From understanding self-organization in biology to managing artificial complex systems

Fabrice Saffre & José Halloy

Part 1: from living to artificial complex system

Plan of the presentation

- Complex systems in biology
  - General concepts
  - Examples in animal populations
- Natural vs. artificial complex systems
  - Existence of generic rules for autonomous behaviour
- Methodology, framework & toolbox
  - Deterministic and stochastic dynamical systems modelling
  - Agent based computer simulation, experiments and prototyping

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Biological complex systems: a model for « autonomic computing »

- Classically, problem-solving is based on the "Knowledge" of central units which must make decisions after collecting all necessary information.
- However an alternative method is extensively used in nature: collective behaviour. In systems consisting of a large number of events, problems are *collectively self-solved in real time* through the simple behaviour of individual sub-units, which interact with each other and with the environment.
- Imperfect or incomplete information, randomness and amplifying communication play a key role in such systems.

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Biological complex systems: a model for « autonomic computing »

- Societies are multi-agents systems that process information, solve problems, take decision, are factories and or fortresses
- These systems in which the units are mixed with the environment exhibit organizational structures that are functional, robust, and adaptive.
- Well known experimental and theoretical examples are found in animal societies which are in essence similar to artificial systems in IT!
- Societies offer :
  - a complete blend of individual capacities and collective levels of intelligence and complexity;
  - a wide spectrum of size, physical constraints, …;
  - a wide spectrum of sharing of costs and benefits among members.

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Biological systems are not fully self-organized !

- A limited number of organizations are at work in social systems:
- Template
- Leadership & Collection of specialists
- Sharing external signal

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(Deneubourg & Goss, 1989; Deneubourg & Camazine, 1994; Camazine et al, 2001)

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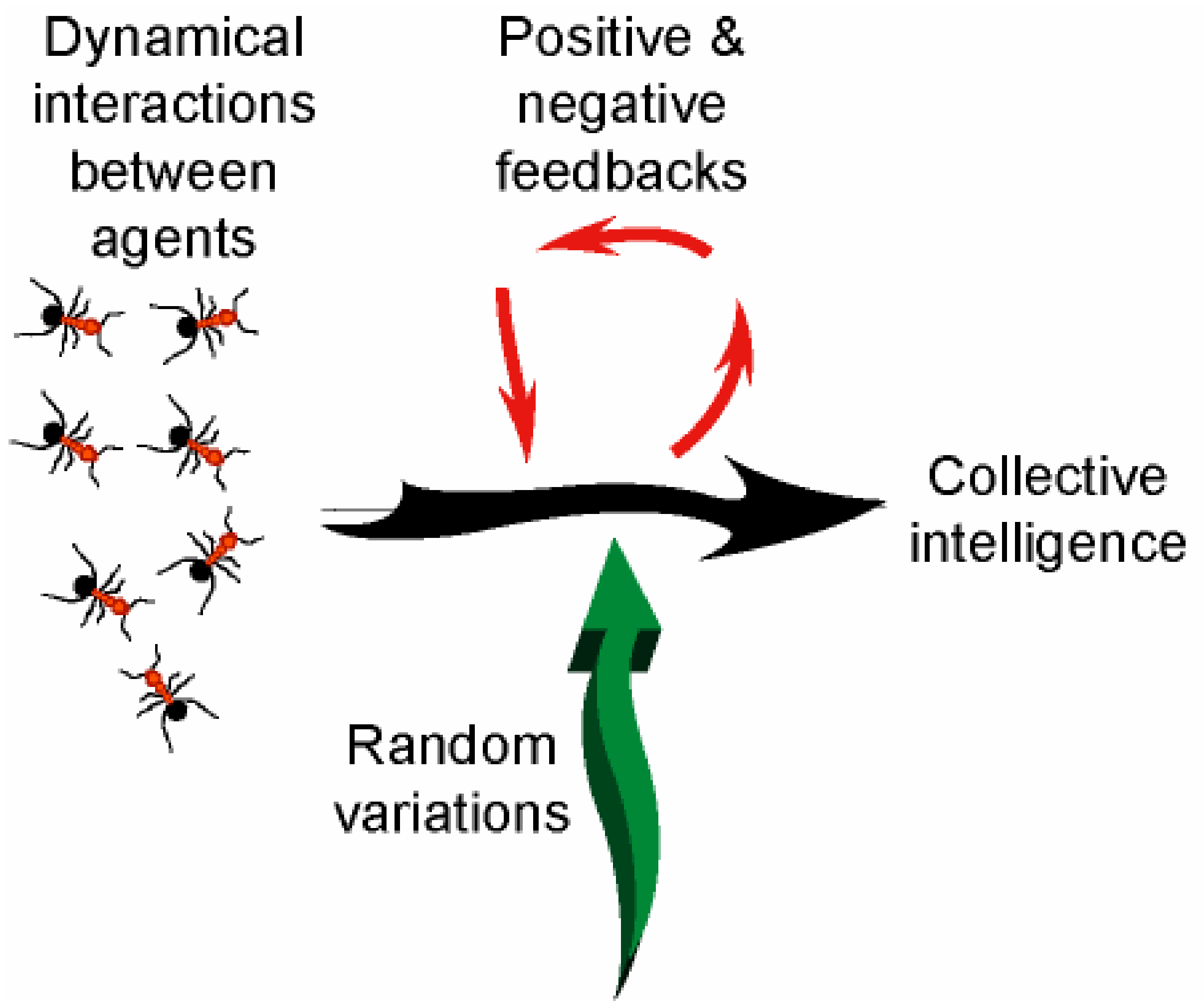
Concepts



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Concepts

- **Emergent behaviour and self-organization**
  By emergent behaviour we mean a collective behaviour *that is not explicitly programmed in each individual* but emerge at the level of the group from the numerous interactions between these individuals that only follow local rules (no global map, no global representation) based on incomplete information.

- **Randomness**
  Individual actions include a level of intrinsic randomness. An action is never certain but has an intrinsic probability of occurring. The behaviour of each individual becomes then less predictable. The predictability of a system depends also on the level of description and the type of measures done. Randomness and fluctuations play an important role in allowing the system to find optimal solutions. In some cases, there is even an optimal level of noise that contributes to the discovery of optimal solutions. This noise is either at the level of the individuals or the interactions. It can be controlled in artificial systems and modulated in living systems.

- **Predictability**
  The global outcome of population presenting emergent behaviour is *certain* in well characterized systems. For instance, the result of emergent collective foraging in ant colonies is certain and efficient. Ants do bring food home or they simply die! Because often the system present multiple possible states coexisting for the same conditions, the specific solutions that accomplish the global behaviour at the level of the group are *statistically predictable*. For instance the optimal solution to solve a problem is chosen in 85% of the cases while a less optimal solution is selected in 15% of the cases. Nevertheless, the problem is solved in 100% of the cases! The discussion is then shifted towards knowing if 15% of suboptimal behaviour is acceptable and not if the global outcome is predictable.

- **Evolution and emergent behaviour**
  We think that emergent behaviour is not an equivalent of evolution or even a necessity for evolution to take place. Emergent behaviour does not produce, in itself, new and unexpected behaviour.

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Self-organization and emergent behavior

- Identified in natural systems
- A limited number of so generic rules are at work in biological systems (from the cellular level to animal societies, including plants) and produce optimal emergent collective patterns for resources and work allocation.
- What are these generic rules and their building blocks?
- What are these patterns?
- Most of the works are focused on the “pattern” without discussing the functionality
- Functional self-organization (Aron, Deneubourg, Goss & Pasteels, 1990)

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A taxonomy of organization?

- Based on the phylogenetic systematics
- Based on the basic biological functions (reproduction, foraging,…)
- Based on the network of interactions (diffusion, broadcasting, network) and individual mobility
- Based on the number of behavioral programs/number of specialists involved in the tasks
- Based on the dynamics or patterns involved in the tasks
- Based on the network of feed-backs involved in the tasks

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Demonstrated examples of the emergence of autonomous behavior

- Sophisticated spatial pattern formation

  - nest building

  - trail network

  - aggregation patterns

- Collective choice

  - food source

  - settlement place

  - strategies selection

- Regulation of activity, task allocation

- Synchronization or de-synchronization of activity without external pacemaker

- Social differentiation & division of labour

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Different dynamics /patterns

- Aggregation et related patterns
- Network
- Synchronization
- Regulation

Identical or different agents

- Emergence of individual specialization

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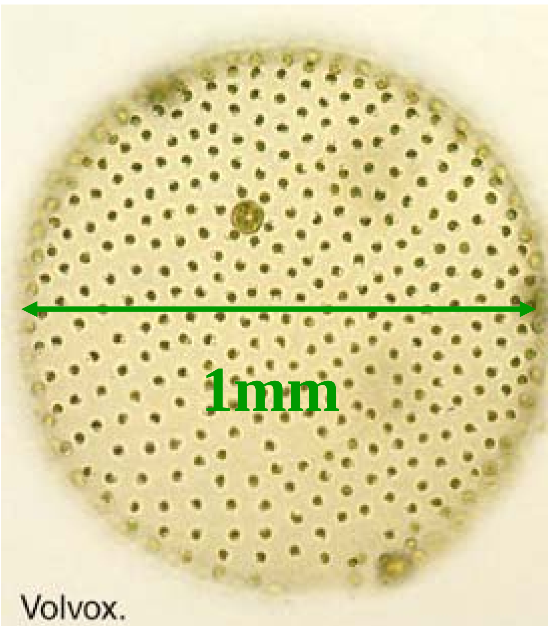
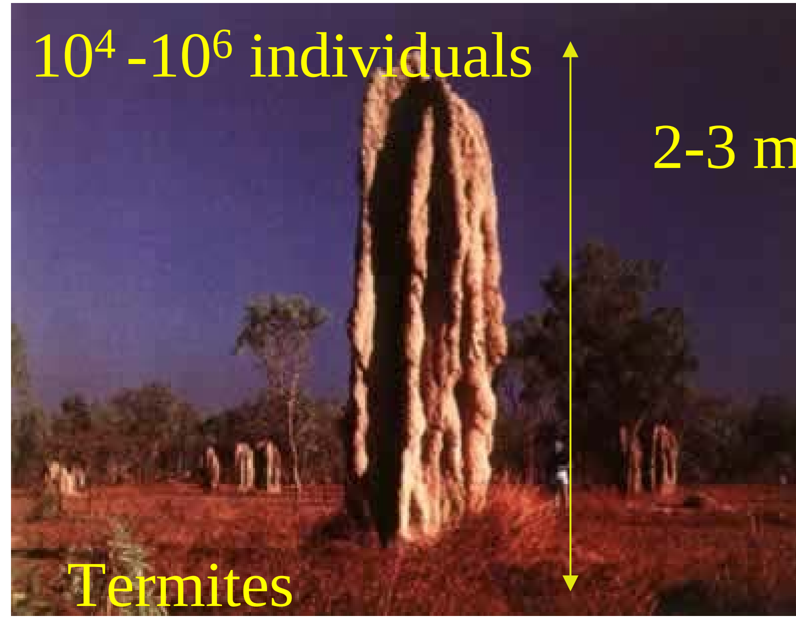
Biological complex systems

