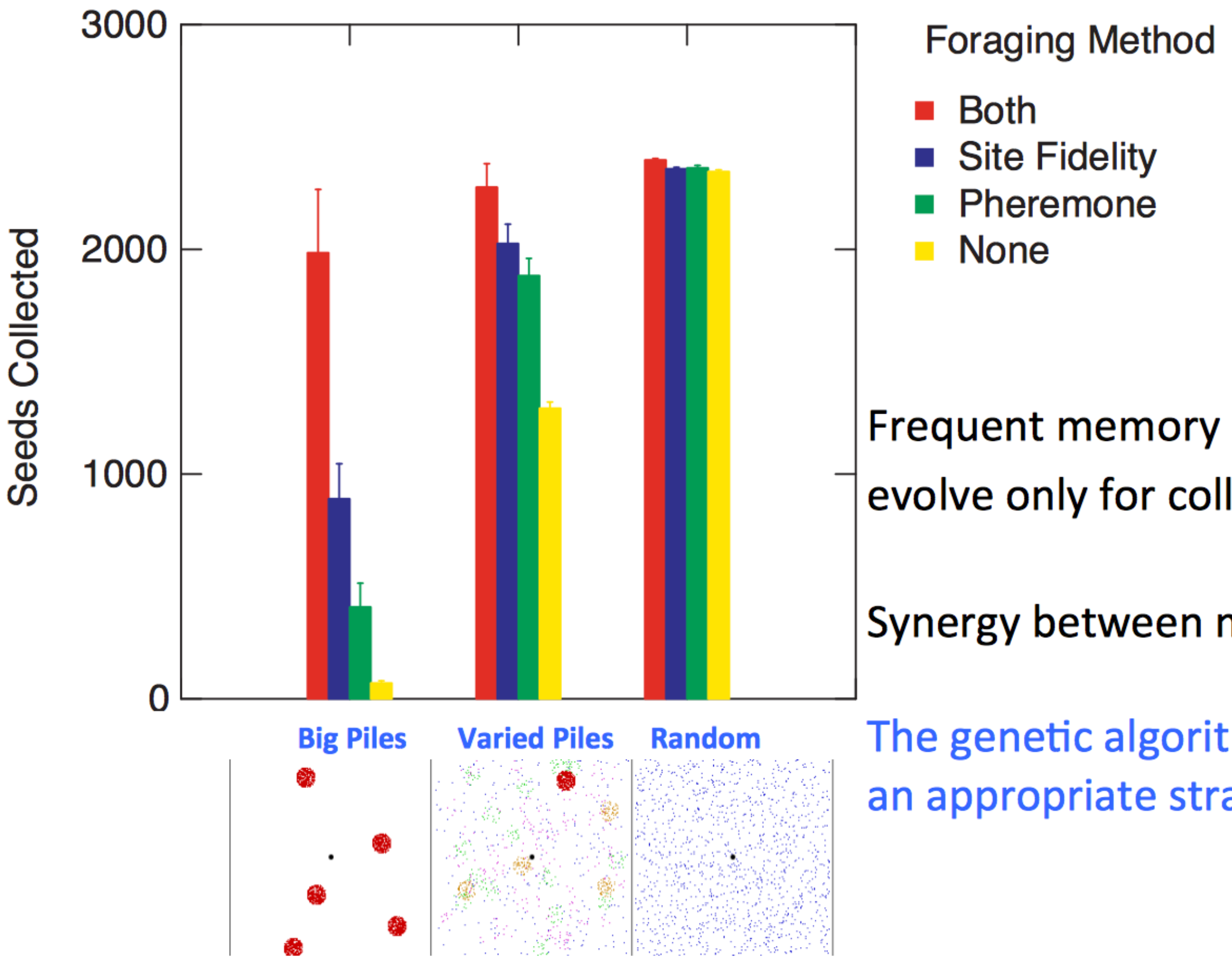
RESULT: Simulated colonies 'evolved' to maximize foraging rate

Simulated colonies evolve to collect from different environments

Big Piles | **Varied Piles** | **Random**



Different strategies are useful in different environments



Frequent memory + rare communication evolve only for collecting from piles

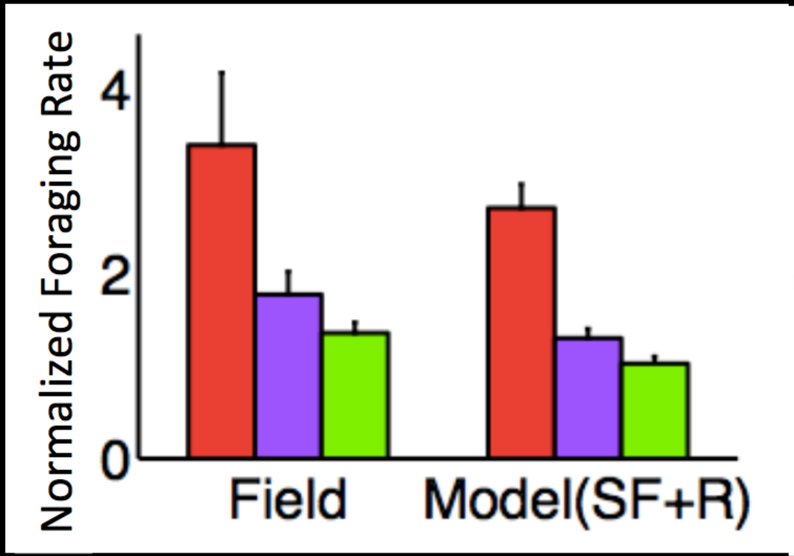
Synergy between memory & communication

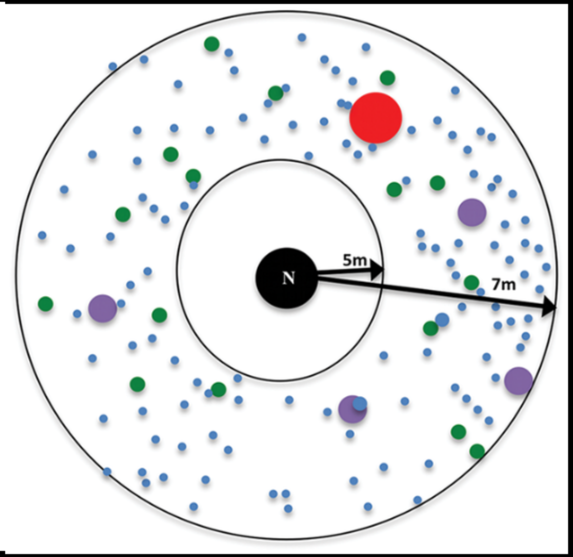
The genetic algorithm automatically evolves an appropriate strategy for each environment

Letendre & Moses GECCO 2013

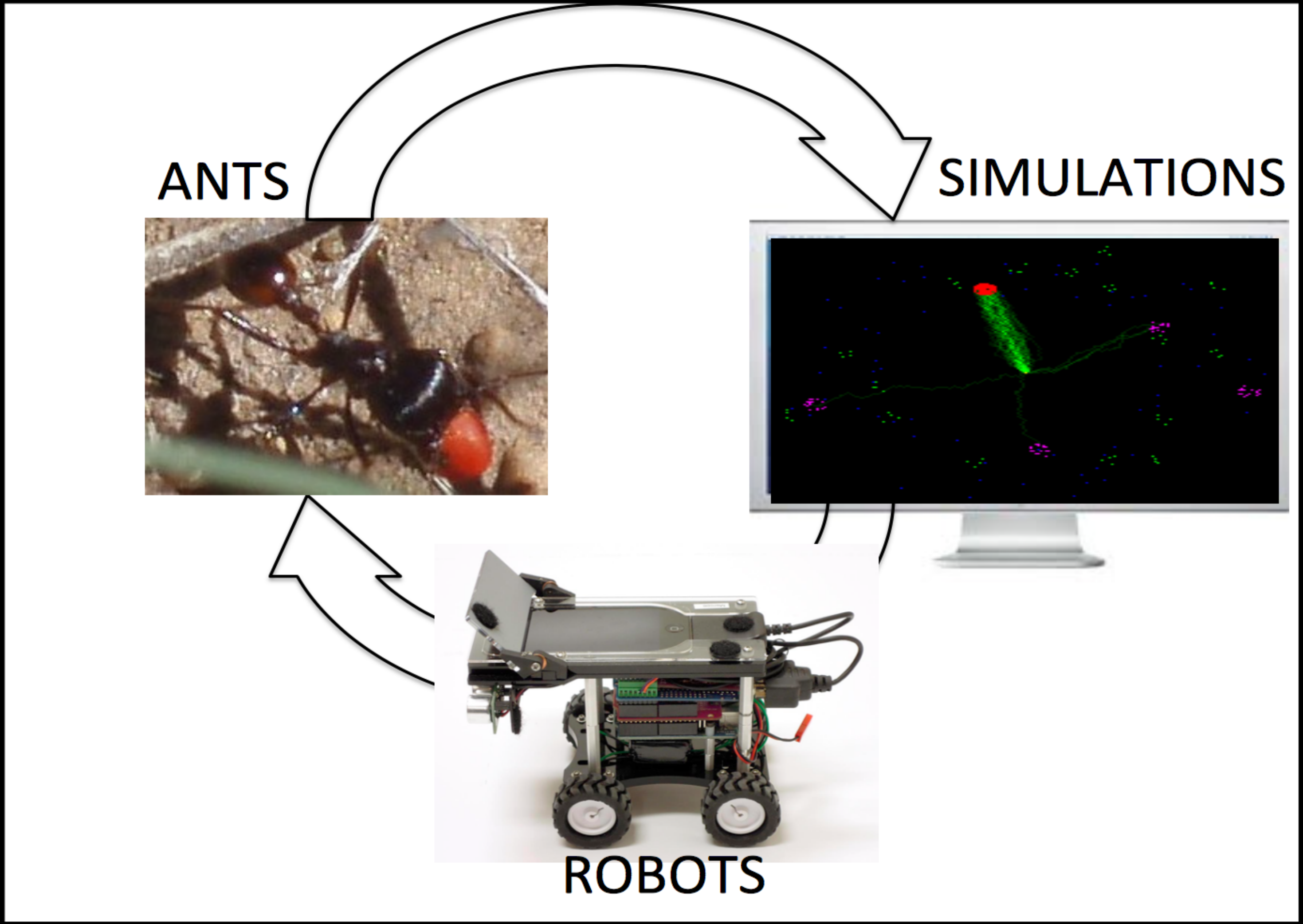
Real ants forage as efficiently as simulated ants

Simulations reveal interactions among ants and their environment that lead to efficient foraging





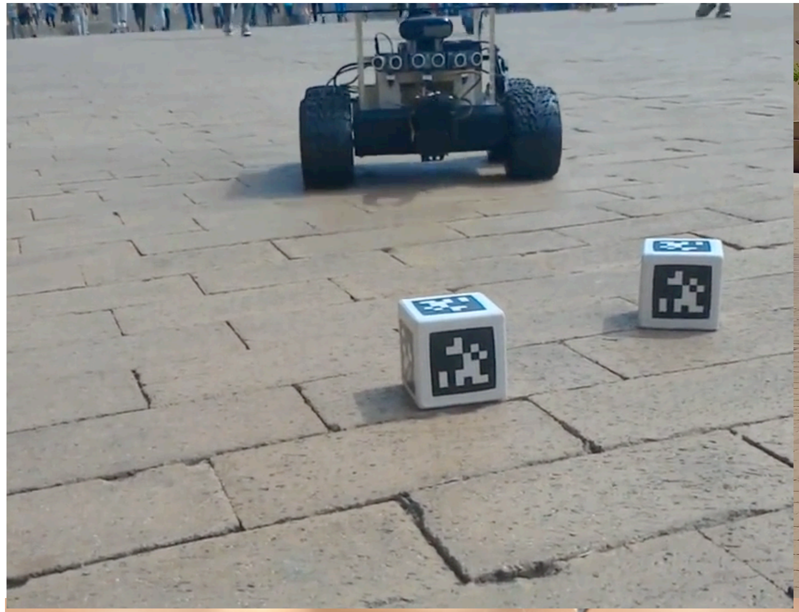
Program robots to cooperate using ant-like behaviors



iANT SWARM ROBOTS

How can robots cooperate to search effectively in variable environments with noise, error, and no one in charge?

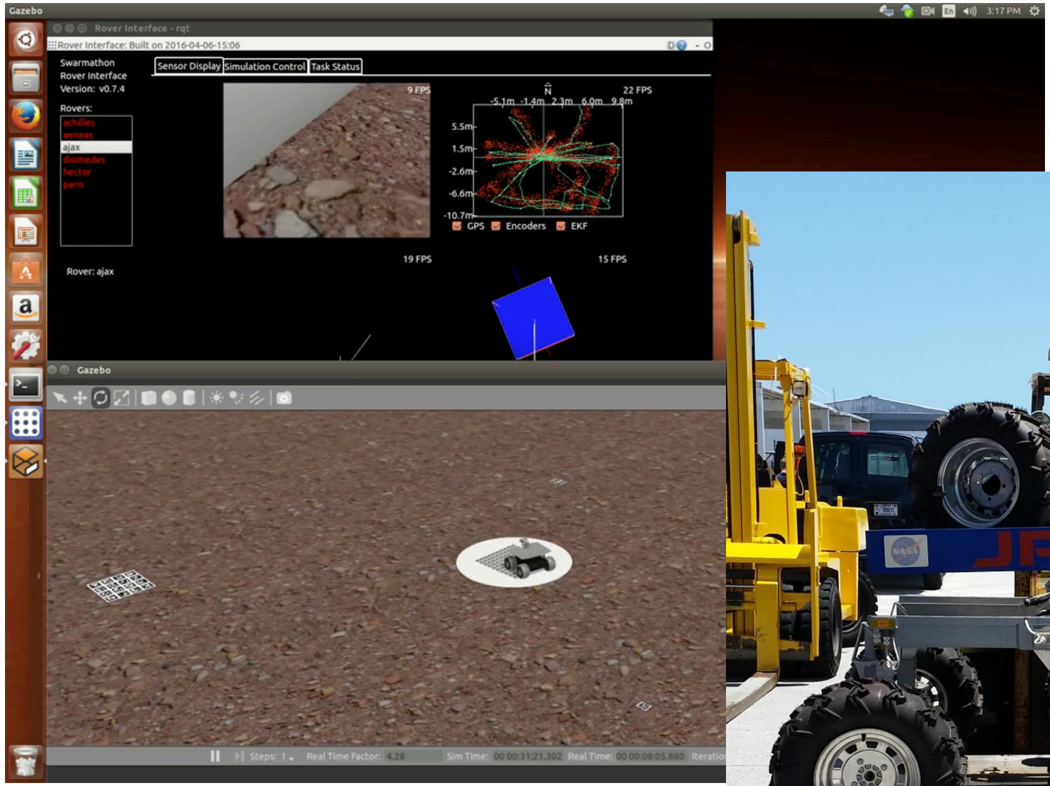
Problem we are trying to solve: **Central Place Foraging**



