

Distributed Intelligent Systems

EPFL, WS 2019-2020

https://disal.epfl.ch/teaching/distributed_intelligent_systems/

Distributed Intelligent Systems – W1

Part I: Course Organization, Team, and Content

Team Involved in the Course

<https://disal.epfl.ch>

- **Instructor:** Alcherio Martinoli
- **Guest lecturer:** Anwar Quraishi
- **Teaching assistants:**
 - Cyrill Baumann (Head TA, PhD student)
 - Chiara Ercolani (TA, PhD student)
 - Anwar Quraishi (TA, PhD student)
 - Faezeh Rahbar (TA, PhD student)
- **Support staff:**
 - Zeki Erden (help TA, Robotics master student)
 - Alicja Wasik (PhD student)

Access to e-Material and Computer Room

- **Moodle** web site for the course:
 - Students registered for the course on IS-Academia are automatically registered for the course on Moodle (re-synch daily over night)
 - If issues in accessing the Moodle web site despite registration in ISA, please contact dis-ta@groupes.epfl.ch
 - For PhD students and other special cases (supported by a section), because of limited enrollment, please contact me first
- For **non-SIE students** we need to request for you explicit access rights for the computer room and GR building; we will do so based on the final enrollment list (frozen on September 27)

Rationale for This Course

Rationale

- Well-balanced course: theory, algorithms and experimental labs
- Understand quantitatively natural collective phenomena (focus on biological societies) and how to combine bio-inspired principles with advanced engineering methods
- Understand how to model, design, control, evaluate, and optimize distributed intelligent systems
- Learn to process scientific literature efficiently: prioritize readings, dig out papers, find connections

What is this Course about

- Distributed **natural** and **artificial** systems
- **Coordination** algorithms
- Distributed **sensing** and **action**
- **Models, simulation tools, and machine-learning** targeted to distributed intelligent systems
- Multi-robot systems and wireless sensor networks

Course Prerequisites

- C and Matlab knowledge
- Fundamentals of programming
- Fundamentals of probability calculus
- Fundamentals of analysis (differential equations, continuous and discrete time)
- Fundamentals of linear algebra
- Fundamentals in signal and systems

For SIE students: BS introductive course on Signals, Instruments, and Systems highly recommended!

Organization of the Course

This Edition

- Preserved good innovations: lab verification test, primary/secondary reading breakdown, limited number of well-prepared TAs in the lab sessions, single topic for the course project
- Major differences with last edition:
 - Back to 10 labs in total
 - Lab verification test including all labs
 - Course project starts 2 weeks earlier
 - DISAL Arduino/Xbee node instead of MICA-Z
- dis-ta@groupe.epfl.ch for any inquiries and for scheduling office hours

This Edition

- Limited enrollment (60 places)
- Can unenrol during the first two weeks (until Sep 27), then no longer possible; enrollment possible if seats available (until Sep 27).
- I keep a waiting list, please make up your mind as soon as possible; I noticed the enrolment is already quite dynamic (some students on the waiting list made it in already)
- 5 seats buffer (for PhD students and special cases supported by sections)

Credits and Workload

- 5 ECTS
- 1 ECTS = 30 h workload → 150 h workload
- Rough breakdown
 - 60 h lecture (including reading and exam prep)
 - 45 h exercise (including preparation and test)
 - 45 h course project (including report and defense)

Grade

- Final **written** exam, winter session:
 - 180 minutes;
 - open book with simple non-programmable calculator;
 - all topics covered in the lecture/exercise and selected distributed reading material
- 50% performance during semester, 50% performance during the exam (compromise US/Europe style)
- During semester: lab verification test 25%; course project 25%

Lecture

- Tue 10:15-12:00
- **This week and 13th week** exceptionally also on Wednesday (09:15 – 12:00) instead of exercises, in the same room
- **Last week:** project defenses in the same lecture room (see syllabus for details)

Lecture Notes

- **Preliminary** lecture slides in pdf format available for download on Moodle **before** each lecture (Monday late evening), **definitive** ones **after** lecture by Friday at latest)
- Will notify when ready in definitive format via Moodle forum (i.e. you will receive an e-mail)

Reading and Handouts

- Policy: master, research-oriented course → no manuscript!
→ slides + papers/book chapters + web
- Break down in 3 categories:
 - **Primary**: covered substantially during the lecture; available on moodle
 - **Secondary**: covered marginally during the lecture; available on moodle
 - **Tertiary**: pointers on the lecture notes for interested students, not covered in the lecture and not available for download
- Roughly **50 single-column pages/week** of **primary** literature to read; list and primary/secondary breakdown subject to change during the semester
- Primary and secondary reading distributed the week before for easing exercise preparation & lecture understanding

Suggestions for a **Successful** Course Material Processing

From last years experience:

- For high-gear courses such as this one with a lot of raw material to process: it is worth taking advantage of the lecture for having an idea about what's important and what not
- Trained ability: reading what's needed and quickly, seeing connections between various “raw” pieces of the puzzle

Labs

- Lab session: 3 h on Wed, 09:15-12:00, GR B0 01 and GR C0 02
- Mini-tutorial (< 10 min) by the main lab designer at the beginning of the lab
- 3 TAs per lab session (1 designer, 2 testers)
- 10 lab sets total, **not graded (solution distributed)**
- 1 lab verification test, in the computer room, **graded (personalized feedback)**, mixture of computer-based and paper-based exercises, on W12, on content of all labs

From last years experience:

- Read the lab assignments in advance, in this way you will be more efficient when the TAs are around for helping you on the toughest questions ...
- Have an idea of the point distribution of any assignment: this roughly corresponds to the breakdown in time you should have; if your time is tight invest where it is worth!
- Take lab notes so that you will find them for the lab verification test
- If you do not work enough independently during labs, it will be difficult to solve the problem set alone in the test
- “Paper-based” questions are a good training for the final exam
- Previous edition lab/test assignments are on the web

Course Project (1)

- **Single topic** for the whole class
- Student team consolidation and team grouping for office hours in W5
- 45 h effort, from W6 (kick-off during lab session) to W14 (oral presentation)
- Team of **3 students (default)** or 4 students (if needed); goal: **2 different teaching programs/sections per team**
- Assistance for course projects: up to 4 weekly office hours (30-60 min per TA) between kick-off (W6) and wrap-up week (W13); **no extra office hours possible (even up to appointment) for the project; no course project questions during lab sessions**

Course Project (2)

- Will distribute hardware and software at home
- Project report to be submitted (max # of pages and format pre-established) end of W13
- Final presentation in front of the class
- Each of the project will have another team of students as reviewers
- Each team member has to present
- Project defenses during W14 (lecture & lab hours)

Suggestions for a Successful Course Project

From last years experience:

- Take advantage of the first 4 weeks for asking questions to TAs about the course project, check course web site for previous editions in order to get an idea of the effort
- Between W3 and W4, form your team
- Plan your effort (milestone, time, etc.), coordinate roles within your team

Collaboration Policy

- Lecture and exam preparation: encouraged
- Lab: discussion encouraged but work individually
- Course project: team work
- Lab verification test and final exam: collaboration penalized ...

Course Syllabus and Summary

Goal

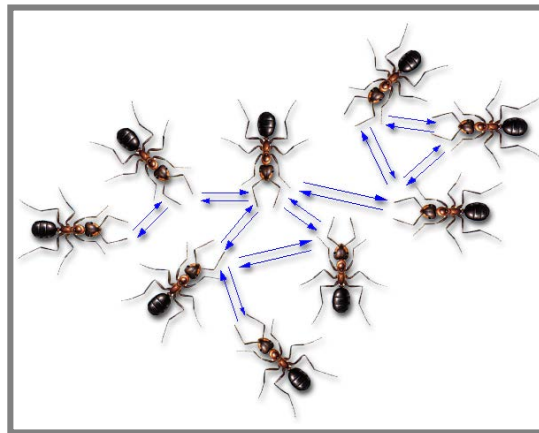
- Course overview
- Course flavor
- 4 main blocks
- A few slides per block

Block I – Swarm Intelligence

- Key Principles of Swarm Intelligence
- Trail laying/following mechanisms
- Ant Colony Optimization as an example of a successful multi-agent metaheuristic

From Natural to Artificial Systems

- **Modeling** to understand microscopic to macroscopic transformation
- **Modeling** as interface to artificial systems



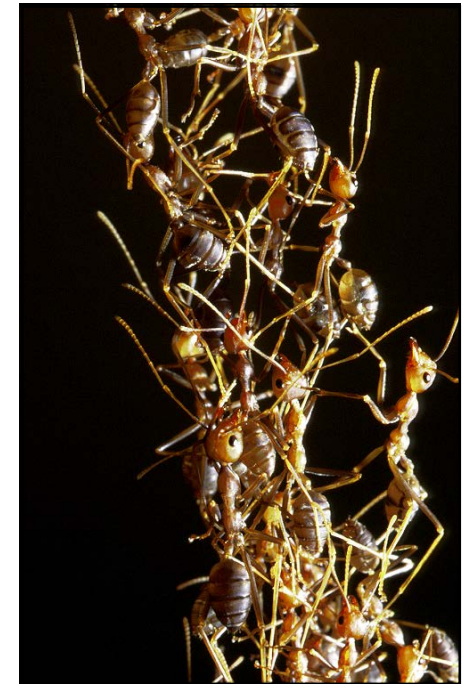
Individual behaviors
and local interactions



Modeling

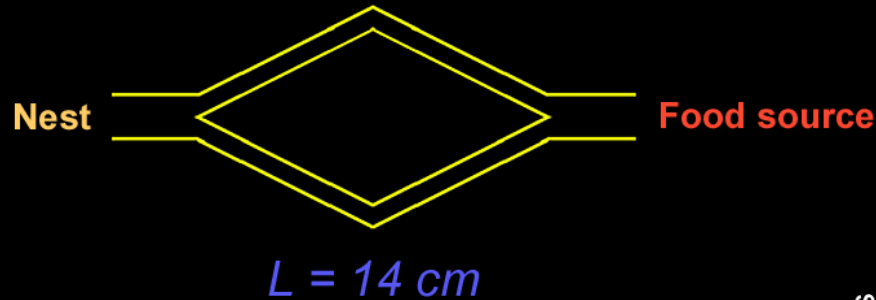


Ideas for
artificial
systems

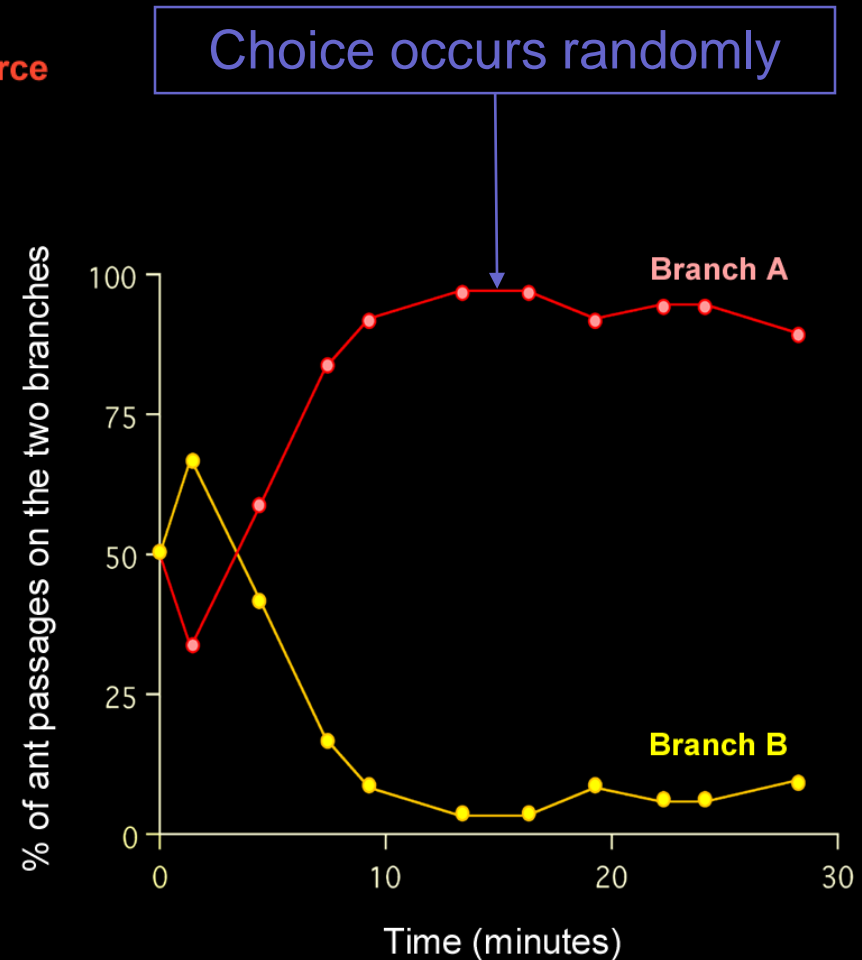


Global structures
and collective
decisions

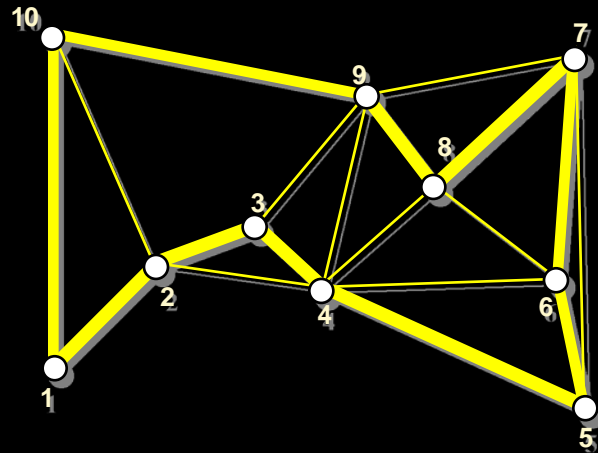
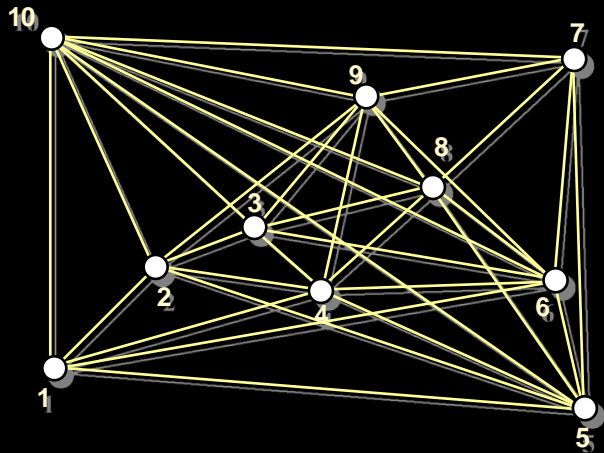
Biological Mechanisms and Models



(Deneubourg *et al.*, 1990)



The Traveling Salesman Problem



Graph (N, E)

N : set of cities (nodes)

E : set of connecting roads (links)

d_{ij} : distance between city i and j

Problem: Find the shortest path which allow the salesman to visit once and only once each city in the graph

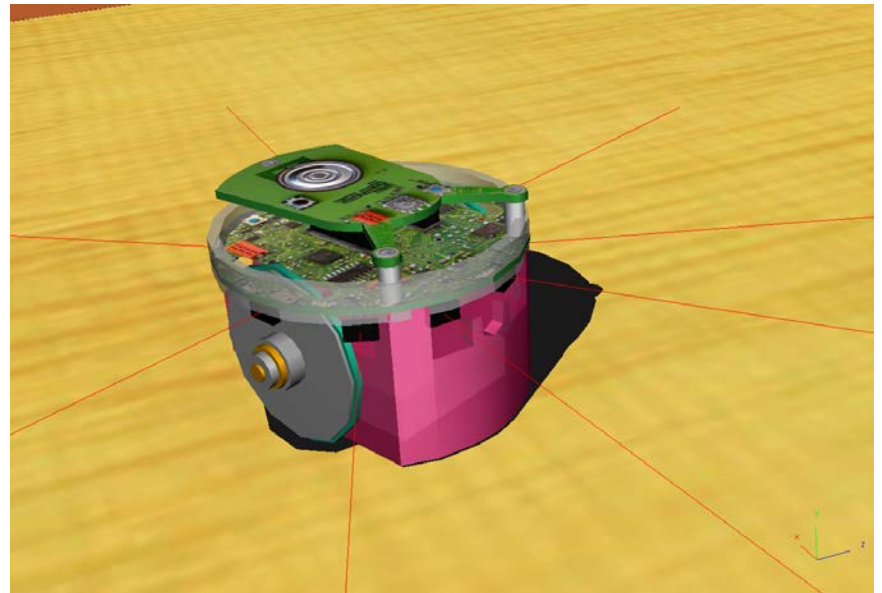
Difficulty: NP-hard problem; time for computing the shortest route grows in a nonpolynomial way with the number of cities in the network -> metaheuristics provide near-optimal solutions!

Block II – Individual Nodes

- Introduction to mobile robotics
- Robotic tools (simulation and real HW)
- Basic control architectures

Real and Simulated e-puck

- Appropriate size for desktop
- Multi-robot operation ok
- No manipulation, no highly accurate odometry
- Webots realistic robotic simulator
- Discrete sensor and actuators
- Single and multi-robot simulator

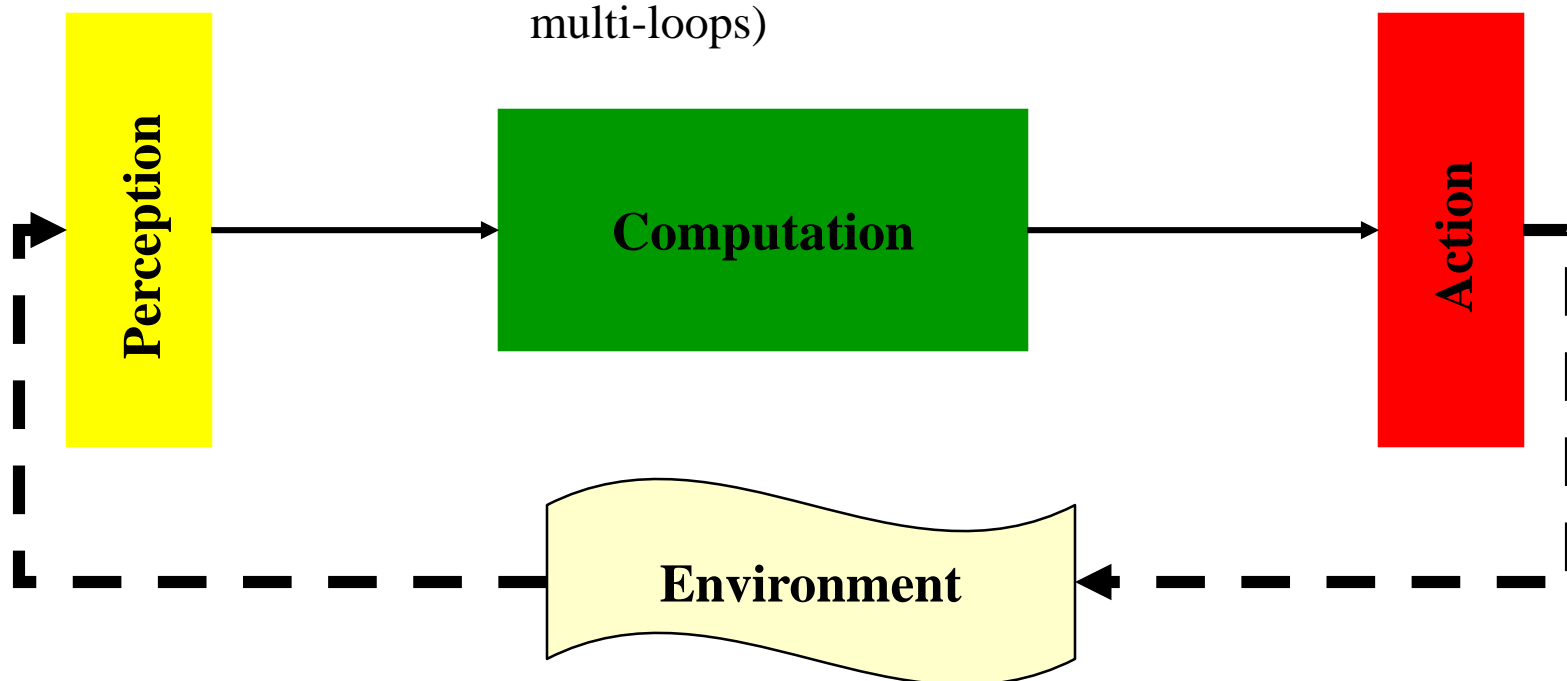


Perception-to-Action Loop

• sensors

- Reactive (e.g., nonlinear transform, single loop)
- Reactive + memory (e.g. filter, state variable, multi-loops)
- Deliberative (e.g. planning, multi-loops)

• actuators

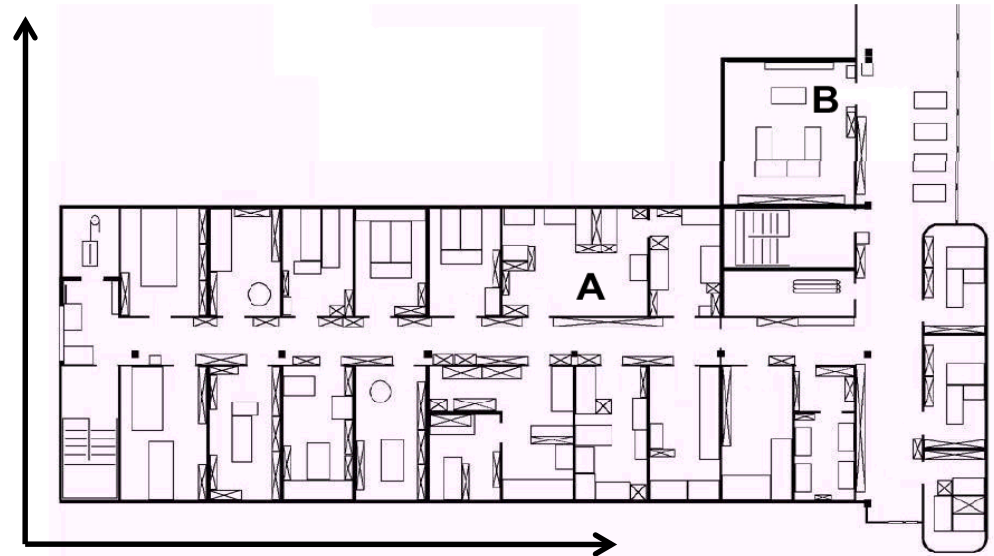


Robot Localization



N 46° 31' 13"
E 6 ° 34' 04"

- Key task for:
 - Path planning
 - Mapping
 - Referencing
 - Coordination
- Type of localization
 - Absolute coordinates
 - Local coordinates
 - Topological information



Block III – Coordination Algorithms, Modeling and Optimization

- Collective movements, consensus, task-allocation, and decision-making
- Multi-level modeling
- Particle Swarm Optimization

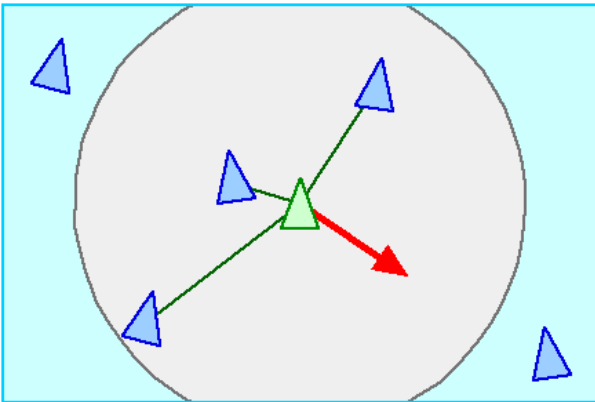
Ex. of Collective Movements



Reynolds' Rules for Flocking

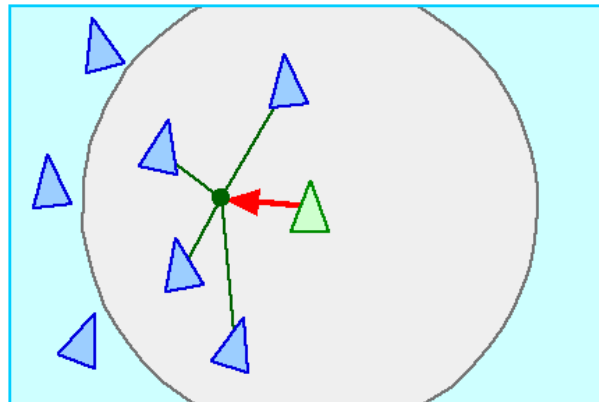
1. **Separation**: avoid collisions with nearby flockmates
2. **Alignment**: attempt to match velocity (speed and direction) with nearby flockmates
3. **Cohesion**: attempt to stay close to nearby flockmates