A ball of cells



10^2 -10^3 individuals



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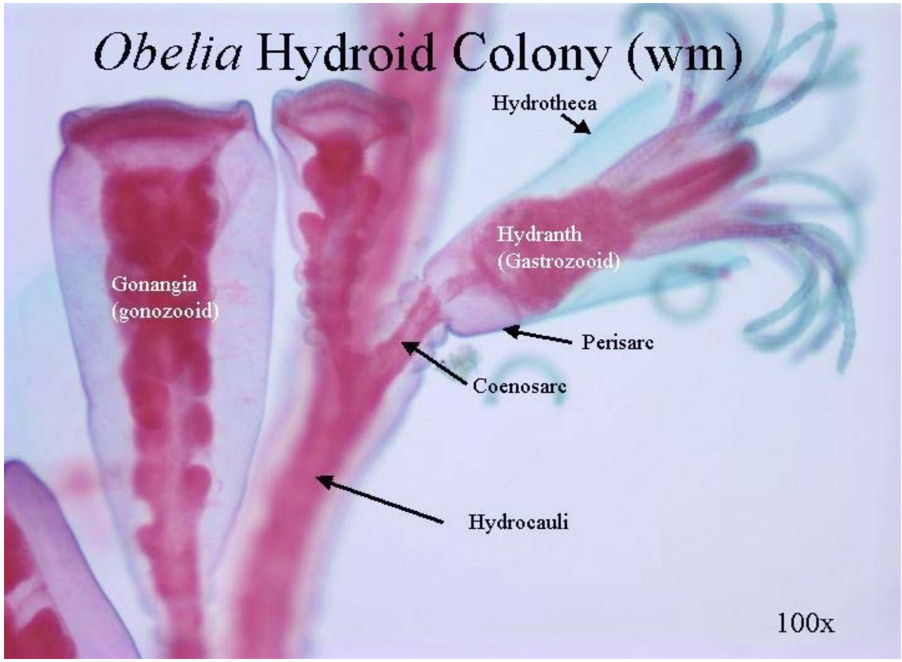
Synchronization of specialized individuals

Colonial organisms: self-assembled structures

A collection of highly specialized agents.
Various units function in food gathering
reproduction defence of the colony



Giant siphonophores (length 40 m)

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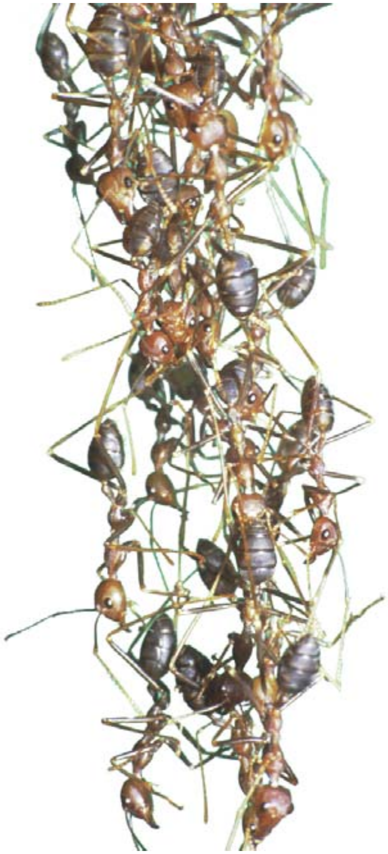
Circular pattern

Self-organized aggregation



Self-assembled structures

(Lioni & Deneubourg, 2004)

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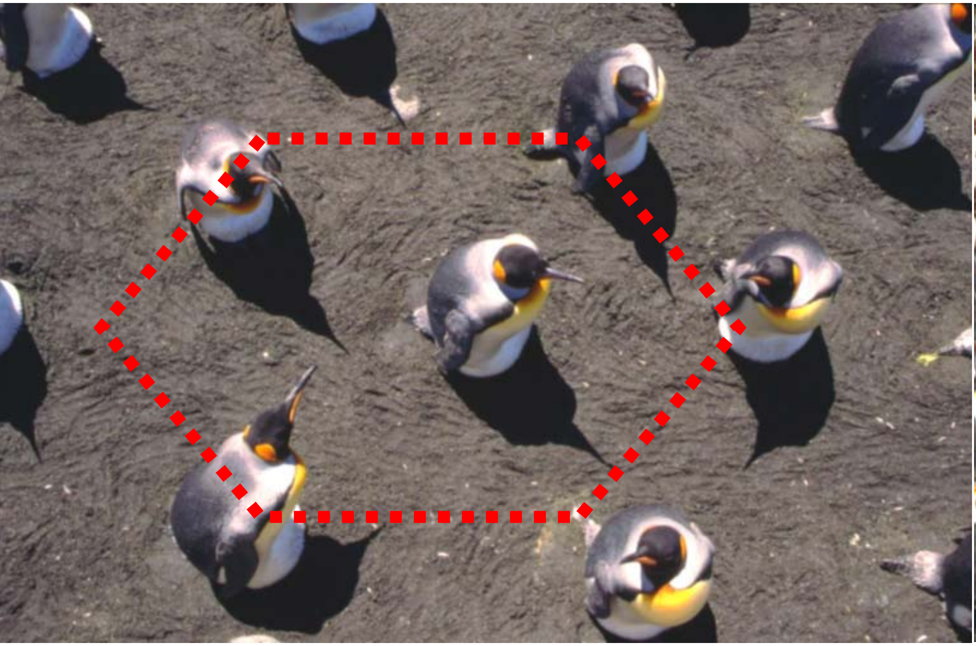
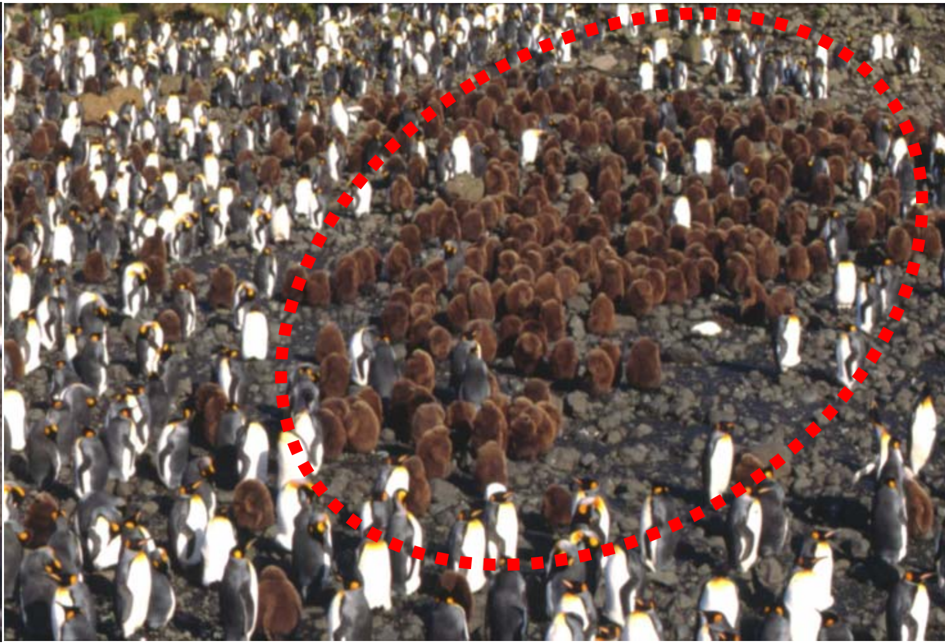
Lattice

Sorting





Modified from Lebohec *et al*

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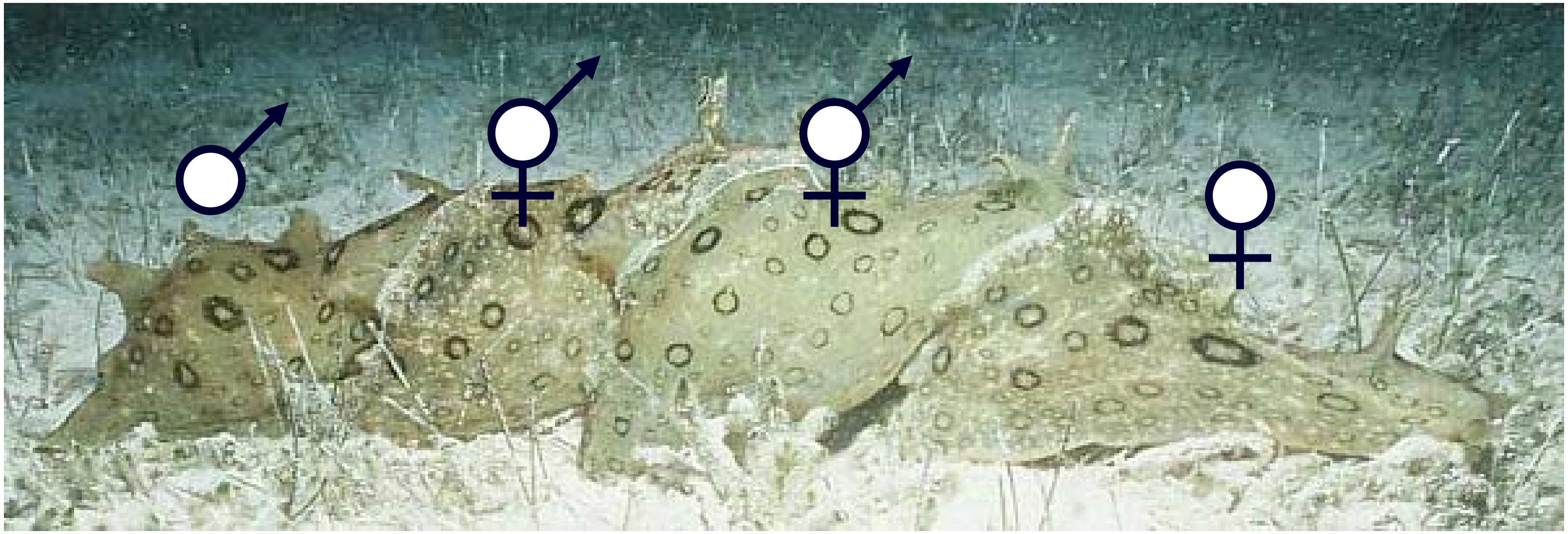
Self-organized(?) collective sex



Mating chain : *Aplysia dactylomela* (Molluscs)

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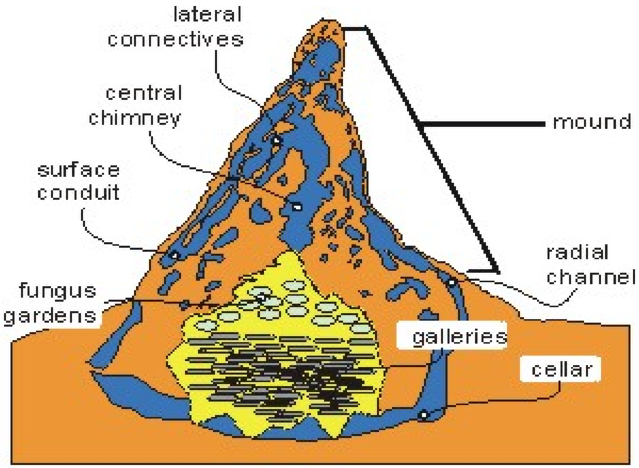

Synergy between template
& self-organization in termite nest

Self-organized network made by ants (ULB)