Introduction

‘Living off the land’ - Mars 2030

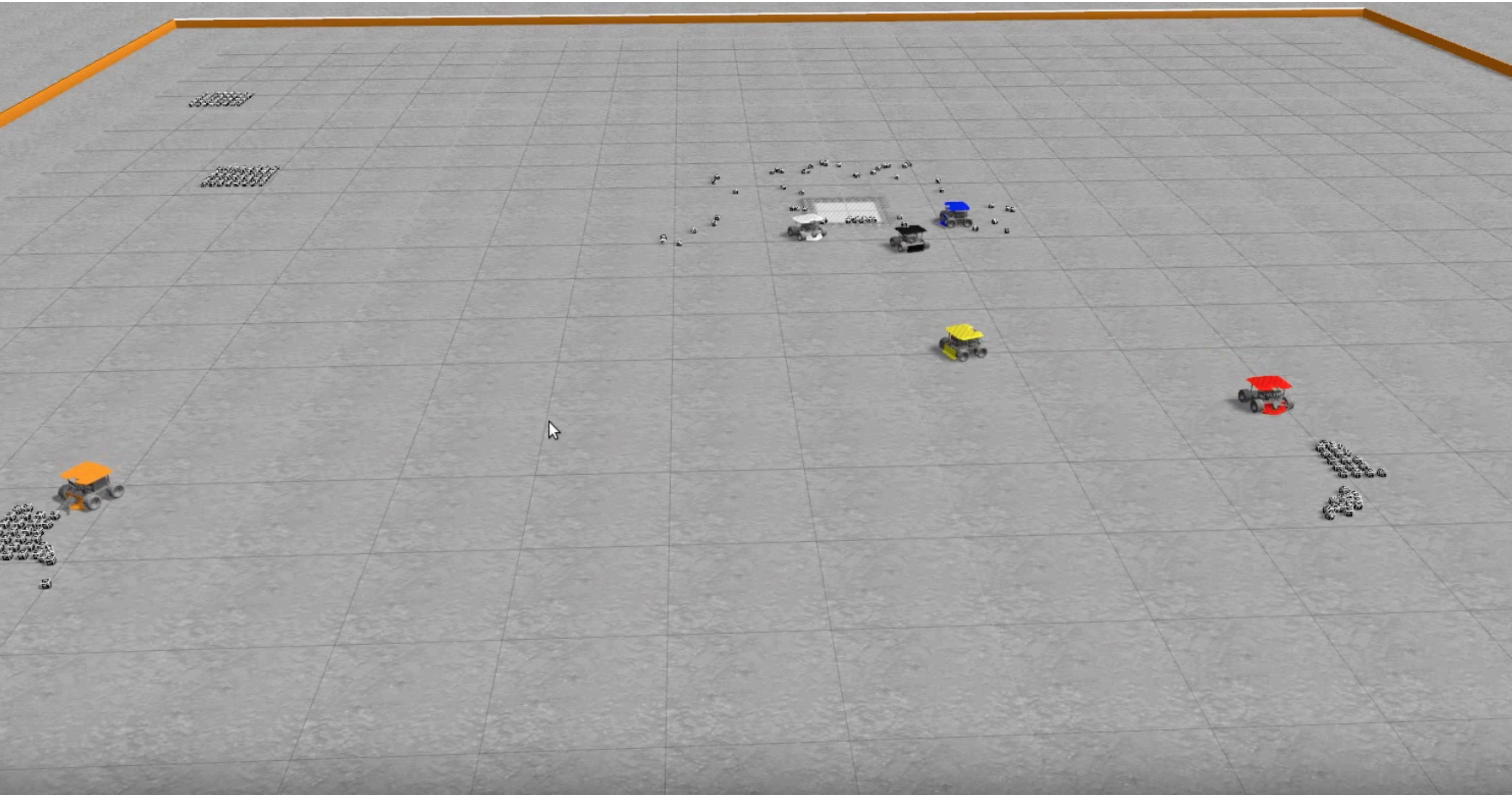
nasaswarmathon.com

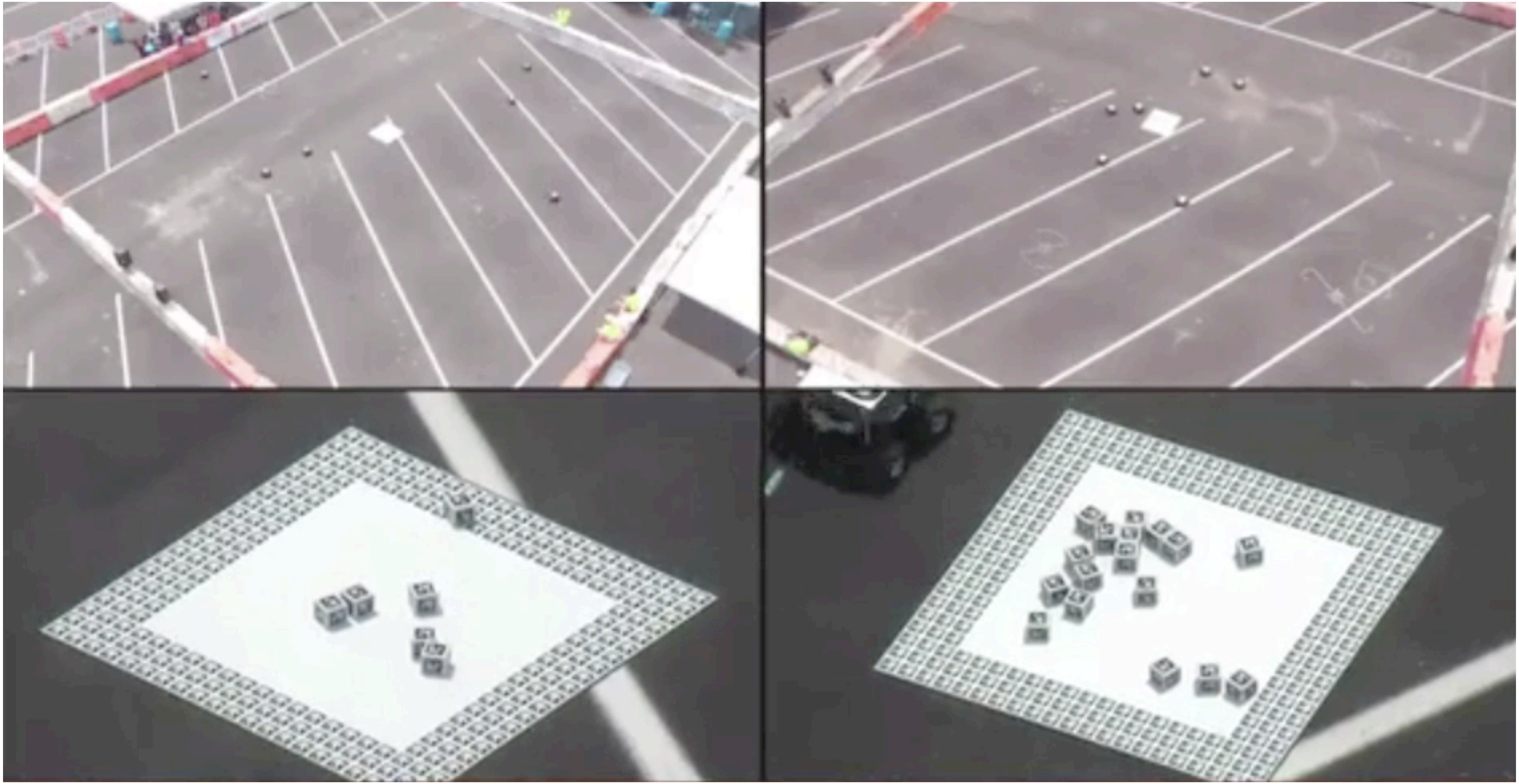


Managed by UNM, 40 colleges and universities competed

Build ~100 robots so far…

Introduction



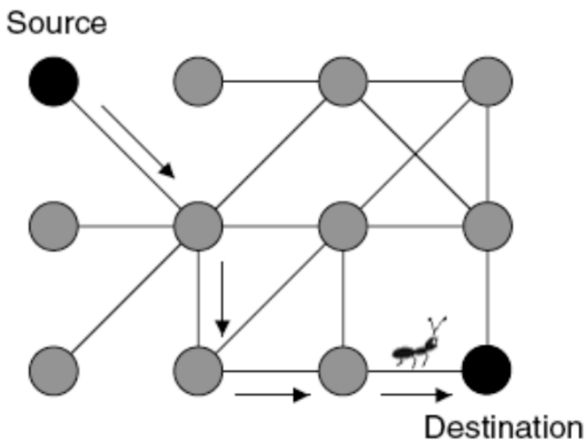


Ant Colony Optimisation (ACO)

Key Concepts From Dorigo's ACO

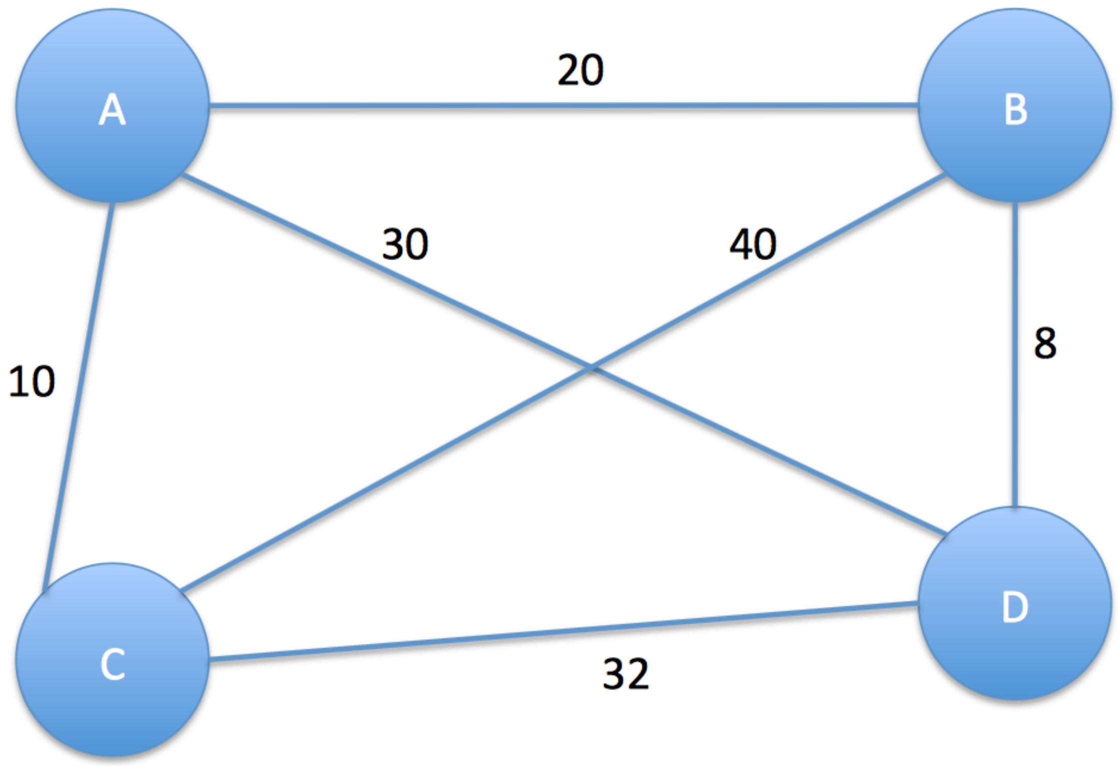
- Ant algorithms use 'self-organizing principles' to coordinate agents to solve computational problems
- Stigmergy: indirect communication and coordination through signals that modify the environment and stimulate other agents
- Pheromones: a chemical signal that triggers a response in another agent
  - Pheromone concentration increases the probability that an ant will follow a path
  - Evaporation removes stale solutions and mitigates premature convergence

Simple-ACO



- S-ACO modifications of previous models
  - Ants remember their paths
  - Only backward pheromone deposition
  - Deterministic backward path
  - Pheromone evaporation
  - Pheromone deposition rate depends on quality of solution (ants deposit more pheromone on shorter paths)
  - Loop avoidance

Use the Ant System ACO to solve this TSP



Ant System

-Pheromone is stored in a matrix
-Heuristic information (distances between nodes) is stored in another matrix
-Ants remember where they've been on a given tour and do not repeat cities

```
Initialize Pheromone
While termination condition not met
    Construct Ant Solutions
        For each ant,
            choose a start city,
            construct a tour, biasing steps by pheromone, until it returns home
    Optionally Apply local search
    Update Pheromone
endwhile
```

Variations: elitist, rank based, max-min: alter pheromone deposition and update

Ant System

- Ant cycle: pheromone deposit is determined globally (not very ant like) based on the length of the tour
- Initialization:

Initialize pheromone and $\tau_{i,j} = \frac{m}{C^{nn}}$ m = # ants

heuristic information for all i,j: $\eta_{i,j} = \frac{1}{d_{i,j}}$ C^{nn} = length of nearest neighbor CYCLE

$d_{i,j}$ = distance from i to j

We define the transition probability from town i to town j for the k-th ant as

$$p_{ij}^{k}(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}]^{\beta}}{\sum_{k \in allowed_k} [\tau_{ik}(t)]^{\alpha} \cdot [\eta_{ik}]^{\beta}} & \text{if } j \in allowed_k \\ 0 & \text{otherwise} \end{cases}$$

- Tour construction formula
- What do alpha and beta represent?

Carlo Dorigo's PhD Thesis (1992)

Ant System

The amount of pheromone on edge (i,j)

like) based on the length of the tour

- Initialization:

Initialize pheromone and $\tau_{i,j} = \frac{m}{C^{nn}}$ m = # ants

heuristic information for all i,j: $\eta_{i,j} = \frac{1}{d_{i,j}}$ C^{nn} = length of nearest neighbor CYCLE

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Ant System

The amount of pheromone on edge (i,j)

like) based on the length of the tour

- Initialization:

Initialize pheromone and heuristic information for all i,j:

$$\tau_{i,j} = \frac{m}{C^{nn}} \qquad \eta_{i,j} = \frac{1}{d_{i,j}}$$

m = # ants

C^{nn} = length of nearest neighbor CYCLE

$d_{i,j}$ = distance from i to j

The attractiveness of an edge other than pheromone level. (Distance to city)

nt as

$$p_{ij}^{k}(t) = \begin{cases} \dfrac{\cdots}{\sum_{k \in allowed_k} [\tau_{ik}(t)]^{\alpha} \cdot [\eta_{ik}]^{\beta}} & \\ 0 & \text{otherwise} \end{cases}$$

- What do alpha and beta represent?

Ant System

- Ant cycle: pheromone deposit is determined globally (not very ant like) based on the length

α and β tune the relative importance of pheromone and local information.

How does this relate to GAs and the mutation rate?

CYCLE

We define the transition probability from town i to town j for the k-th ant as

- Tour construction formula
- What do alpha and beta represent?

$$p_{ij}^{k}(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}]^{\beta}}{\sum_{k \in allowed_k} [\tau_{ik}(t)]^{\alpha} \cdot [\eta_{ik}]^{\beta}} & \text{if } j \in allowed_k \\ 0 & \text{otherwise} \end{cases}$$

Ant System

- Ant cycle: pheromone deposit is determined globally (not very ant like) based on the length of the tour
- Initialization:

m

ts

Probability of ant following edge (i,j)

heuristic infor ation for all i,j: $\eta_{i,j} = \frac{\quad}{d_{i,j}}$ C^{nn} = length of nearest neighbor CYCLE

$d_{i,j}$ = distance from i to j

We define the transition probability from town i to town j for the k-th ant as

- Tour construction formula

$$p_{ij}^{k}(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}]^{\beta}}{\sum_{k \in allowed_k} [\tau_{ik}(t)]^{\alpha} \cdot [\eta_{ik}]^{\beta}} & \text{if } j \in allowed_k \\ 0 & \text{otherwise} \end{cases}$$

- What do alpha and beta represent?

- Pheromone update

$$\tau_{ij} \leftarrow \tau_{ij} + \Delta\tau^k.$$

$$\Delta\tau^k_{i,j} = \frac{1}{C^k}$$

C^k is tour length of k^{th} ant
If (i,j) are on the tour of the k^{th} ant
0 otherwise

- Pheromone evaporation

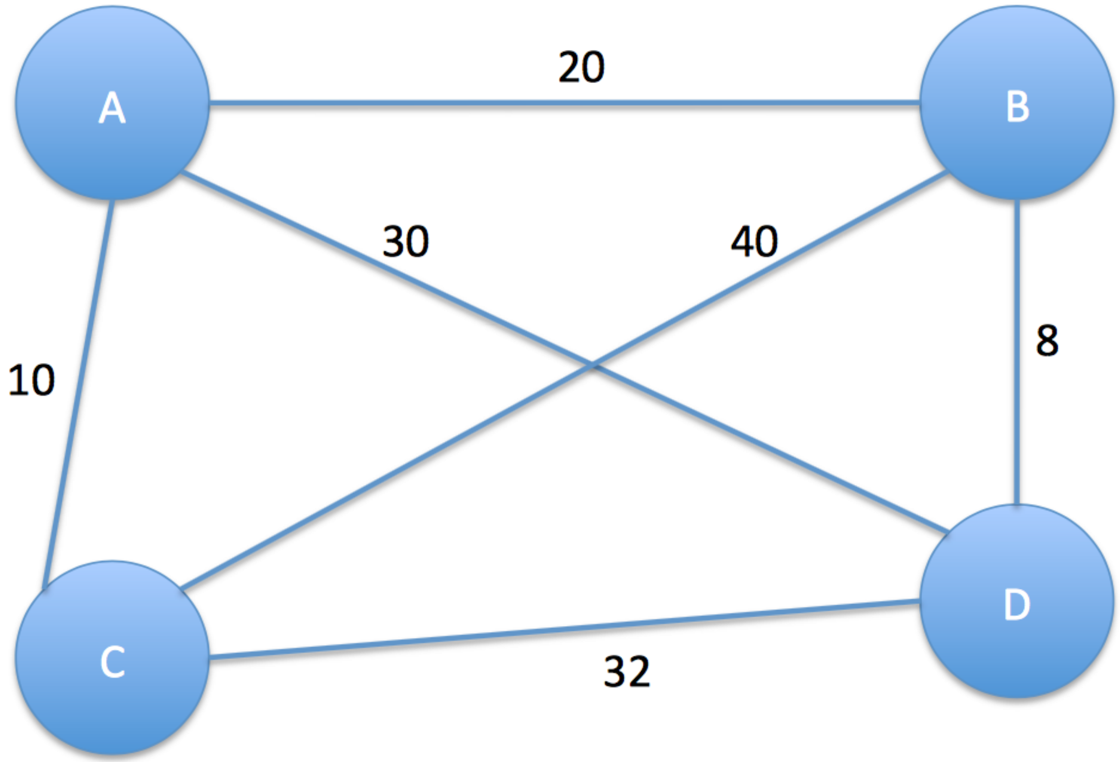
$$\tau_{ij} \leftarrow (1-\rho)\tau_{ij}, \quad \forall (i,j) \in A,$$

where $\rho \in (0,1]$ is a parameter.

- AS parameter settings:
  - alpha = 1
  - beta = 2 to 5
  - rho = 0.5
  - m = n (number of ants = number of cities)
  - Tau_0 initialization = m/C^{nn}
- Ant Cycle: pheromone update depends on tour length,
  So it is updated only after a completed tour
- Elistist AS: Reinforce T^{bs} (best so far tour)

$$\tau_{i,j} = \tau_{i,j} + \sum_{k=1}^{m} \Delta\tau^k_{i,j} + e\Delta\tau^{bs}_{i,j}$$