Position control



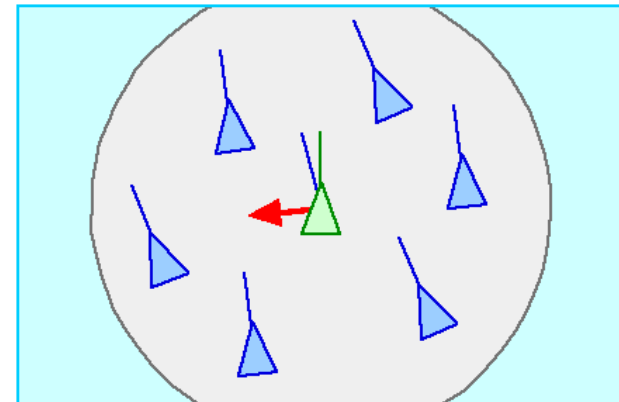
separation

Velocity control



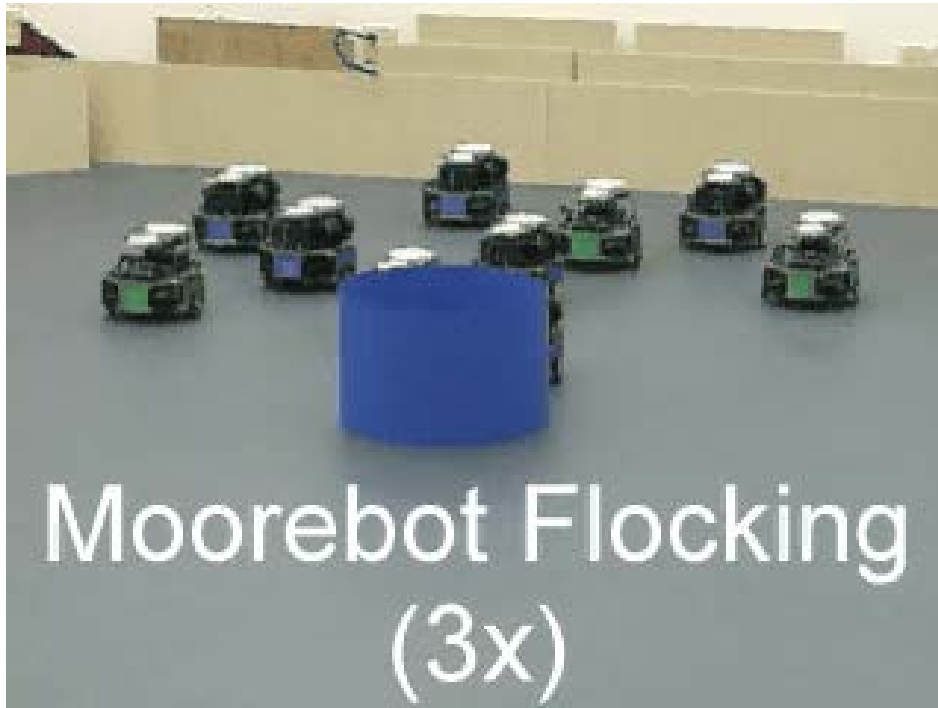
alignment

Position control

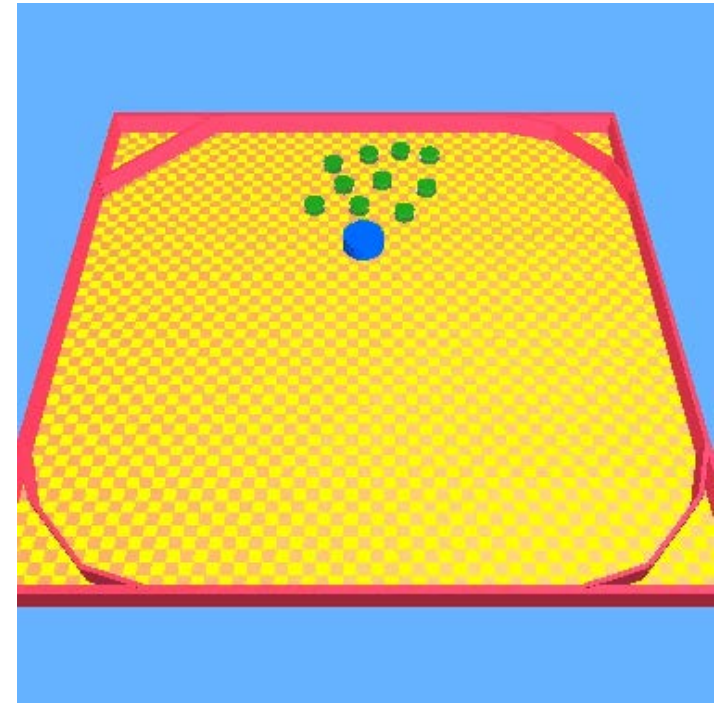


cohesion

Implementation of Flocking Rules in Artificial Embedded Agents

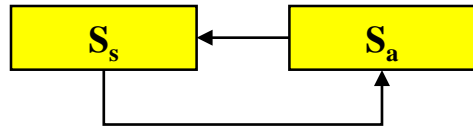


Real robots



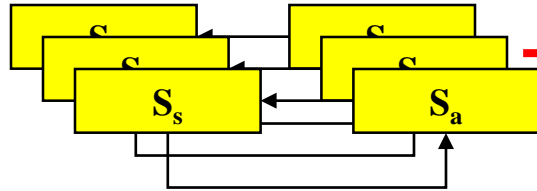
Realistic simulator (Webots)

Multi-Level Modeling Methodology

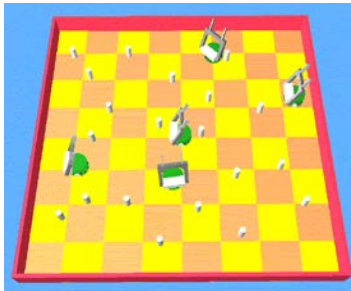


$$\frac{dN_n(t)}{dt} = \sum_{n'} W(n | n', t) N_{n'}(t) - \sum_{n'} W(n' | n, t) N_n(t)$$

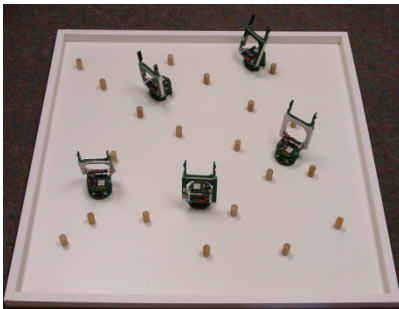
→ **Macroscopic**: rate equations, mean field approach, whole swarm



→ **Microscopic**: multi-agent models, only relevant robot feature captured, 1 agent = 1 robot



→ **Submicroscopic**: intra-robot (e.g., S&A, transceiver) and environment (e.g., physics) details reproduced faithfully



→ **Target system** (physical reality): info on controller, S&A, communication, morphology and environmental features

Experimental time

Abstraction

Common metrics

The Main PSO Loop

(Eberhart, Kennedy, and Shi, 1995, 1998)

At each time step t

for each particle i

for each component j

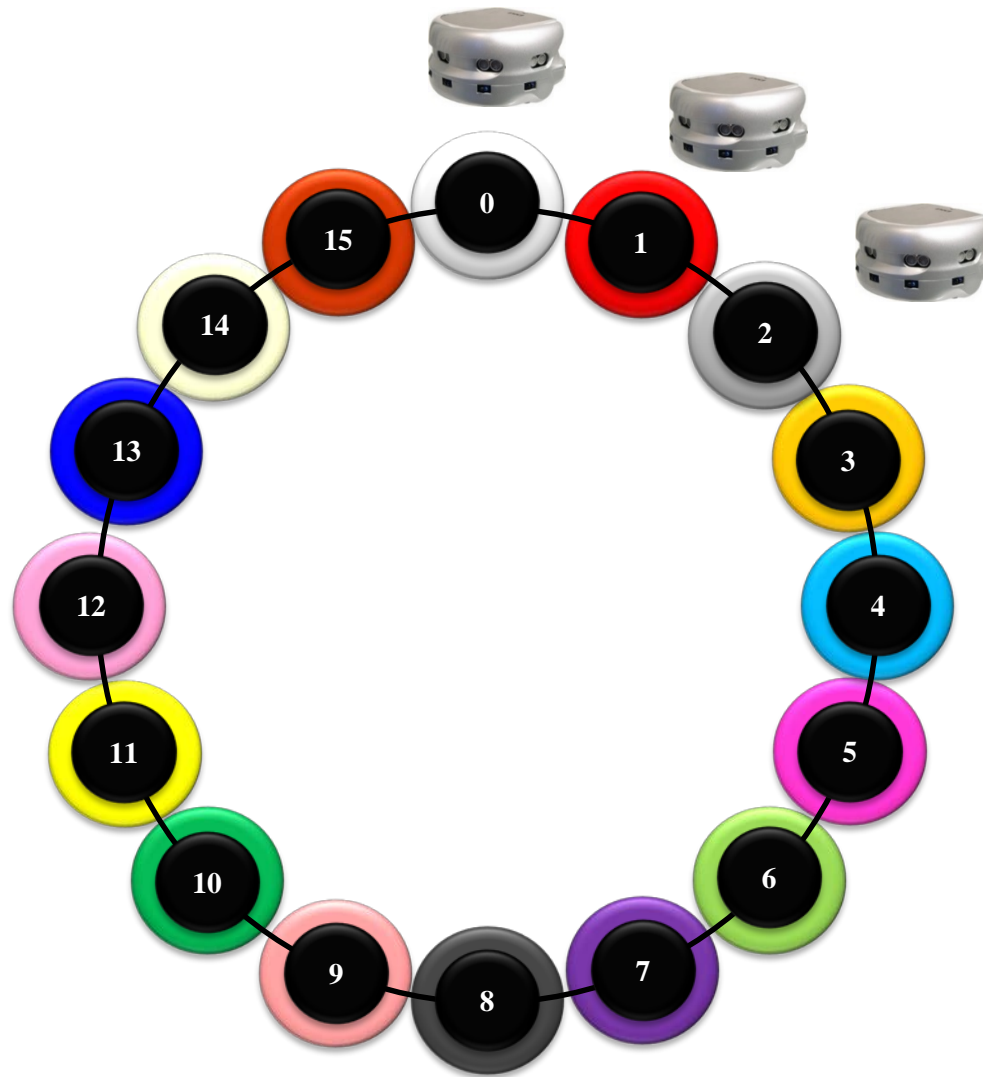
update the
velocity

$$v_{ij}(t+1) = wv_{ij}(t) + c_p rand()(x_{ij}^* - x_{ij}) + c_n rand()(x_{i'j}^* - x_{ij})$$

then move

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1)$$

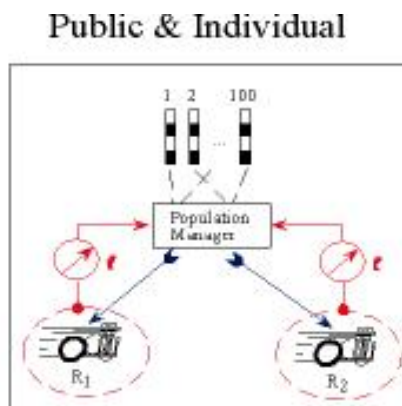
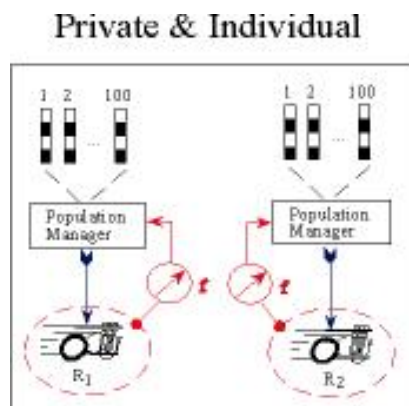
PSO with Single Robot



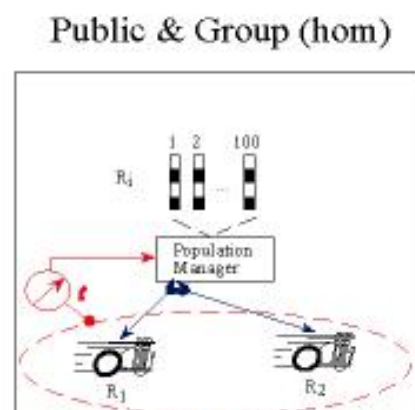
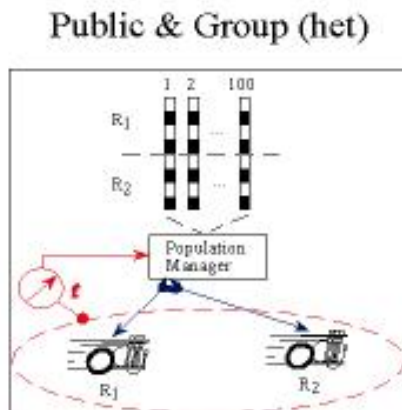
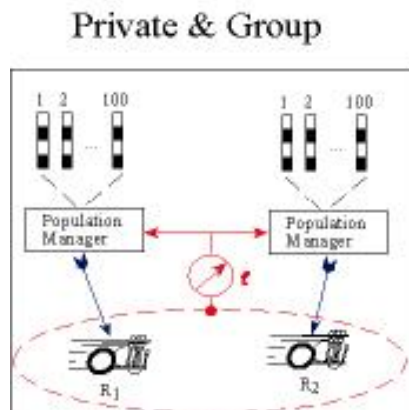
Co-Learning Collaborative Behavior

Three orthogonal axes to consider (extremities or balanced solutions are possible):

- **Individual** and **group** fitness
- **Private** (non-sharing of parameters) and **public** (parameter sharing) policies
- **Homogeneous** vs. **heterogeneous** systems

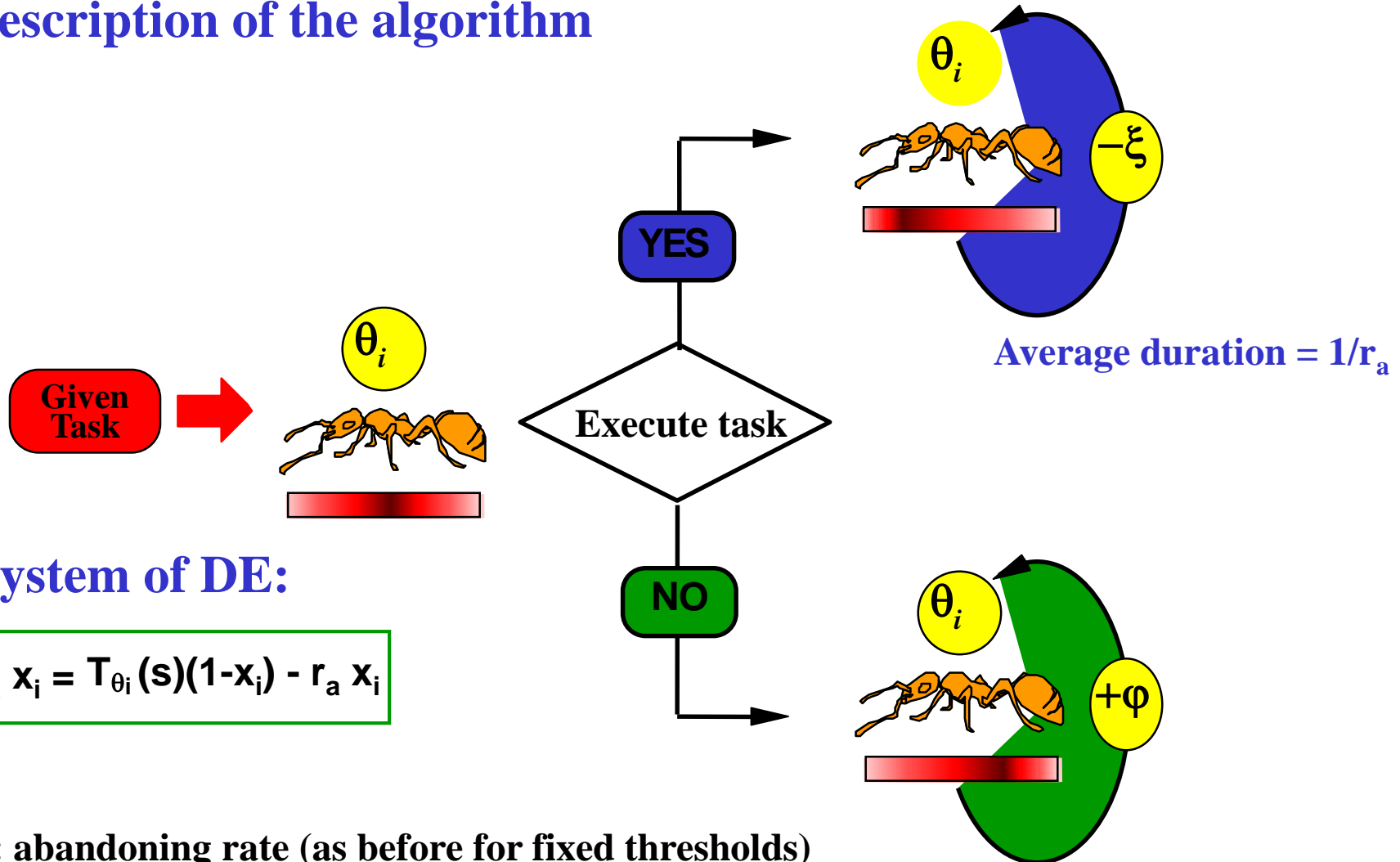


Example with binary encoding of candidate solutions



Threshold-Based Task Allocation

Description of the algorithm



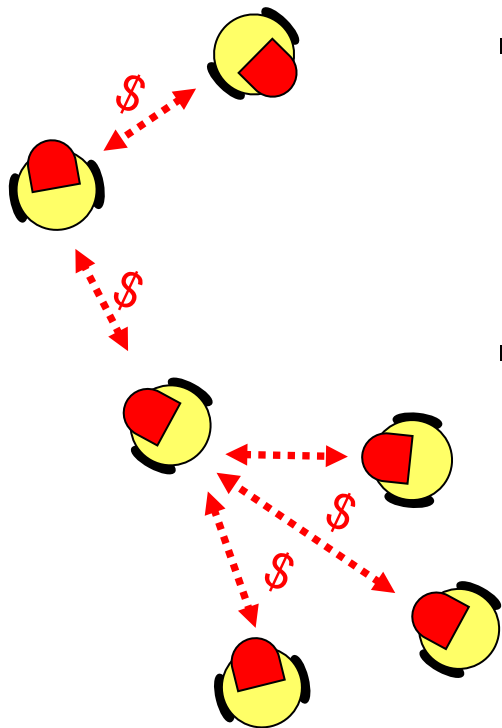
Market-Based Task Allocation

Robots simulate a market economy:

- Tasks, resources are commodities of measurable worth.
- When robot performs task:
 - gets paid for service it provided (+ \$)
 - pays for resources it consumed (- \$)
- Robots trade tasks and resources to maximize profit

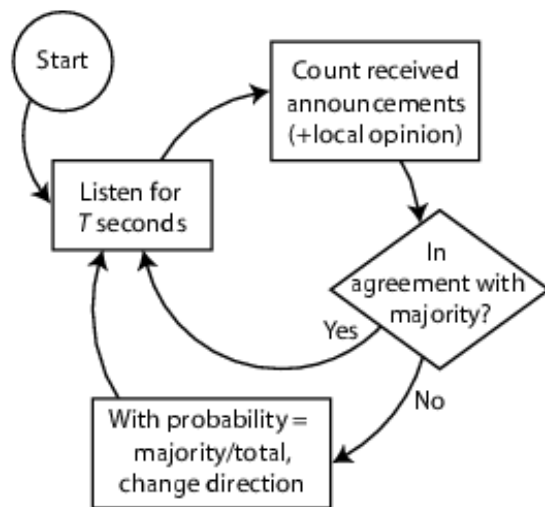
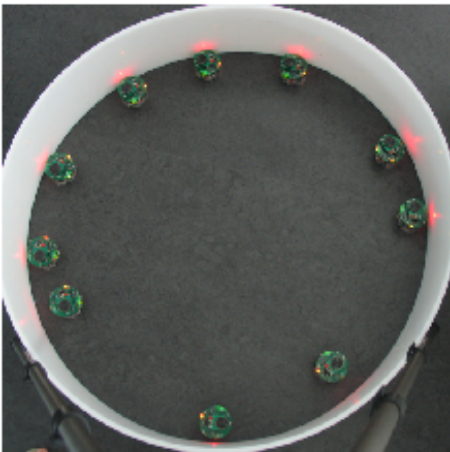
Idea! pursuit of individual profit leads to efficient team solutions.

- ✓ Robust, fast, handle complex tasks
- ✓ Can take advantage of centralized planning



Collective Decision-Making: Selecting the Rotation Direction

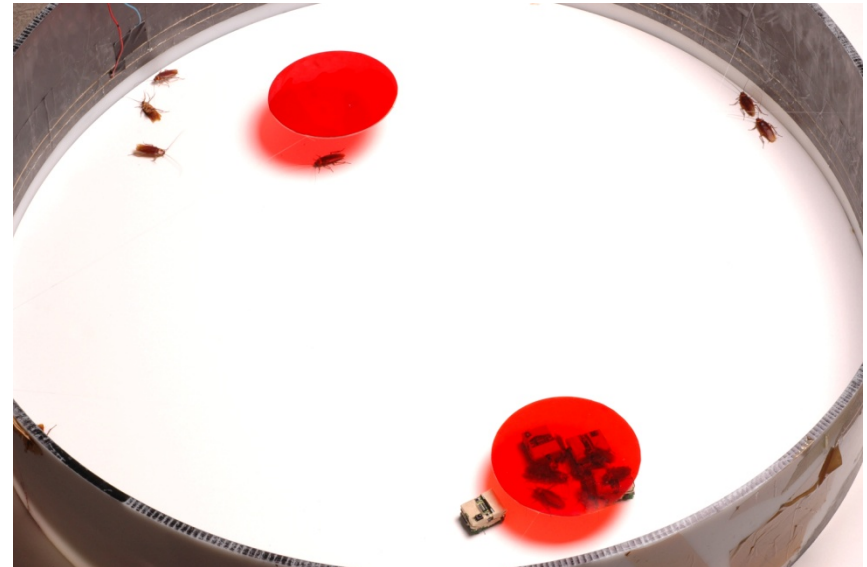
- 10 robots execute wall-following behavior (CW or CCW, initially random)
- announce their current direction on the radio channel



- # of votes not constant
- probabilistic decision
- communication **range** affects time to convergence.