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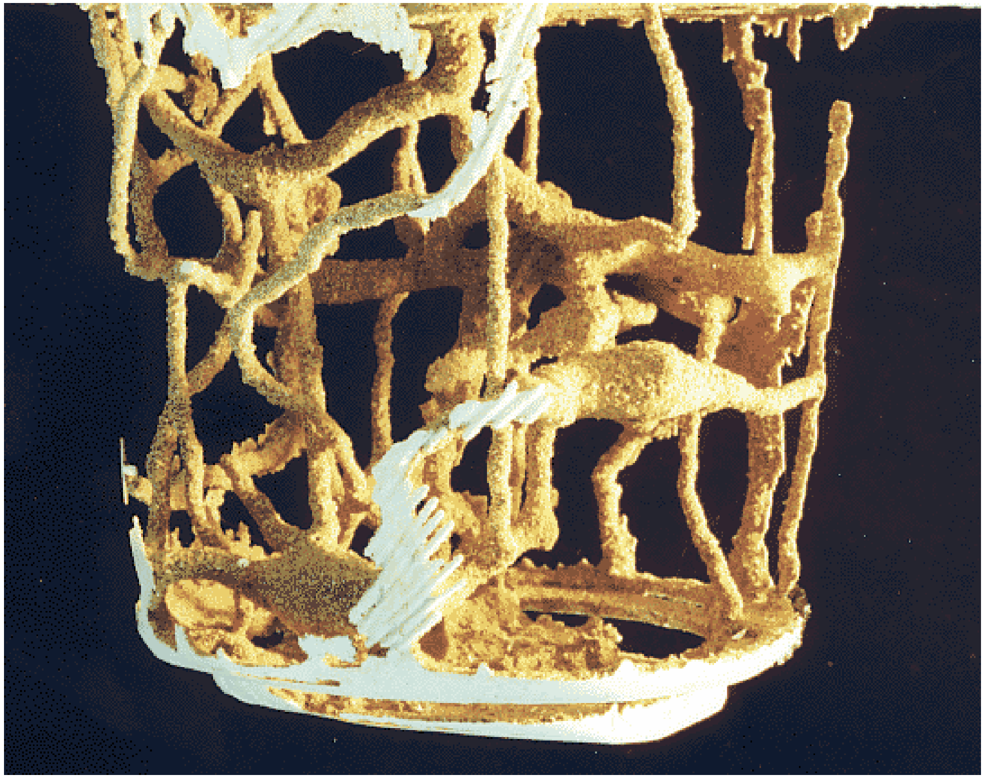
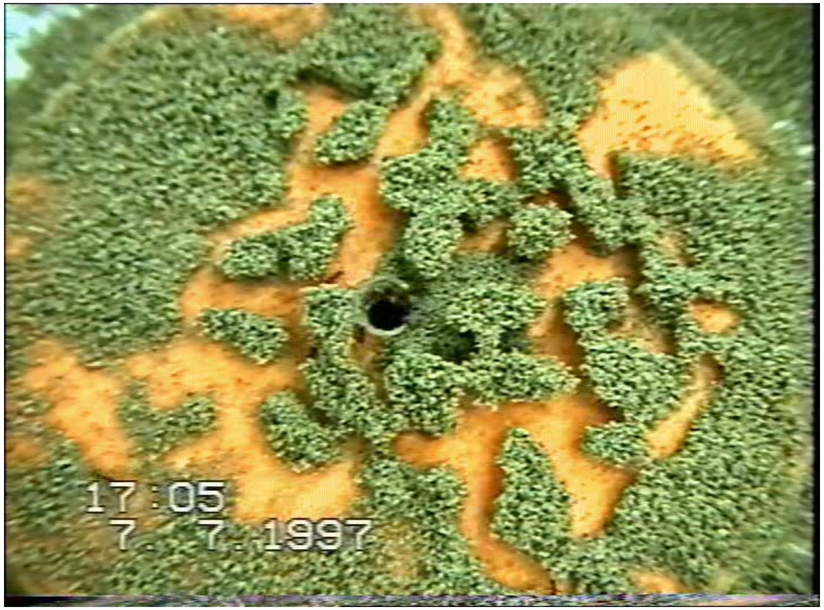
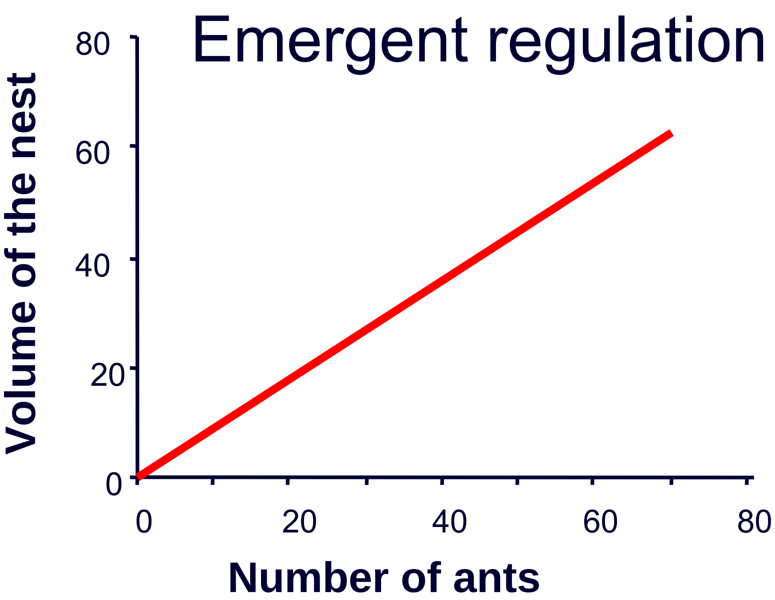
Ants: **experimental** demonstration of SO

Self-organized networking by ants







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(P. Rasse & J-L Deneubourg, 2001)

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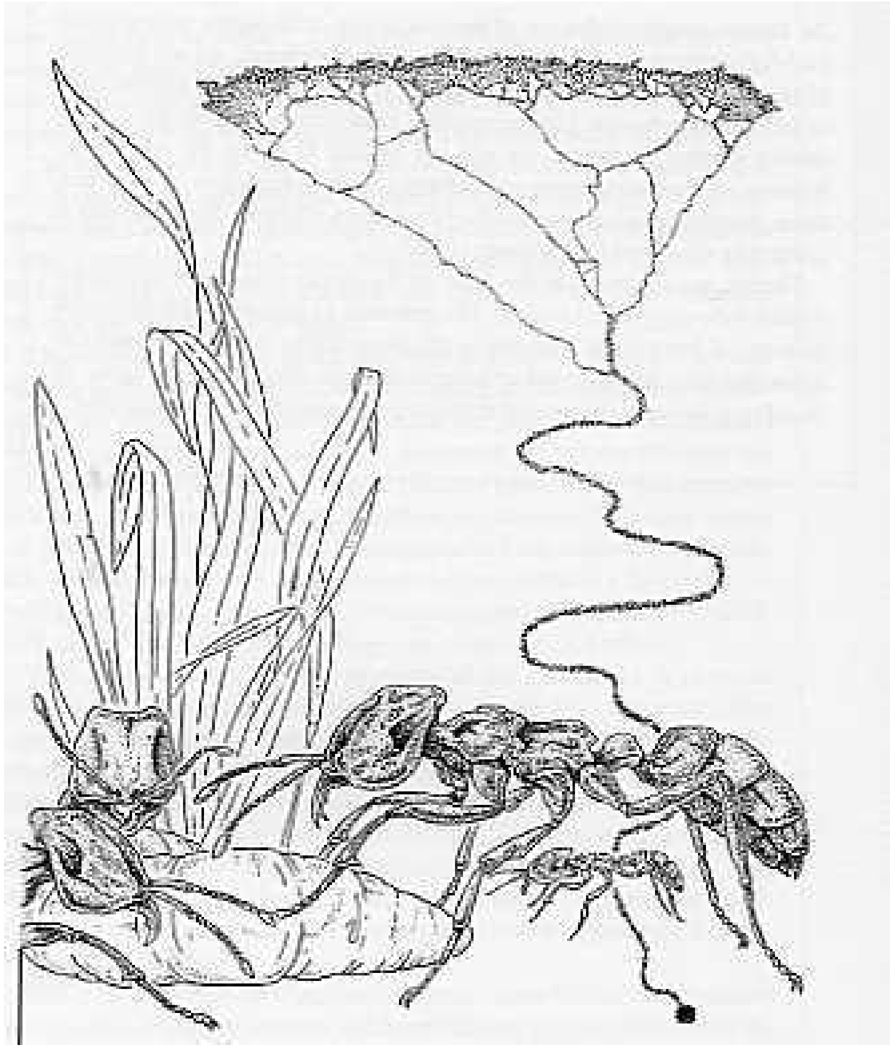
Experimental studies of trails and networks

Dorylus



(Deneubourg, Goss, Franks & Pasteels, 1989
Franks, Gomez, Goss & Deneubourg,1991)

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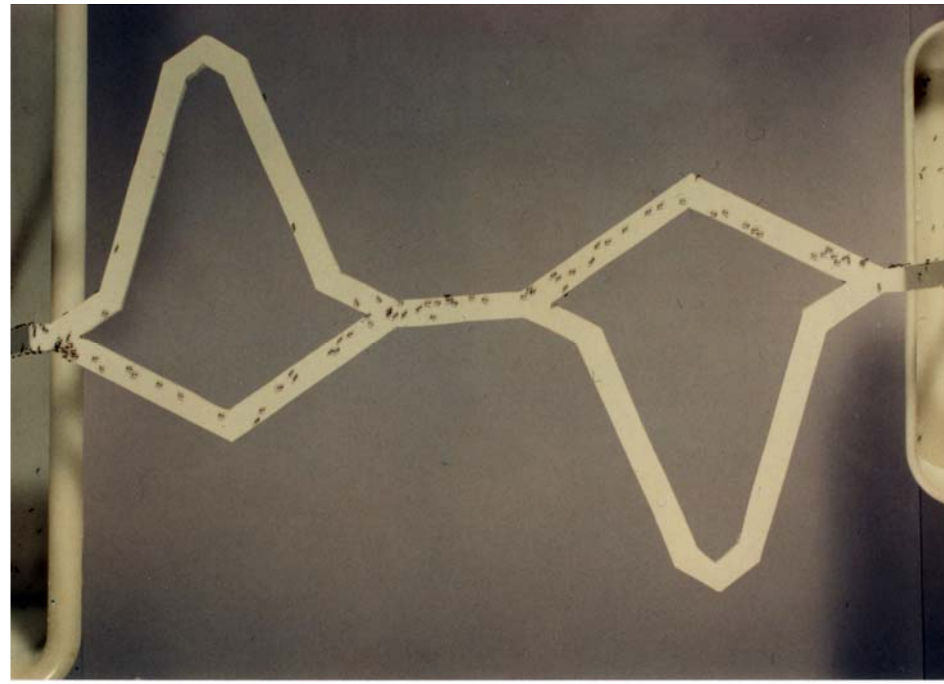
Path choices by ant colony



Shortest path selection

R. Beckers, J.L. Deneubourg, S. Goss (1992). Journal of Theoretical Biology , 159, 397-415.

Traffic flow regulation

Dussutour A *et al*. Nature. 2004. 428(6978):70-3.