$$\Delta\tau^{bs}_{i,j} = \frac{1}{C^{bs}}$$


A
B
C
D
20
30
40
10
8
32

Initialize

$$\tau_{i,j} = \frac{m}{C^{nn}}$$

$$\eta_{i,j} = \frac{1}{d_{i,j}}$$

C^{nn} = length of nearest neighbor CYCLE

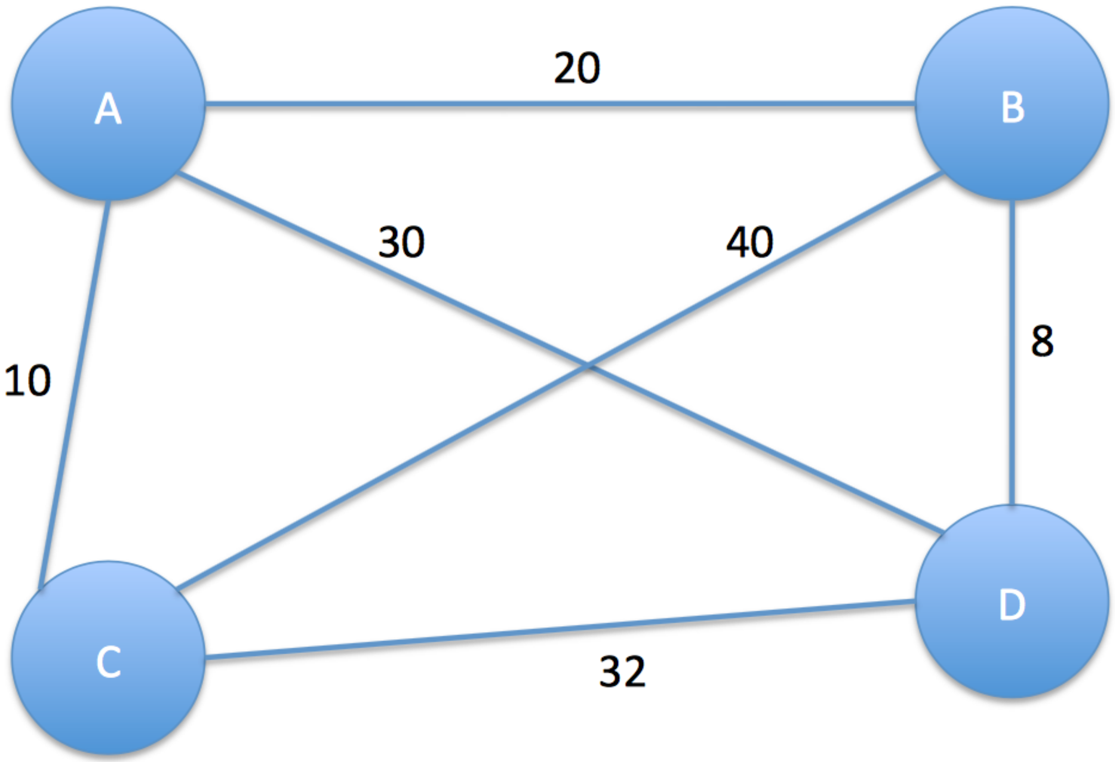
$d_{i,j}$ = distance from i to j

Start at A

$C^{nn} = 10 + 32 + 8 + 20 = 70$

A, C, D, B

m = # cities = # ants = 4



Initialize

$$\tau_{i,j} = \frac{m}{C^{nn}}$$

$$\eta_{i,j} = \frac{1}{d_{i,j}}$$

C^{nn} = length of nearest neighbor CYCLE

$d_{i,j}$ = distance from i to j

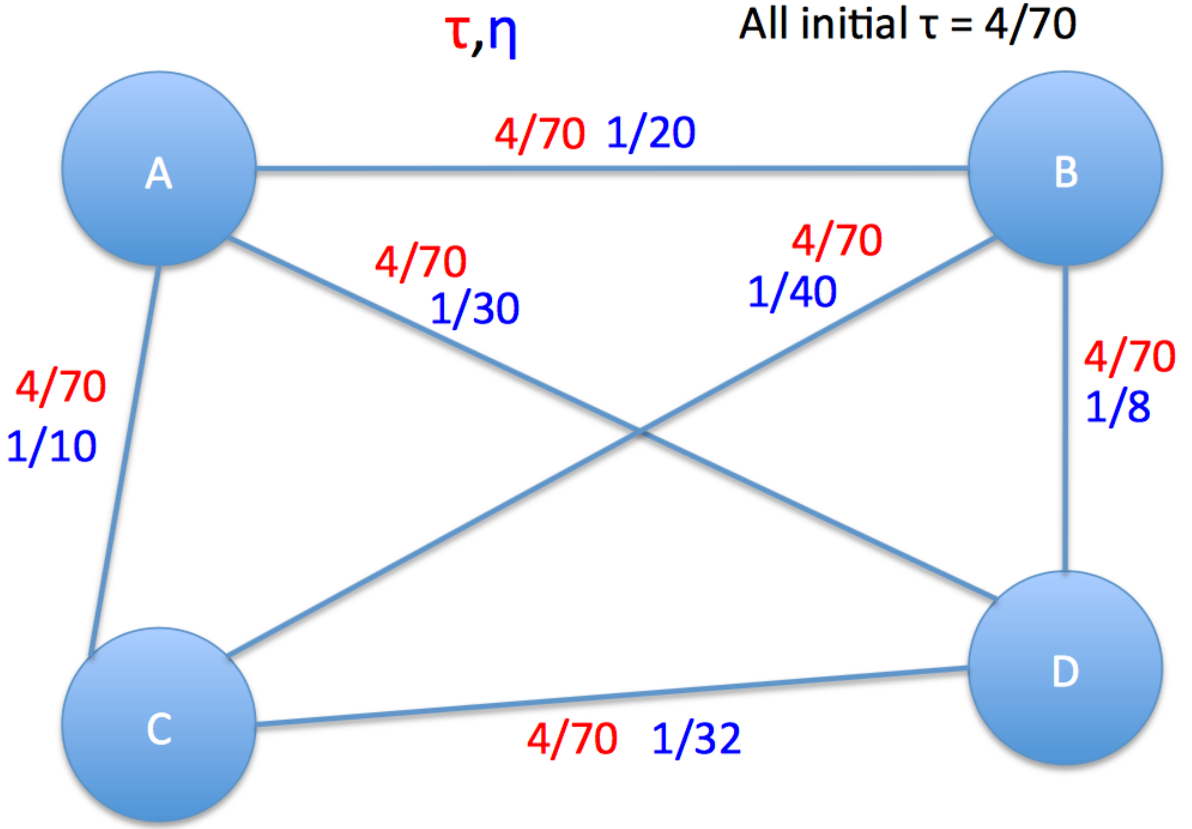
Start at A

C^{nn} = 10 + 32 + 8 + 20 = 70

A, C, D, B

m = # cities = # ants = 4

All initial τ = 4/70



We define the transition probability from town i to town j for the k-th ant as

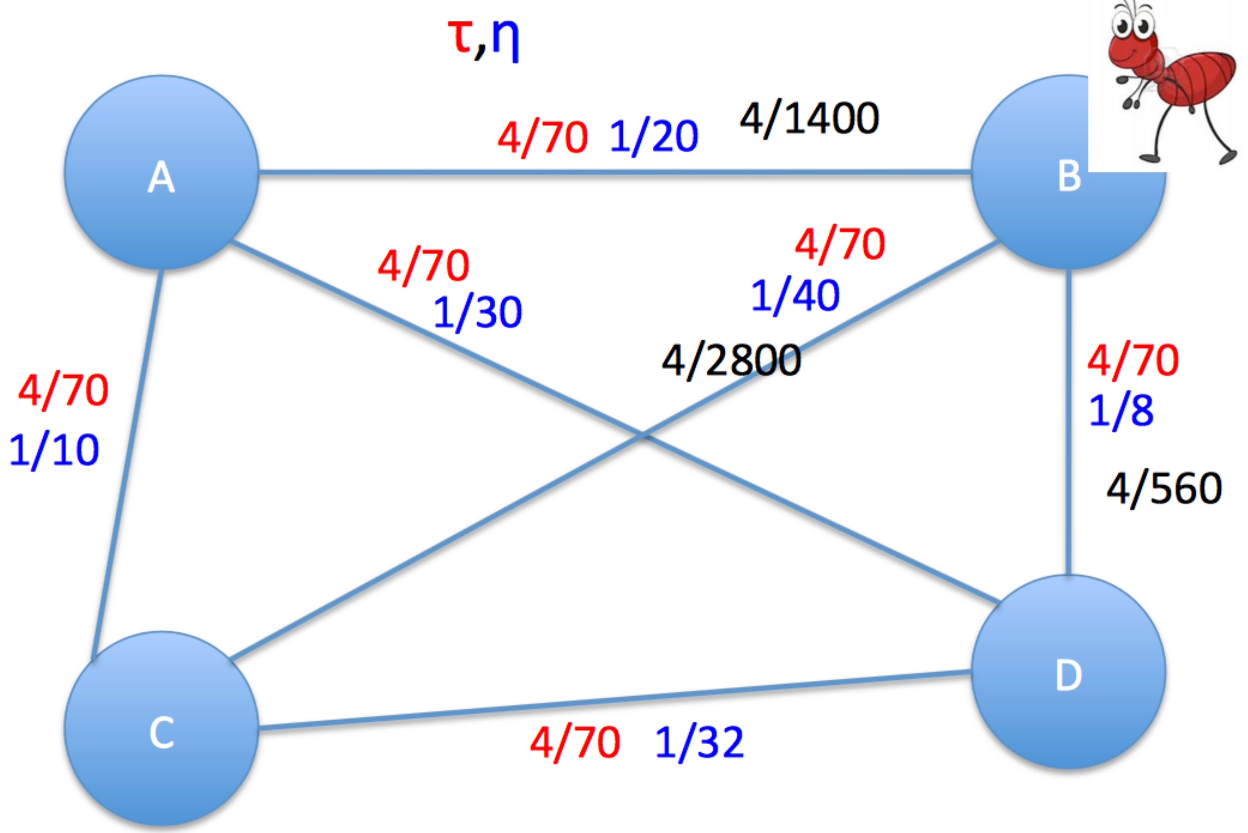
TRAVERSE

$$p_{ij}^{k}(t) = \begin{cases} \dfrac{\left[\tau_{ij}(t)\right]^{\alpha} \cdot \left[\eta_{ij}\right]^{\beta}}{\sum_{k \in allowed_k} \left[\tau_{ik}(t)\right]^{\alpha} \cdot \left[\eta_{ik}\right]^{\beta}} & \text{if } j \in allowed_k \\ 0 & \text{otherwise} \end{cases}$$

denominator=(8+4+20)/2800

$\alpha = 1$

$\beta = 1$ (usually 2 – 5)



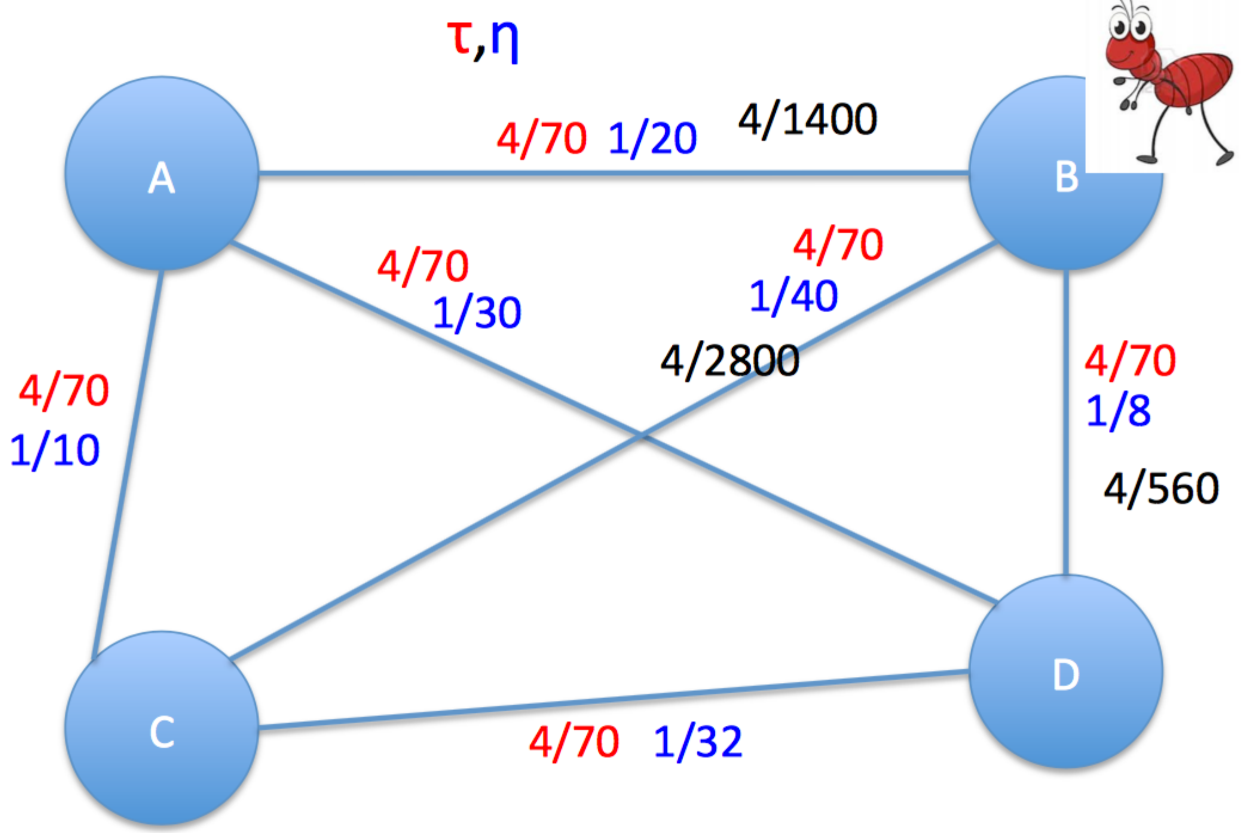
We define the transition probability from town i to town j for the k-th ant as **TRAVERSE**

$$p_{ij}^{k}(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}]^{\beta}}{\sum_{k \in allowed_k} [\tau_{ik}(t)]^{\alpha} \cdot [\eta_{ik}]^{\beta}} & \text{if } j \in allowed_k \\ 0 & \text{otherwise} \end{cases}$$

denominator=(8+4+20)/2800

$\alpha = 1$

$\beta = 1$ (usually 2 – 5)



Usually : B, D, A, C, B: Cycle = 8+30+10 +40 = 88

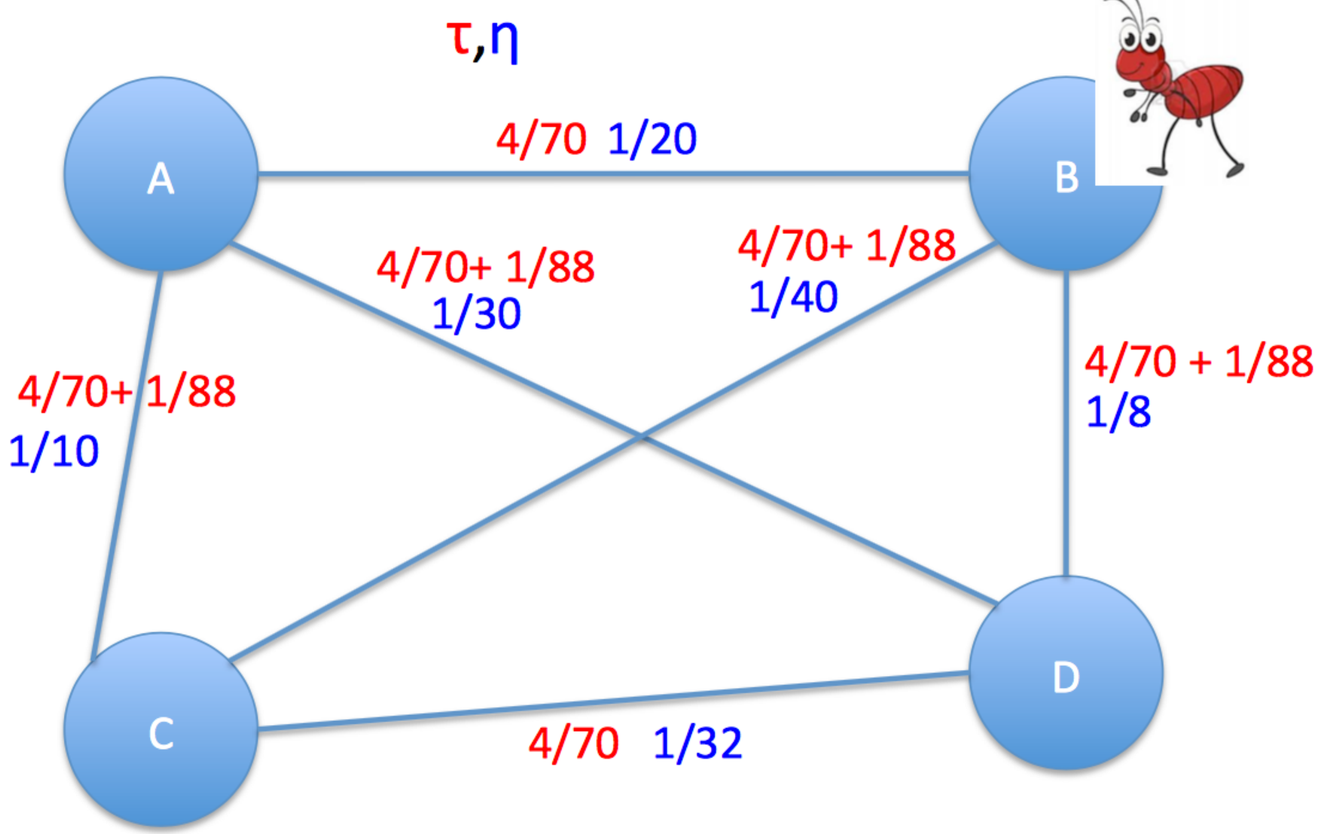
Rarely: B,D,C,A, B: Cycle = 8+32+10 + 20 = 70

We define the transition probability from town i to town j for the k-th ant as

$$p_{ij}^{k}(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}]^{\beta}}{\sum\limits_{k \in allowed_k} [\tau_{ik}(t)]^{\alpha} \cdot [\eta_{ik}]^{\beta}} & \text{if } j \in allowed_k \\ 0 & \text{otherwise} \end{cases}$$

UPDATE Pheromone

$$\Delta\tau_{i,j}^{k} = \frac{1}{C^k}$$



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Rarely: B,D,C,A, B: Cycle = 8+32+10 + 20 = 70

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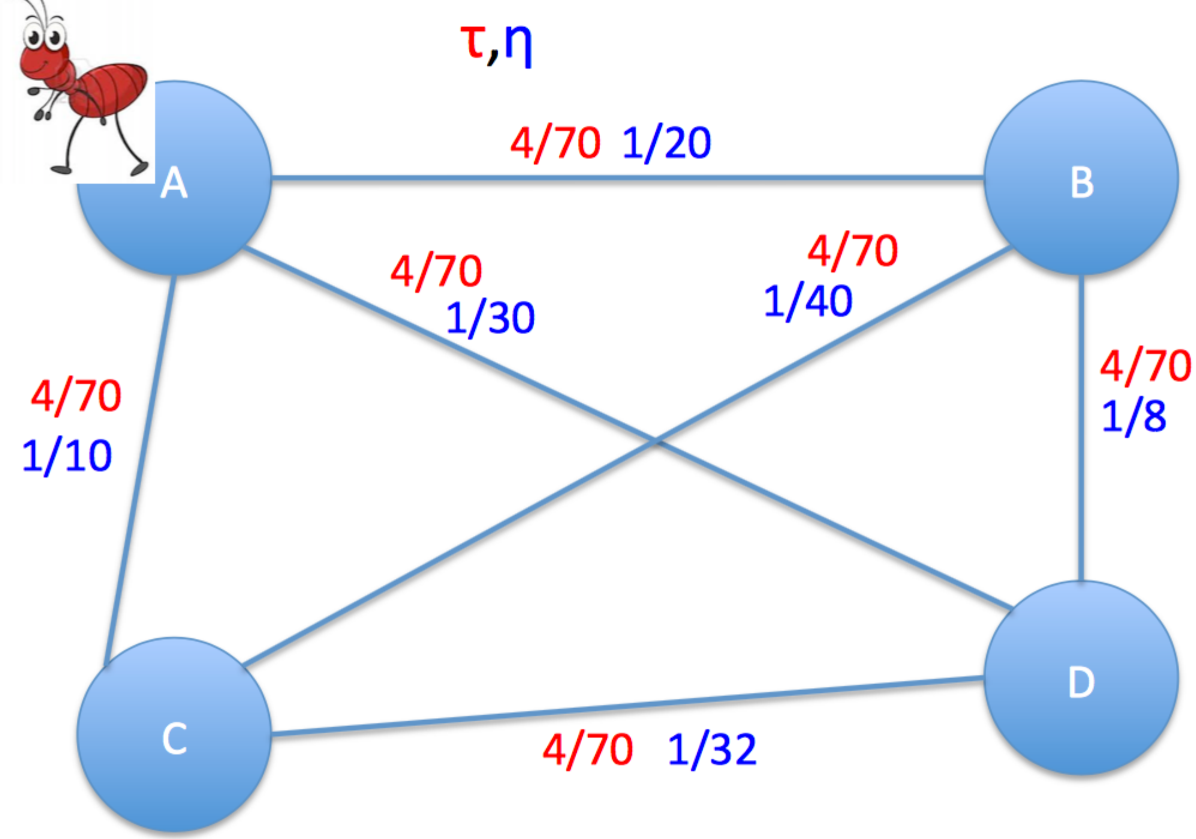
$\alpha = 1$
$\beta = 1$