Collective Decision-Making: Selecting a Shelter

- **Leurre**: European project focusing on mixed insect-robot societies (<http://leurre.ulb.ac.be>)
- A simple decision-making scenario: 1 arena, 2 shelters
- Shelters of the same and different darkness
- Groups of pure cockroaches (16), mixed robot+cockroaches (12+4)
- Infiltration using chemical camouflage and statistical behavioral model



Block IV –Topics in Distributed Environmental Sensing

- Static and mobile sensor networks
- Robotic sensor networks

Wireless Sensor Networks

Features:

- Very low sampling frequency $< 1\text{Hz}$
- Very low power consumption: 25mW
- Solar panel
- Radio communication

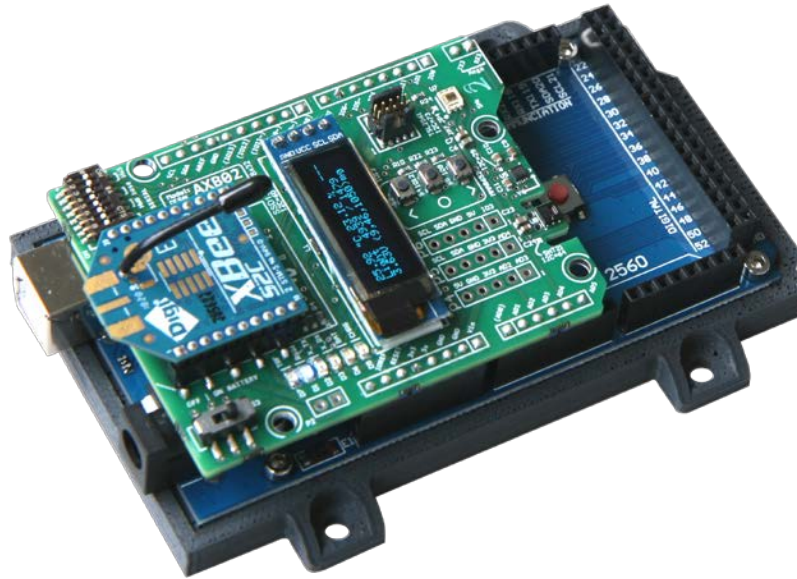
Sensors:

- Air Temperature and Humidity
- Infrared Surface Temperature
- Anemometer
- Solar Radiation
- Pluviometer
- Soil moisture
- Soil pressure



<http://sensorscope.epfl.ch>

DISAL Arduino Xbee Node



- Arduino Mega 2560 board (ATMega 2560 microcontroller)
- Zigbee-complaint transceiver (Xbee)
- On-board mini-display
- Sensors:
 - Light sensor (TSL2561-T, ams)
 - Humidity and Temperature sensor (SHT20, Sensirion)
 - Digital Accelerometer (MMA8652, NXP)
- 14 hours autonomy fully on (70 mA on 1000 mAh Li-Po battery)
- Can be programmed in C leveraging Arduino libraries

Air Pollution Monitoring

NANO

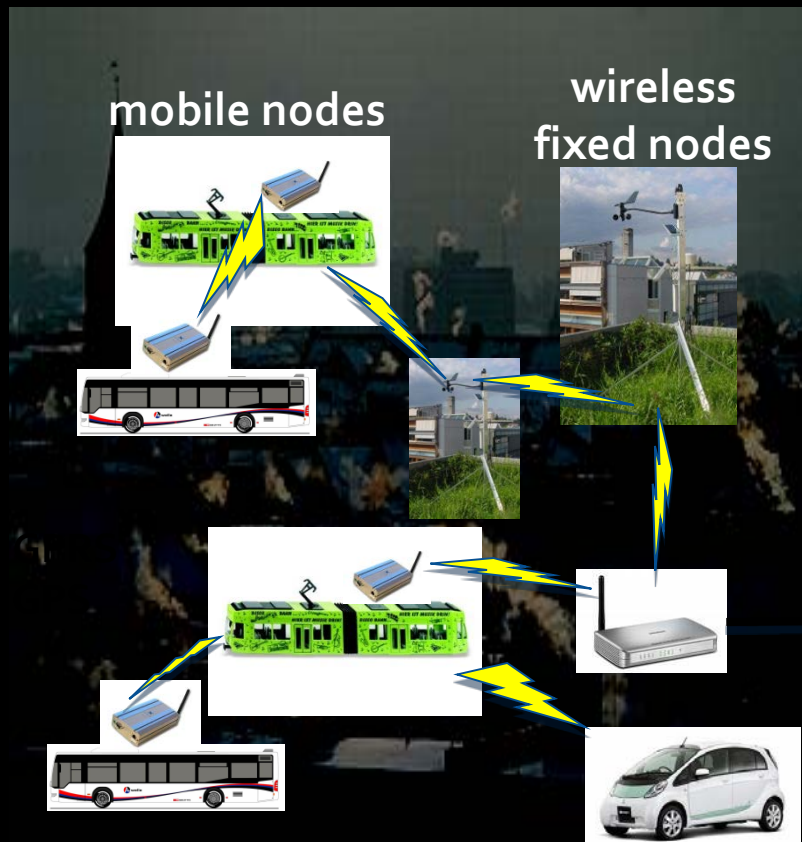
SENSING SYSTEM

From many wireless, mobile, heterogeneous, unreliable raw measurements ...

INFORMATION SYSTEM

... to reliable, understandable and Web-accessible real-time information

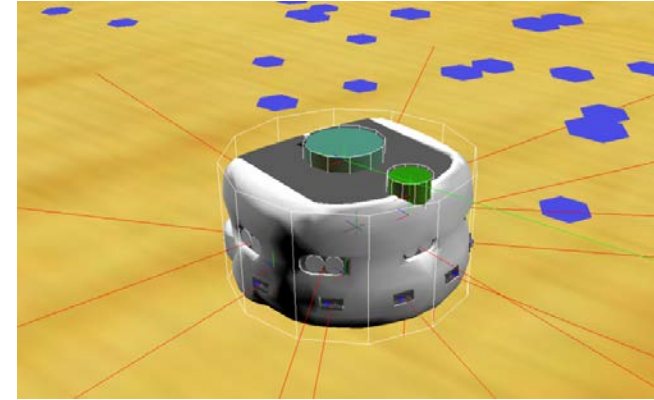
TERA



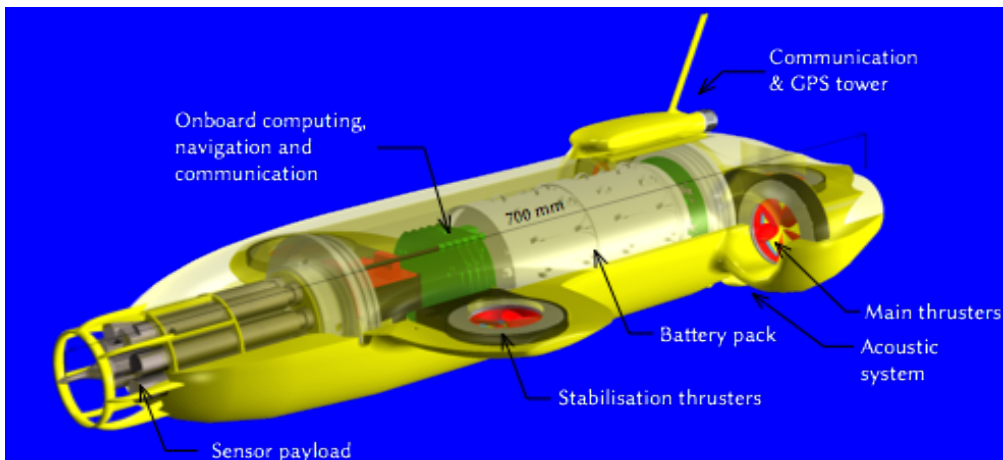
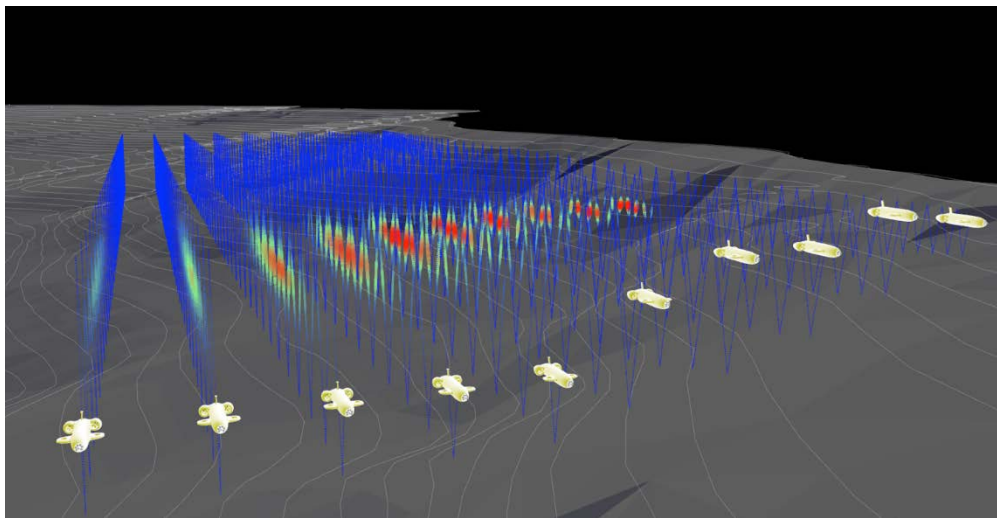
electric vehicle
(C-Zero)

Distributed Odor Source Localization

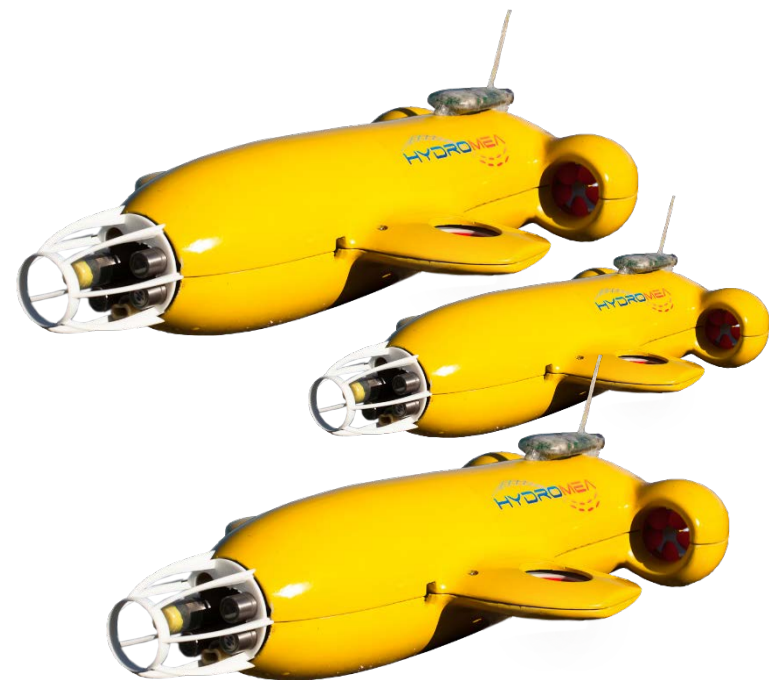
- Bio-inspired, formation-based and probabilistic algorithms
- Distributed control and sensing
- Integration of anemometry, olfaction, and inter-robot localization capabilities
- Wind tunnel and simulation experiments
- Possible applications: environmental pollution, search and rescue operations, humanitarian demining



Multi-AUVs for Limnology



eawag
aquatic research ooo



Conclusion

Take Home Messages

1. Course is rich and intensive: check previous editions on the web for exercises, exam questions, discuss with TAs if appropriate, and consider your overall semester load before finalizing your enrollment
2. Seats are limited: the sooner you make up your mind, the more you help students on the waiting list
3. Balanced theoretical contents and hands-on experience; first lab session give an idea of the workload
4. The course is close to research in its purpose and remains a partial showcase of what we do (biased selection of topics and material distributed)
5. Next course edition: Spring Semester AY 2020-2021

Distributed Intelligent Systems – W1

Part II: An Introduction to
Swarm Intelligence,
Foraging Strategies in Ant
Societies, and Ant-Inspired
Metaheuristics

Outline

- Swarm Intelligence
 - A possible paradigm and motivation
 - Key principles
- Foraging Strategies
 - Recruitment-based mechanisms
 - Inaccuracies of chemical communication
- Bridges experiments in the lab
- Open space and multi-source experiments
- Ant networks
- The Traveling Salesman Problem (TSP)
- An Ant System (AS) for the TSP



An Introduction to Swarm Intelligence – Motivation, Definitions, and Key Principles

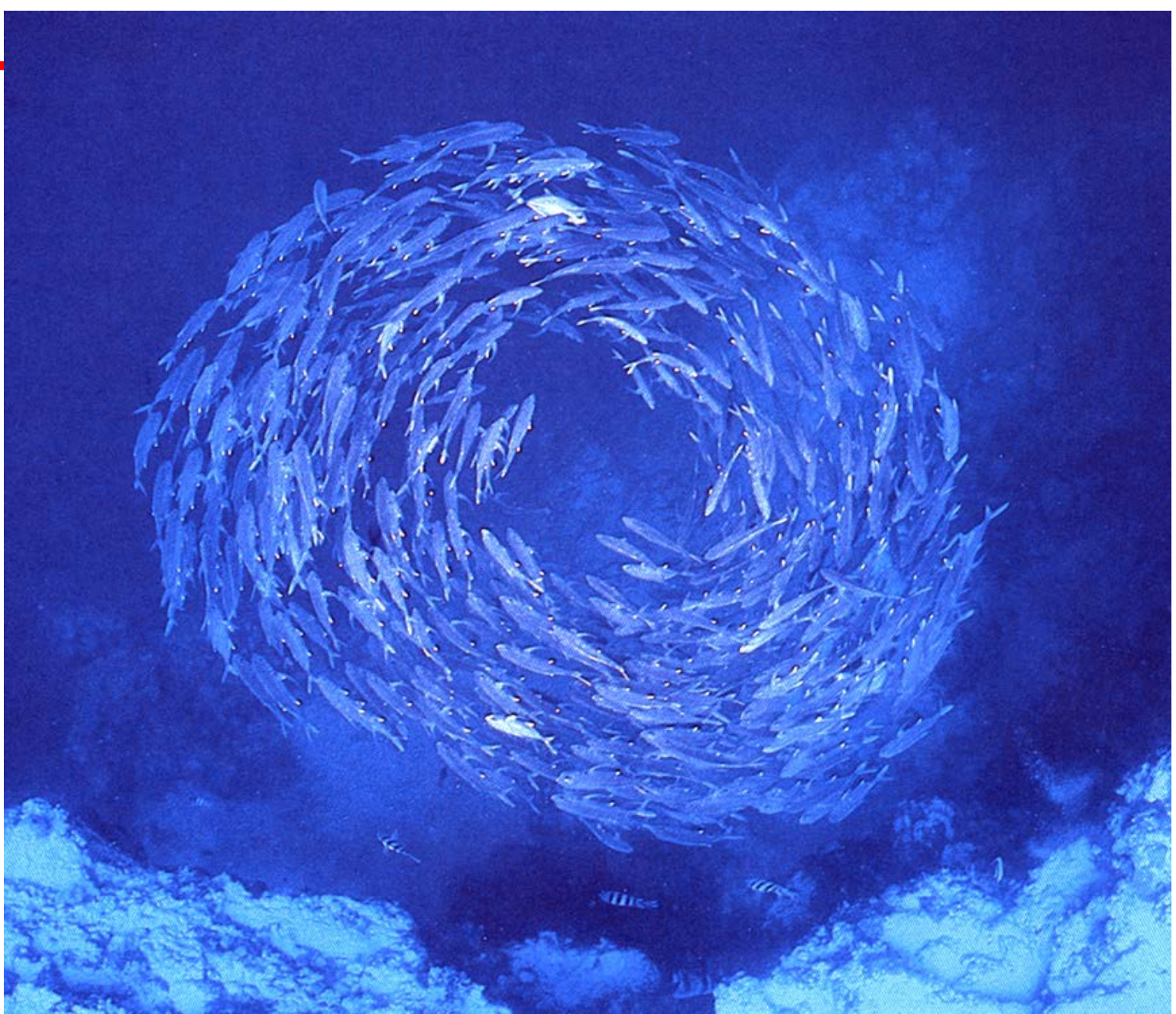
Some natural collective
phenomena implying a close
interconnection among individuals

...



All rights reserved







© Guy Theraulaz, UPS, 1999

Collective Phenomena

- **Limited local information**

Each individual in the group **has access only to limited local information and has no global knowledge of the structure** which it is engaged in constructing together with the other members of the group

- **A set of simple individual rules**

Each individual obeys **a collection of a few simple behavioral rules**. This rule set permits the group collectively to coordinate its activities and to build a global structure or configuration.

- **The global structures which emerge accomplish some function**

These structures often allow the group to solve problems. They are **flexible** (adapting easily to a novel environment), and they are **robust**, (if one or several individuals fail in their behavior or make a simple mistake, the structures spontaneously re-form).

From Natural to Artificial Systems and more ...

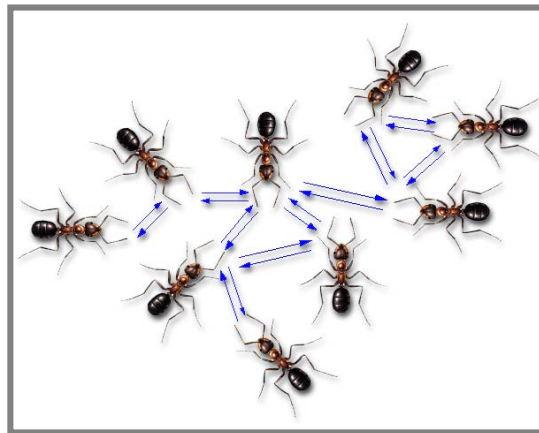
Collective/Swarm Intelligence?

Some questions arise ...

- How do animal societies manage to perform **difficult** tasks, in dynamic and varied environments, **without any external guidance** or control, and **without central coordination**?
- How can **a large number of entities with only partial information** about their environment solve problems?
- How can **collective cognitive capacities** emerge from individuals with limited cognitive capacities?

From Natural to Artificial Systems

- **Modeling** to understand microscopic to macroscopic transformation
- **Modeling** as interface to artificial systems



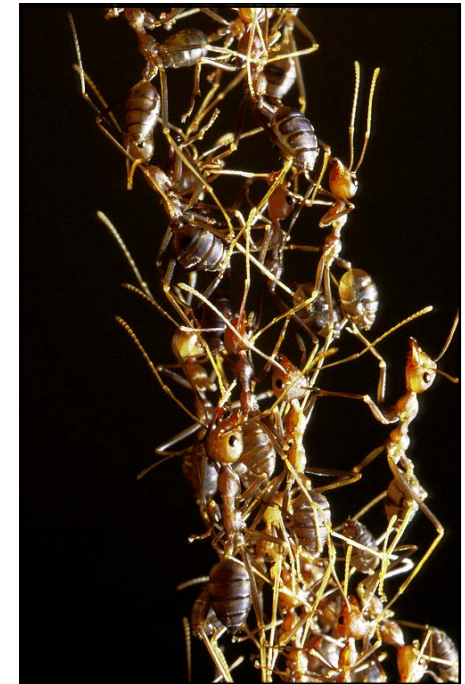
Individual behaviors
and local interactions



Modeling



Ideas for
artificial
systems



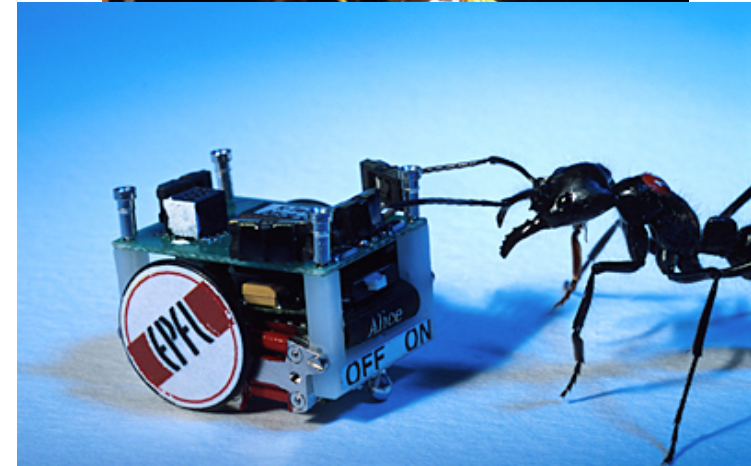
Global structures
and collective
decisions

Digital Swarm-Intelligent Systems

- In a virtual world, most of the mechanisms shown by natural SI can be easily reproduced
- Some of the mechanisms are intentionally modified and further ones are added in order to improve the performance of a given algorithm

Physical Swarm-Intelligent Systems

- **Beyond pure bio-inspiration:** combine natural principles with engineering knowledge and technologies
- **Unit coordination**
 - fully distributed control (+ env. template)
 - individual autonomy
 - self-organization (extend definition)
- **Communication**
 - explicit/implicit local communication
 - indirect communication through signs in the environment (stigmergy)
- **Scalability**
- **Robustness vs. efficiency trade-off**
 - redundancy
 - balance exploitation/exploration
 - individual simplicity
- **System cost effectiveness**
 - individual simplicity
 - mass production



Some Definitions of Swarm Intelligence

- Beni and Wang (1989):
 - Used the term in the context of cellular automata (based on cellular robots concept of Fukuda)
 - Decentralized control, lack of synchronicity, simple and (quasi) identical members, self-organization
- Bonabeau, Dorigo and Theraulaz (1999)
 - Any attempt to design algorithms or distributed solving devices inspired by the collective behavior of social insect colonies and other animal societies

Some Definitions of Swarm Robotics

- Beni (2004)
 - Intelligent swarm = a group of non-intelligent robots (“machines”) capable of universal computation
 - Usual difficulties in defining the “intelligence” concept (non predictable order from disorder, creativity)
- Dorigo and Sahin (2004)
 - Swarm robotics is the **study of how a large number of relatively simple physically embodied agents can be designed such that a desired collective behavior emerges from the local interactions among agents and between the agents and the environment.**
- Sharkey (2007)
 - *Scalable* swarm robotics (not minimalist and not directly nature-inspired)
 - *Practical minimalist* swarm robotics (not directly nature-inspired)
 - *Nature-inspired minimalist* swarm robotics

Key Mechanisms behind Natural Swarm Intelligence

Two Key Mechanisms in Natural Swarm-Intelligent Systems

1. Self-Organization

2. Stigmergy

Self-Organization

- Set of dynamical mechanisms whereby **structure appears at the global level** as the result of **interactions among lower-level components**
- The rules specifying the interactions among the system's constituent units are executed on the basis of **purely local information**, without reference to the global pattern, which is an **emergent property of the system** rather than a property imposed upon the system by an external ordering influence

Characteristics of Natural Self-Organized Systems

- **Creation of spatio-temporal structures**
 - E.g., foraging trails, nest architectures, clusters of objects, ...
- **Multistability**
(i.e., possible co-existence of several stable states)
 - E.g., ants exploit only one of two identical food sources, build a cluster in one of the many possible locations, ...
- **Existence of bifurcations when some parameters change**
 - E.g., termites move from a non-coordinated to a coordinated phase only if their density is higher than a threshold value

Basic Ingredients of Natural Self-Organized Systems

- **Multiple interactions**
- **Randomness**
- **Positive feedback**
 - E.g., recruitment, reinforcement
- **Negative feedback**
 - E.g., limited number of available foragers, pheromone evaporation

Stigmergy

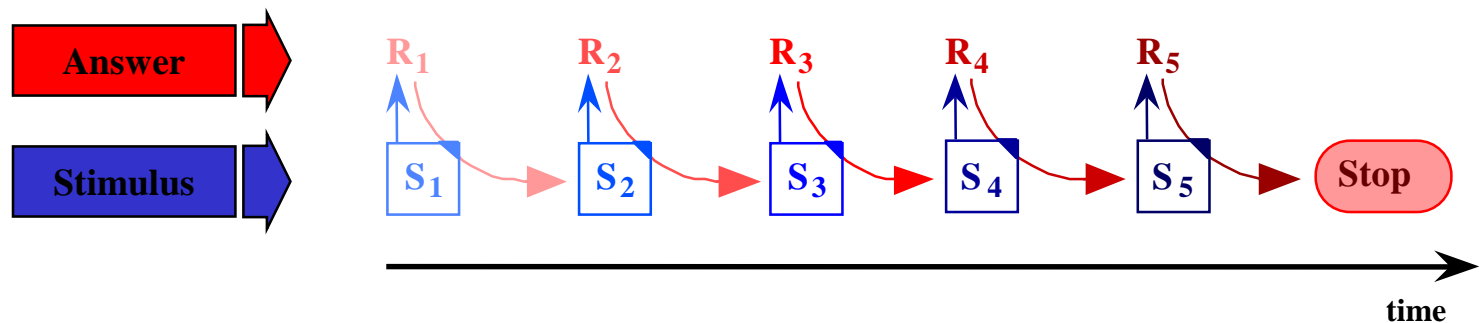
Grassé P. P., 1959

- “La coordination des tâches, la regulation des constructions ne dependent pas directement des ouvriers, mais des constructions elles-memes. *L’ouvrier ne dirige pas son travail, il est guidé par lui*. C’est à cette stimulation d’un type particulier que nous donnons le nom du **STIGMERGIE** (*stigma*, piqueure; *ergon*, travail, oeuvre = oeuvre stimulante).”
- [“The coordination of tasks and the regulation of constructions does not depend directly on the workers, but on the constructions themselves. *The worker does not direct his work, but is guided by it*. It is to this special form of stimulation that we give the name **STIGMERGY** (*stigma*, sting; *ergon*, work, product of labor = stimulating product of labor).”]