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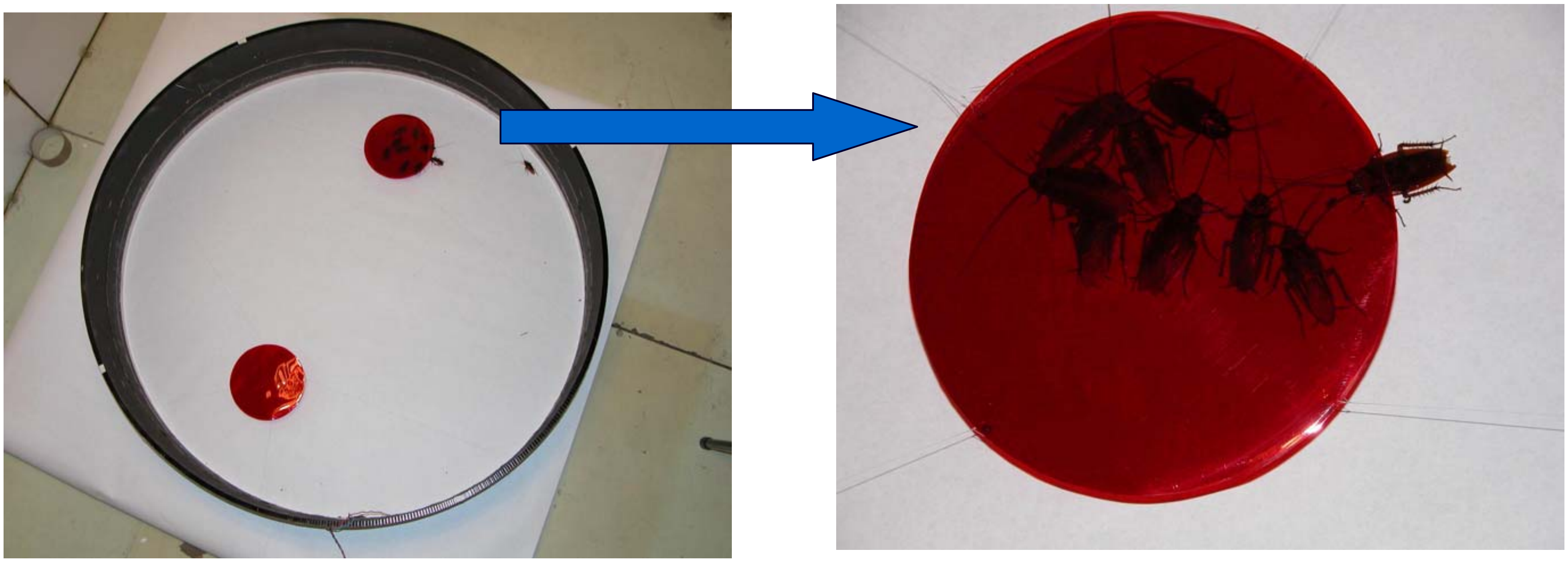
Collective choice



All together now! (without leader)

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Identified in biological complex systems

A ***limited number of simple generic rules*** are at work in biological systems (from the cellular level to animal societies) and produce, **autonomously**, optimal emergent collective patterns for resources and task allocation, synchronisation or de-synchronisation without external pacemaker, clustering and sorting

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Main features

- Dynamical systems with a large number of events: it does **not** necessarily mean a large number of agents
- The size of the population and the characteristics of communication play an important role (all to all, nearest neighbour, etc.)
- Randomness is a benefic ingredient to find optimal solutions
- Biological systems are not fully self-organized complex systems, they present a mix between centralized and distributed "management"
- Well known experimental and theoretical examples are found in animal societies which are in essence similar to artificial systems in IT

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Methodology, framework & toolbox

- Experiments at the laboratory (significant number of repetitions!)
- Models based on stochastic or deterministic equations (ODE, PDE, etc.)
- Stochastic computer simulation or “agents” based simulations
- Experimental & theoretical results -> validated models -> predictions -> prototyping

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Natural vs. artificial complex systems

- It is not a question of biological relevance but of appropriate context of use.
- Emergent behavior is very useful when decisions have to be made while action is still taking place, i.e. when the problem cannot be specified and solved proactively (before the situation occurs).
- Only limited “cognitive” capabilities of agents are needed and/or available to collect and process information.
- In the natural world, emergent behavior appears most useful in persistent populations of individuals that have to cooperate autonomously over long periods of time.
- Some applications of the so called “ant algorithms” do not fall into this category. For example, in “ant colony optimization”, the problem is solved a priori, then the solution is implemented in a centralized manner. For that reason, and even though the approach has yielded useful results, we believe that it is not the best possible use-case for emergent behavior in artificial complex systems.

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Control of collective decision making in insect groups by artificial agents

- We address collective choice or aggregation based on inter-attraction
- We focus on the experimental case of shelter selection by cockroaches (*Blatella germanica, Periplaneta americana*, Rennes & ULB)
- We discuss choices among shelters of identical or different quality
- We present a mathematical model based on experimental data in the framework of dynamical system theory
- The choices are described as bifurcations leading to multi-stationary states
- The stationary states corresponds to the number of individuals under a shelter
- We show how it can be used to make prediction in mixed groups of animals and machines

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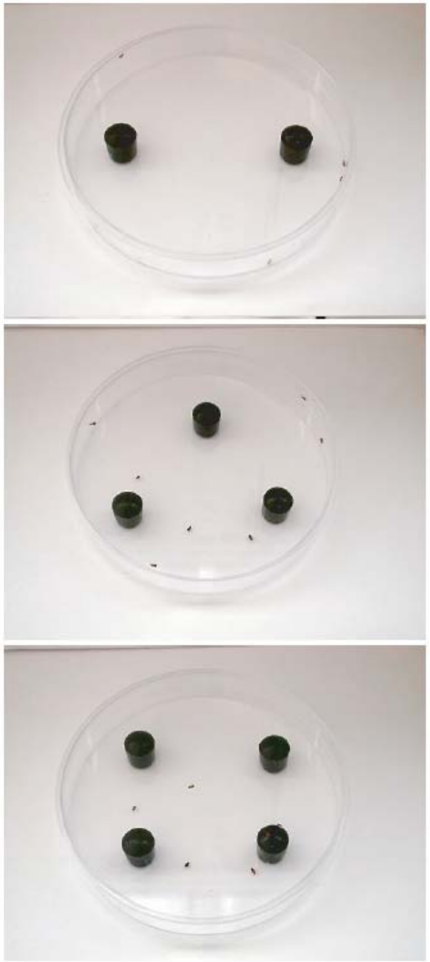
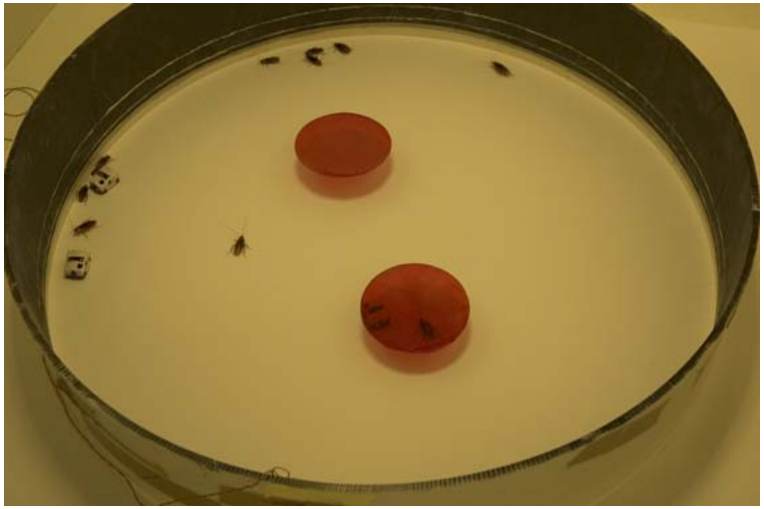
Behavioral studies: collective decision making in cockroach group

Experimental setup of shelter selection by cockroaches (Rennes & ULB)





ULB: G. Sempo, S. Canonge, J-M Amé
S. Depickère, J. Halloy, J-L Deneubourg

Blatella germanica: 300 tests of 24H each (in parallel)
Periplaneta americana: 400 test of 3H each (4 in parallel)

Rennes: C. Rivault & *J-M Amé*

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Collective decision making in cockroach group: model based on inter-attraction taking into account crowding effect

$$\frac{dx_i}{dt} = \mu_i x_e \left(1 - \frac{x_i}{S_i}\right) - \frac{\theta_i x_i}{1 + \rho\left(\frac{x_i}{S_i}\right)^n} \qquad i = 1, \cdots, p$$

$$N = x_e + \sum_{i=1}^{p} x_i$$

- n inter-attraction factor
- p number of shelters present in the system
- N total number of individuals
- x_i number of individuals in shelter i
- x_e number of individuals outside the shelters
- S_i carrying capacity of the shelters

This model is very well characterized experimentally on 2 species of cockroaches (Rennes & ULB, Halloy *et al.* PNAS, 2006)

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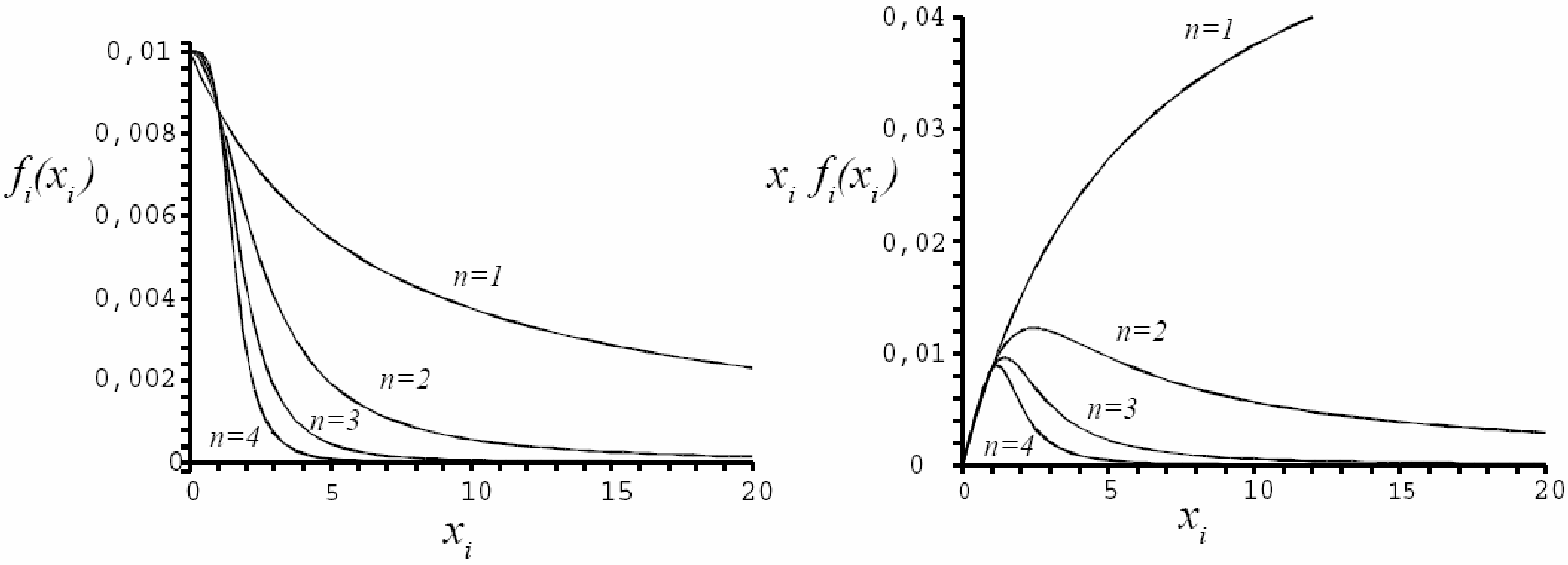
Model based on inter-attraction taking into account crowding effect

Main experimental fact: the inter-attraction between individuals decreases the probability to leave the shelter.



This fact is modeled by a threshold function (with n>1), leading to a saturation effect in the individual outflow from a shelter.