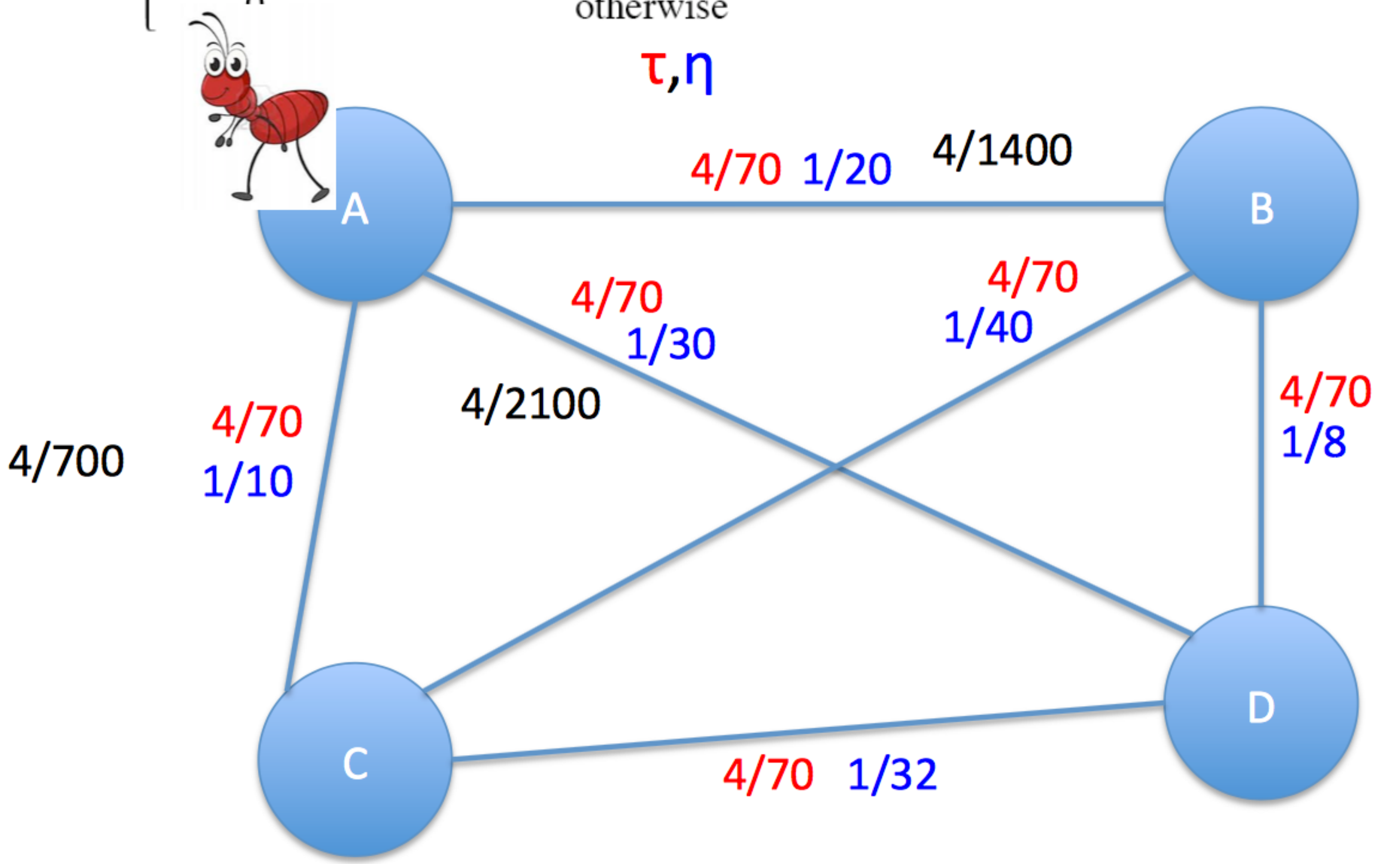


We define the transition probability from town i to town j for the k-th ant as

$$p_{ij}^{k}(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}]^{\beta}}{\sum_{k \in allowed_k} [\tau_{ik}(t)]^{\alpha} \cdot [\eta_{ik}]^{\beta}} & \text{if } j \in allowed_k \\ 0 & \text{otherwise} \end{cases}$$

$\alpha = 1$

$\beta = 1$ (usually 2 – 5)



Usually : A, C, D, B,A Cycle = 10+32+8 +20 =70

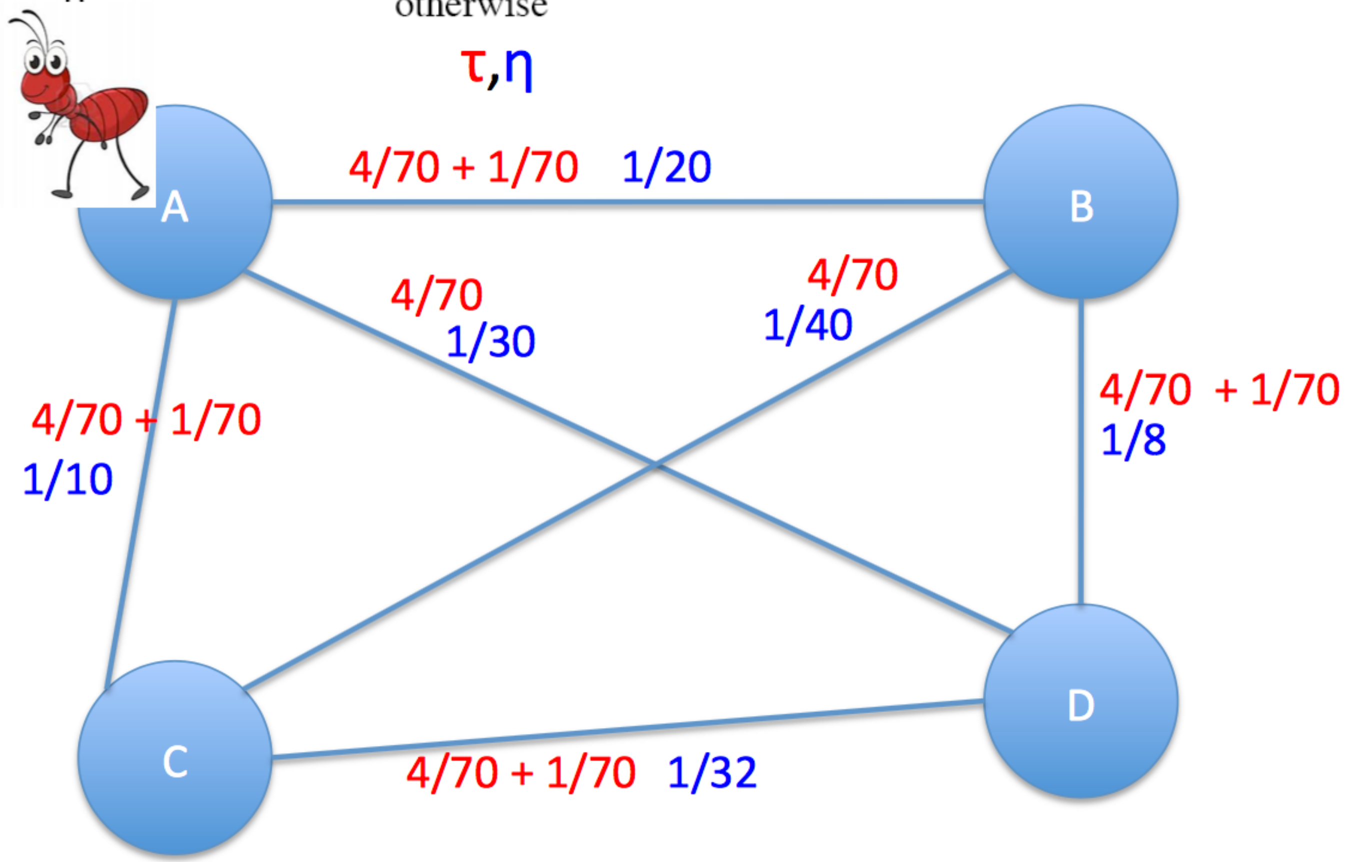
Very Rarely: A,D, C, B, A Cycle = 30+32+40+20 = 122

We define the transition probability from town i to town j for the k-th ant as

$$p_{ij}^k(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}]^{\beta}}{\sum\limits_{k \in allowed_k} [\tau_{ik}(t)]^{\alpha} \cdot [\eta_{ik}]^{\beta}} & \text{if } j \in allowed_k \\ 0 & \text{otherwise} \end{cases}$$

UPDATE Pheromone

τ, η

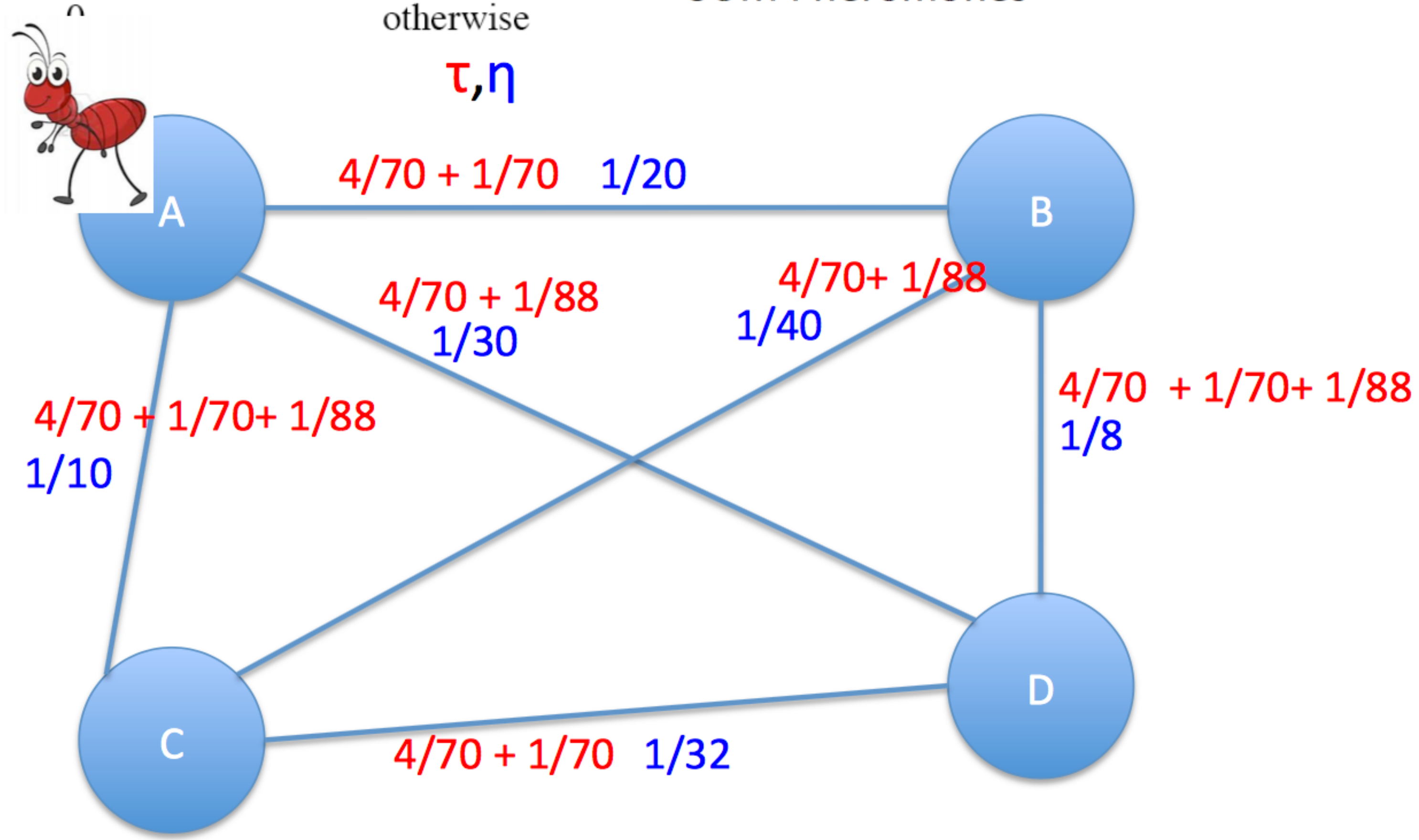


Usually : A, C, D, B, A Cycle = 10+32+8 +20 =70
Rarely: A,D, B, C, A Cycle = 30+8+40+10 = 88

We define the transition probability from town i to town j for the k-th ant as

$$p_{ij}^{k}(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}]^{\beta}}{\sum_{k \in allowed_k} [\tau_{ik}(t)]^{\alpha} \cdot [\eta_{ik}]^{\beta}} & \text{if } j \in allowed_k \\ 0 & \text{otherwise} \end{cases}$$

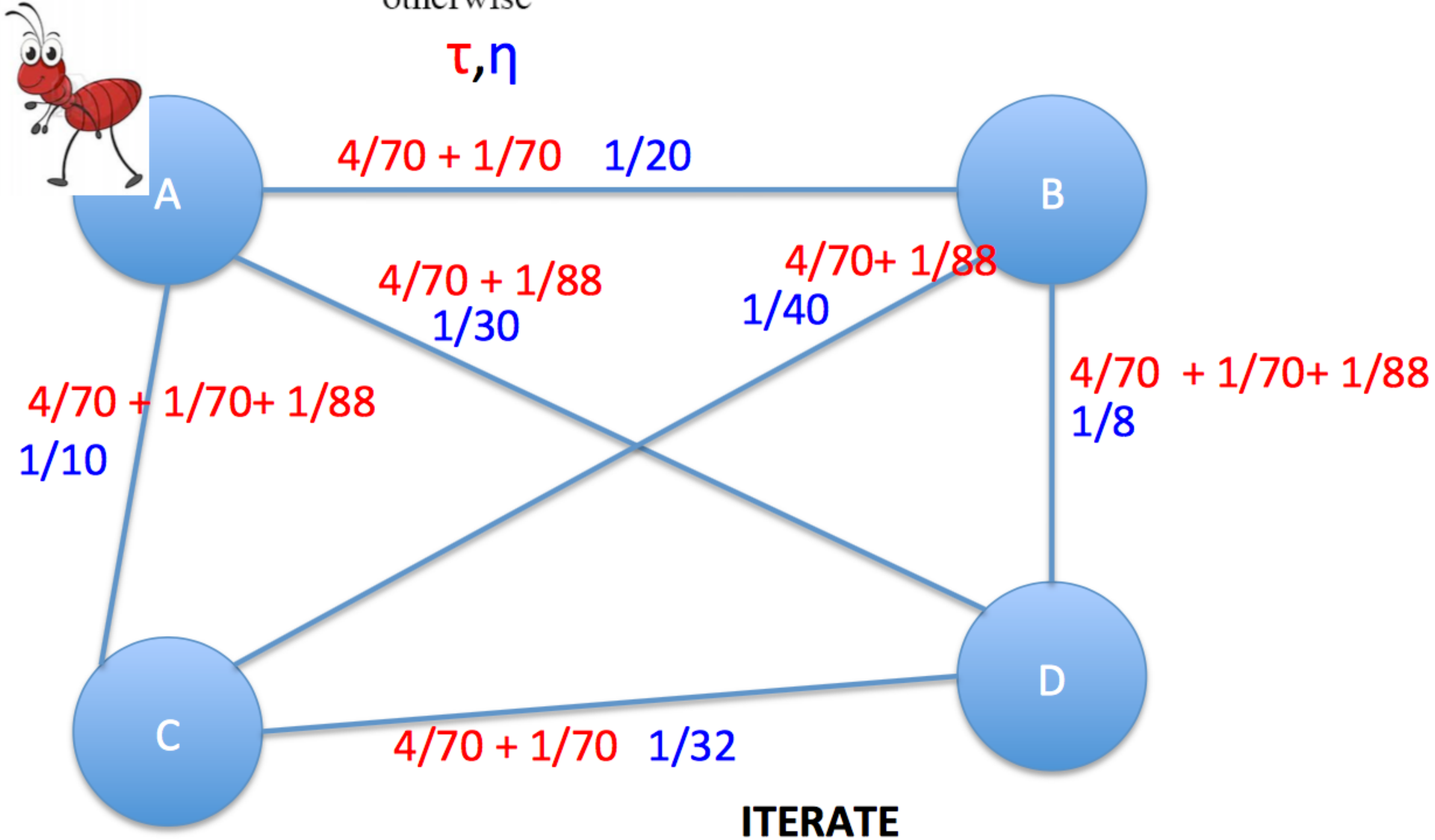
SUM Pheromones



We define the transition probability from town i to town j for the k-th ant as

$$p_{ij}^{k}(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}]^{\beta}}{\sum\limits_{k \in allowed_k} [\tau_{ik}(t)]^{\alpha} \cdot [\eta_{ik}]^{\beta}} & \text{if } j \in allowed_k \\ 0 & \text{otherwise} \end{cases}$$