Stigmergy

Definition

It defines a class of mechanisms exploited by social insects to coordinate and control their activity via **indirect interactions**.



Stigmergic mechanisms can be classified in two different categories:

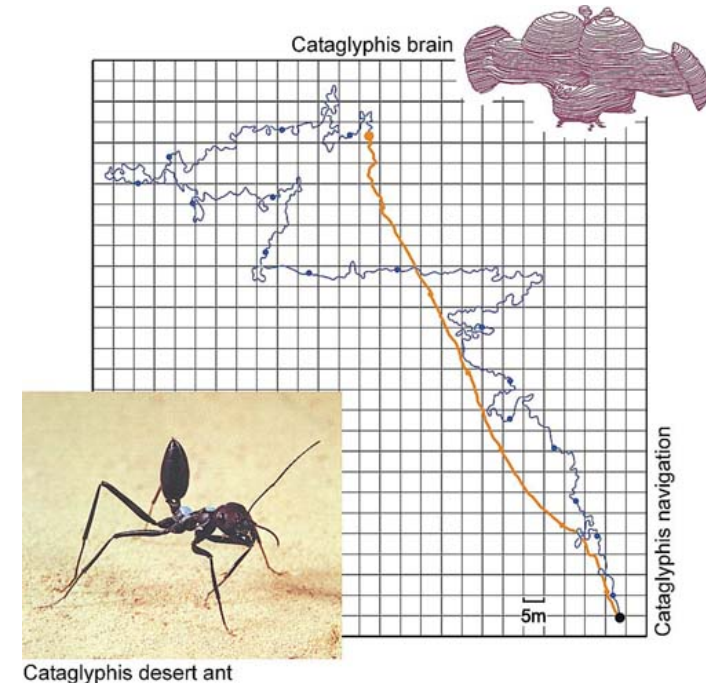
- **quantitative** (or **continuous**) stigmergy
- **qualitative** (or **discrete**) stigmergy

Foraging Strategies in Ants

Different Ants, Different Strategies

Not All Foraging Strategies are Collective and based on Stigmergy ...

- Example: **Cataglyphis desert ant**
- Excellent study by **Prof. R. Wehner** (University of Zuerich, Emeritus)
- Individual foraging strategy
- Underlying mechanisms
 - Internal compass (polarization of sun light)
 - Dead-reckoning (path integration on neural chains for leg control)
 - Local search (around 1-2 m from the nest)
- Extremely accurate navigation:
averaged error of a few **tens of cm over 500 m path!**



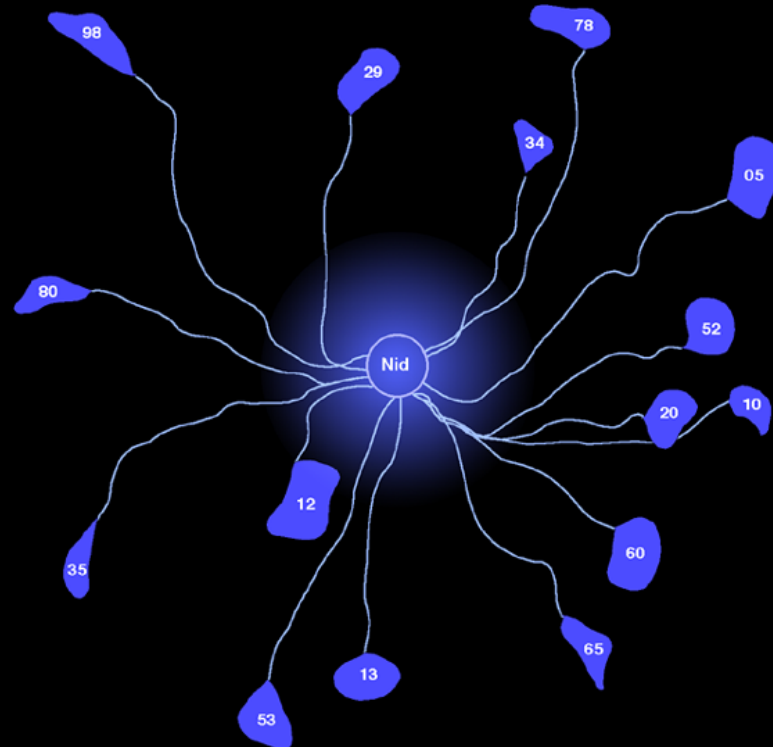
More individual Foraging Strategies

Individual navigation + learning capabilities for memorizing the foraging zone

Les différentes stratégies de récolte chez les fourmis

1. Récolte individuelle

*Distribution spatiale de l'activité de récolte et carte des routes empruntées par les ouvrières chez la fourmi *Neoponera apicalis**



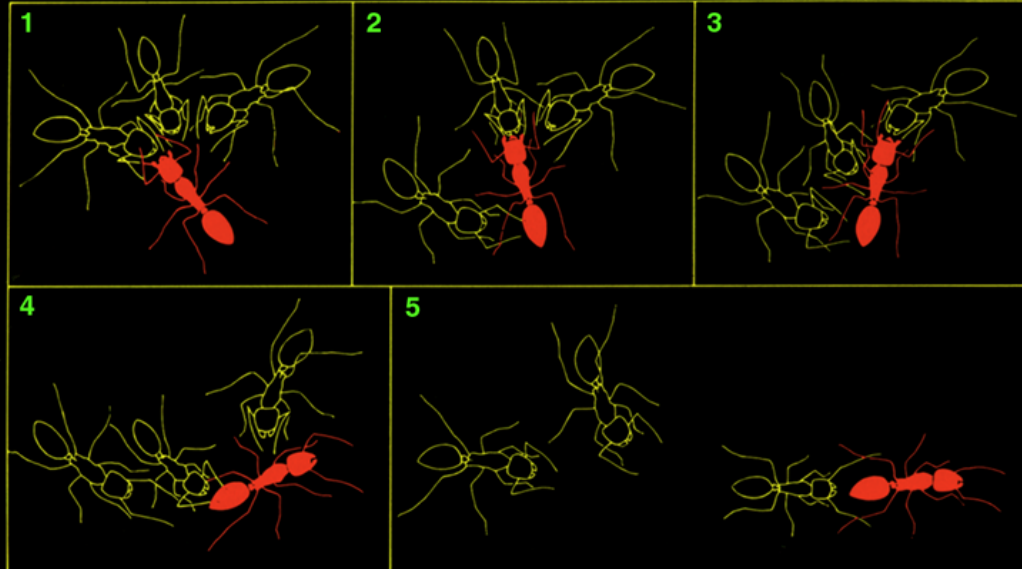
Tandem Recruitment Strategies

- Mediated by thropallaxis, antennal contact
- Based on food chemical signatures on the ant body

Les différentes stratégies de récolte chez les fourmis

2. Recrutement en tandem

*Recrutement en tandem chez la fourmi asiatique
Camponotus sericeus*



Group Recruitment Strategies

Les différentes stratégies de récolte chez les fourmis

3. Recrutement de groupe

*Recrutement de groupe chez la fourmi *Camponotus socius**



Mass Recruitment Strategies

Les différentes stratégies de récolte chez les fourmis

4. Recrutement de masse

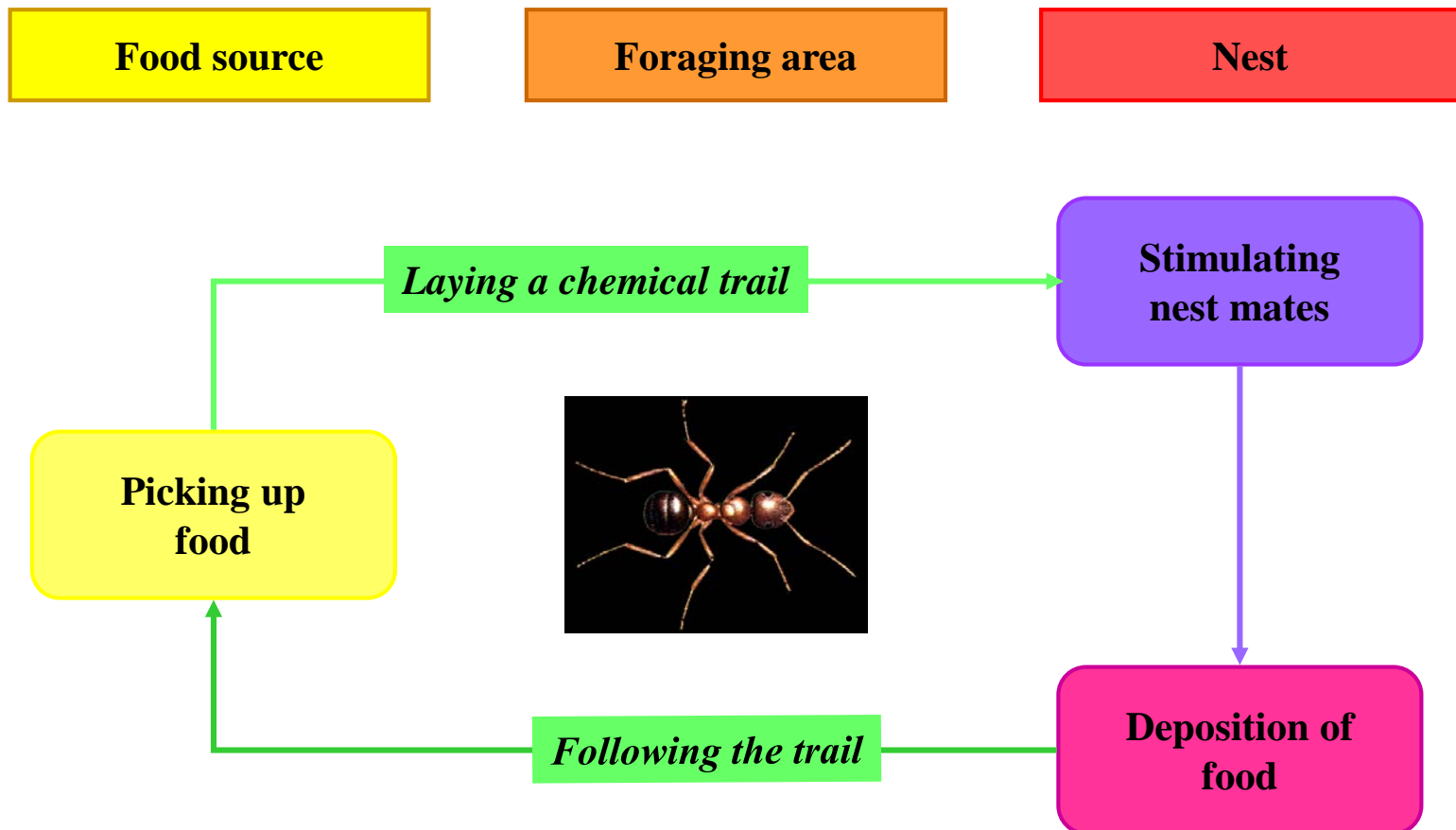
*Recrutement de masse chez la fourmi *Solenopsis geminata**



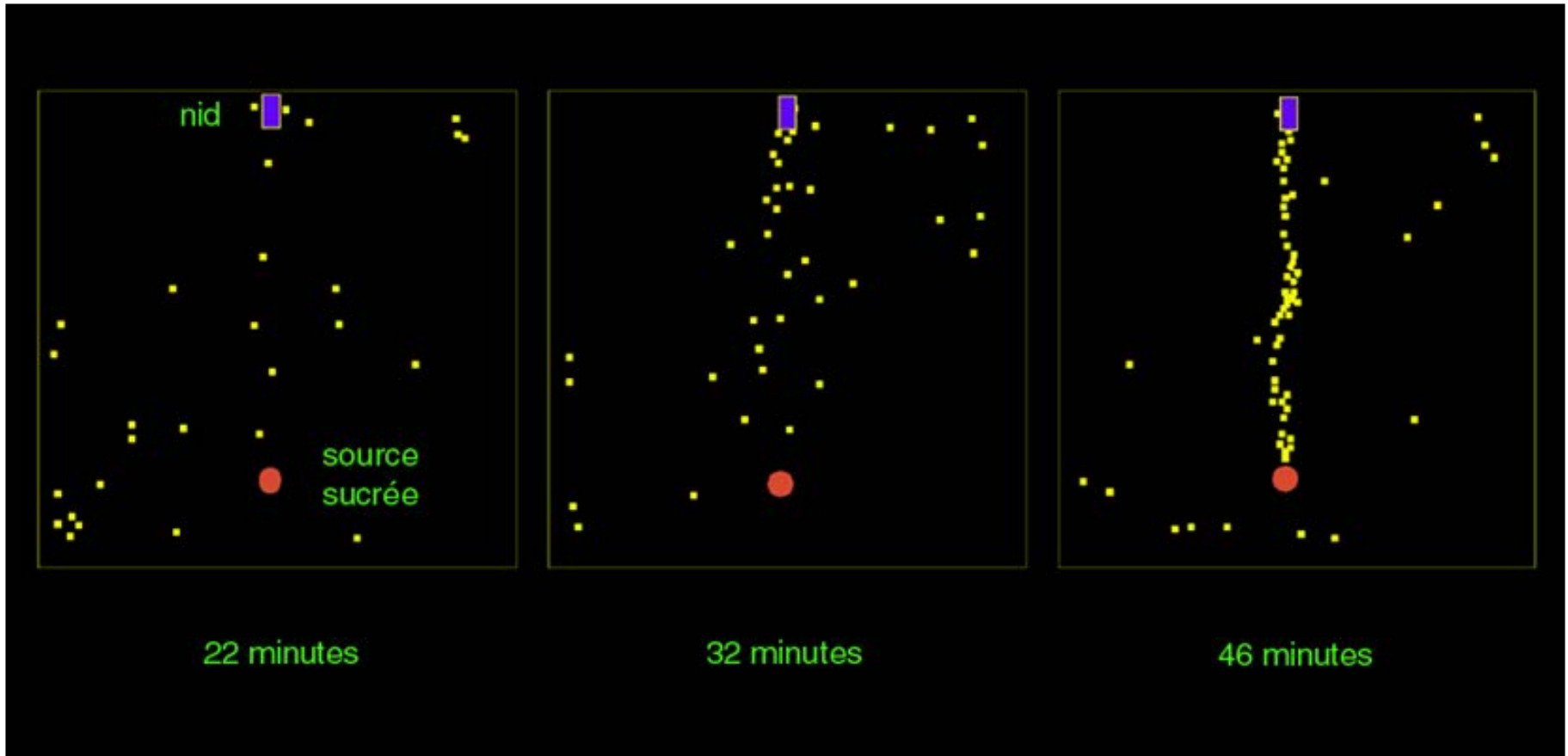
Mass Recruitment

Behavior of Individual Ants

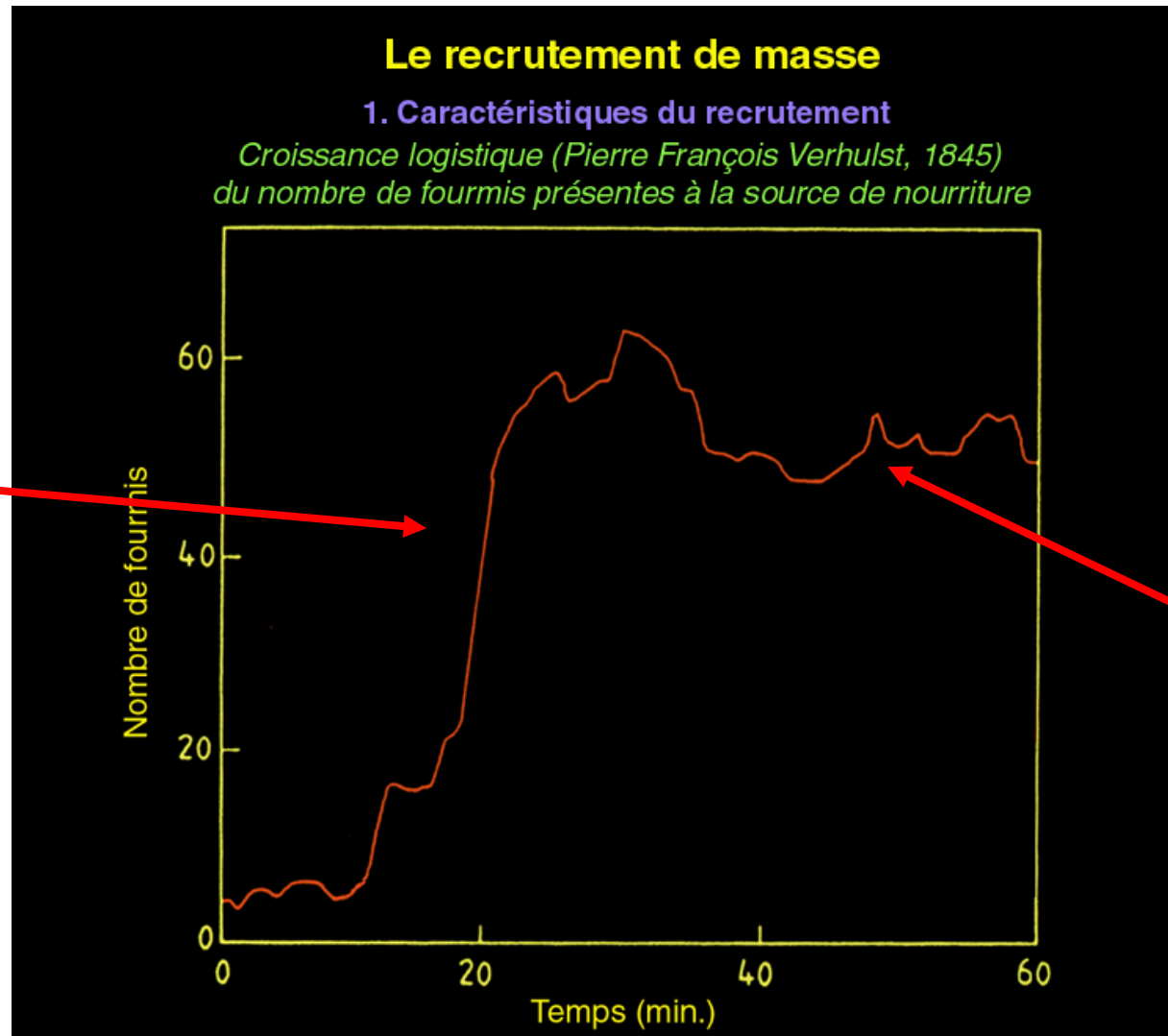
Sequence of actions performed by an ant communicating the discovery of a food source



Formation of Recruitment Trails in Ants



Number of Ants at the Food Source vs. Time



Growing phase
(positive
feedback)

Saturation
phase
(negative
feedback)

Stochastic Individual Behavior Combined with the Amplification of Information can lead to Collective Decisions

The Role of Randomness in the Organization of Foraging

How does individual behavior with a strong stochastic component lead to **statistically predictable behavior** at the level of the colony and **collective decisions**?



© Guy Theraulaz

Experimental Strategy

- Most of the studies to assess **quantitatively** the role of randomness have been carried out in the lab because:
 - Controlled environmental conditions
 - Repeated runs for statistics
- Studies in the field can lead often only to **qualitative** conclusions because they might be influenced by:
 - Multiple food sources
 - Predators and competitors
 - Environmental changes (temperature, climate, etc.)

Exploration: The Inaccuracy of Chemical Communication

Termite Following a Pheromone Trace



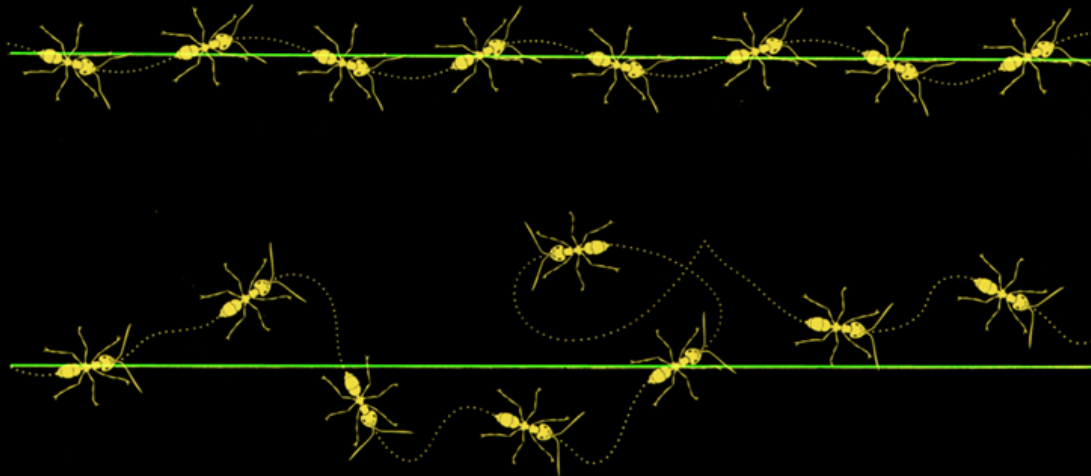
Prof. J.-L. Deneubourg (ULB, Bruxelles)

Ants can Reacquire a Trail by Local Search

Rôle du hasard et du bruit dans l'organisation de la récolte

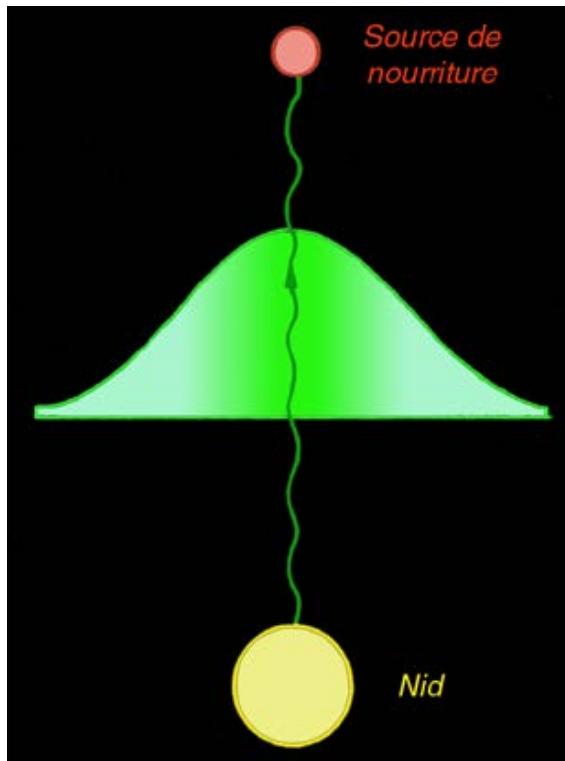
1. Orientation des fourmis le long d'une piste

Osmotropotaxie (Hangartner, 1967)



Probability of Trail Losing depends on the Ant Species

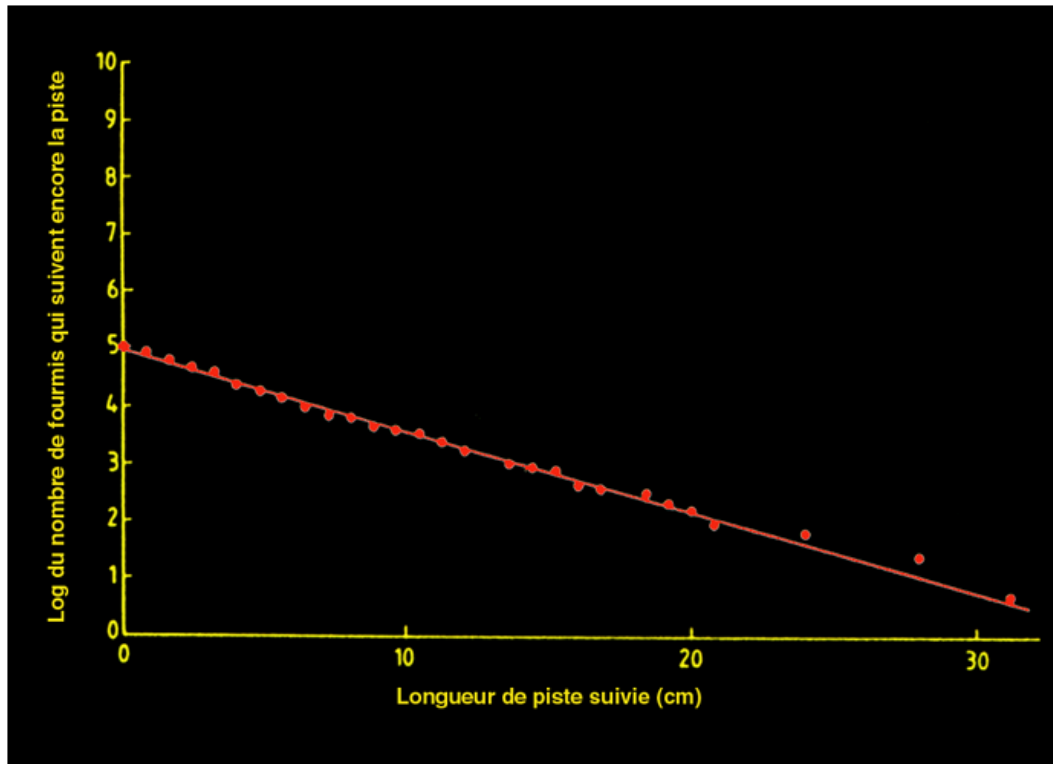
Example: Accuracy of recruitment of the first recruit (Verhaeghe et al., 1980)



	<i>Tetramorium impurum</i>	<i>Tapinoma erraticum</i>
Successful recruitments (%)	18	74
Length of trail followed (%)	17	68

➡ *Tapinoma* follow trails much more reliably than *Tetramorium* → depends on the environment the species have evolved (food scattering, etc.)