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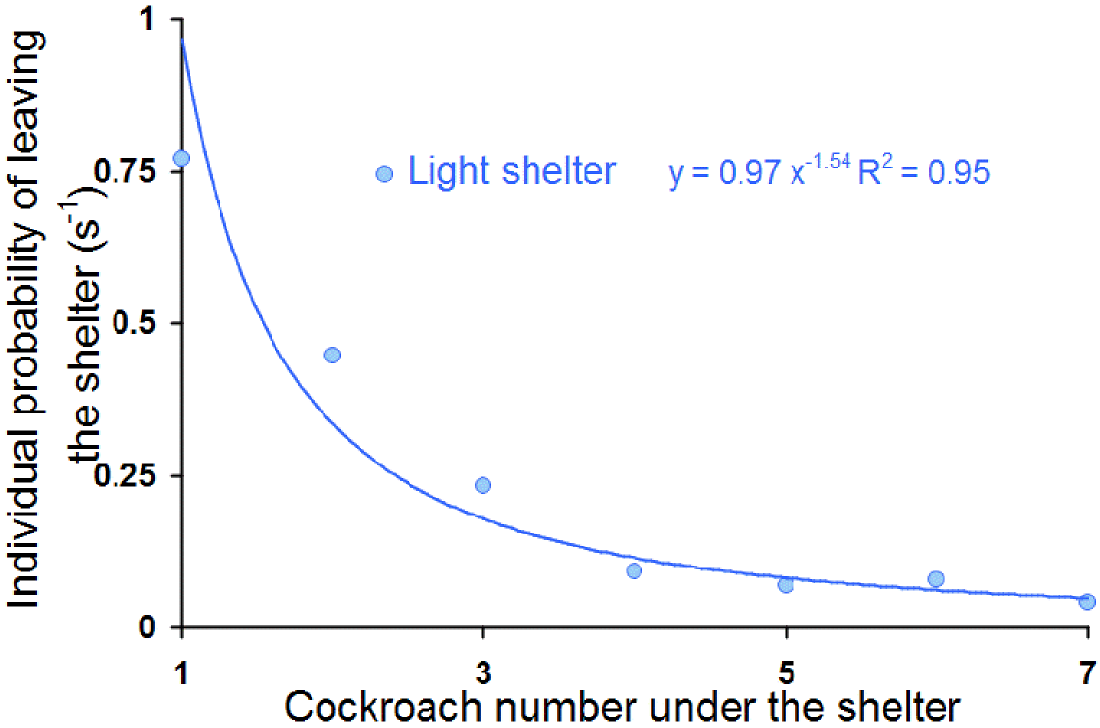
Model based on inter-attraction taking into account crowding effect

Experimental measure of the probability of leaving the shelter as a function of the number of individuals (*P. americana*)



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The black magic ingredients of the model…

- Individuals explore the system and encounter randomly the shelters
- They are capable of detecting the shelters and estimate their quality
- They are capable of identifying their conspecifics and sense their number
- They are constrained by a crowding effect

- **Experimental measures on cockroach case studies**

- Probability to be inside or outside the shelters is calculated from the time distributions inside or outside the shelters
- Probability of leaving the shelter according to the number of individuals present is calculated from the time distribution inside a shelter as a function on the number of conspecific
- The number of individuals present in the shelters and outside
- The other parameter value are drawn from curve fitting of the experimental data

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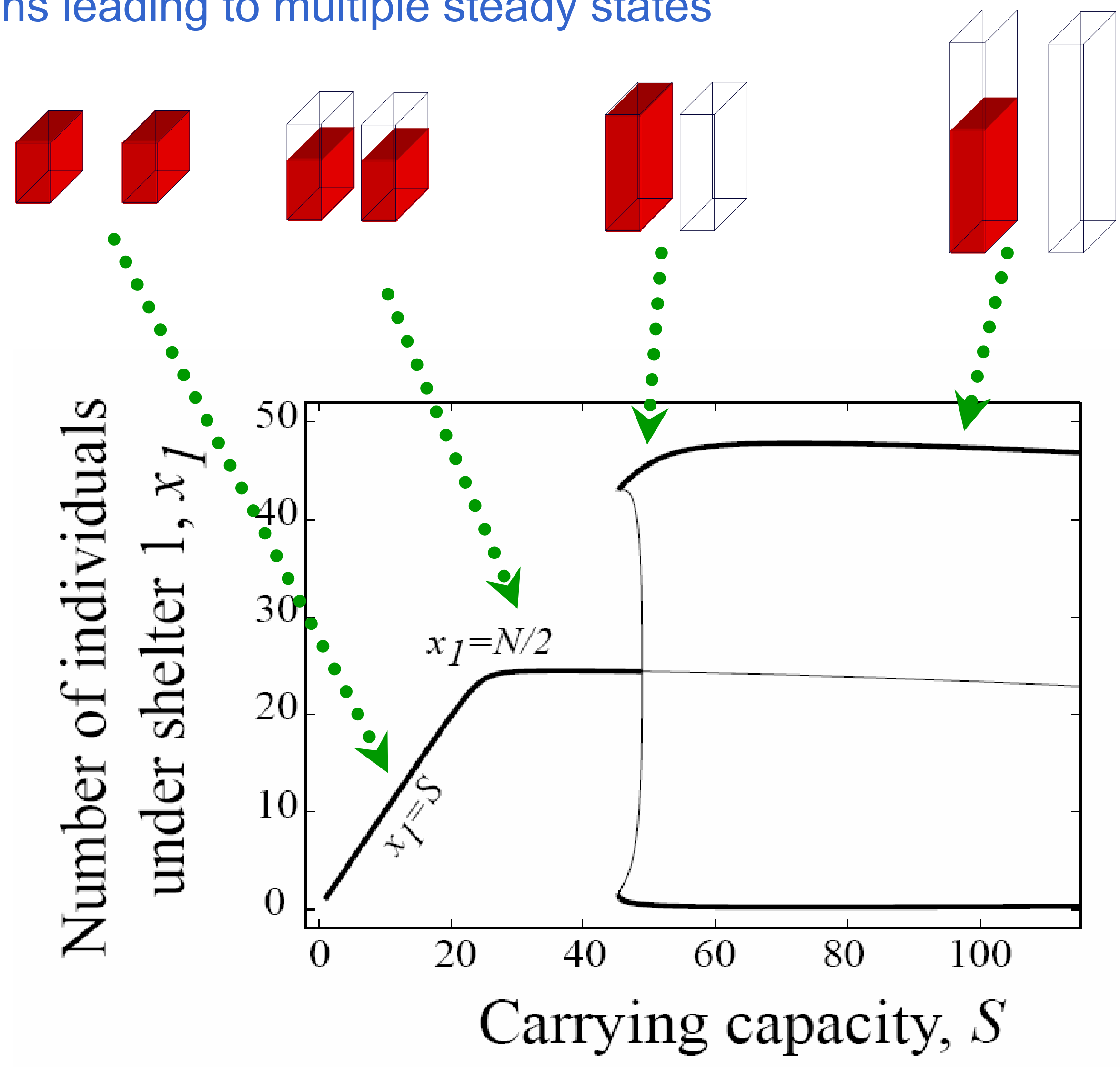
Collective decision making in cockroach group described by bifurcations leading to multiple steady states



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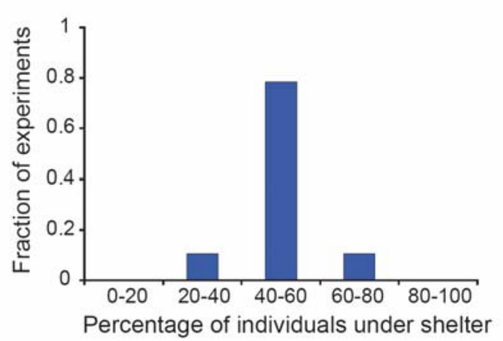
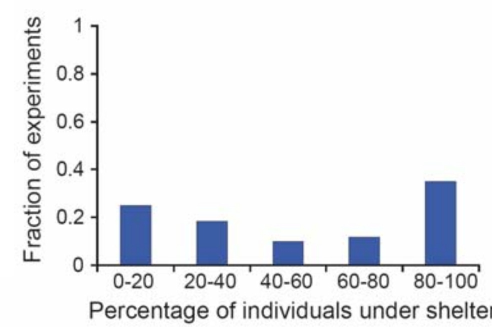
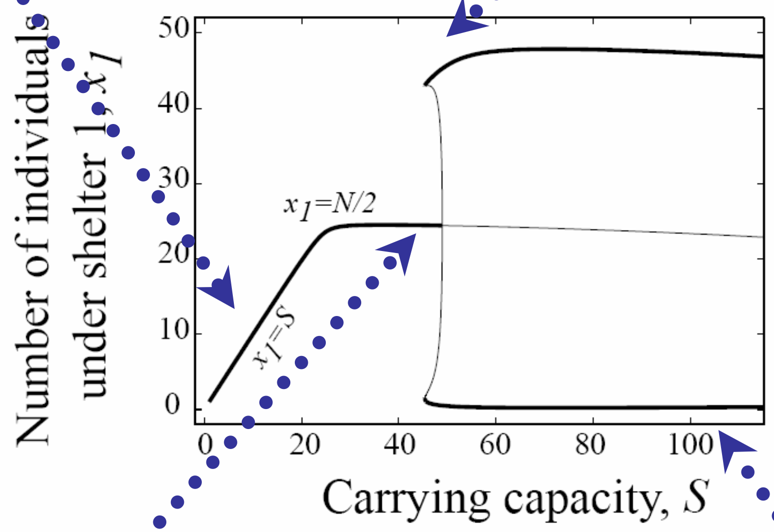
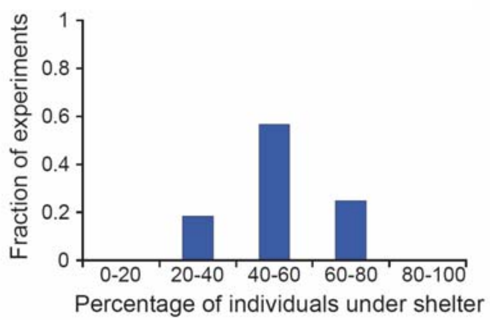
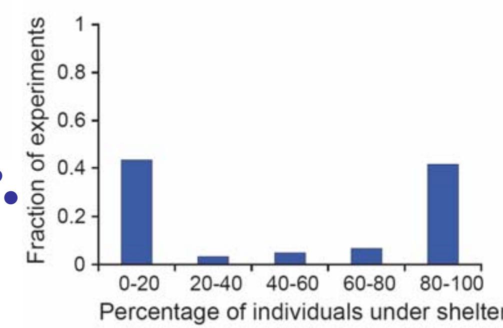
Experimental results and theoretical predictions