Evap Pheromones: multiply by 0.5



ITERATE

η doesn't change

τ varies as ants choose and assess tours

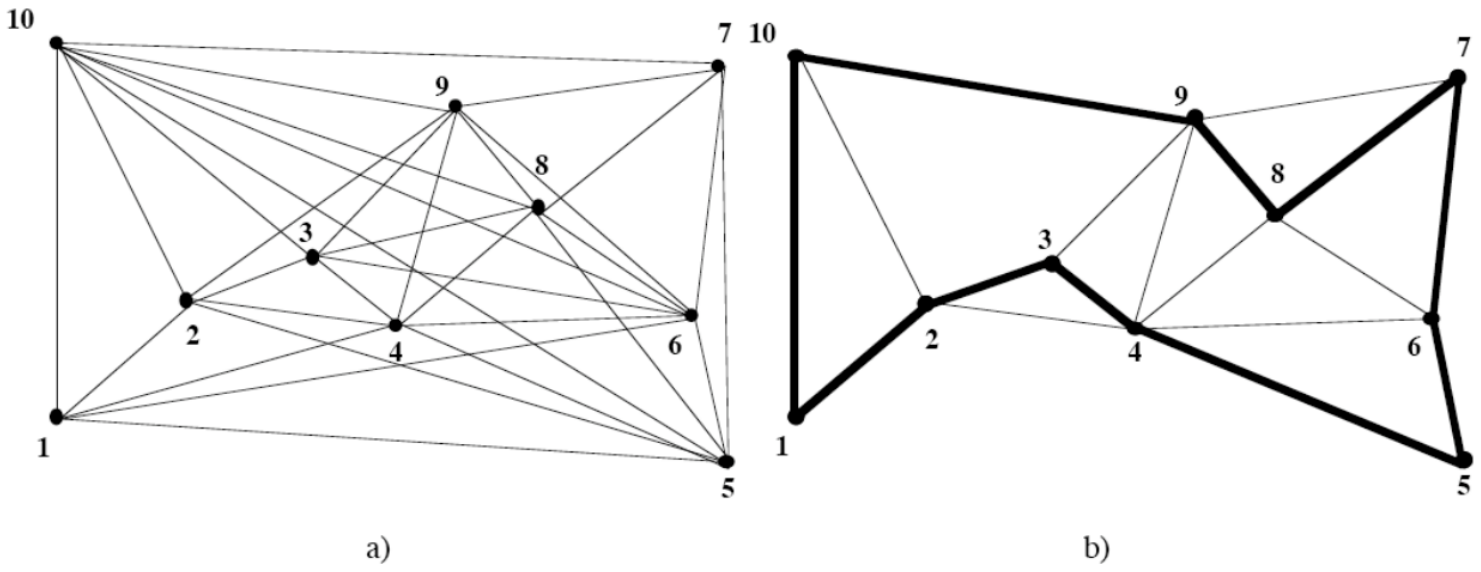
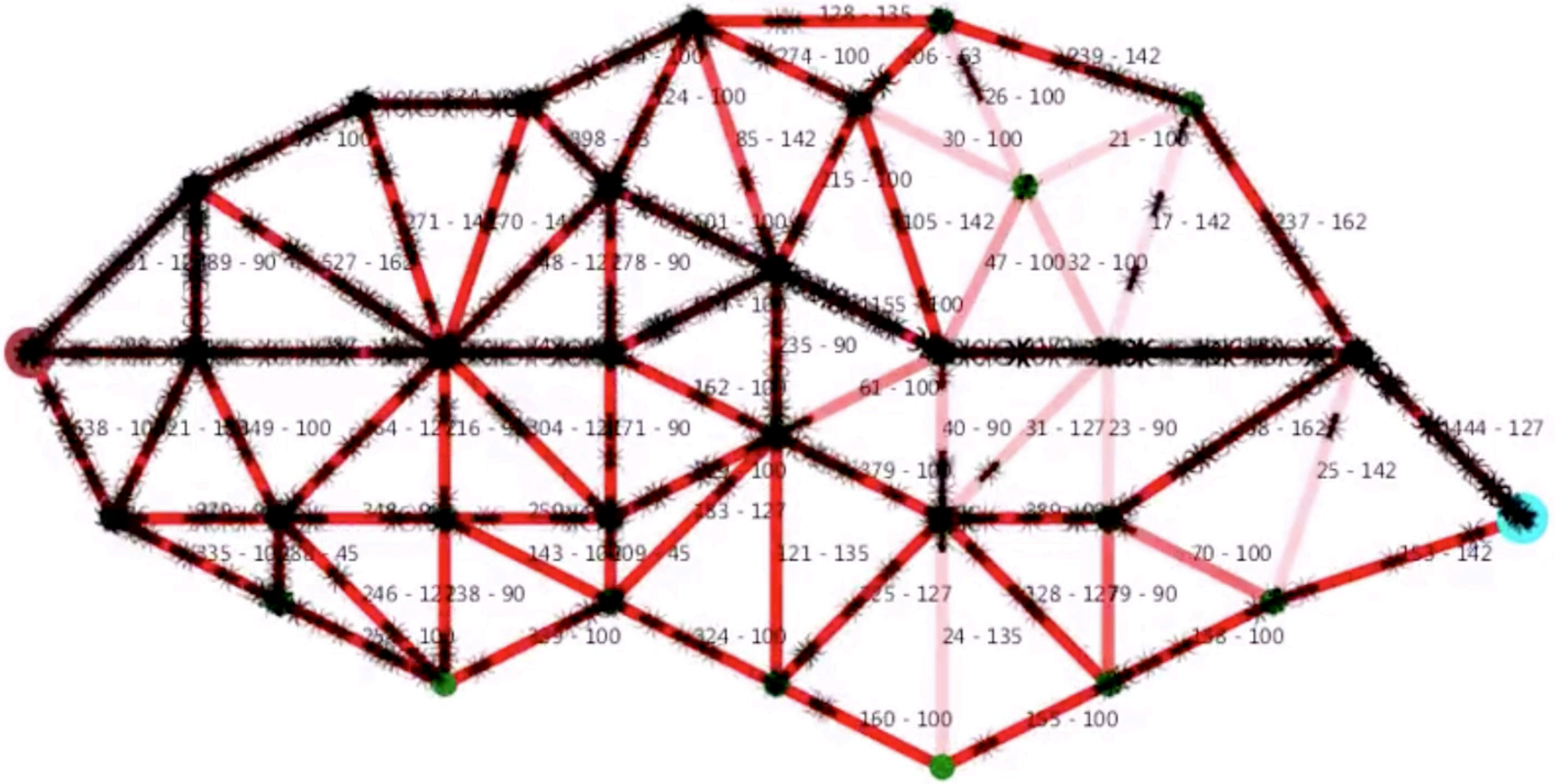
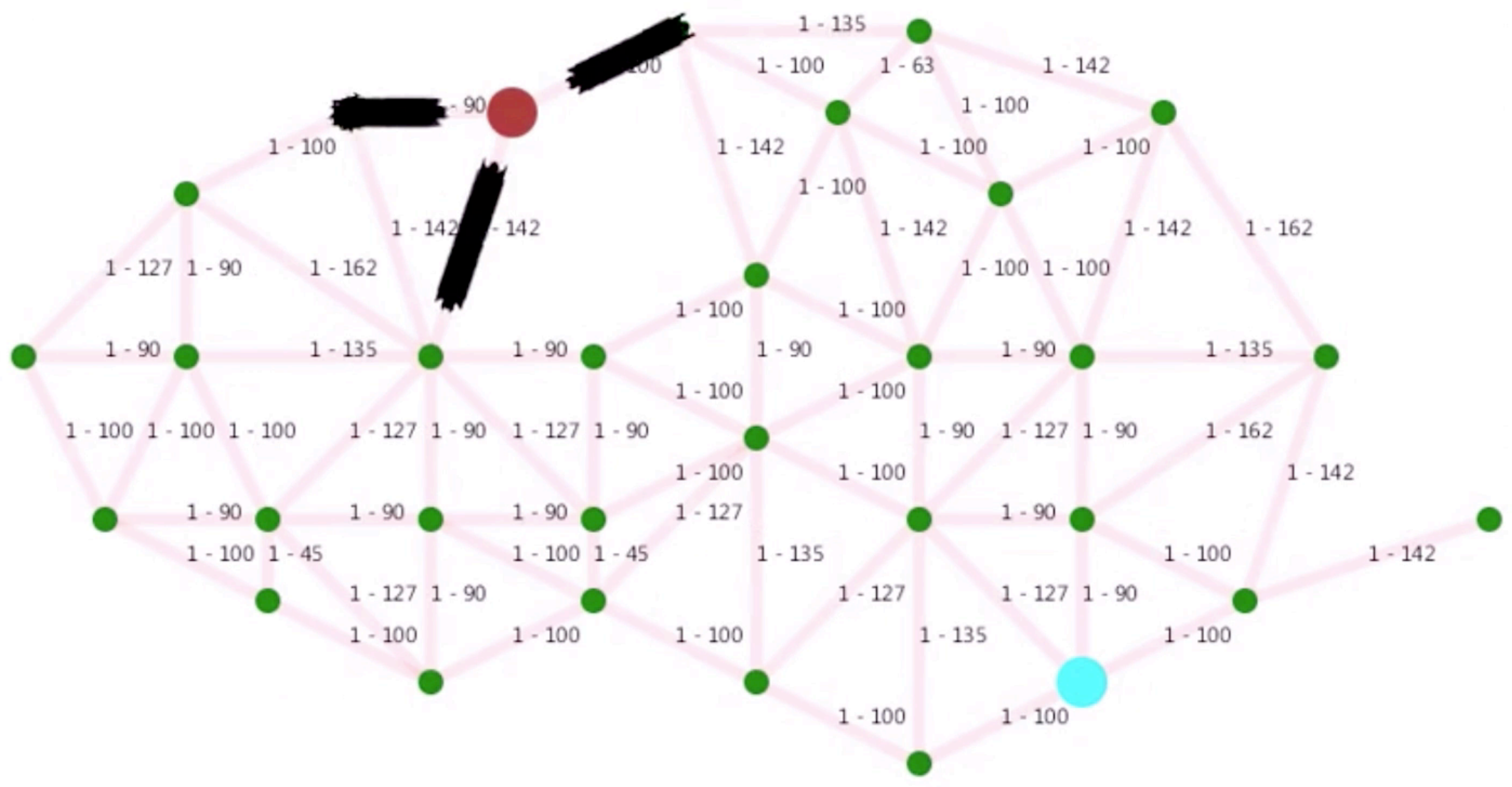


Fig. 6. Evolution of trail distribution for the CCA0 problem.
a) Trail distribution at the beginning of search.
b) Trail distribution after 100 cycles.

Dorigo 1996



https://www.youtube.com/watch?v=eVKAIufSrHs

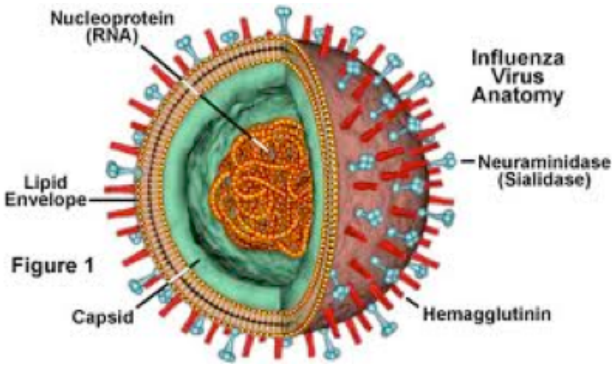


https://www.youtube.com/watch?v=eVKAIufSrHs

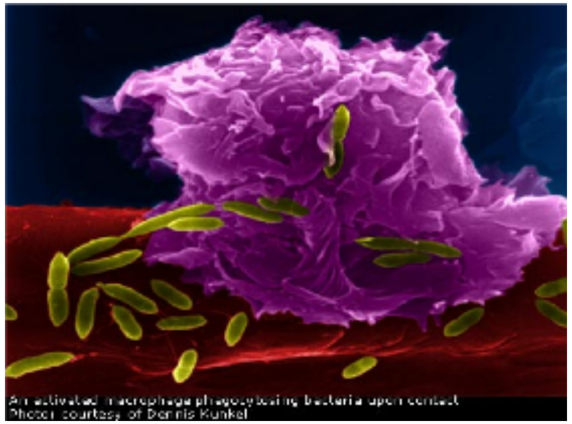
The Immune System

Introduction

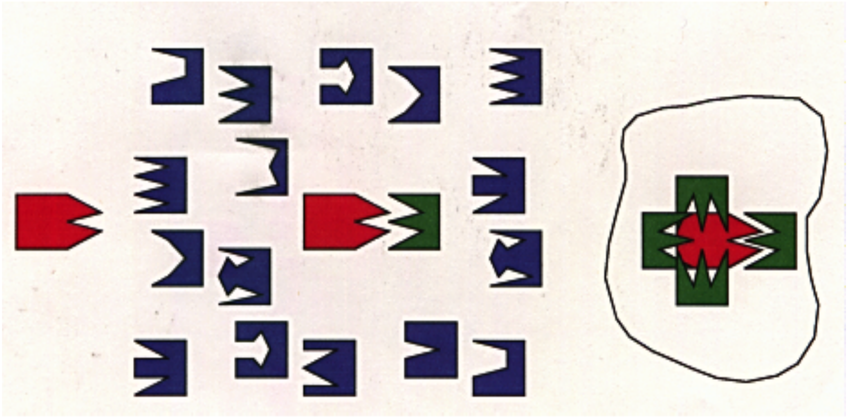
- Immune systems protect the body against foreign pathogens
  - Viruses
  - Bacteria
  - Parasites



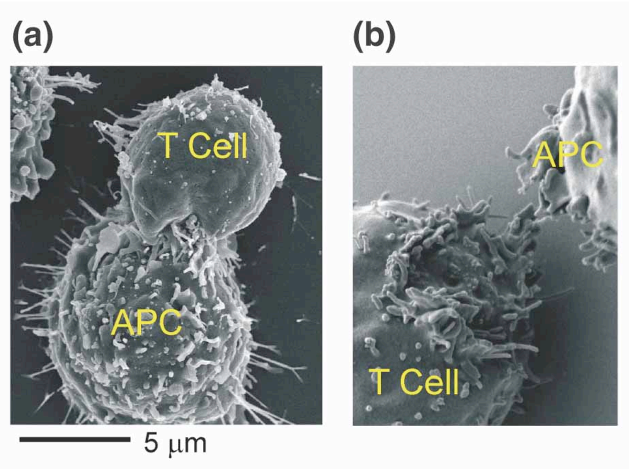
Downloaded from micro.magnet.fsu.edu (2010)



A Brief Introduction to the Immune System



Infect   Recognize   Eliminate



http://wires.wiley.com/WileyCDA/WiresArticle/wisId-WNAN1195.html

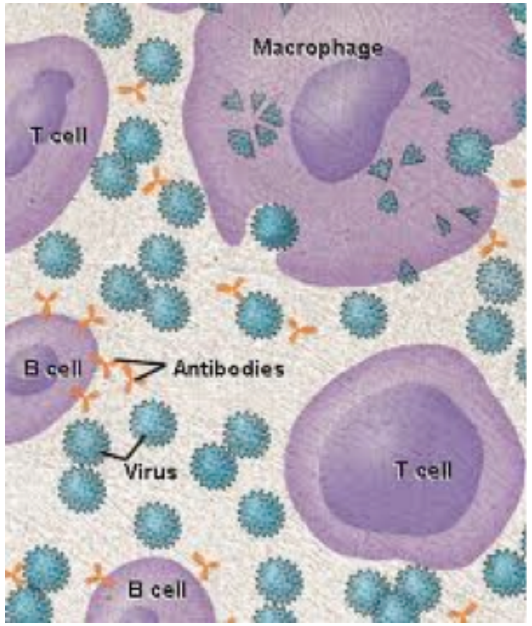
- Cells and molecules
- Recognition implemented as binding
- Specific recognition to avoid autoimmunity

An Information Processing Perspective

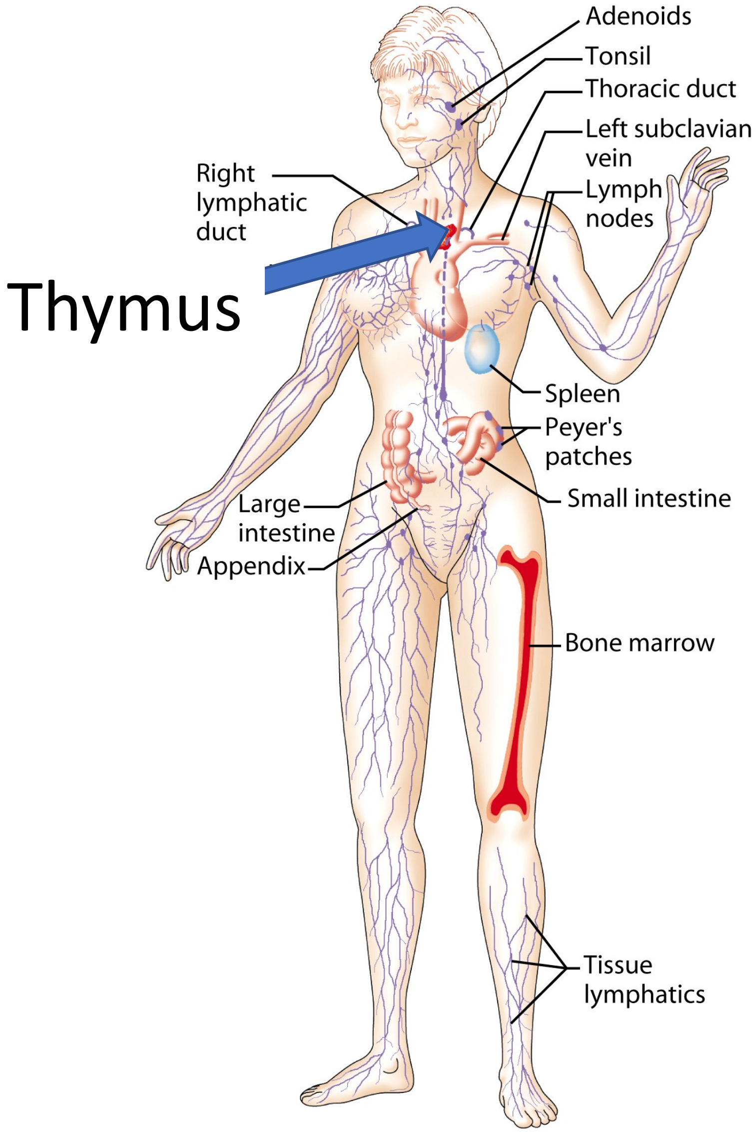
- Immune systems learn to recognize relevant patterns:
  - Primary response to new foreign antigen
  - Evolved biases towards common pathogens
  - Learned distinction between self and dangerous other
- Immune systems remember patterns seen previously
  - Secondary response
  - Cross-reactive memory
- Combinatorics to construct pattern detectors
  - $10^{11} – 10^{16}$ different foreign patterns from 30,000 genes
- Massive parallelism and distributed control

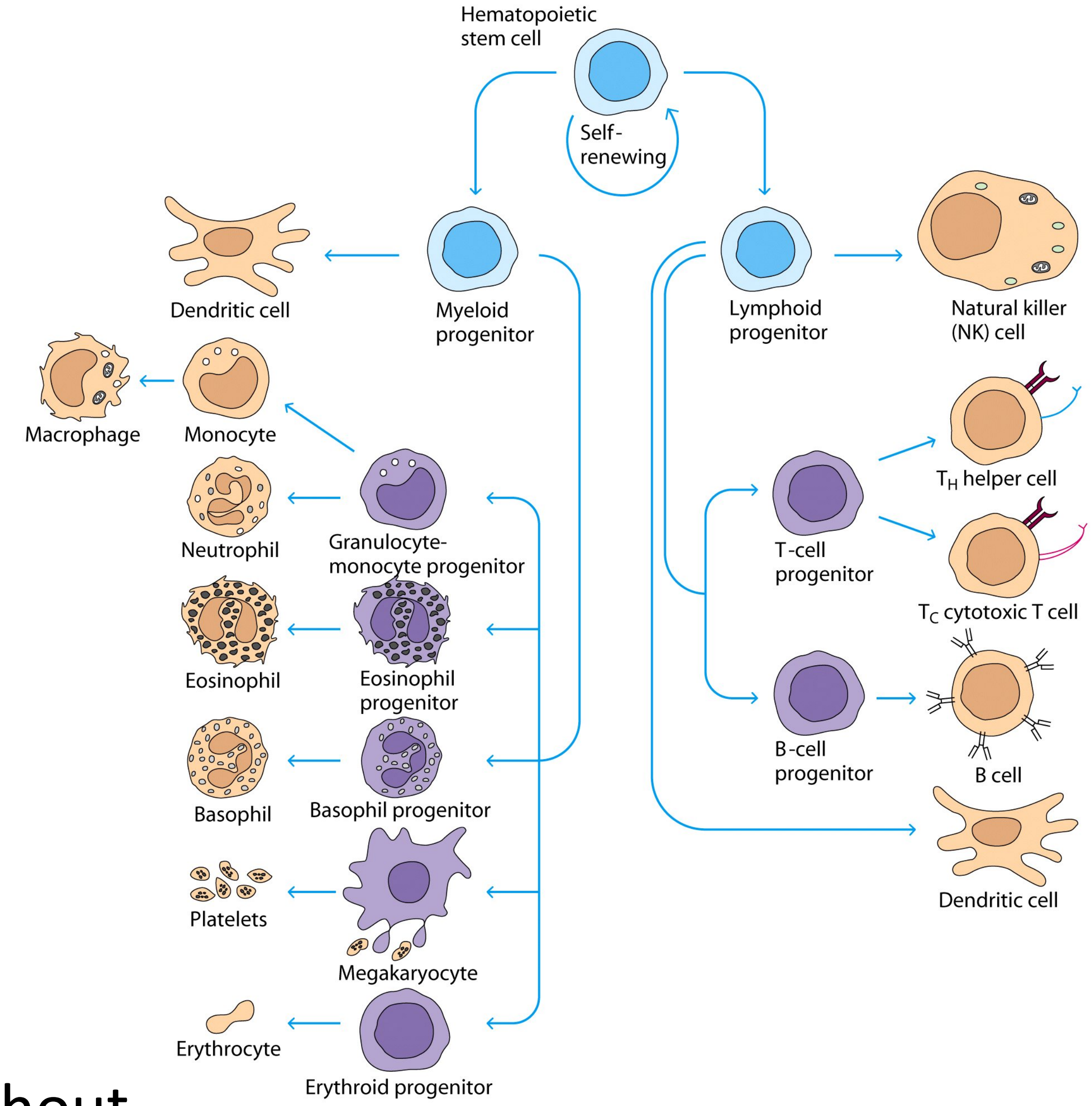
- Innate response
  - Generic
  - Inflammation
- Adaptive response
  - Specific
  - Self-tolerant
  - Learning, memory