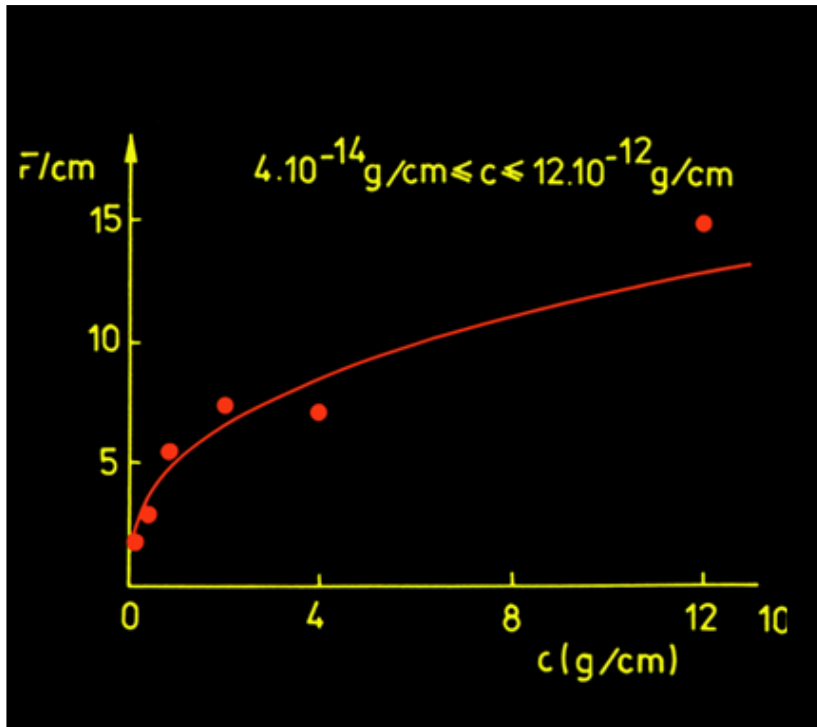
Probability of Trail Losing is Constant over Time



- The longer the traveled path and the smaller is the number of ants on the trail
- Appears to be **independent of** phenomena such as **learning or sensory adaptive response** (at least under such short time scale)

Log # of ants on the trail as a function of the traveled path for a constant pheromone concentration

Probability of Trail Losing depends on Chemical Concentration



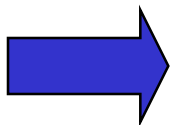
The higher is the pheromone concentration and the more reliably can be followed a trail

Mean path length as a function of the pheromone concentration

Biological Significance of the Exploitation-Exploration **Balance**

Does the accuracy of the chemical communication channel used by ants increase or decrease their efficiency?

- Noise can have a certain **flexible value** for the organization of the society.
- The fact that a significant proportion of recruits get lost en route can be of benefit when food is scattered throughout the environment or when several sources are present simultaneously.
- If too many ants get lost for a given food scattering the efficiency of recruitment also decreases.

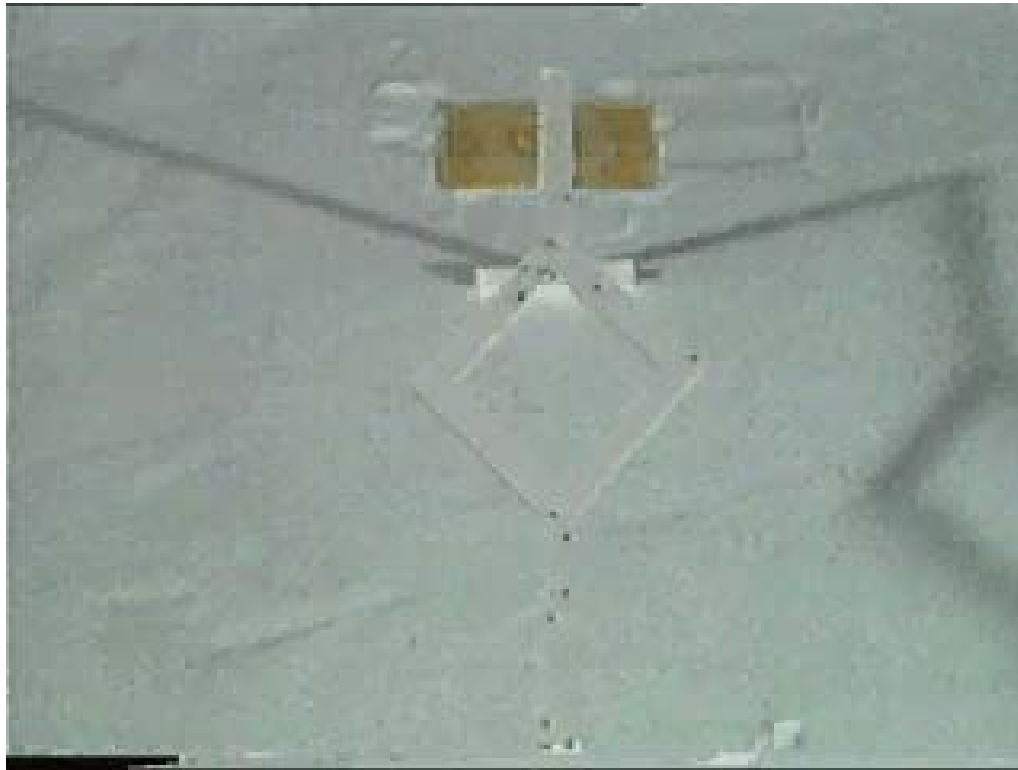


Sacrifice a little bit efficiency in order to be robust at facing environmental unpredictability

Bridge Experiments: Selecting the Shortest Path

The Suspended, Symmetric Bridge Experiment

Food source

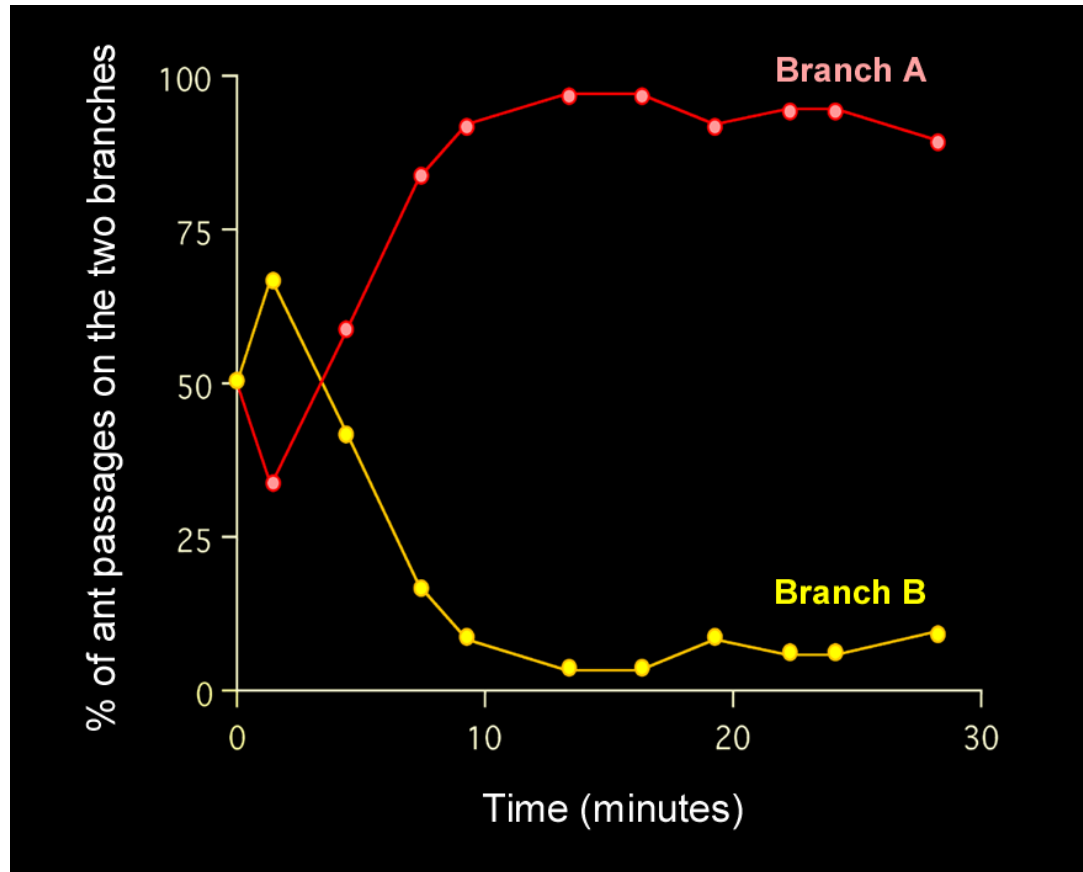


Two branches (A and B) of the **same length** connect nest and food source

© J.-L. Deneubourg

Nest

Experimental Results



Microscopic Model (Deneubourg 1990)

$$P_A = \frac{(k + A_i)^n}{(k + A_i)^n + (k + B_i)^n} = 1 - P_B$$

Probabilistic choice of an agent at the bridge's bifurcation points

P_A and P_B : probability for the ant $i+1$ to pick up the branch A or B respectively

A_i : number of ants having chosen branch A

B_i : number of ants having chosen branch B

n (model parameter): degree of nonlinearity

k (model parameter): degree of attraction of a unmarked branch

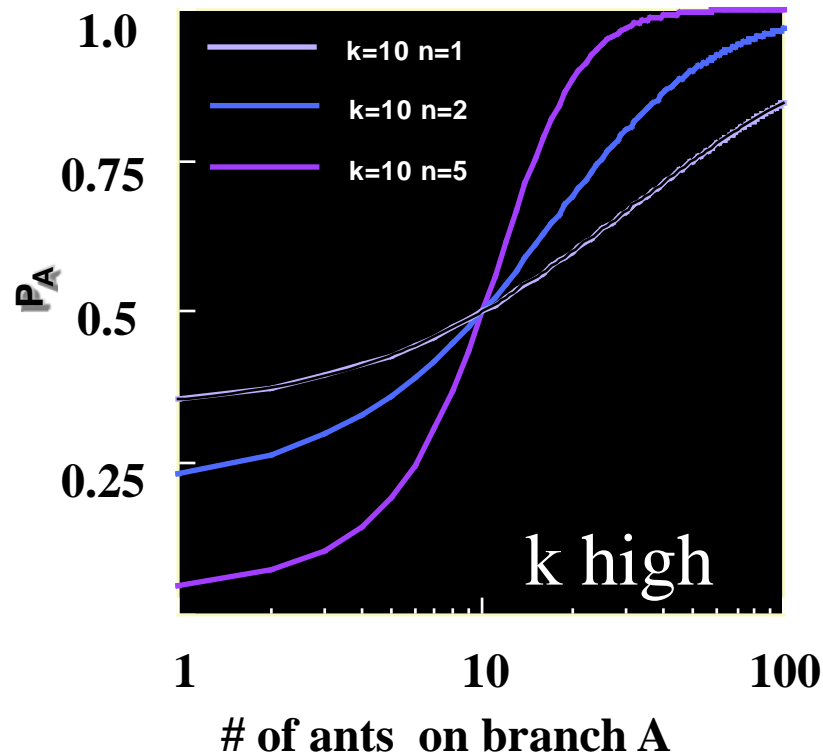
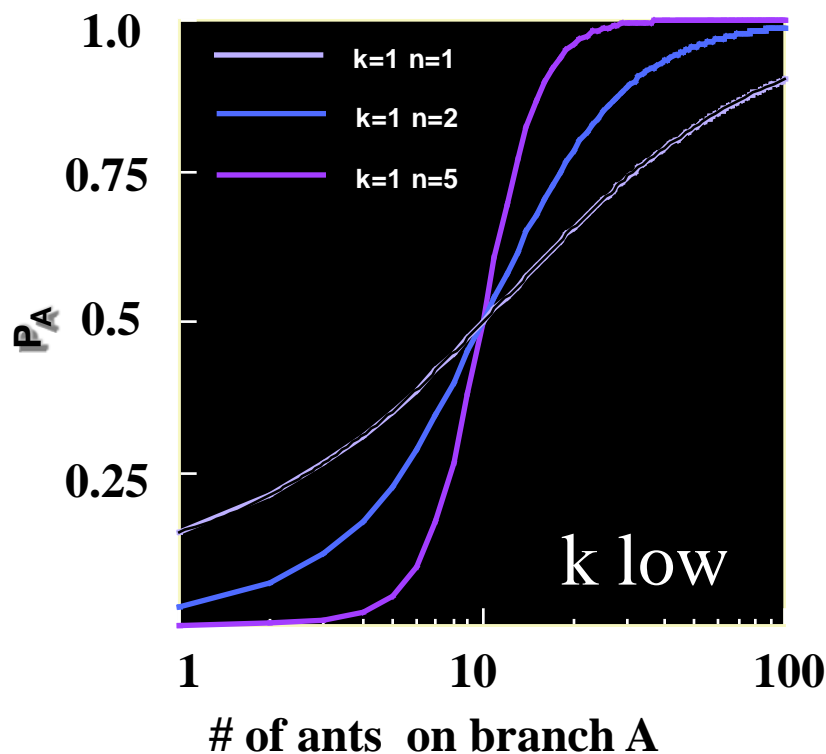
$$A_{i+1} = \begin{cases} A_i + 1 & \text{if } \delta \leq P_A \\ A_i & \text{if } \delta > P_A \end{cases}$$

$$B_{i+1} = \begin{cases} B_i + 1 & \text{if } \delta > P_A \\ B_i & \text{if } \delta \leq P_A \end{cases}$$

$$A_i + B_i = i$$

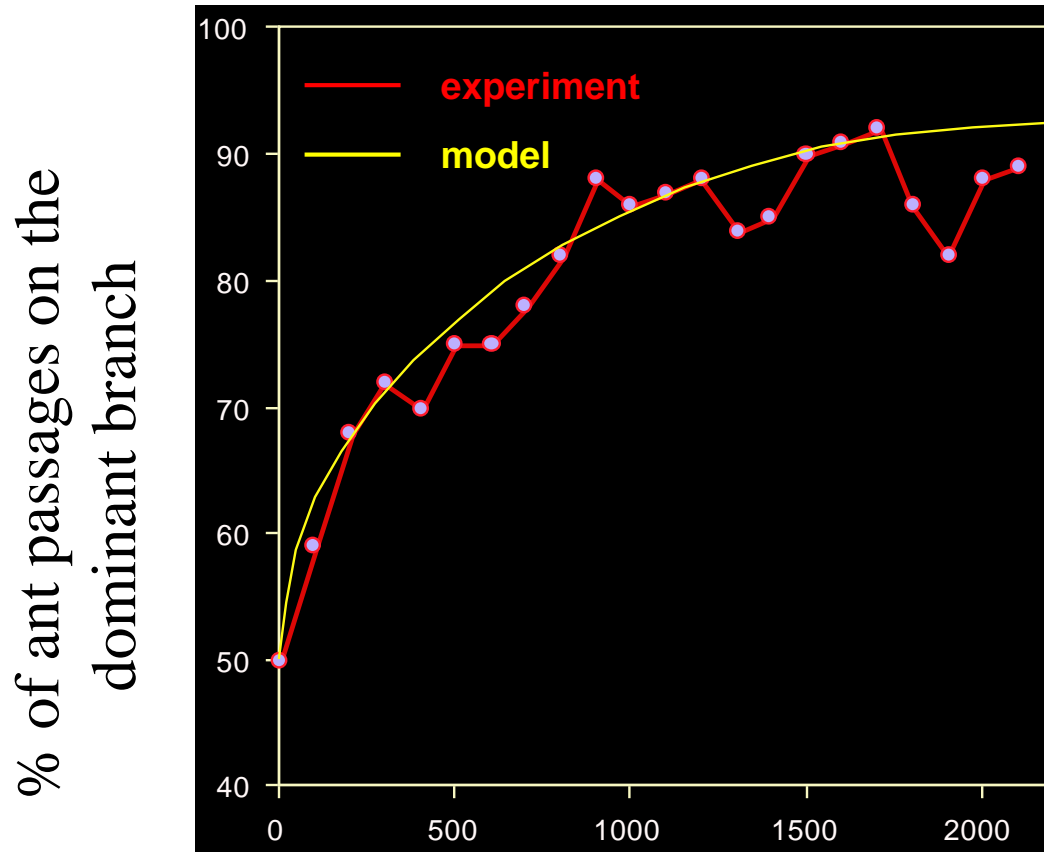
δ = uniform random variable on $[0,1]$

Parameters of the Choice Function



- The higher is n and the faster is the selection of one of the branches (sharper curve); **n high corresponds to high exploitation**
- The greater k , the higher the attractivity of a unmarked branch and therefore the higher is the probability of agents of making random choices (i.e. not based on pheromones concentration deposited by other ants); **k high corresponds to high exploration**

Model vs. Experiments



Parameters that fit
experimental data:

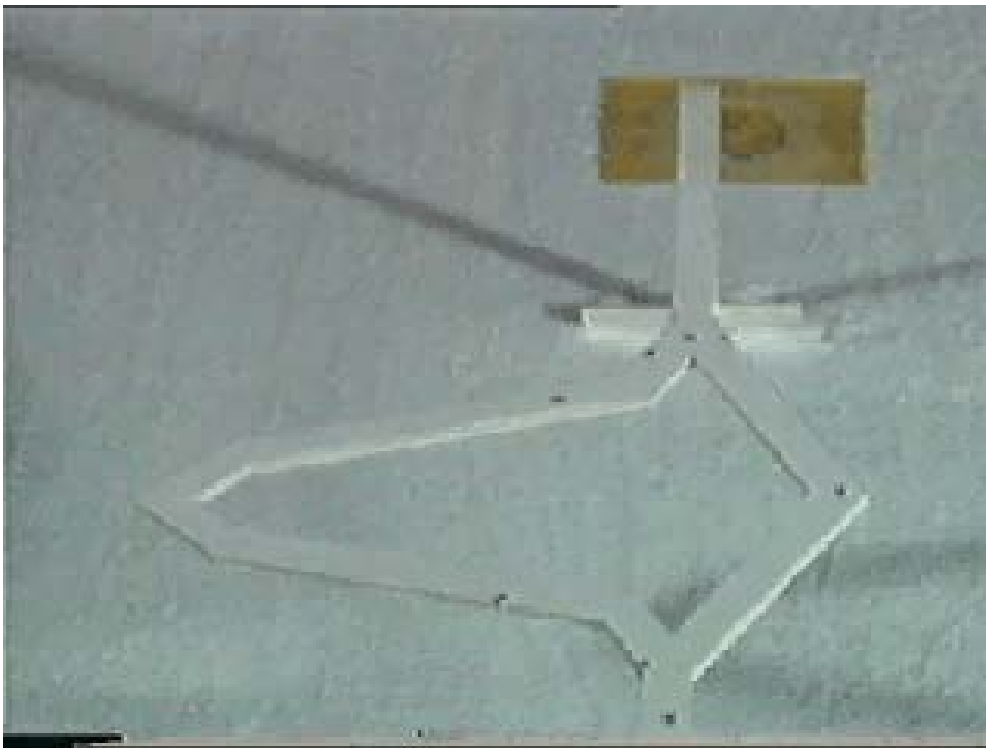
$$n = 2$$

$$k = 20$$

Total number of ants having
traversed the bridge

The Suspended, Asymmetric Bridge Experiment

Food source



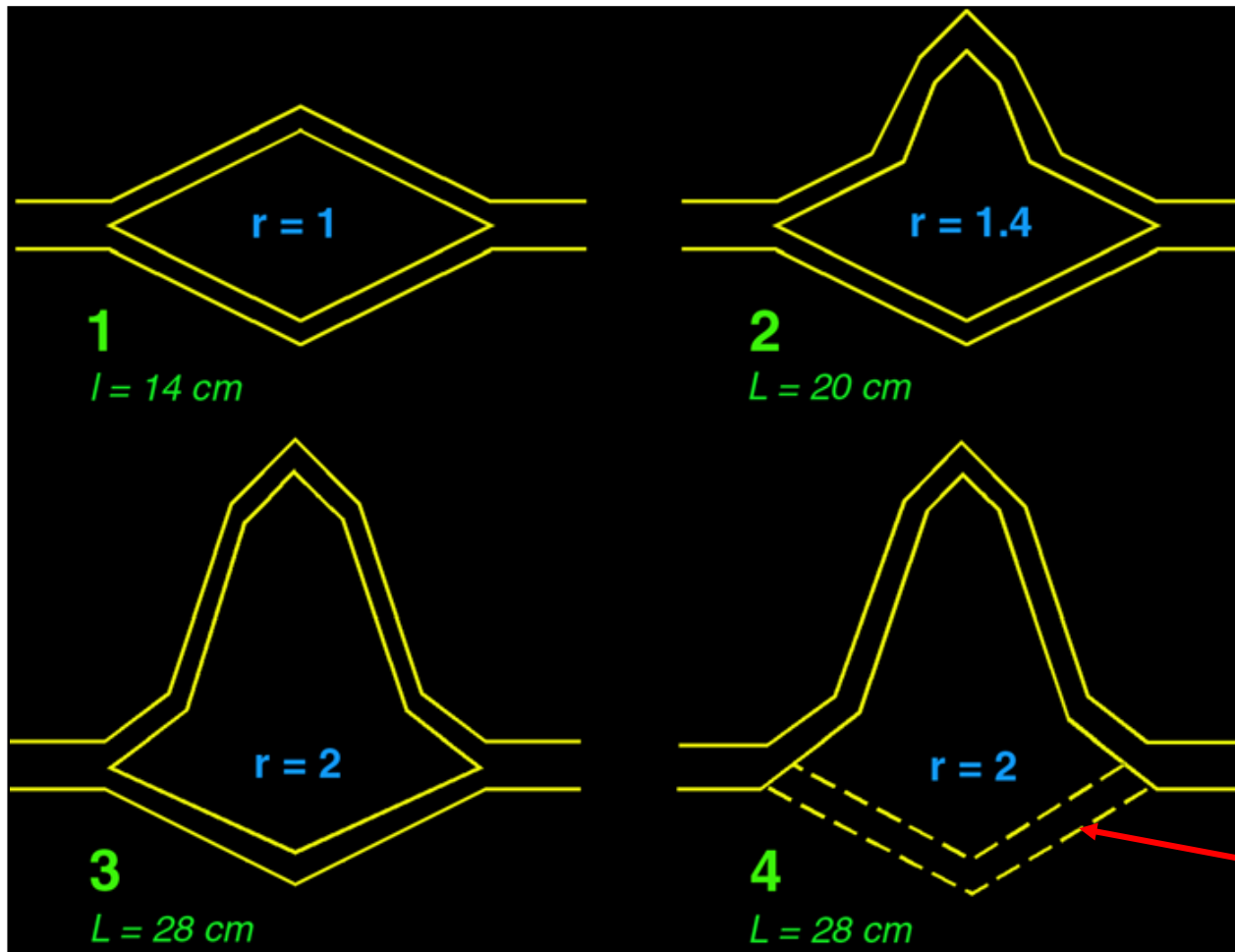
- Two branches (A and B) differing in their length (**length ratio r**) connect nest and food source
- Test for the optimization capabilities of ants