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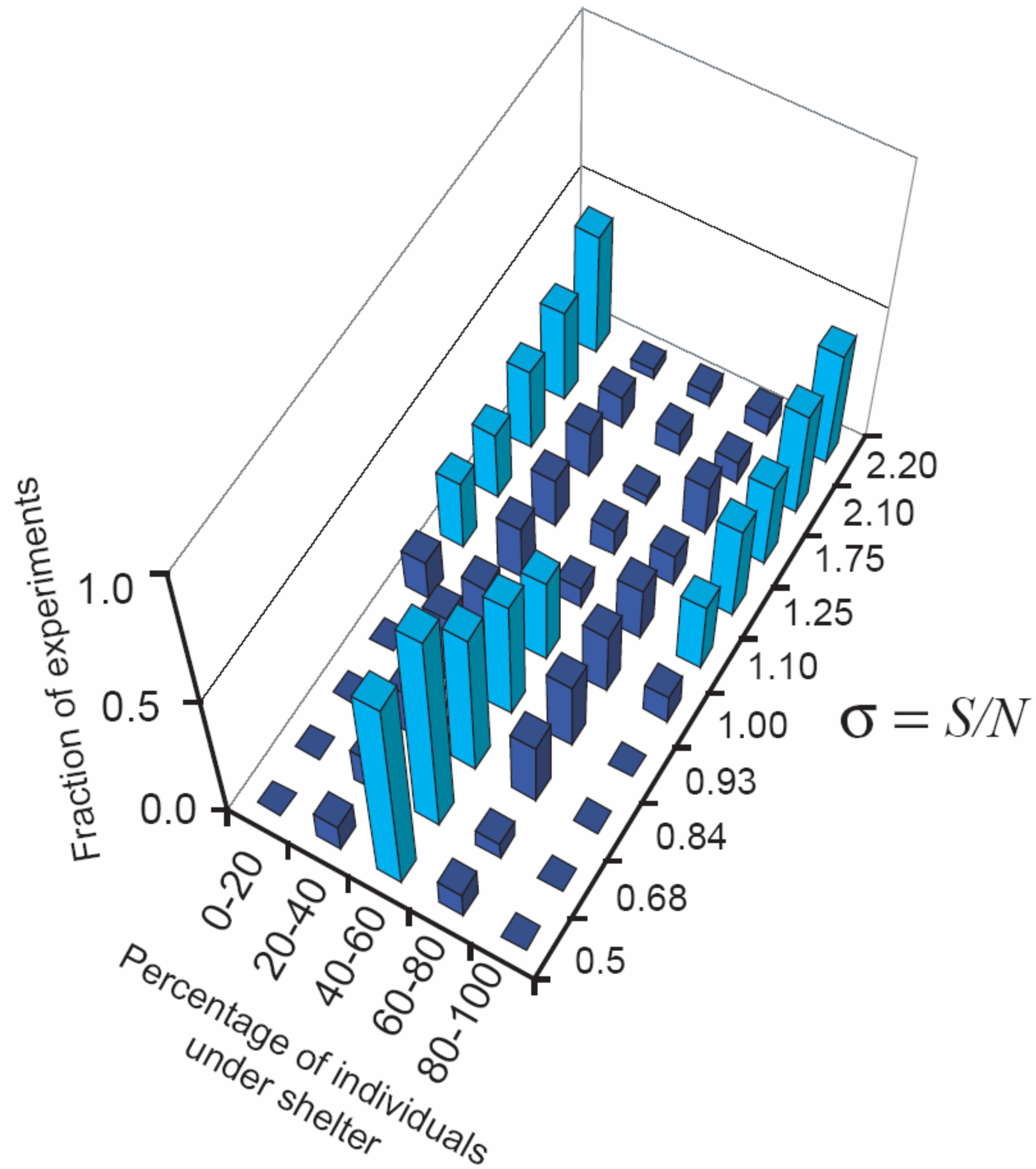
Collective decision making: experimental bifurcation diagram



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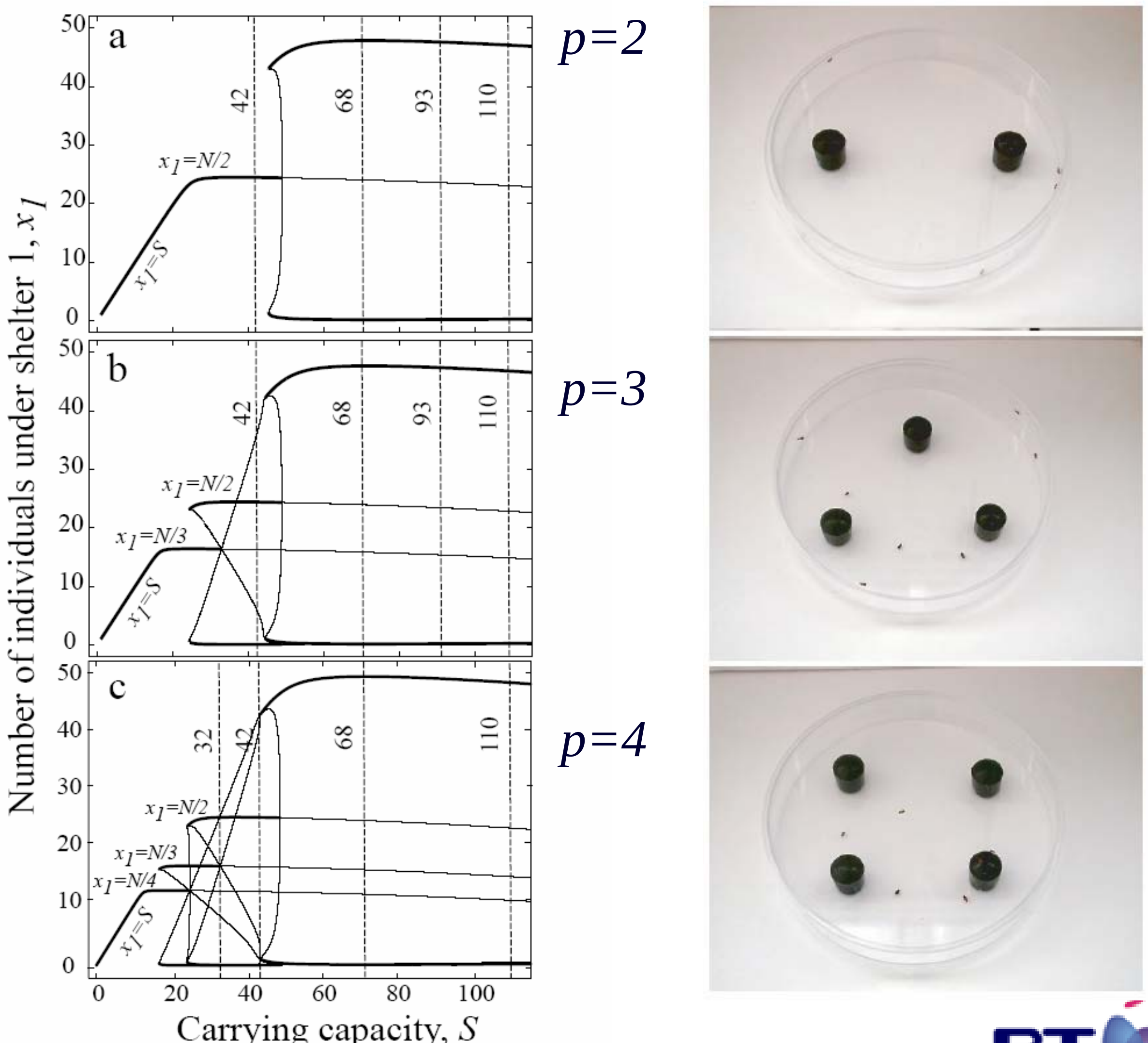
Collective decision making : bifurcation cascade

Collective choice described by a structured cascade of bifurcations

Example: varying the number of shelters and their carrying capacity



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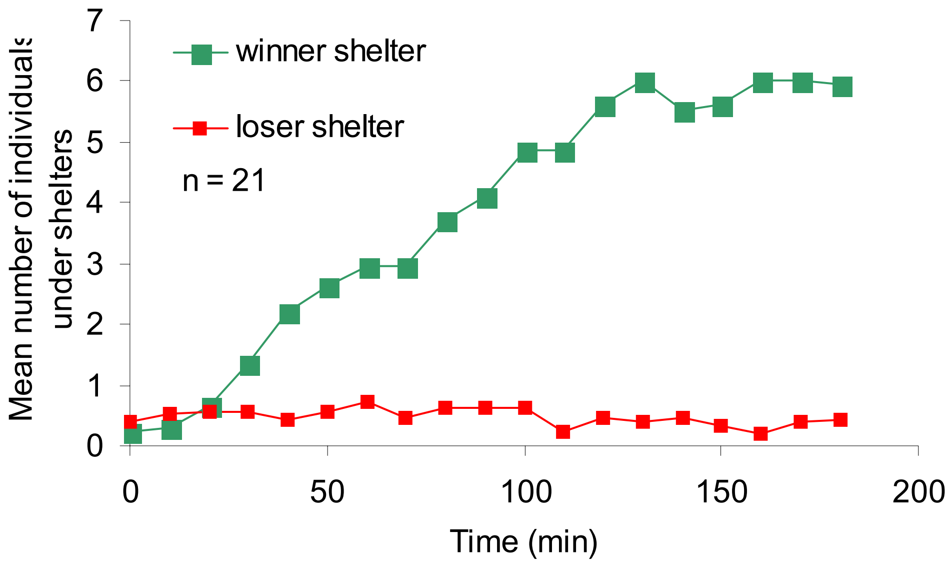
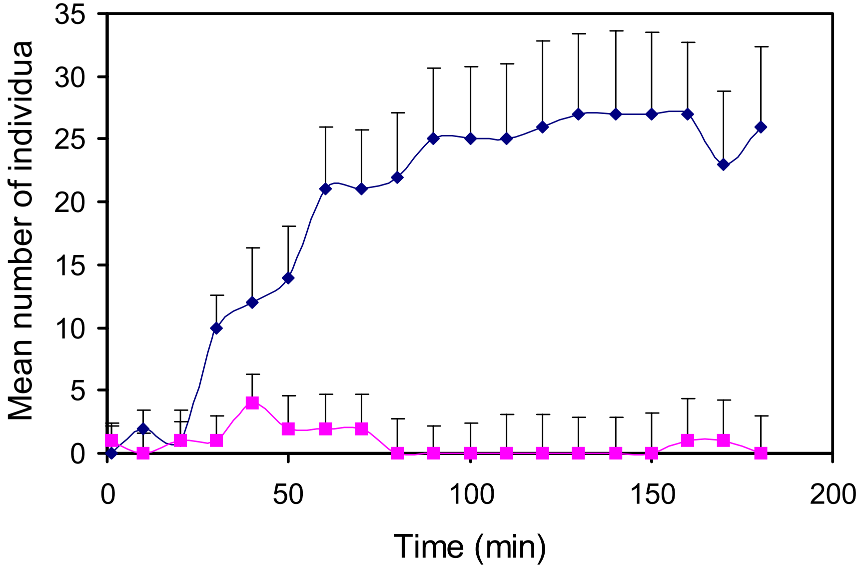
Dynamics of the choice



10 individuals



30 individuals

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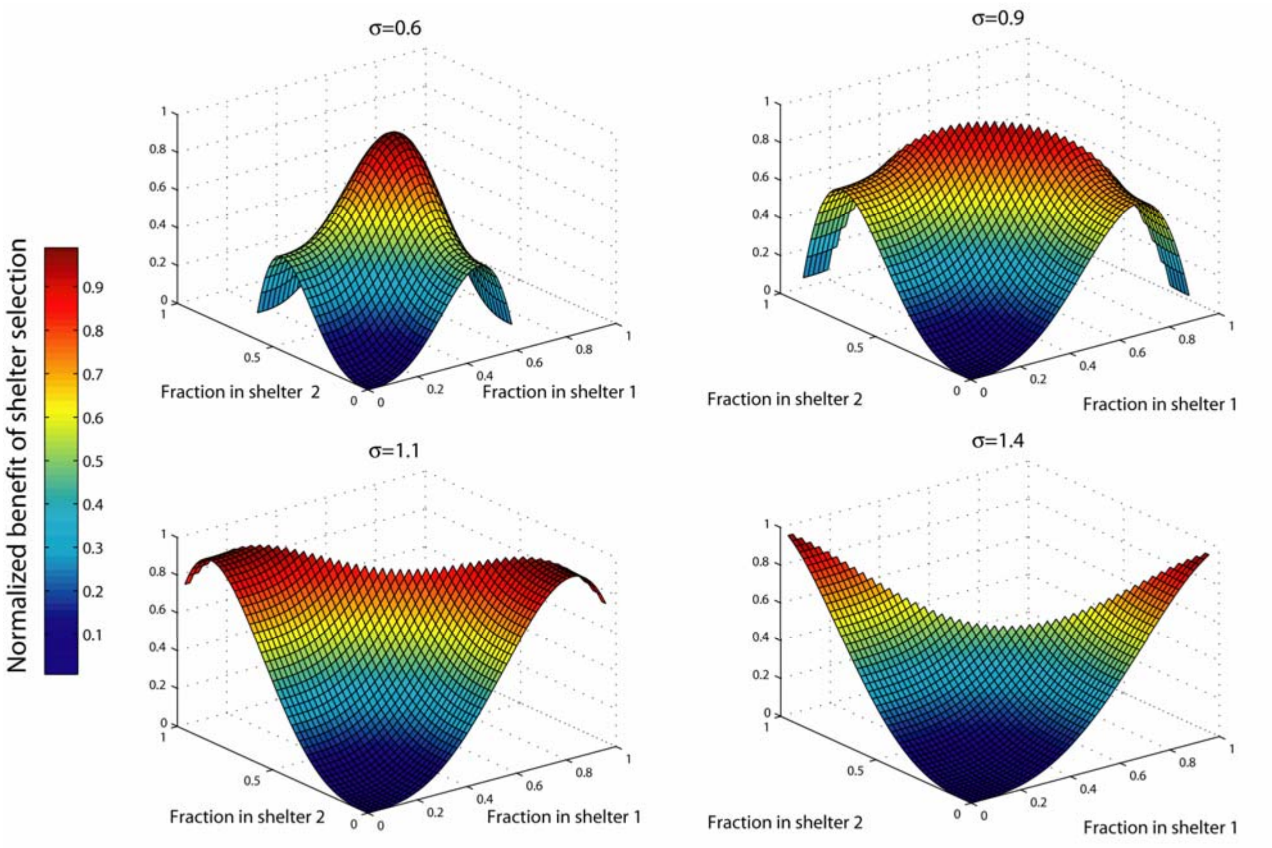
Benefit analysis of the collective choice

$$B = \frac{\mu}{N}\sum_{i=1}^{p} x_i \left[1 + \left(\frac{\rho x_i}{S}\right)^2\right]\left[1 - \left(\frac{x_i}{S}\right)\right]$$