Figure 2-8a
Kuby IMMUNOLOGY, Sixth Edition

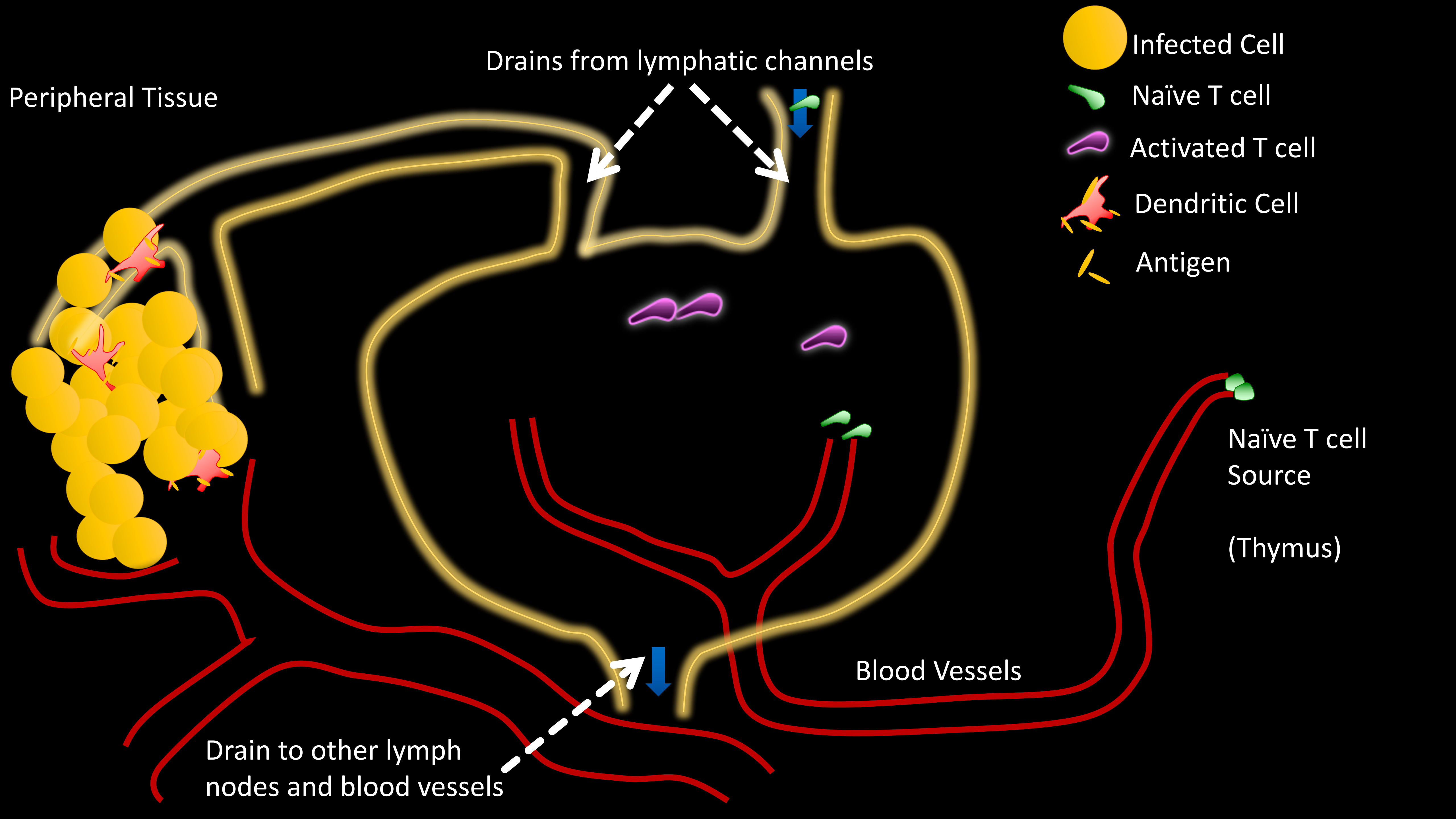


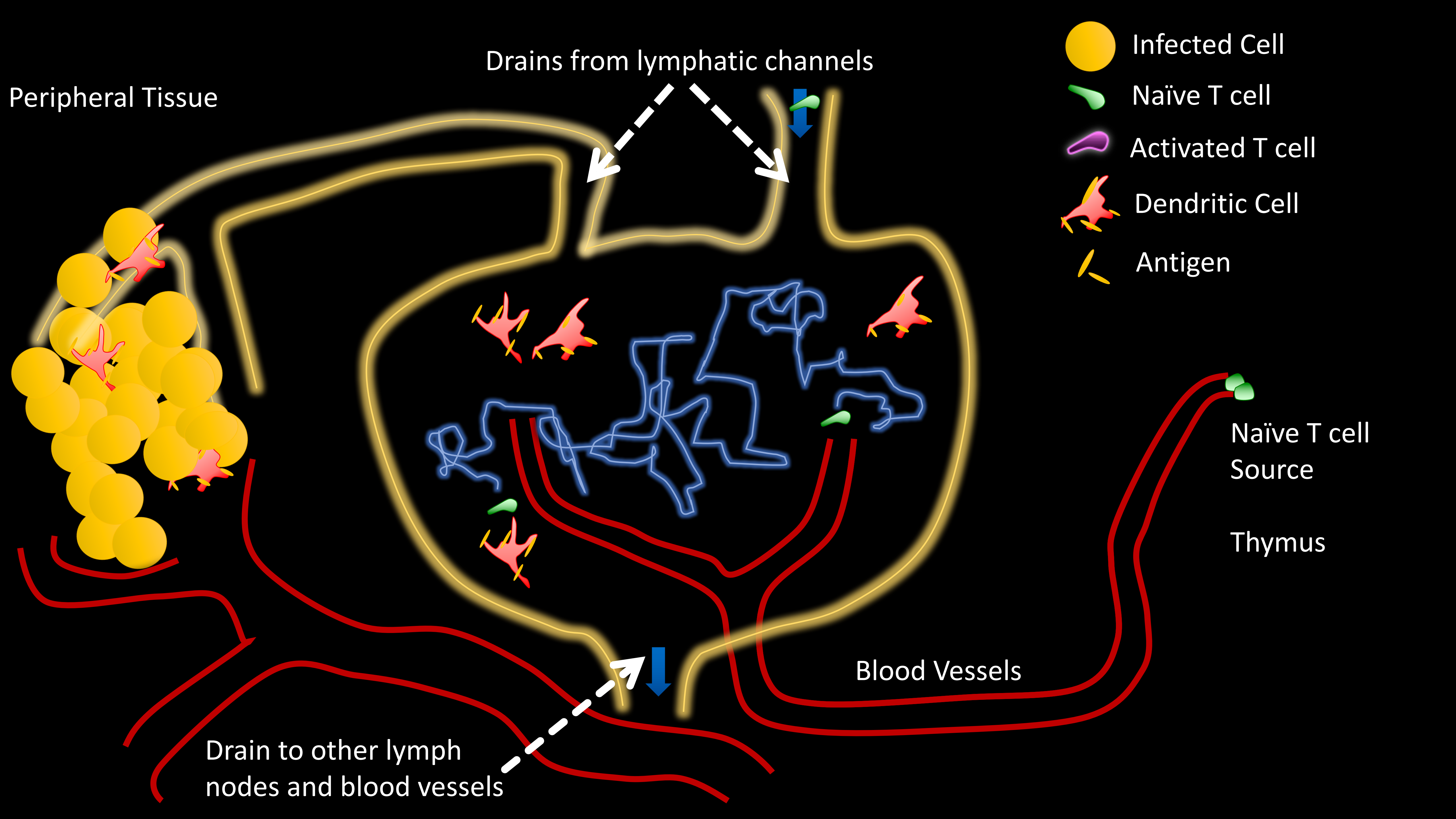
How is it implemented?





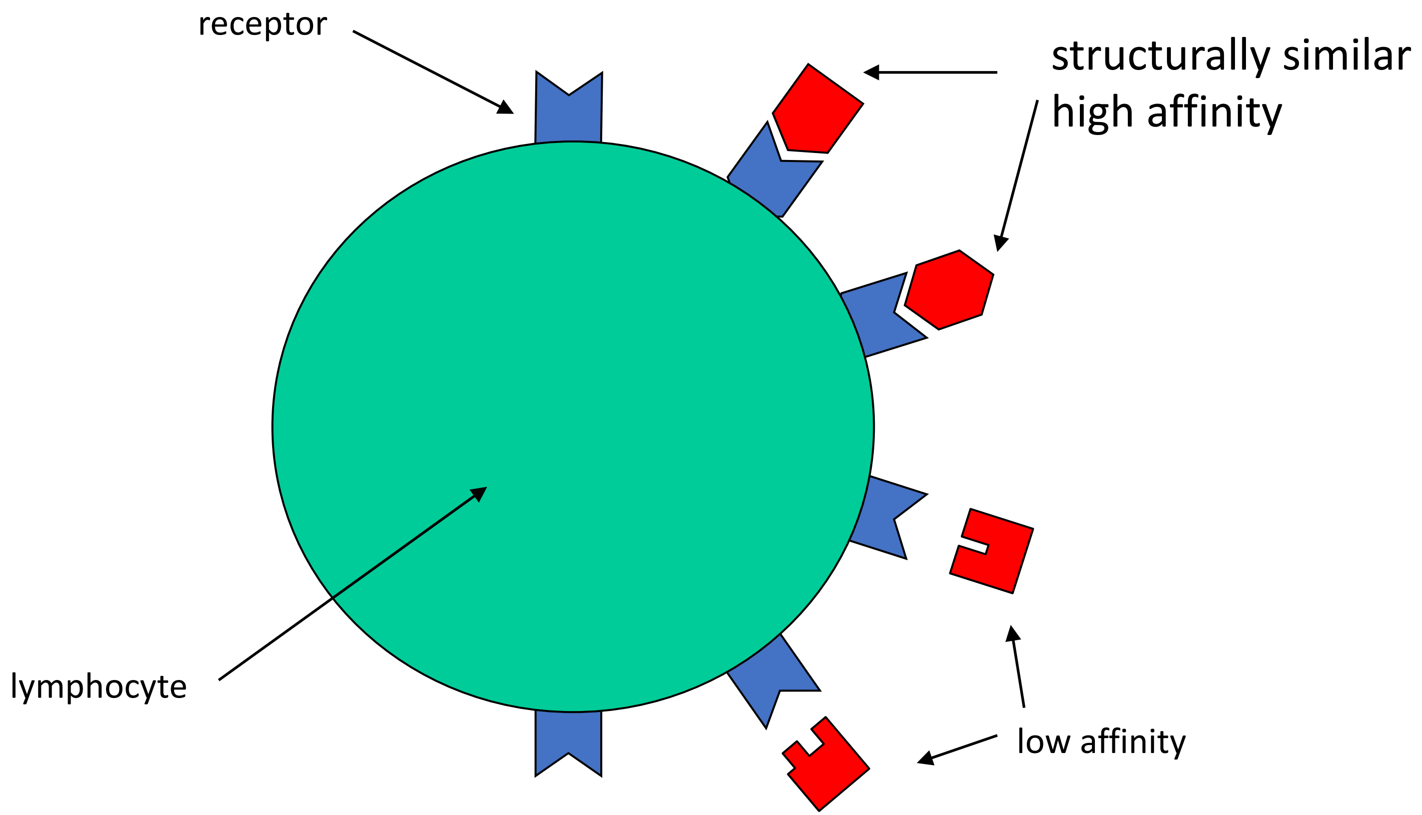
Lymph Nodes distributed throughout


Peripheral Tissue
Drains from lymphatic channels
Infected Cell
Naïve T cell
Activated T cell
Dendritic Cell
Antigen
Naïve T cell
Source
(Thymus)
Blood Vessels
Drain to other lymph
nodes and blood vessels

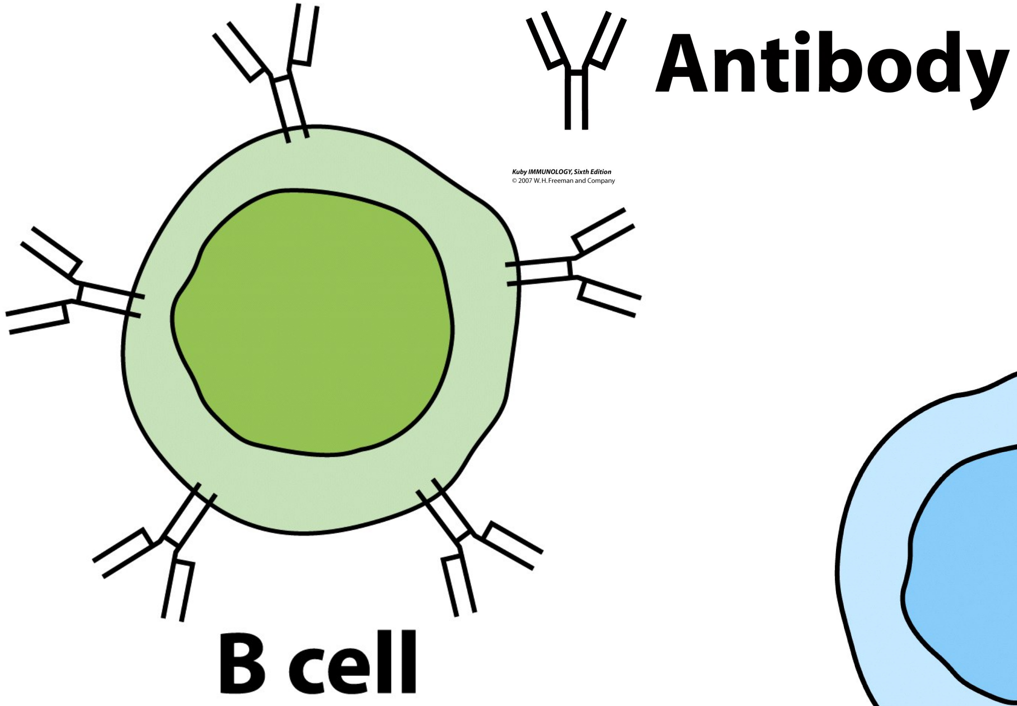

Peripheral Tissue
Drains from lymphatic channels
Infected Cell
Naïve T cell
Activated T cell
Dendritic Cell
Antigen
Naïve T cell Source
Thymus
Blood Vessels
Drain to other lymph nodes and blood vessels