Nest

© J.-L. Deneubourg

All Bridge Experiments

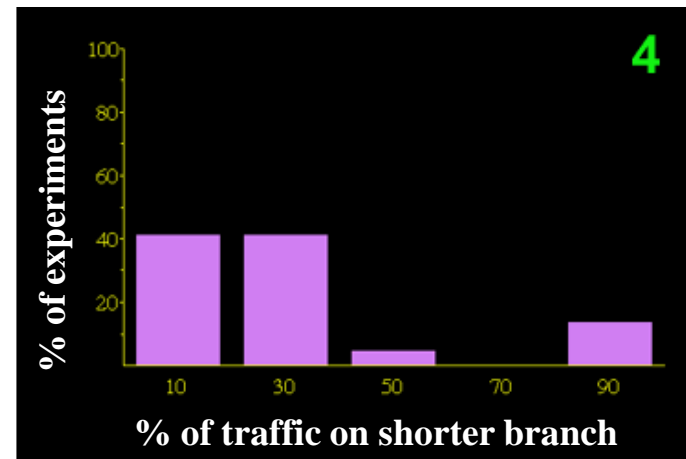
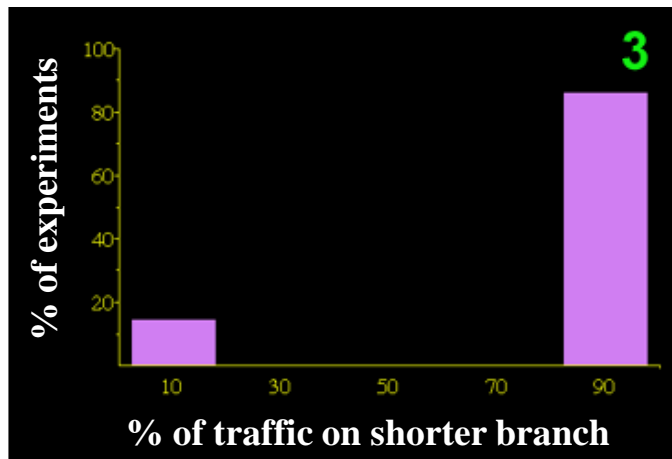
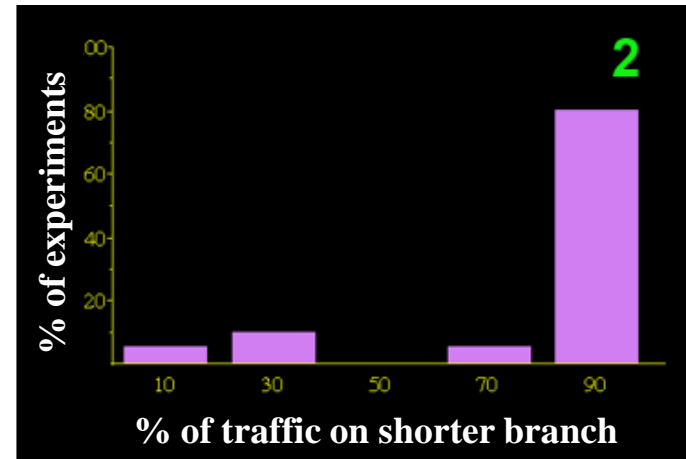
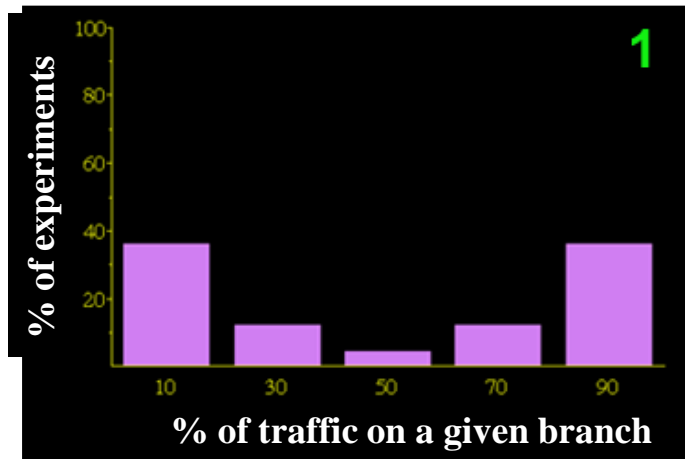
4 different experimental scenarios



Shortest branch
added later

Selection of the Shortest Branch

Repeated experiments with different ant colonies of the same ant species (*Linepithema Humile*) – finite experimental time window



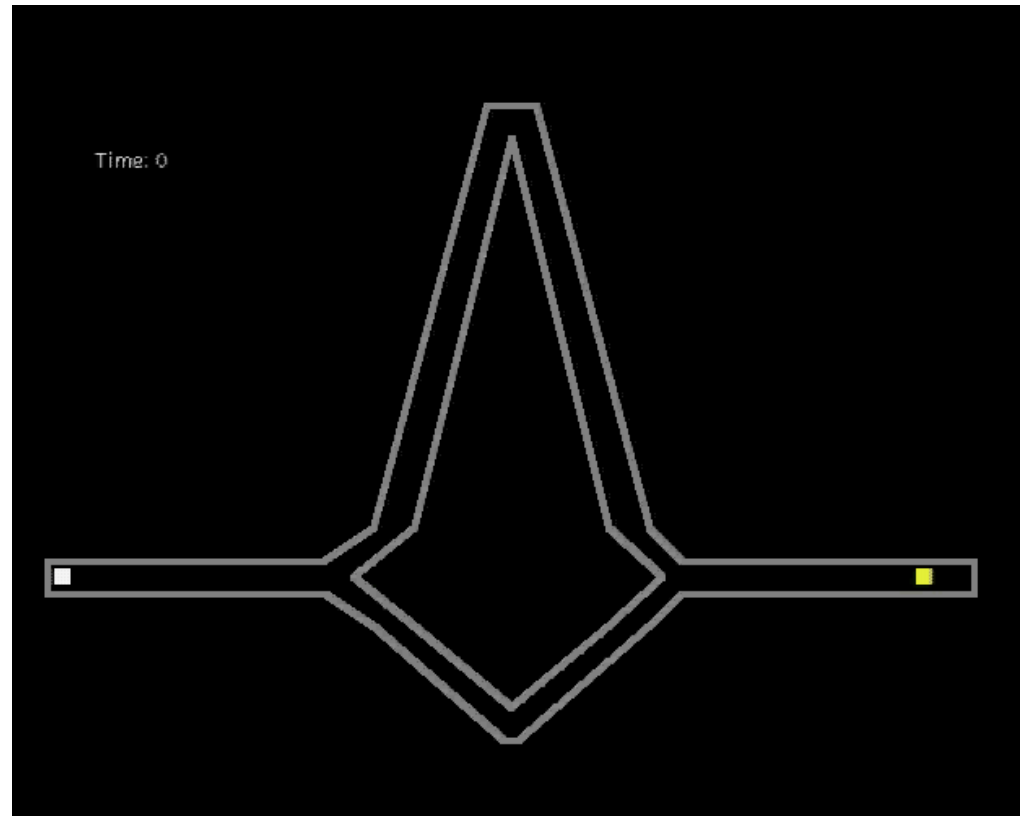
Asymmetric Bridge – Ant Species Differences

What happens if the shorter branch is presented after 30 minutes?

- Argentine Ants (*Linepithema Humile*) get stuck on the longer branch (mainly pheromone-based navigation), see previous slide.
- *Lasius Niger* ants find the shorter branch because they integrate other navigation modalities (compass, dead-reckoning) with pheromone navigation
-> **U-Turns (different from random walk)!**
- *Pharaoh ants* recognize the right way to go from **geometry of trails** (trails geometry provide polarity information!), again dead-reckoning/compass capabilities!

Asymmetric Bridge – Microscopic Modeling

- The previous model does not work any more:
distance/traveling time has to be considered in order to incorporate the geometry of the bridge.
- Multi-agent simulation incorporating pheromone deposition, avoidance rules, ...
point simulator (take into account trajectories but no body) by Prof. M. Dorigo (ULB Bruxelles).

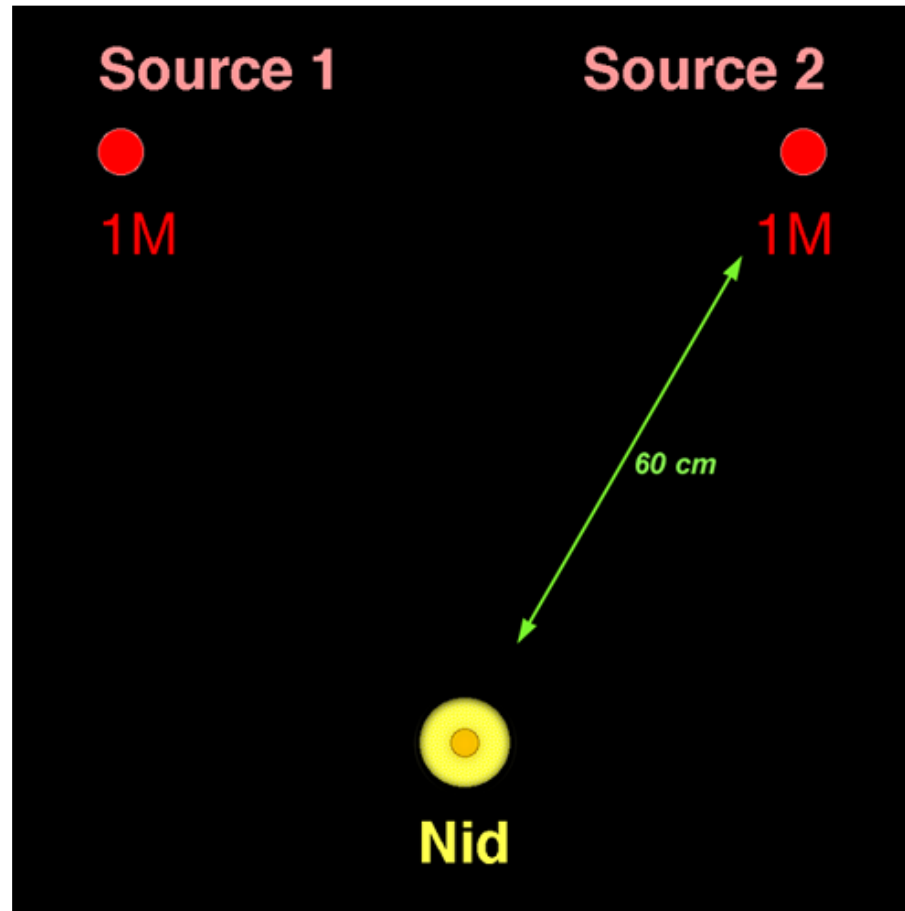


Foraging in Free Space

Selecting the Richest Source

Three different experimental scenarios:

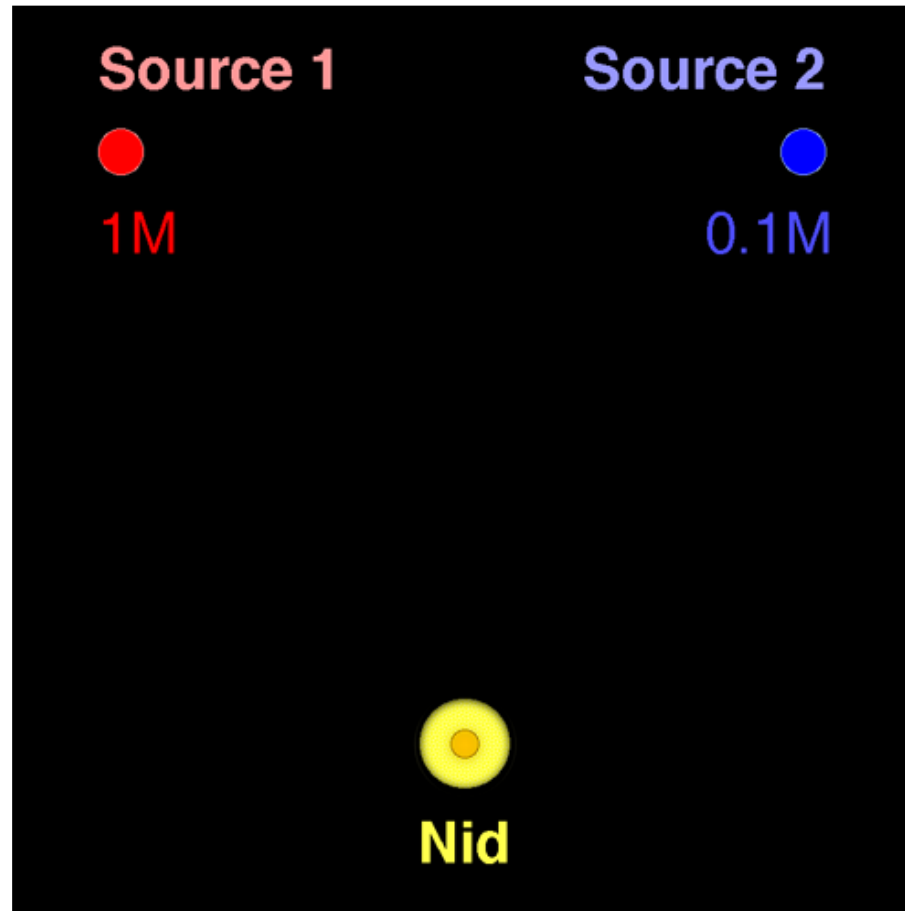
Experiment N°1



Selecting the Richest Source

Three different experimental scenarios:

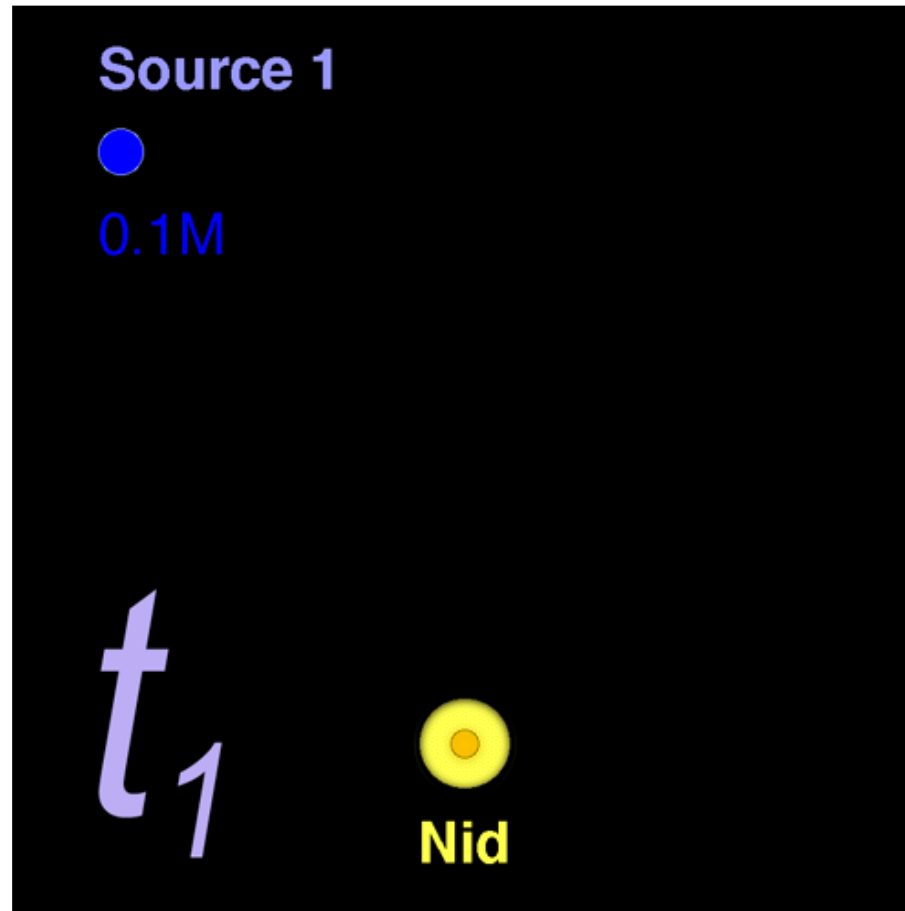
Experiment N°2



Selecting the Richest Source

Three different experimental scenarios:

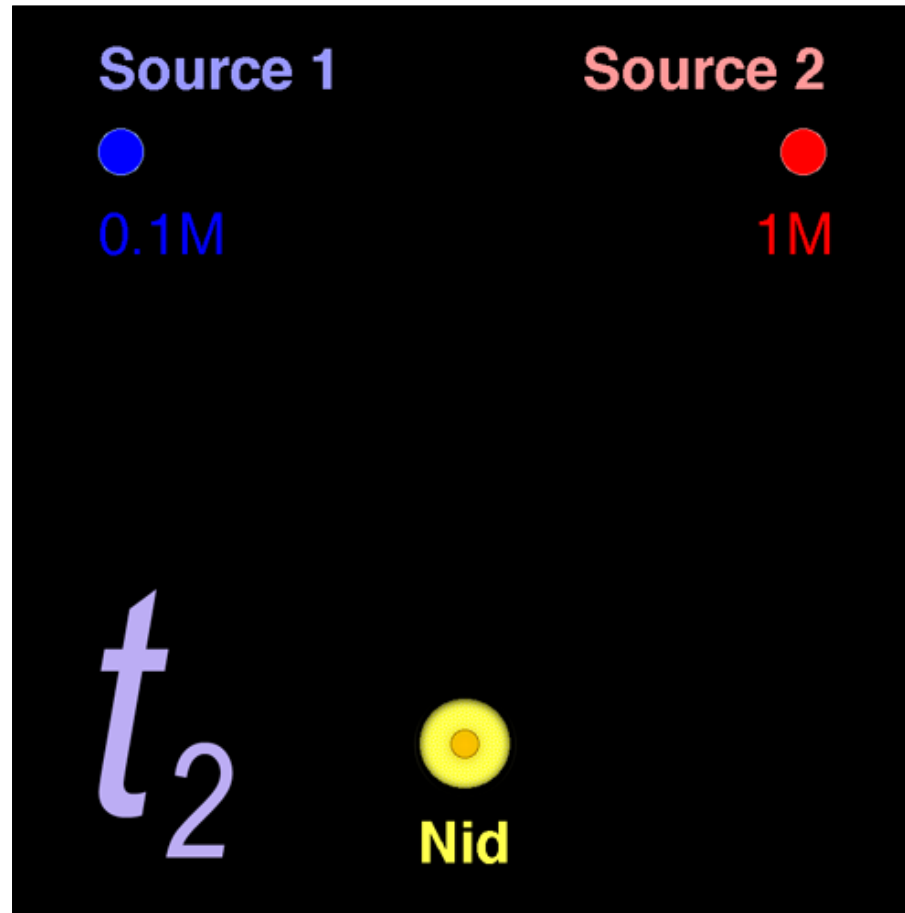
Experiment N°3



Selecting the Richest Source

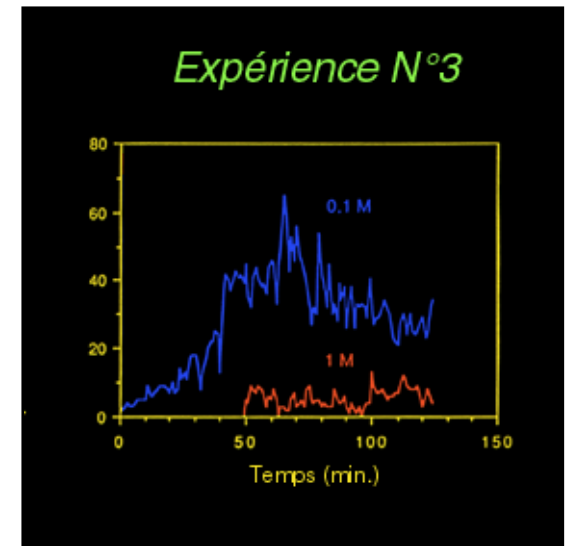
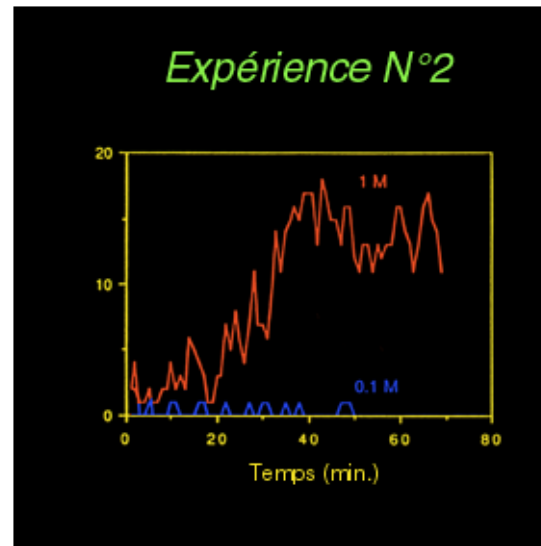
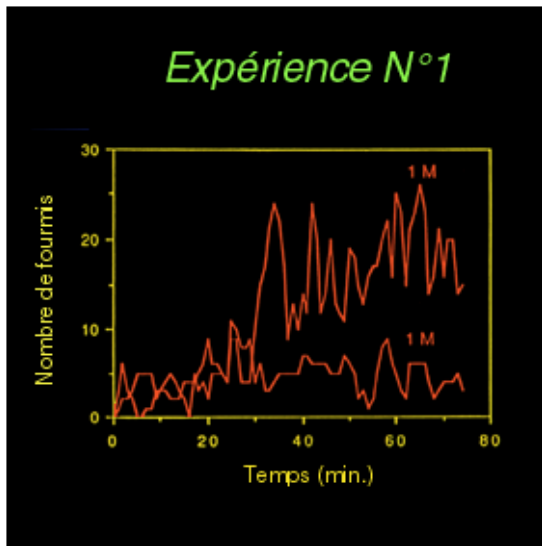
Three different experimental scenarios:

Experiment N°3



Selecting the Richest Source

Results obtained with *Lasius Niger* ants:

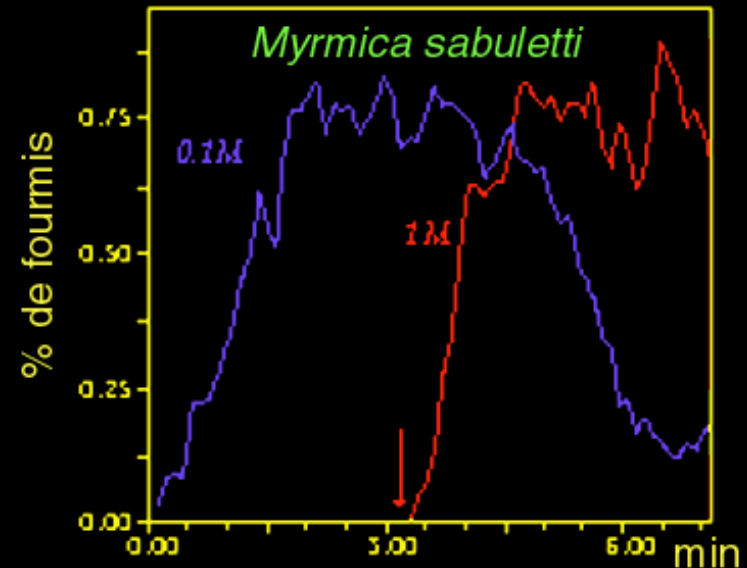
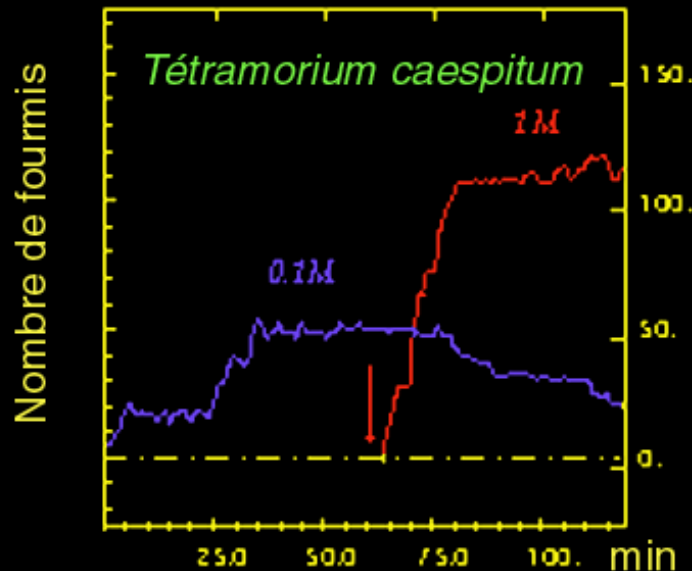


➡ The ants might get stuck within their trail system and therefore the colony exploits primarily the first food source that has been discovered even if this might lead to neglecting a richer source which just appeared at a later time.