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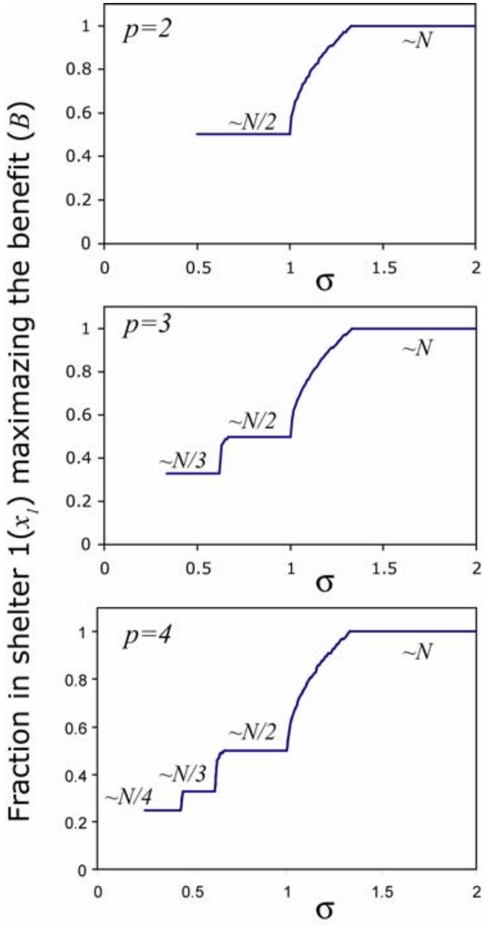
View of the benefit cascade as a function of the number of shelters and their carrying capacity



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Self-organized collective decision making

- The mathematical model makes the link between the individual behavior and the collective dynamics leading to multiple patterns of aggregation produced by collective decisions.
- The model is characterized by 5 parameters that have been measured experimentally for cockroaches.
- This type of collective decision making can be viewed as democratic and without explicit voting by individuals that must change their « opinion » frequently.
- The choice results from the dynamics of the inter-individual interactions with all individuals having the same influence on each other and in absence of leadership or hierarchy.
- The system present an interesting elegant cascade of bifurcation leading to regions of coexisting stable solutions corresponding to remarkable fraction of repartition N/p, N/(p-i) for i=1,..,p-1
- These results point to the existence of a generic self-organized dynamics of pattern formation independently of the level of sociability and of the type of animal group.

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Self-organized collective decision making

- This is not the model…
- The model does not refer to any particular species.
- The model does not even refer specifically to biology.
- There is a model only when the hypothesis discussed above are respected!
- Thus, the model can describe artificial agent software or hardware.
- This abstract layer of modeling allows exploring the existence of generic features in the mechanism leading to collective choice by natural or artificial agents.
- The model gives a framework for the experiments with pure or mixed groups of natural and artificial agents.

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Controlling emergent behavior in mixed group of natural and artificial agents

- Control

  (a) : to exercise restraining or directing influence over : REGULATE

  (b): to have power over : RULE

- We use the meaning (a) of control

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Modeling the collective choice of mixed groups

- Individuals end up in the shelters and none remain outside (approximation)
- The carrying capacity of the shelters is large enough to avoid crowding effects
- Two shelters are present in the set-up

$$\frac{dx_1}{dt} = \frac{\theta_2 x_2}{k + (x_2 + \beta r_2)^2} - \frac{\theta_1 x_1}{k + (x_1 + \beta r_1)^2}$$

$$x_1 + x_2 = N$$

$$r_1 + r_2 = R$$

$$\frac{dr_1}{dt} = \frac{\theta_{r2} r_2}{k + (\gamma x_2 + \delta r_2)^2} - \frac{\theta_{r1} r_1}{k + (\gamma x_1 + \delta r_1)^2}$$

N total number of insects
R total number of robots

Inter-influence	Parameter
Insect on insect	*1*
Insect on robot	γ
Robot on insect	β
Robot on robot	δ

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Array of possible interaction modulations

Parameter	No interaction robot/robot and robot/animal	Animals influence robots	Robots influence animals	Robots influence robots
γ	0	>0	0	0
β	0	0	>0	0
δ	0	0	0	>0

Parameter	Animals/robots influence robots/animals	Animals influence robots & robots influence robots	Robots influence animals and robots	All interactions
γ	>0	>0	0	>0
β	>0	0	>0	>0
δ	0	>0	>0	>0

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Mathematical modeling (ODE): example 1

$\gamma = \beta = \delta = 1$

- The robots and the insects exert mutual influence
- Presence of 2 identical shelters

$$\theta_{r2} = \theta_{r1} = \theta_r$$
$$\theta_2 = \theta_1 = \theta$$

$$\frac{dx_1}{dt} = \frac{\theta\ x_2}{k + (x_2 + r_2)^2} - \frac{\theta\ x_1}{k + (x_1 + r_1)^2}$$

$$\frac{dr_1}{dt} = \frac{\theta_r r_2}{k + (x_2 + r_2)^2} - \frac{\theta_r r_1}{k + (x_1 + r_1)^2}$$

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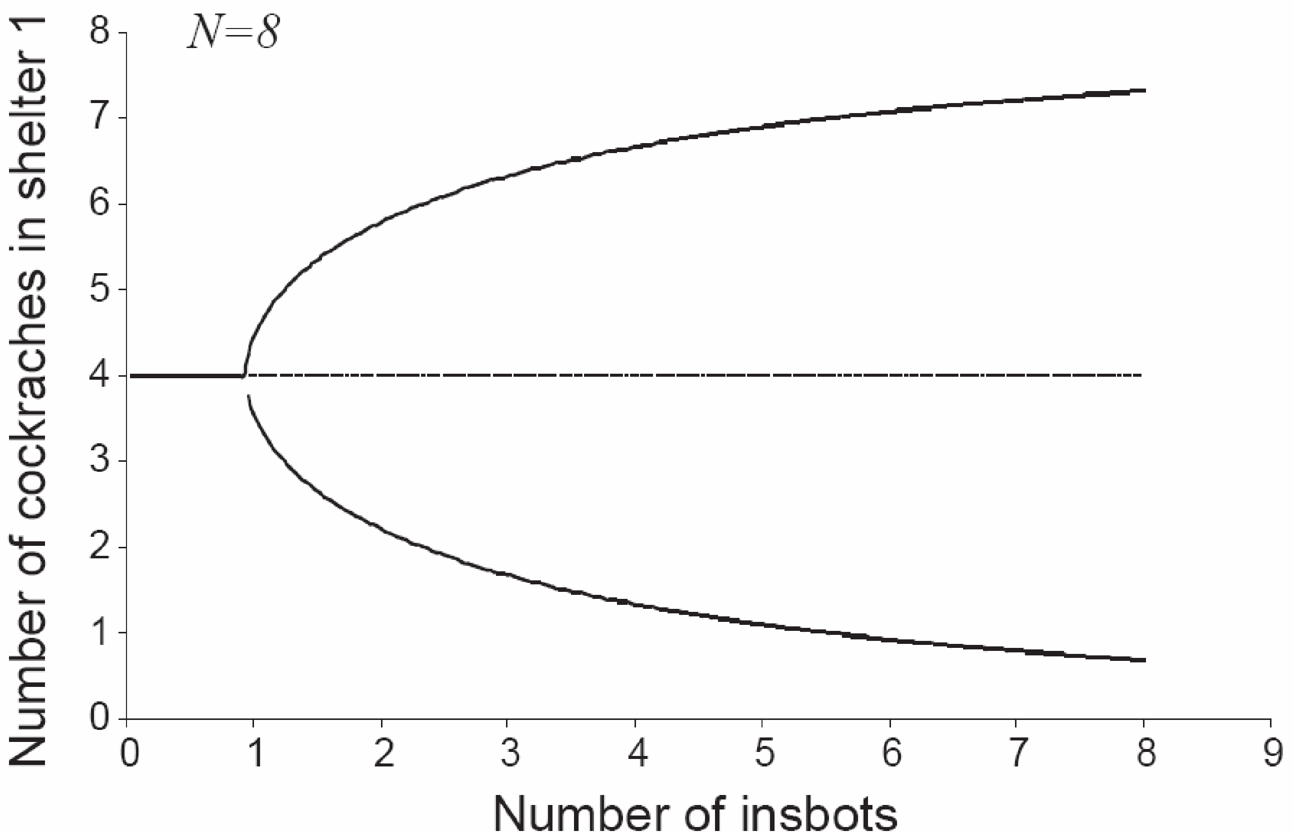
The collective choice is induced in the mixed group by a simple effect of individual number increase above bifurcation threshold



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Control as a phase transition

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Mathematical modeling: example 2