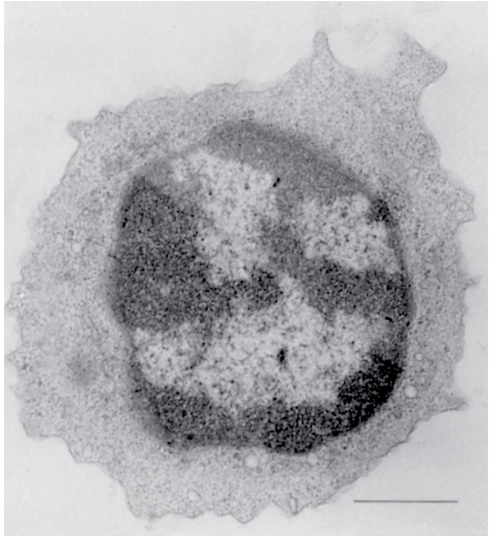
Detection

Lymphocyte Binding and Cross-reactivity



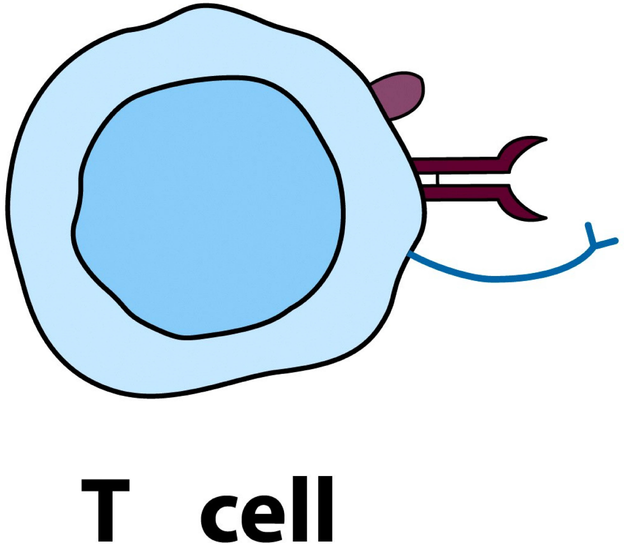
B-cells and T-cells



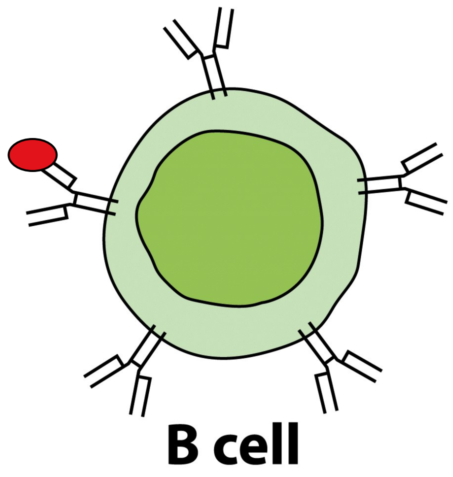


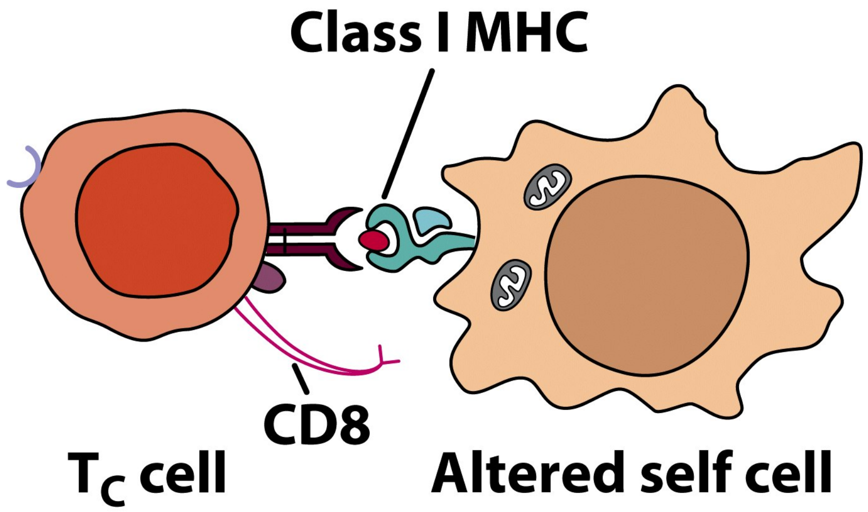
Small lymphocyte (T or B)
6 μm diameter

Figure 2-6b part 1

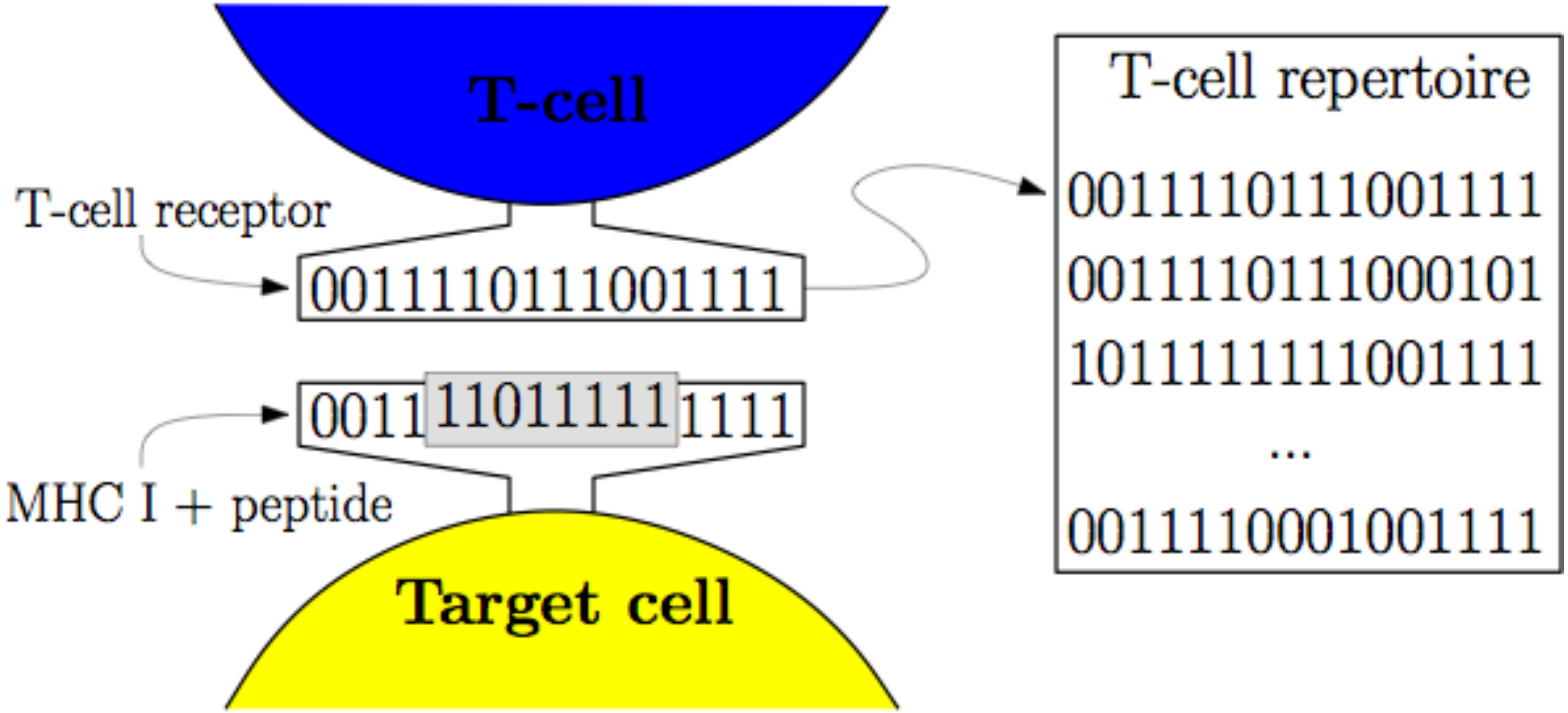



Antigen
Antibody


B cell

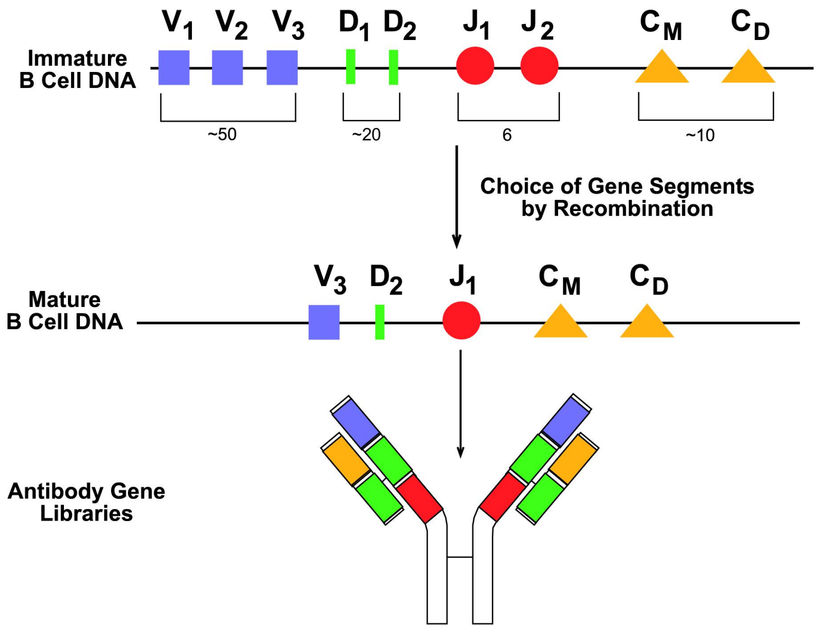

Class I MHC
CD8
T_C cell
Altered self cell

Fundamental Modeling Abstraction

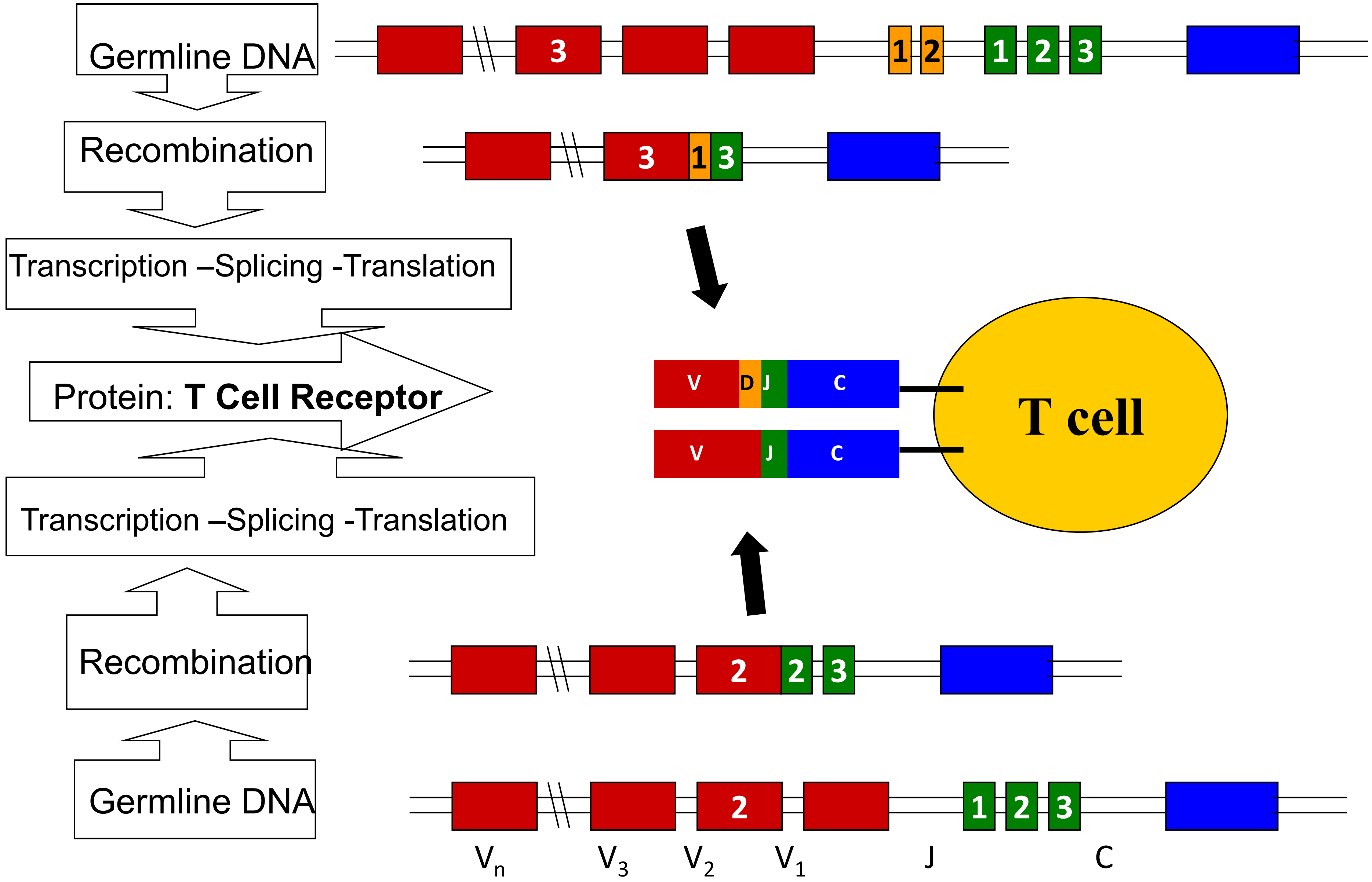


How does the I.S. make so many different receptor patterns?

- Recombination of gene fragments
- Junctional diversity
- Diploid genetics
- Somatic mutation



Generation of Diversity in Antigen Receptors



Element	Immunoglobulin		α:β receptors	
	H	κ+λ	β	α
Variable segments (V)	65	70	52	~70
Diversity segments (D)	27	0	2	0
D segments read in 3 frames	rarely	–	often	–
Joining segments (J)	6	5(κ) 4(λ)	13	61
Joints with N- and P- nucleotides	2	50% of joints	2	1
Number of V gene pairs	3.4×10^6		5.8×10^6	
Junctional diversity	$\sim 3 \times 10^7$		$\sim 2 \times 10^{11}$	
Total diversity	$\sim 10^{14}$		$\sim 10^{18}$	

Fig 4.13 © 2001 Garland Science

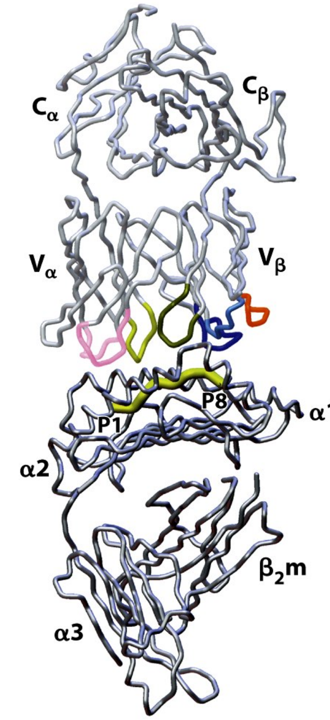


Figure 9-14b
Kuby IMMUNOLOGY, Sixth Edition

How much diversity?

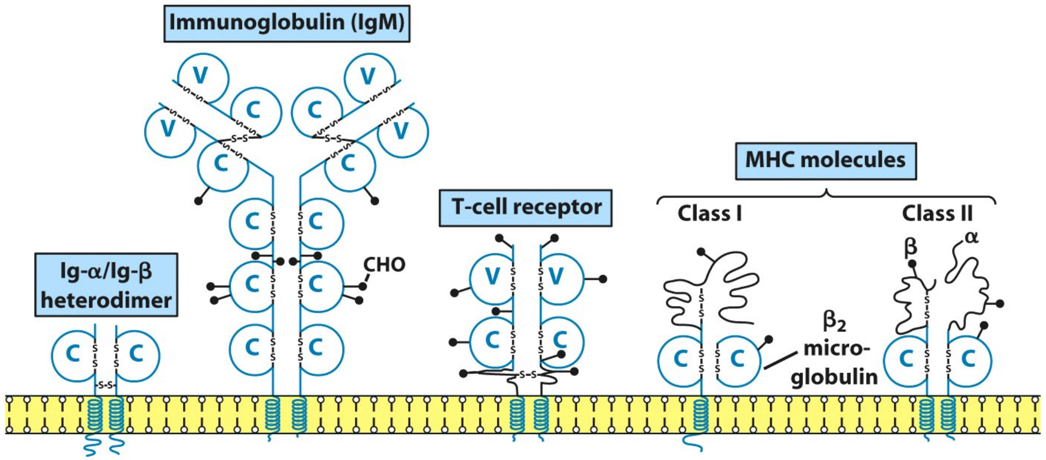


Figure 4-24 part 1
Kuby IMMUNOLOGY, Sixth Edition

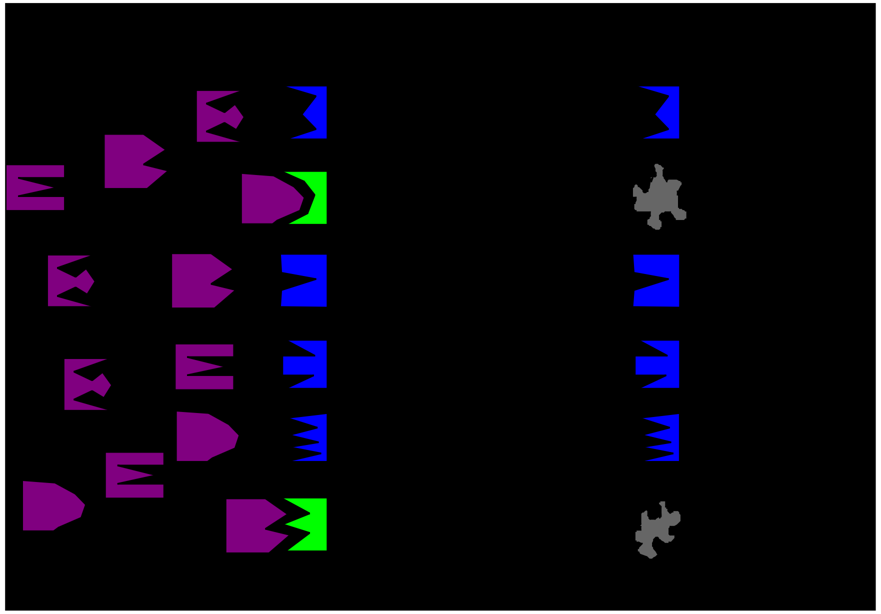
How does the I.S. make a diverse set of receptors that avoids autoimmunity?

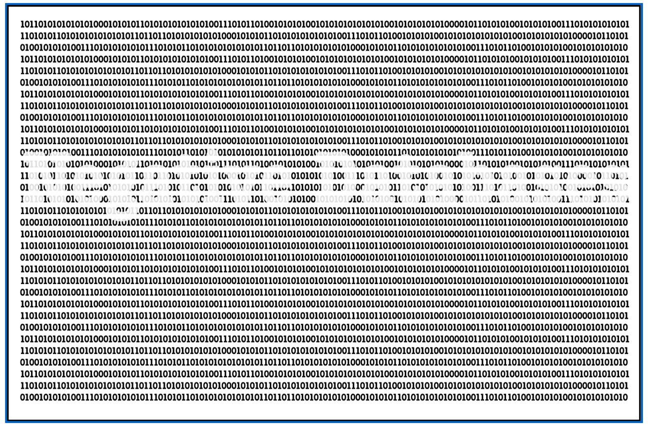
- Clonal Selection Theory
- Believed that any correct theory must explain:
  - How antigen selects correct specificity
  - Why only a single specificity is produced
  - How self tolerance is maintained
  - Why second response to same antigen is so much
  - larger than the first

Frank Macfarlane Burnet
Nobel Prize, 1958

Clonal Selection Theory

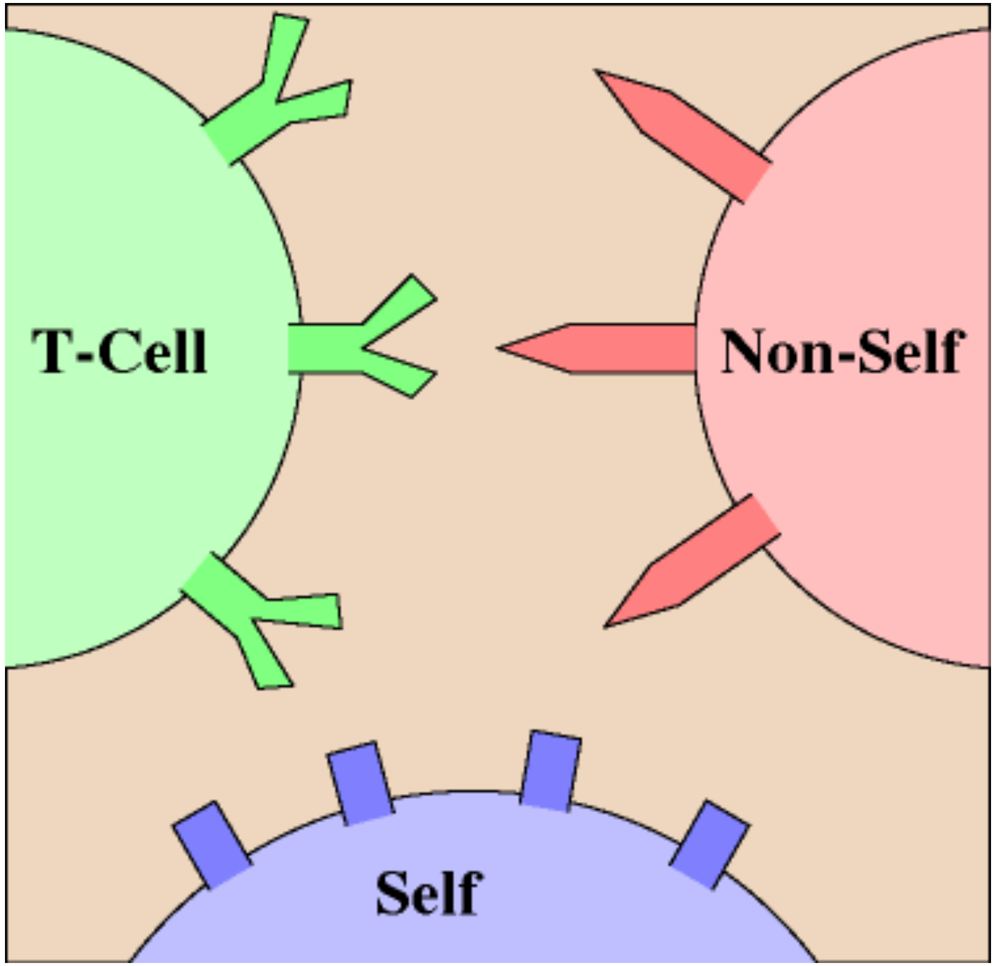
- Each lymphocyte is a unique clone with its own specificity
- Negative selection
  - If an immature lymphoctye binds Ag*, it dies
  - Mature pool of cells represents those that did not bind to Ag during development
- A mature lymphocyte is stimulated to divide when it encounters Ag*
  - Clonal expansion

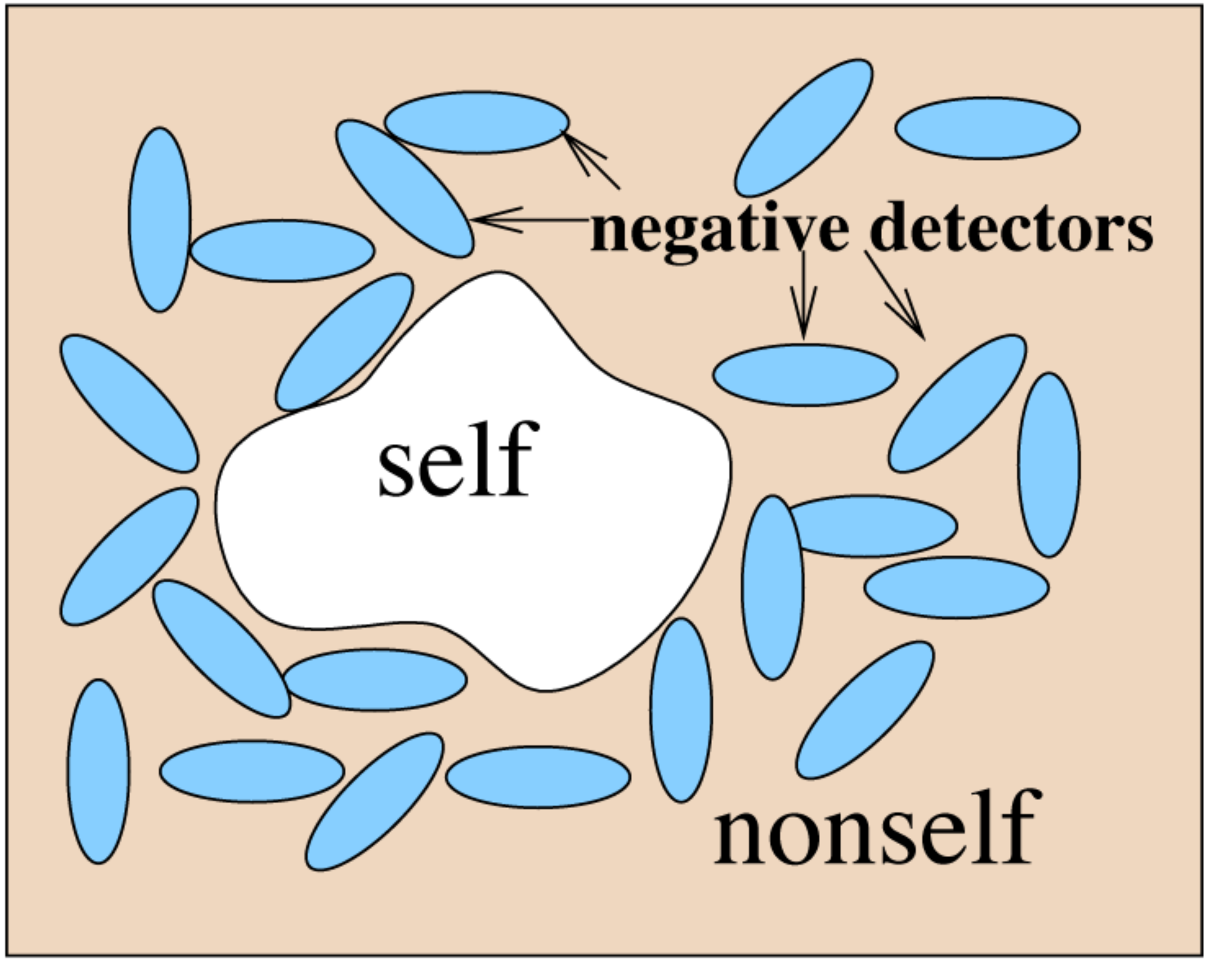




*Ag stands for antigen.