Lasius niger: exclusively uses pheromone-based recruitment mechanisms although has good individual navigation capabilities; probably since nest-sources path not so misaligned, u-turn strategy does not help in this scenario! 111

Selecting the Richest Source – Scenario 3

Results obtained with *Tetramorium caespitum*, *Myrmica sabuletti*

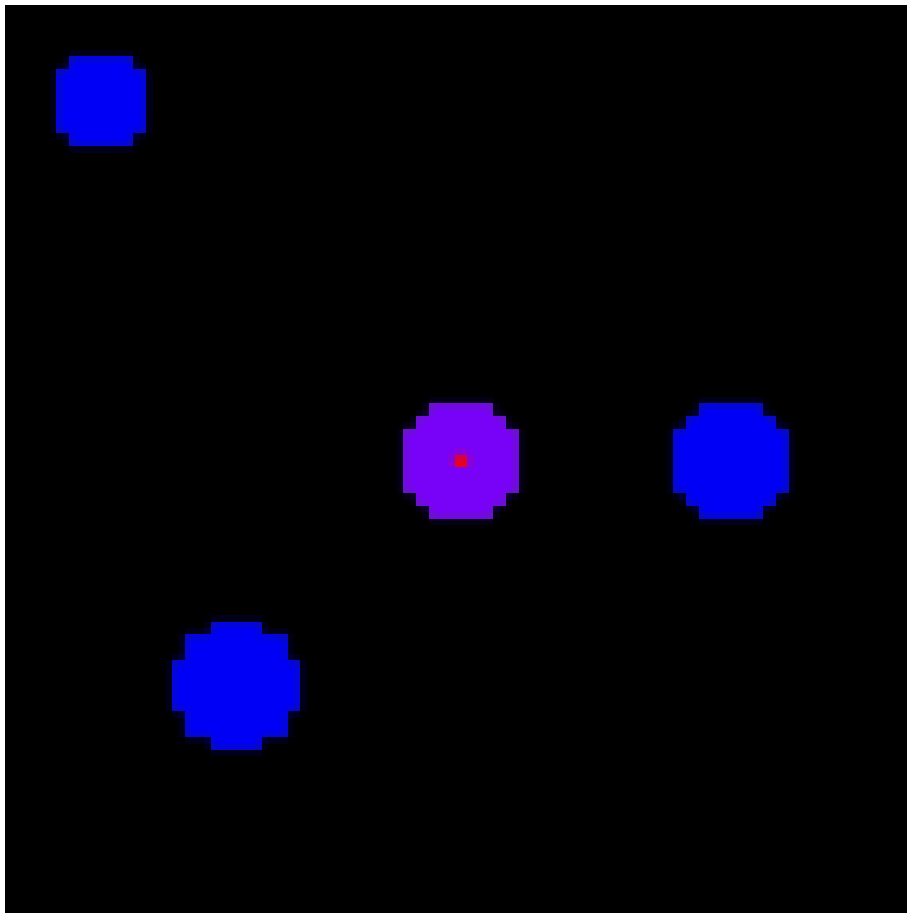


- These two ant species exploit mixed recruitment strategies: mass (trail laying/following) and group (no stigmergy) and do not get stuck in their trail network

Mitchel
Resnick, MIT,
Media Lab



An Example with Three Different Food Sources



- Different richness
- Different distances from nest
- Obstacle-free environment

Ant Networks

Ant Super-Colonies

The organization of inter-nest traffic in ants

- For most social insects, **the fundamental ecological unit is the colony.**
- In a number of ant species, groups of workers, larvae, and reproductives can leave the nest and set up a new nest while maintaining **close connections** with the parent nest.
- The collection of nests, or sub-colonies, forms what is called a **super-colony.**



Super-colony of *Formica Lugubris* (Switzerland)
Prof. D. Cherix (Uni Lausanne)

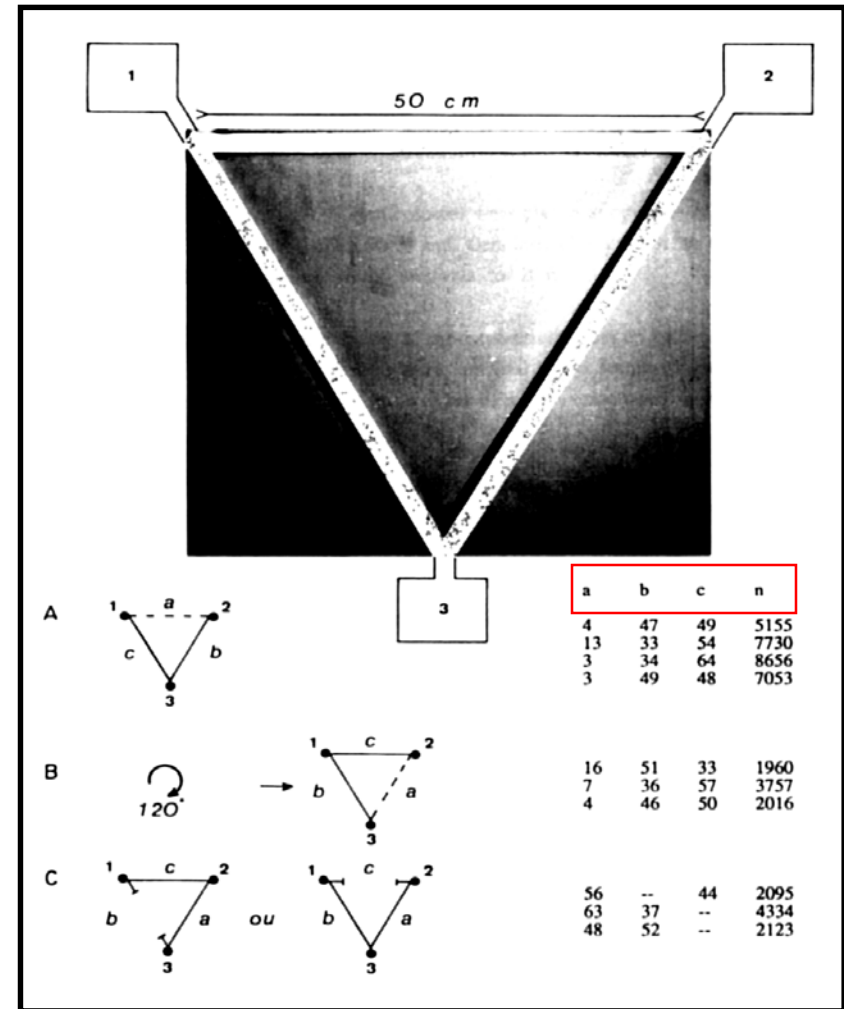
The Organisation of Inter-Nest Traffic in Ants

Results for a triangular network (3 nest super-colony) with *Linepithema humile* (Argentine ants)

a, b, c = % of traffic on branch a, b, or c

n = absolute number of passages

[Aron, Deneubourg, Goss, Pasteels, 1991]

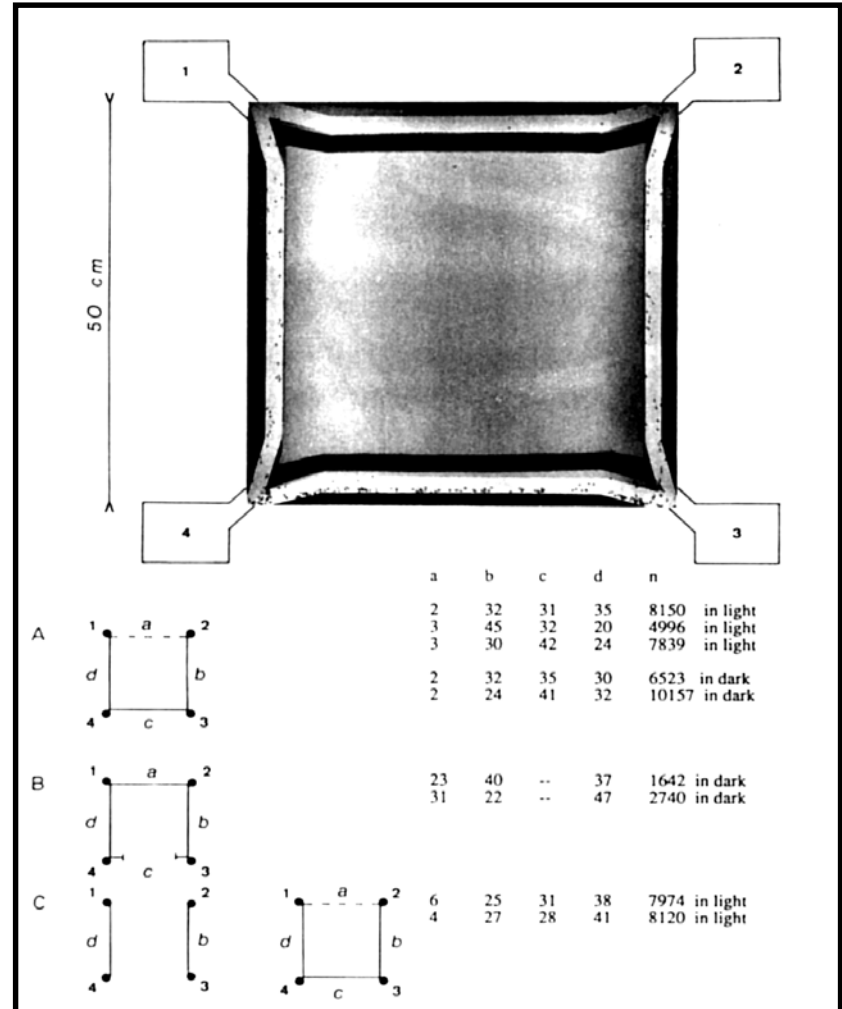


The Organisation of Inter-Nest Traffic in Ants

Results for a quadrangular network (4 nest super-colony) with *Linepithema humile* (Argentine ants)

a, b, c, d = % of traffic on branch a, b, or c
 n = absolute number of passages

[Aron, Deneubourg, Goss, Pasteels, 1991]



Ants are Able to Optimize!

- All the nests are connected either directly or indirectly
- Ants are able to find the **minimal spanning tree** connecting all the nests (probable ecological reasons: cost building and maintaining redundant spanning tree higher + extend predator exposure)
- This is similar to the Traveling Salesman Problem (TSP)
- Can artificial ants solve the TSP?

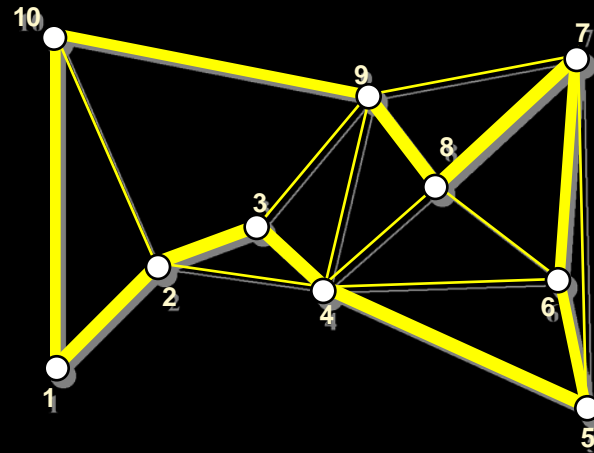
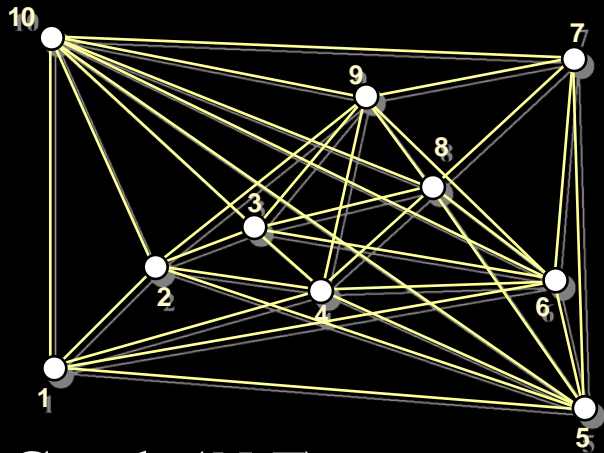
An Introduction to Multi-Agent Systems based on Ant Trail Laying/Following Mechanisms

Motivation

- Ant Colony Optimization (ACO) algorithms as an example of successful transportation of ideas from **natural** systems to **digital artificial** systems (software multi-agent systems)
- ACO algorithms as example of exploitation of **swarm intelligence** principles as a particular form/instance of **distributed/collective intelligence**

The Traveling Salesman Problem

The Traveling Salesman Problem



Graph (N, E)

N : set of cities (nodes)

E : set of connecting roads (links)

d_{ij} : distance between city i and j

Problem: Find the shortest path which allow the salesman to visit once and only once each city in the graph

Difficulty: NP-hard problem; time for computing the shortest route grows in a nonpolynomial way with the number of cities in the network -> metaheuristics/machine-learning class (e.g., ACO, GA) provide near-optimal solutions!

How Hard are NP-Hard Problems?

TSP – Brute force

- A 30 city tour would have to measure the total distance of be 2.65×10^{32} different tours. Assuming a trillion additions per second, this would take 252,333,390,232,297 years.
- Adding one more city would cause the time to increase by a factor of 31.

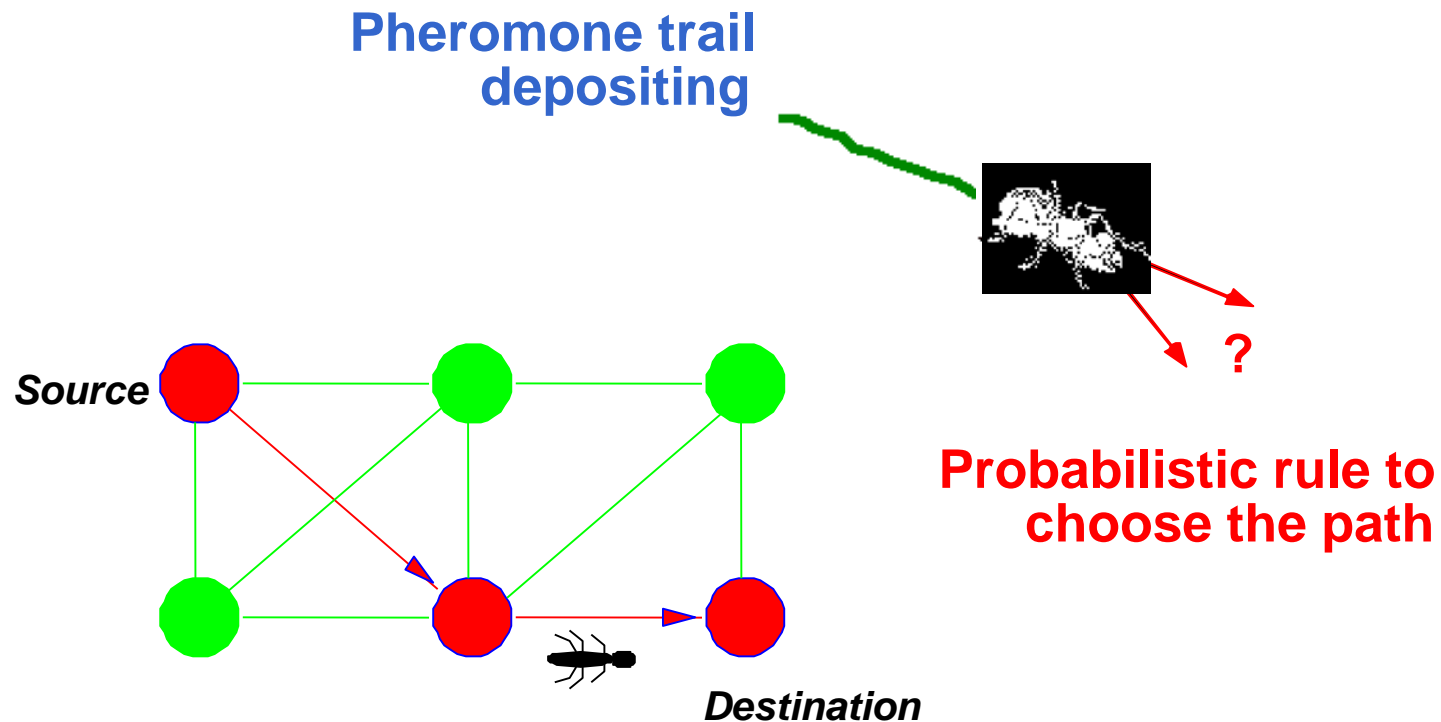
TSP – Exact vs. metaheuristic algorithms

- Tens of thousands of cities (see Applegate et al. 2006)
- Metaheuristic methods: millions of cities

QAP – Exact algorithms (e.g. Bixius & Anstreicher 2001)

- around 30+ max instances
- ex. 36 nodes (wiring application): 180h CPU on a 800 MHz Pentium III PC
- Same problem with ACO: 10 s on the same machine

Artificial Ants and the Shortest Path Problem



Problem!

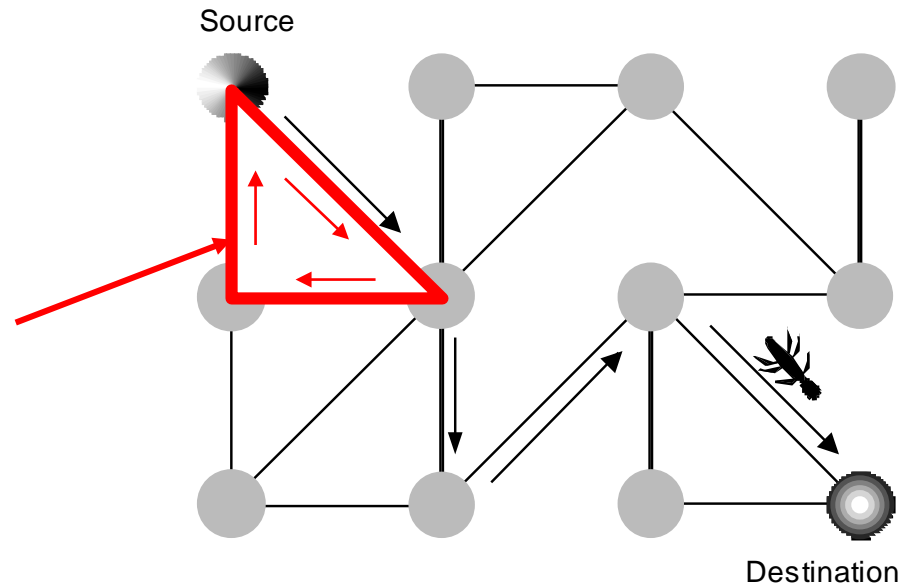
The extension of the real ant behavior (forward/backward trail deposit and slow pheromone decay rate) to artificial ants moving on a graph doesn't work:

problem of self-reinforcing loops

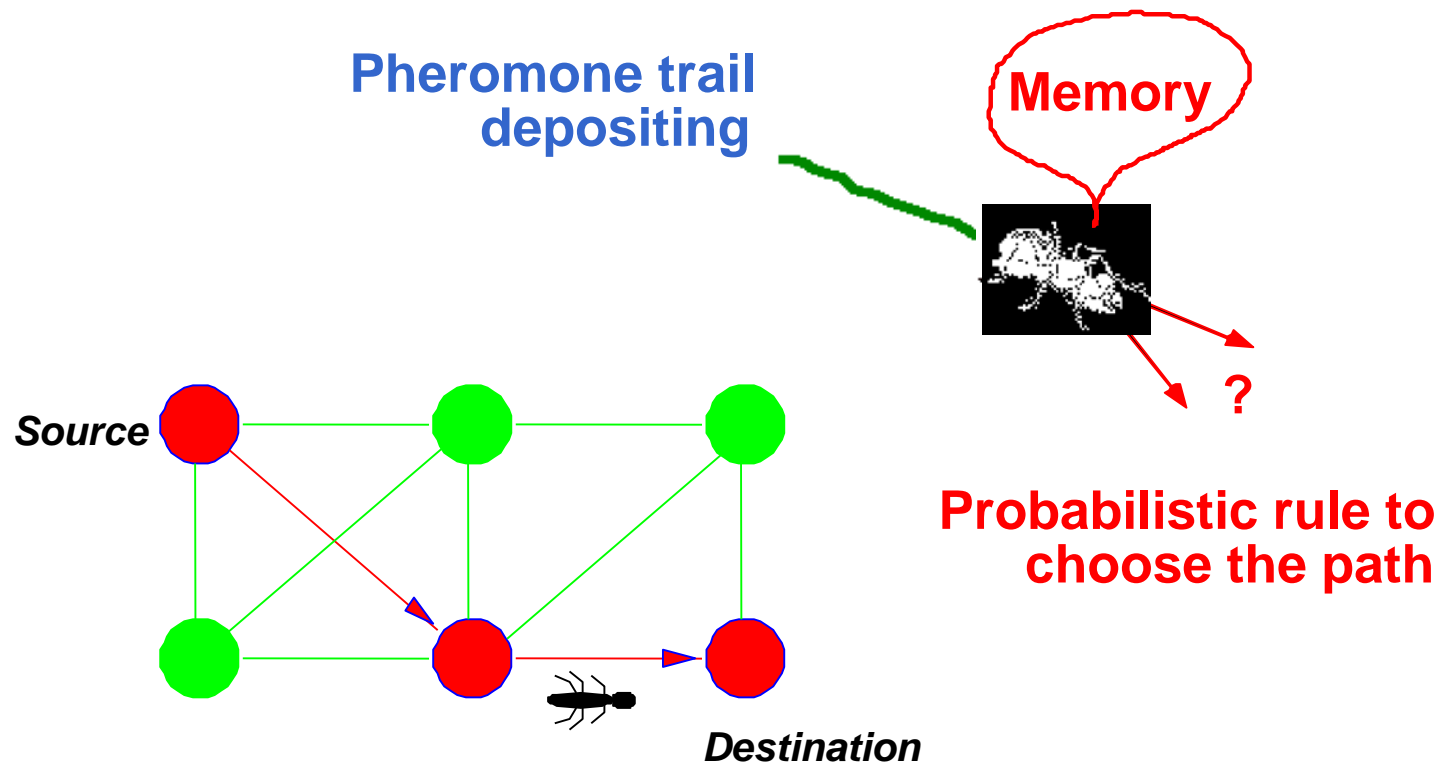
Probabilistic solution generation plus pheromone update

-> self-reinforcing loops

**Example of possible
self-reinforcing loop**



Solution!