Negative Selection





Positive and Negative Selection

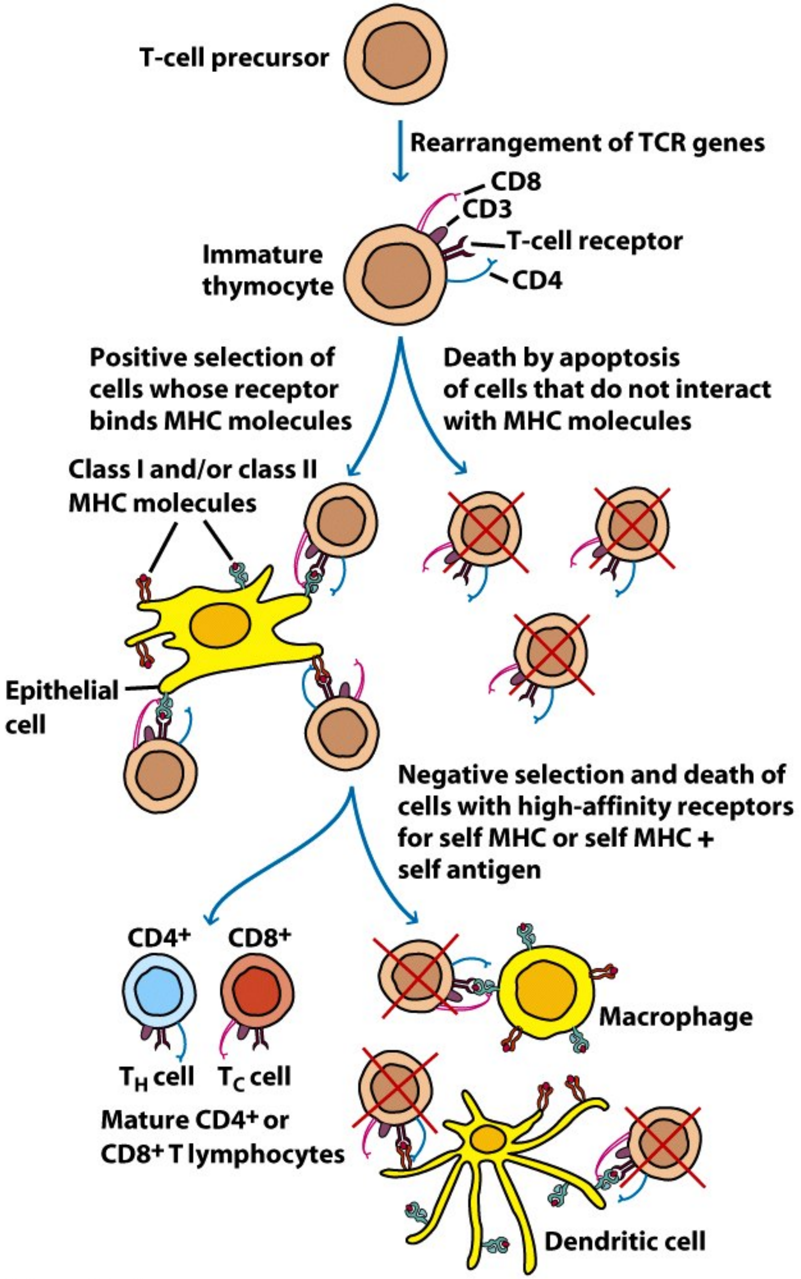
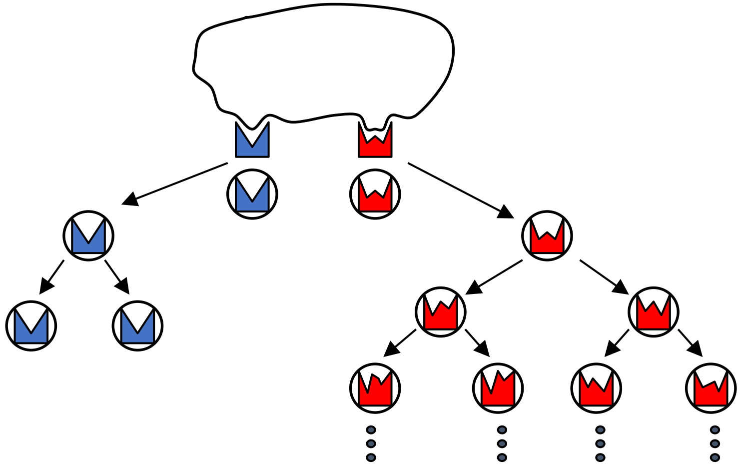
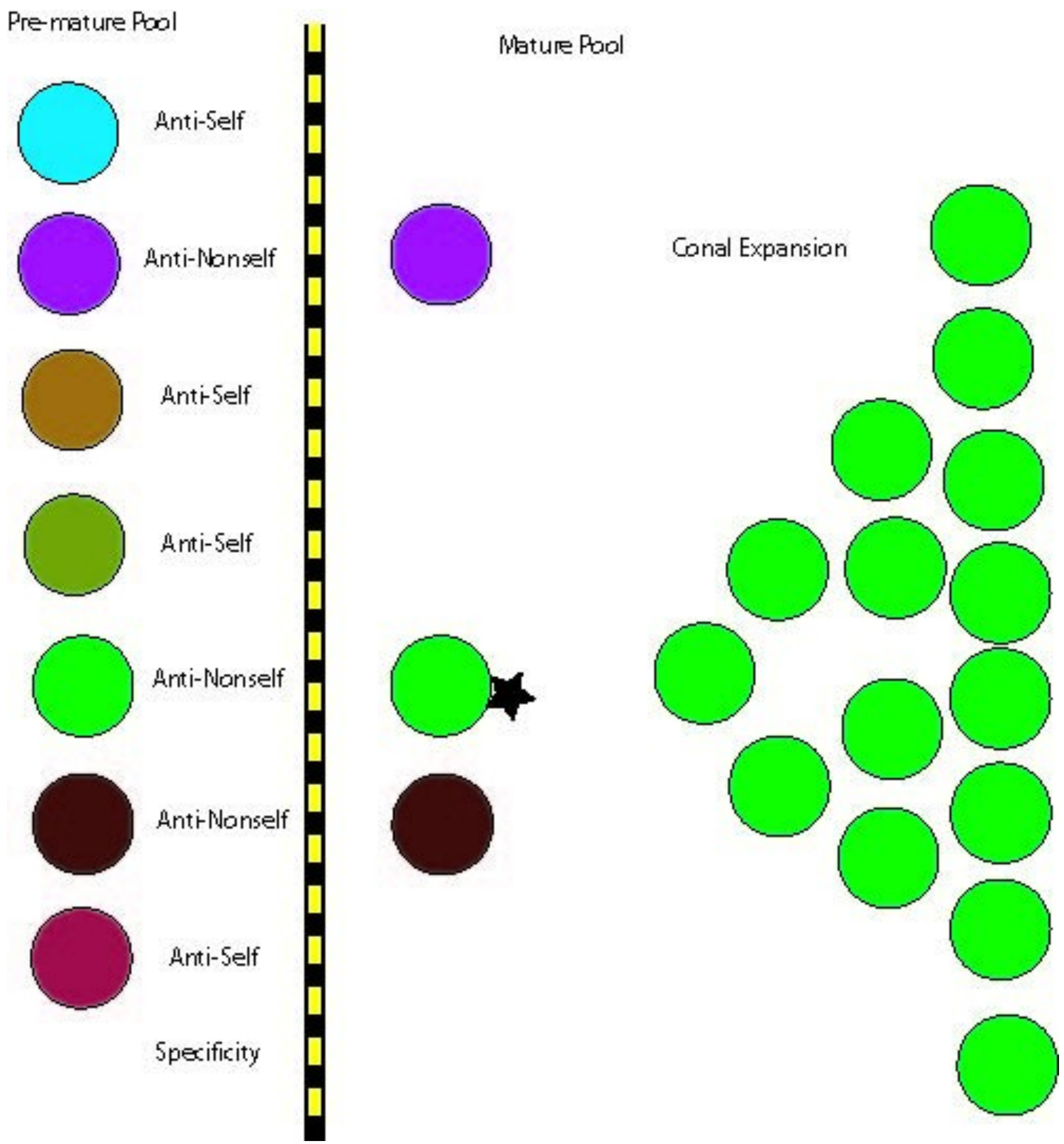


Figure 10-6
Kuby IMMUNOLOGY, Sixth Edition

Clonal Expansion

- B-cells compete for antigen
  - Affinity (binding strength)
  - Avidity (average affinity over all)
- Proliferation phase in LN
- Somatic hypermutation





* = Antigen

Managing the Immune Response

- How does the immune system know what to respond to?
- How does the immune system choose the type of response?
- How does the immune system adjust the magnitude of response?
- How does the response terminate?

- Experimentalists generally focus on the specific cell and molecule types required
- A more abstract view focuses on general pattern matching and distributed control principles

Managing the Immune Response

- Complex network of signaling molecules, called cytokines
  - Interleukin, interferon, etc.
- Every cytokine type affects multiple cells
  - ~100 different cytokine types
- Every function (immune response) is affected by multiple cytokines
- Immune cells secrete a mixture (vector) of cytokines
- Signals are molecules, and therefore distributed (locally) by diffusion
- Signals can be subverted (e.g., viruses can evolve to avoid or interfere with cytokines, e.g., by blocking receptors), so there is an evolutionary pressure towards robust, secure networks
- Current state of knowledge
  - Many points of light
  - No systematic theory

Managing the Immune Response

- Complex network of signaling molecules, called cytokines
  - Interleukin, interferon, etc.
- Every cytokine type affects multiple cells
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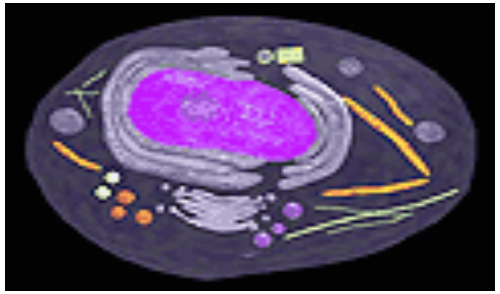
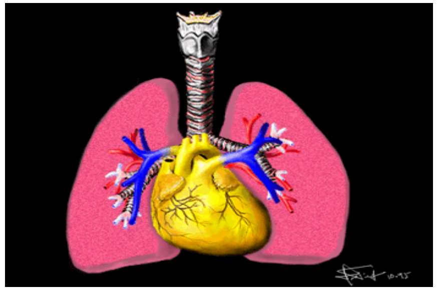
- Immune cells secrete a mixture (vector) of cytokines
- Signals are molecules, and therefore distributed (locally) by diffusion
- Signals can be subverted (e.g., viruses can evolve to avoid or interfere with cytokines, e.g., by blocking receptors), so there is an evolutionary pressure towards robust, secure networks
- Current state of knowledge
  - Many points of light
  - No systematic theory

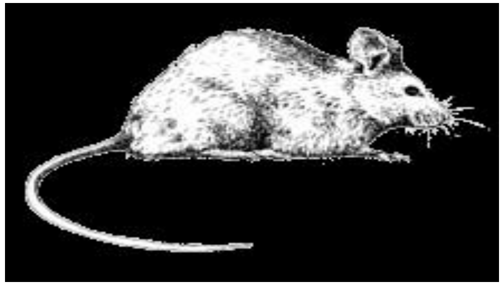
Compare to the foraging strategies of ants

Modeling the Immune System

- Intracellular
- Organ
- Systemic





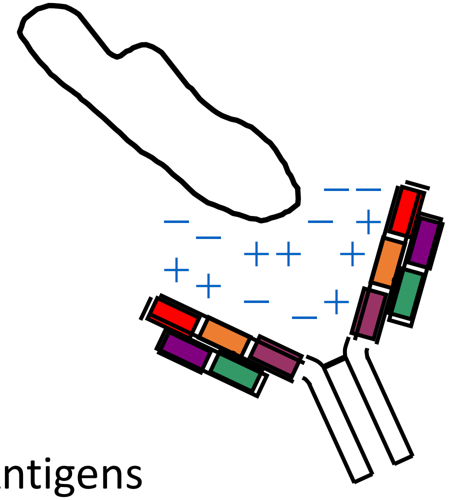


Approaches to Modeling Immune Systems

- Differential equations
  - Each equation describes the concentration of a different antibody/cell type
- Molecular dynamics simulations
- Agent-based models
  - E.g., cellular automata, genetic algorithms, and Smith's B-cell model
- Focus on informational aspects of immune systems

Artificial Immune Systems

Immune System Models



0011000101 Antigen
1100111010 Antibody

Antigens

1101001000100010
0101010101010011
1101010101000111
0000111100010001
0111000100010001
1100001010100110

Antibodies

1100100100010010
0000110100011000
1110001101010011

Antigen Presentation

1100100100010010
1100001010100110

Antigen/Antibody Binding

Mapping

Immune System

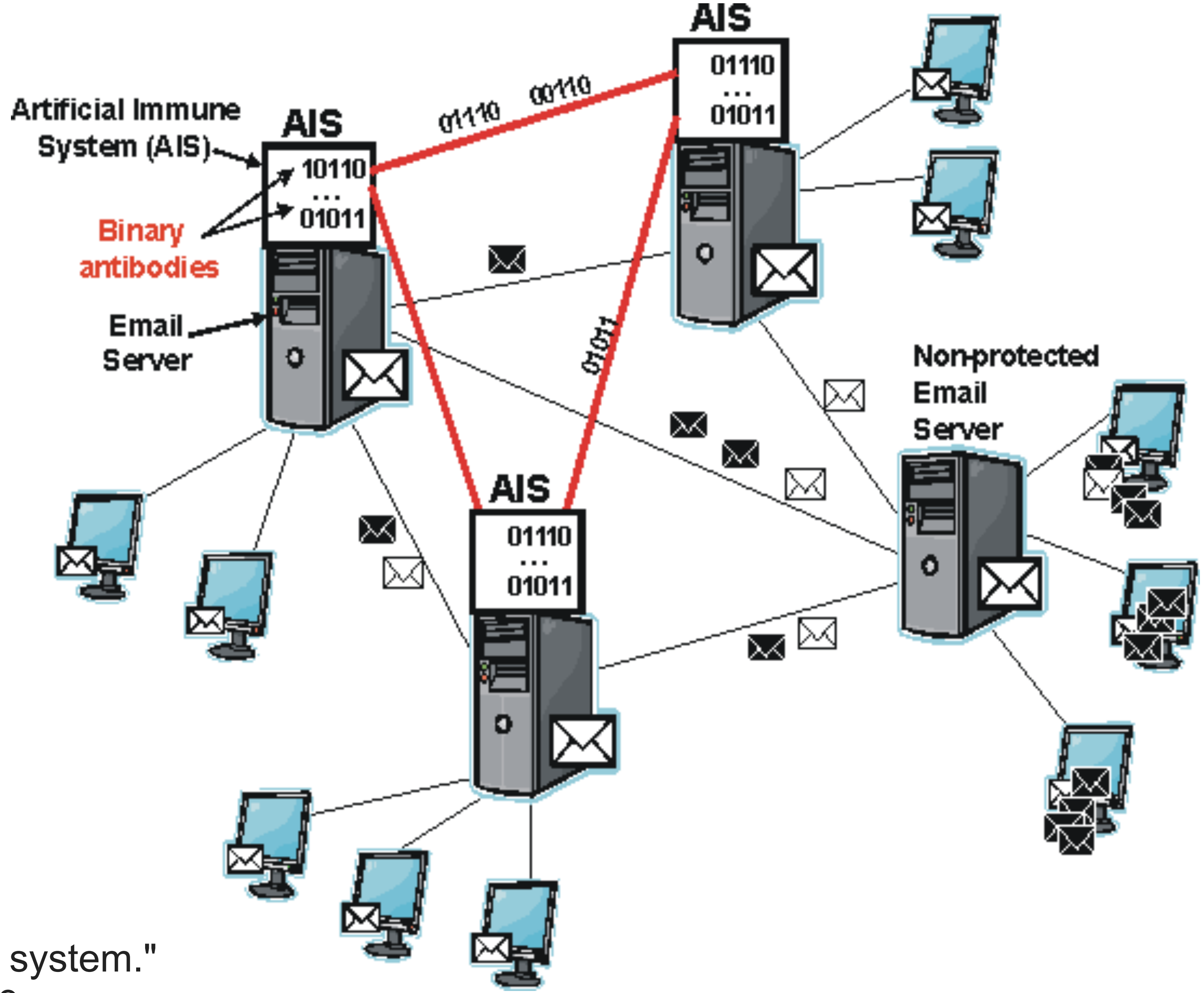
- Lymphocytes (b-cells, t-cells, antibodies)
- Pathogens (antigens)
- Proteins (nucleic acids)
- Inter-molecular binding
- Antibody/pathogen binding

Computer Science

- Detectors
- Intruders, foreign code
- Strings
- Partial string matching
- Pattern matching

Example AIS Application Areas

- Data mining and clustering
- Computer security
- Other anomaly detection problems
- Fault isolation and tolerance
- Recommenders and filterers
- Robotics
- Data storage



Aickelin, Uwe, Dipankar Dasgupta, and Feng Gu. "Artificial immune systems." *Search Methodologies*. Springer US, 2014. 187-211.

Hofmeyr, Steven A., and Stephanie Forrest. "Architecture for an artificial immune system." *Evolutionary computation* 8.4 (2000): 443-473.