The First ACO Algorithm: The Ant System (AS)

Design Choices for AS

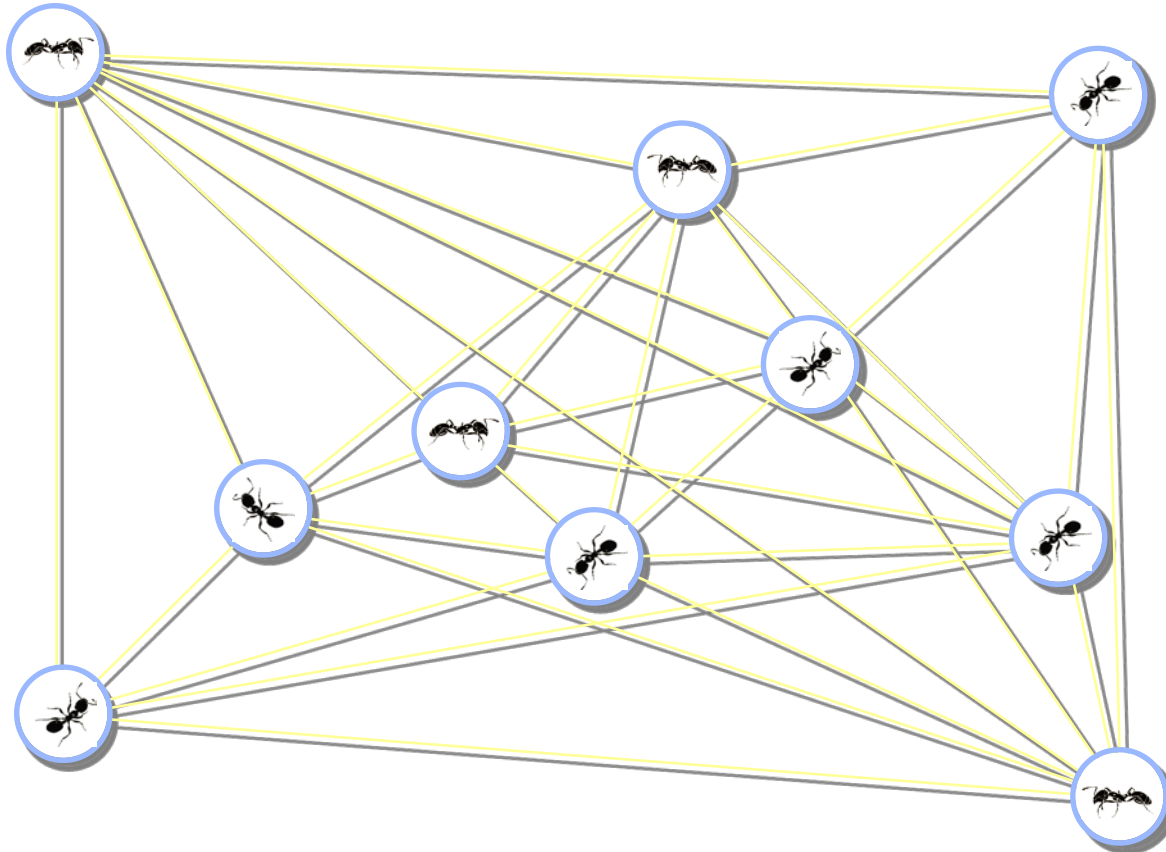
(Dorigo, Colorni, Maniezzo, 1991)

- Ants are given a **memory** of visited nodes
- Ants **build solutions probabilistically** without updating pheromone trails (**forwards ants**)
- Ants **deterministically backward** retrace the forward path **to update pheromone (backwards ants)**
- Ants deposit a **quantity** of pheromone function of the **quality of the solution** they generated
- Pheromones **evaporates** much more quickly than in nature

Assumptions on TSP

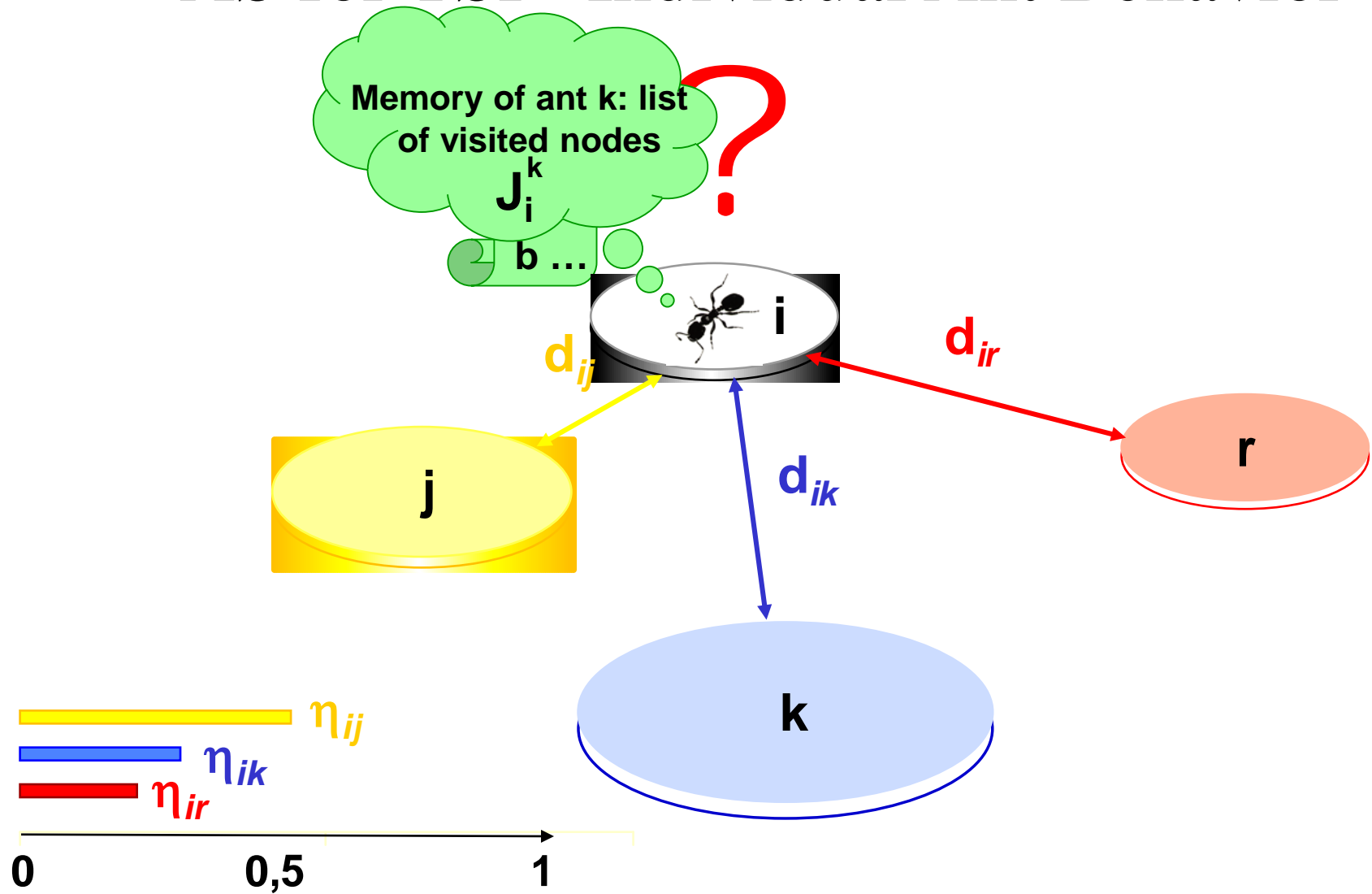
- **Usual assumption:** fully connected graph (i.e. there is a direct route with a given distance from any city in the problem to any other); city list work ok
- **Real problem:** not fully connected; problem with city list
- **Possible solutions:**
 - Assume virtual routes so that fully connected; give very bad scores to ants choosing virtual routes (e.g., high but not infinite virtual distance; Dorigo's suggestion)
 - Alternative: break not valid tours asap and either relaunch a new ant or consider less ants for updating pheromones at the next iteration (Martinoli's suggestion); computationally more efficient but risk to lose constructive aspect of trail laying/following; does not work for dead end edges with end criterion being at the start city
 - Graph connectivity: full – dense – sparse; probably different solutions work better as a function of the connectivity degree; interesting problem

AS for TSP - Overview



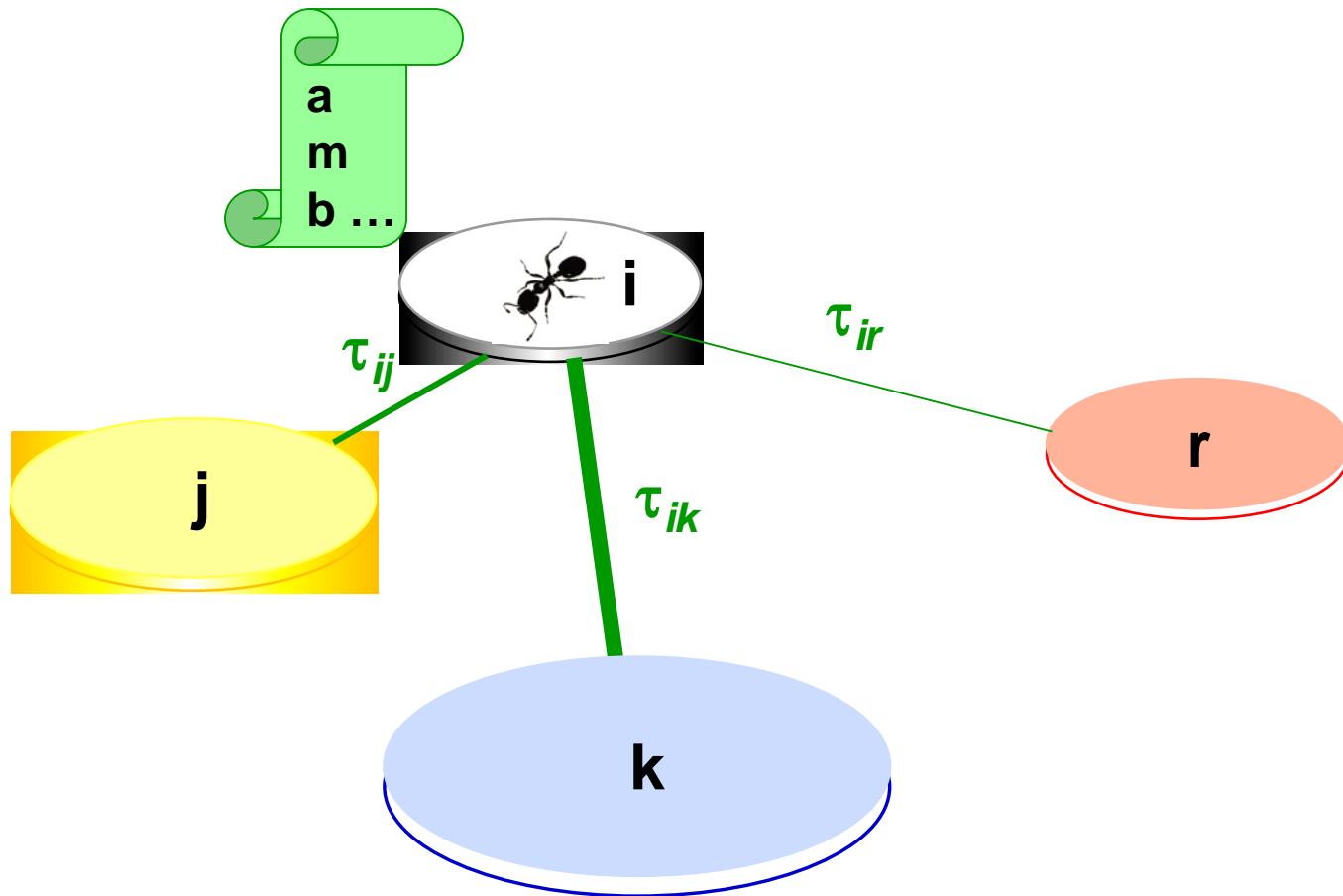
$b_i(t)$, ($i = 1 \dots n$) : number of ants at the **node i** at the **iteration t**

$$m = \sum_{i=1}^n b_i(t) = \text{constant: total number of ants}$$



The **inverted value of the distance** $\eta_{ij} = 1/d_{ij}$ between nodes i and j is called **visibility**; this information (**heuristic desirability**) is static, i.e. not changed during the problem solution

AS for TSP- Individual Ant Behavior



τ_{ij} , quantity of **virtual pheromone** deposited on the link between the node **i** and **j**

AS for TSP - Algorithm

Loop $\backslash^* t = 1^*$

Place one ant on each node \backslash^* there are $n = |N|$ nodes \backslash^*

For $k := 1$ to m \backslash^* each ant builds a tour, in this case $m=n$ \backslash^*

For step $:= 1$ to n \backslash^* each ant adds a node to its path \backslash^*

Choose the next node to move by applying a
probabilistic *state transition rule*

End-for

End-for

Update pheromone trails

Until End_condition \backslash^* e.g., $t = t_{\max}$ \backslash^*

AS for TSP – Transition Rules

- J_i^k : list of nodes still to be visited for ant k when it is at node i ; starting from an exhaustive list of all the cities in the problem, nodes get scratched during a tour T ; at the beginning the list contains all nodes but i ; also called **tabu list**
- T : **tour**, it last $n = |N|$ steps (N = number of nodes in the problem) in which the probabilistic transition rule below is applied
- t : **iteration index**: number of times the whole algorithm is run; $1 \leq t \leq t_{\max}$

During a tour T , an ant k at the node i decided to move towards the node j with the following probability (**idea: roulette wheel**):

$$p_{ij}^k(t) = 0 \quad , \text{ if node } j \text{ have been visited by ant } k \text{ already because of tabu list}$$

$$p_{ij}^k(t) = \frac{[\tau_{ij}(t)]^\alpha [\eta_{ij}]^\beta}{\sum_{l \in J_i^k} [\tau_{il}(t)]^\alpha [\eta_{il}]^\beta} \quad , \text{ if the node have not been visited yet}$$

α : parameter controlling the influence of the virtual pheromone

β : parameter controlling the influence of the local heuristic (visibility)

AS for TSP – Virtual Pheromone Update

At the end of each tour T , **each ant k** deposits a quantity of virtual pheromone $\Delta\tau_{ij}^k$ on the link (i,j) ; pheromones sum up

$$\Delta\tau_{ij}^k = 0 \quad , \text{ when } (i,j) \text{ has not been used during the tour } T$$

$$\Delta\tau_{ij}^k = \frac{Q}{L^k(t)} \quad , \text{ when } (i,j) \text{ has been used during the tour } T$$

$L^k(t)$ = **length of the tour T** done by ant k at iteration t

Q = **parameter** (adjusted by heuristic, not sensitive)

Note: the longer the tour, the lower is the quality of the solution, the smaller the quantity of pheromone dropped

AS for TSP – Default Virtual Pheromone Update

$$\tau_{ij}(t+1) \leftarrow (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij}(t)$$

$$\text{with } \Delta\tau_{ij}(t) = \sum_{k=1}^m \Delta\tau_{ij}^k$$

ρ = evaporation coefficient

At iteration $t = 0$ each link is initialized with a small homogenous pheromone quantity τ_0

AS for TSP – Virtual Pheromone Update with Elitism (EAS)

$$\tau_{ij}(t+1) \leftarrow (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij}(t) + e\Delta\tau_{ij}^e(t)$$

$$\text{with } \Delta\tau_{ij}(t) = \sum_{k=1}^m \Delta\tau_{ij}^k$$

$$\Delta\tau_{ij}^e(t) = Q / L^+ \quad \text{if } (i,j) \text{ belongs to the best tour } T^+ \text{ out of the } m \text{ tours generated by ants at a given iteration}$$

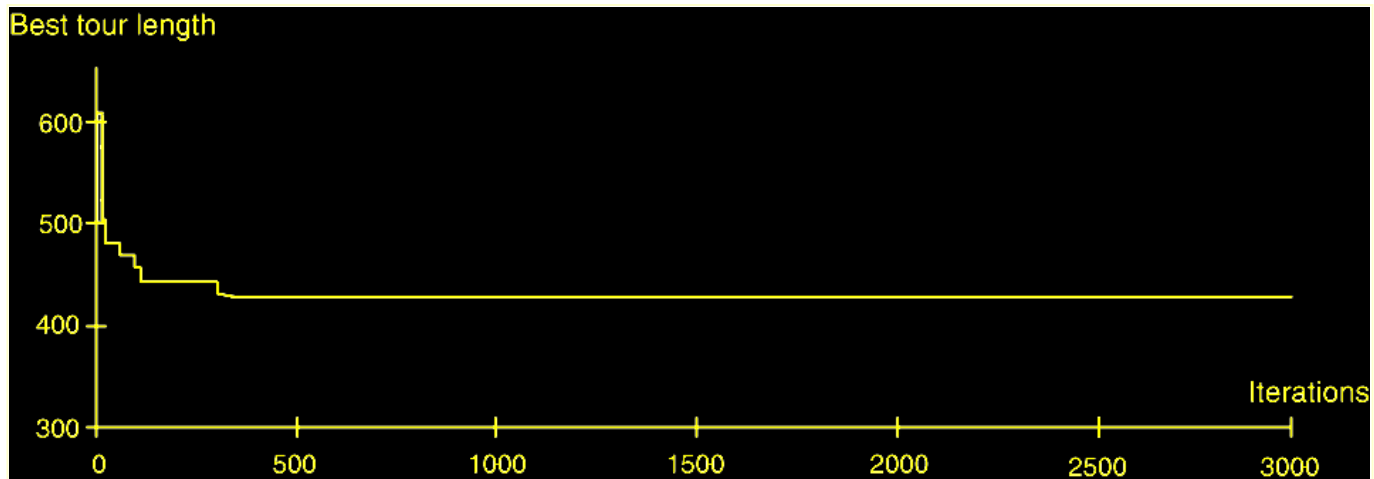
$$\Delta\tau_{ij}^e(t) = 0 \quad \text{otherwise}$$

e = **parameter** (adjusted by heuristic, not sensitive)

Note: idea, best tours get extra reinforcement

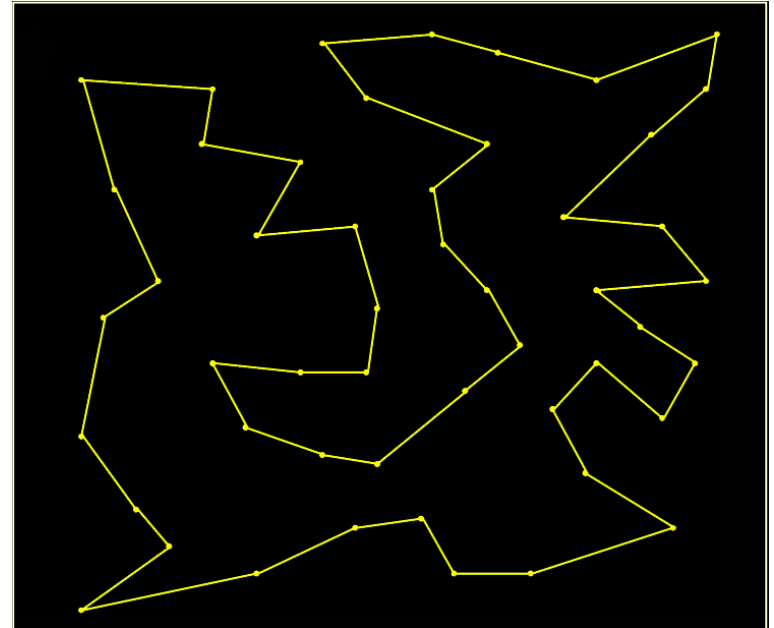
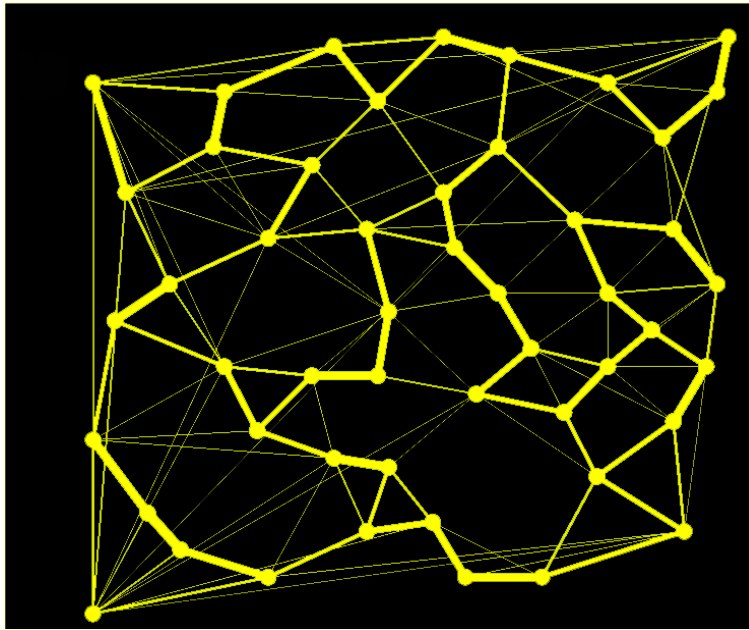
AS for TSP – Evolution of the Best Tour Length

Example: 30 nodes problem



AS for TSP – Results 50 cities

Example of solution found on Eil50 problem



AS for TSP – Performance as a Function of the Problem Dimension

Network	n (dimension)	best solution	Mean number of iterations for to the near- optimal solution	Simulation time (seconds)
4 X 4	16	160	5,6	8
5 X 5	25	254,1	13,6	75
6 X 6	36	360	60	1020
7 X 7	49	494,1	320	13440
8 X 8	64	640	970	97000

Summary of AS

- **Ants** are launched at each iteration from each node to explore the network
- **Ants** build their paths probabilistically with a probability function of:
 - (i) **artificial pheromone values**, and
 - (ii) **heuristic values** (in TSP: city visibility)
- **Ants** memorize visited nodes
- Once they all reached their destination nodes (in TSP the last city on their list) **ants** retrace their paths backwards, and update the pheromone trails

Conclusion

Take Home Messages

1. Differences between artificial and natural SI
2. Differences between computational and physical SI
3. Key mechanisms for natural SI: self-organization and stigmergy
4. Self-organization ingredients: positive feedback, negative feedback, randomness, multiple interactions
5. SI-based systems exploit careful balance between exploration and exploitation
6. Microscopic models help understanding SI-based systems
7. Ants exploit trail laying/following mechanisms and other strategies for foraging

Take Home Messages

8. Ants are able to generate efficient inter-nest networks
9. Trail laying/following mechanisms can be expanded with other properties of the agent easily implementable in software (e.g., memory, modulation of the pheromone quantity, etc.)
10. Ant System has been the first metaheuristic taking advantage of the ant inspiration
11. The first NP hard problem it has been applied was the Traveling Salesman Problem

Additional Literature – Week 1

Books

- Kelly K., "Out of Control: The New Biology of Machines, Social Systems and the Economic World", Perseus Press, 1995.
- Ormerod P., "Butterfly Economics: A New General Theory of Social and Economic Behavior", Pantheon Books, 2001.
- Crichton M., "Prey: A Novel", HarperCollins, 2002.
- Camazine S., Deneubourg J.-L., Franks N. R., Sneyd J., Theraulaz G., Bonabeau E., "Self-Organization in Biological Systems". Princeton Studies in Complexity, Princeton University Press, 2001.
- Hölldobler B. and Wilson E. O., "Journey to the Ants: A story of Scientific Exploration", The Harvard University Press, Cambridge, MA, 1994.
- Hamman H., "Swarm Robotics: A Formal Approach", Springer International Publishing, Cham, Switzerland, 2018.

Additional Literature – Week 1

Papers

- Beni G. and Wang J., “Swarm Intelligence”. *Proc. of the Seventh Annual Meeting of the Robotics Society of Japan*, Tokyo, Japan, 1989, pp. 425-428.
- Bonabeau E. and Theraulaz G. "Swarm Smarts". *Scientific American*, March 2000, pp. 72-79.
- Peter Miller “Swarm Theory”, *National Geographic*, July 2007, pp. 126-147.
- Aron S., Beckers R., Deneubourg J.-L., and Pasteels J.-M., “Memory and Chemical Communication in the Orientation of two Mass-Recruiting Ant Species”. *Insect Society*, 1993, Vol. 40, pp. 369-380.
- Deneubourg J.-L., Aron S., Goss S., and Pasteels J. M., “The Self-Organizing Exploratory Pattern of the Argentine Ant”. *J. of Insect Behavior*, 1990, Vol. 3, pp. 159-168.
- Beckers R., Deneubourg J.-L., and Goss S., “Trails and U-Turns in the Selection of a Path by the Ant *Lasius niger*”. *J. Theor. Biol.*, Vol. 159, pp. 397-415, 1992.
- Jackson D. E., Holcombe M., and Ratnieks F. L. W., “Trail geometry gives polarity to ant foraging networks”. *Nature*, No. 432, pp. 907-909, 2004.
- Dorigo M., Maniezzo V., and Coloni A., “The Ant System: Optimization by a Colony of Cooperating Agents”. *IEEE Trans. Systems, Man, and Cybernetics, Part B*, Vol. 26, pp. 29-41, 1996.