$\gamma=0 \ \ \beta>0 \ \delta=0$

- 2 identical shelters
- Insects do not influence the robots, robots influence insects
- Robots are not social, they are some kind of lonely "leader"

$$\frac{dx_1}{dt} = \frac{\theta \ x_2}{k + \left(x_2 + \beta r_2\right)^2} - \frac{\theta \ x_1}{k + \left(x_1 + \beta r_1\right)^2}$$

$$\theta_{r2} = \theta_{r1} = \theta_r$$

$$\theta_2 = \theta_1 = \theta$$

$$\frac{dr_1}{dt} = \frac{\theta_r}{k}\left(r_2 - r_1\right)$$

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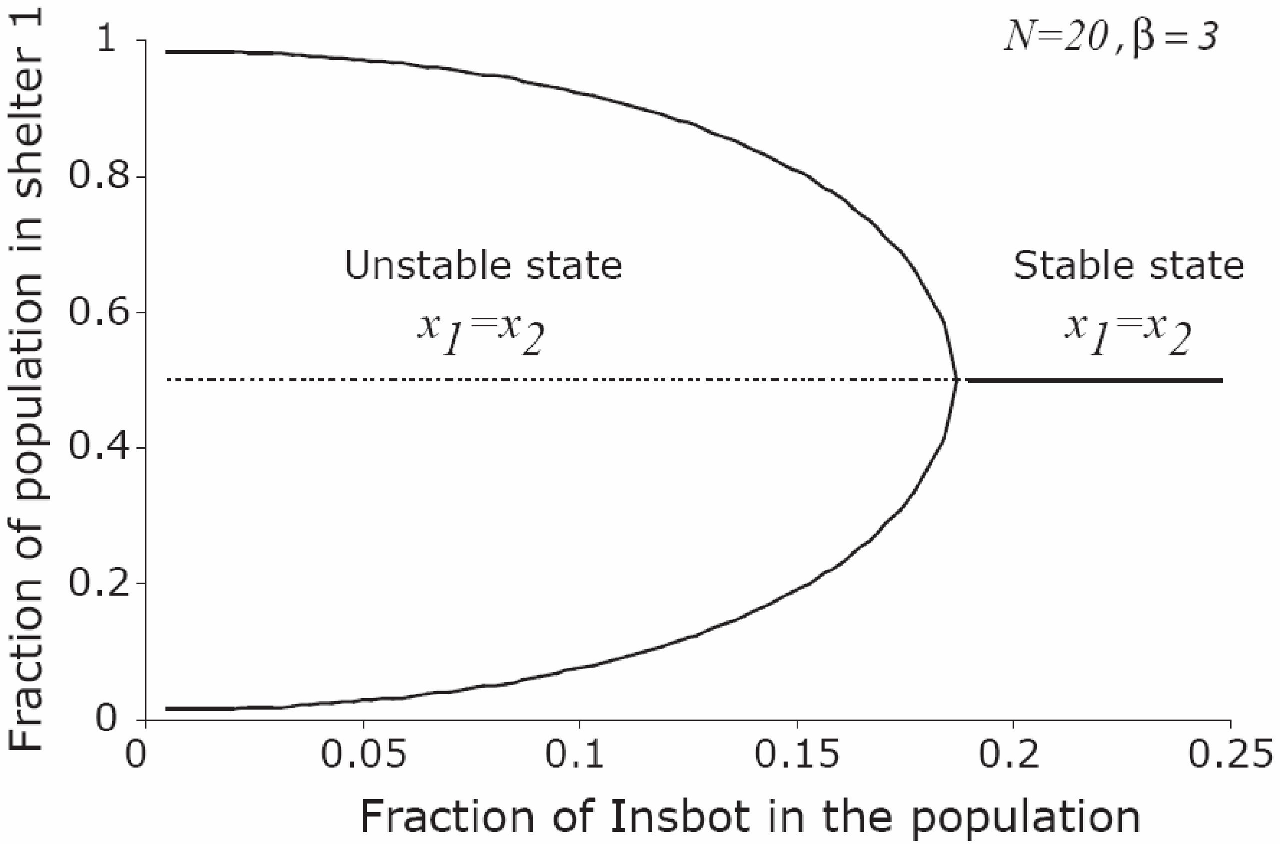
Suppression of the collective choice by adding robots



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Control as a phase transition

Saffre & Halloy, 2005

Example 3

γ=0 β>0 δ=0

- Shelters are identical for the insects but **not for the robots**
- The robots influence the insects
- The robots are not social

$$\frac{dx_1}{dt} = \frac{\theta\, x_2}{k + \left(x_2 + \beta r_2\right)^2} - \frac{\theta\, x_1}{k + \left(x_1 + \beta r_1\right)^2}$$

$$\theta_{r2} \neq \theta_{r1}$$

$$\theta_2 = \theta_1 = \theta$$

$$\frac{dr_1}{dt} = \frac{1}{k}\left(\theta_{r2} r_2 - \theta_{r1} r_1\right)$$

$$x_1 + x_2 = N$$

$$r_1 + r_2 = R$$

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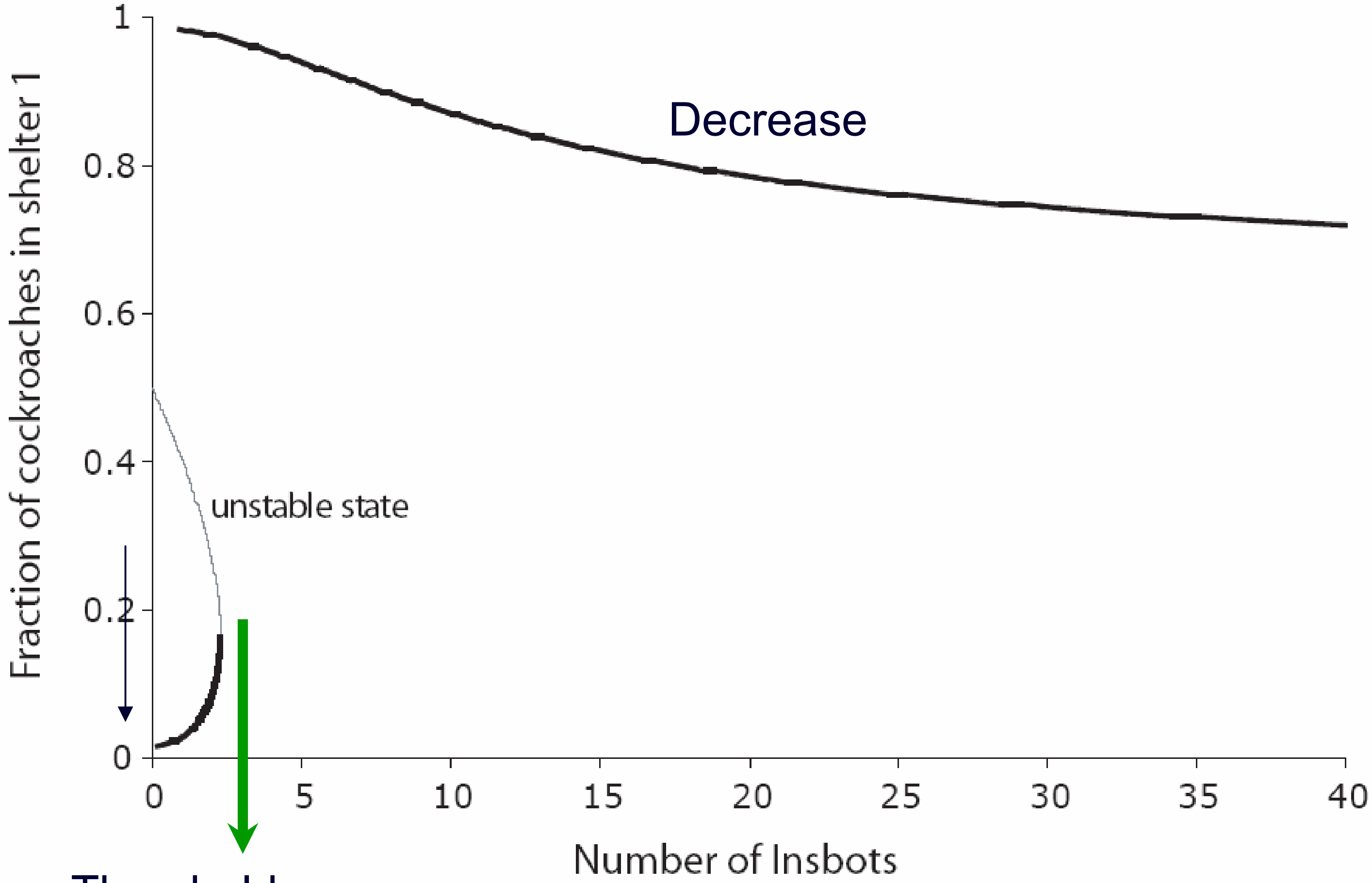
Induced collective choice: the insects gather in the shelter preferred by the robots, although the 2 shelters appear identical from a cockroach point of view.

At steady state



Threshold

Saffre & Halloy, 2005

Example 4: math, simulations and real life experiments

Two different shelters: the cockroaches prefer the dark one , the robots prefer light one
The insects and the robots exert mutual influence
The robots are social among themselves

$\gamma > 0 \ \beta > 0 \ \delta > 0$

$$\theta_{r2} < \theta_{r1}$$

$$\theta_2 > \theta_1$$

$$\frac{dx_1}{dt} = \frac{\theta_2 x_2}{k + (x_2 + \beta r_2)^2} - \frac{\theta_1 x_1}{k + (x_1 + \beta r_1)^2}$$

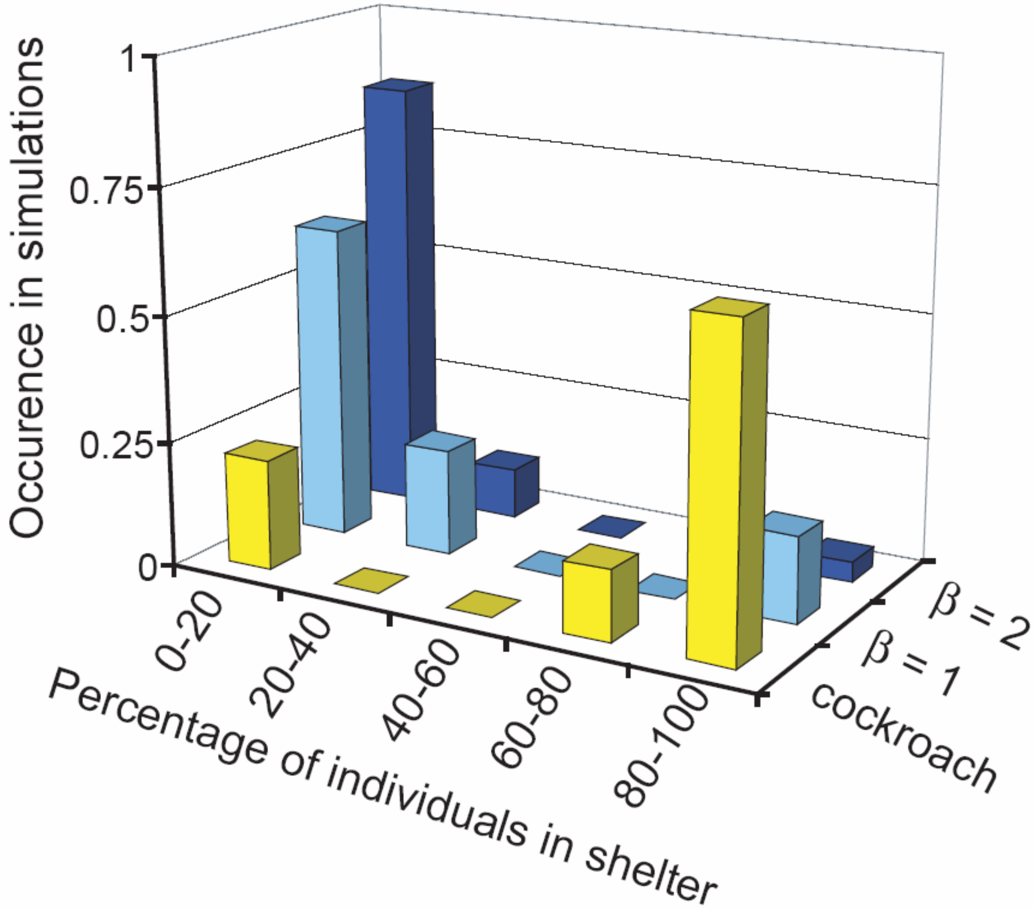
$$\frac{dr_1}{dt} = \frac{\theta_{r2} r_2}{k + (\gamma x_2 + \delta r_2)^2} - \frac{\theta_{r1} r_1}{k + (\gamma x_1 + \delta r_1)^2}$$

Saffre & Halloy, 2005

Modeling the collective choice of mixed groups: stochastic computer simulations

Two different shelters: the cockroaches prefer the dark one, the robots prefer the light one

The robots induce a change in the insect collective preference



Saffre & Halloy, 2005

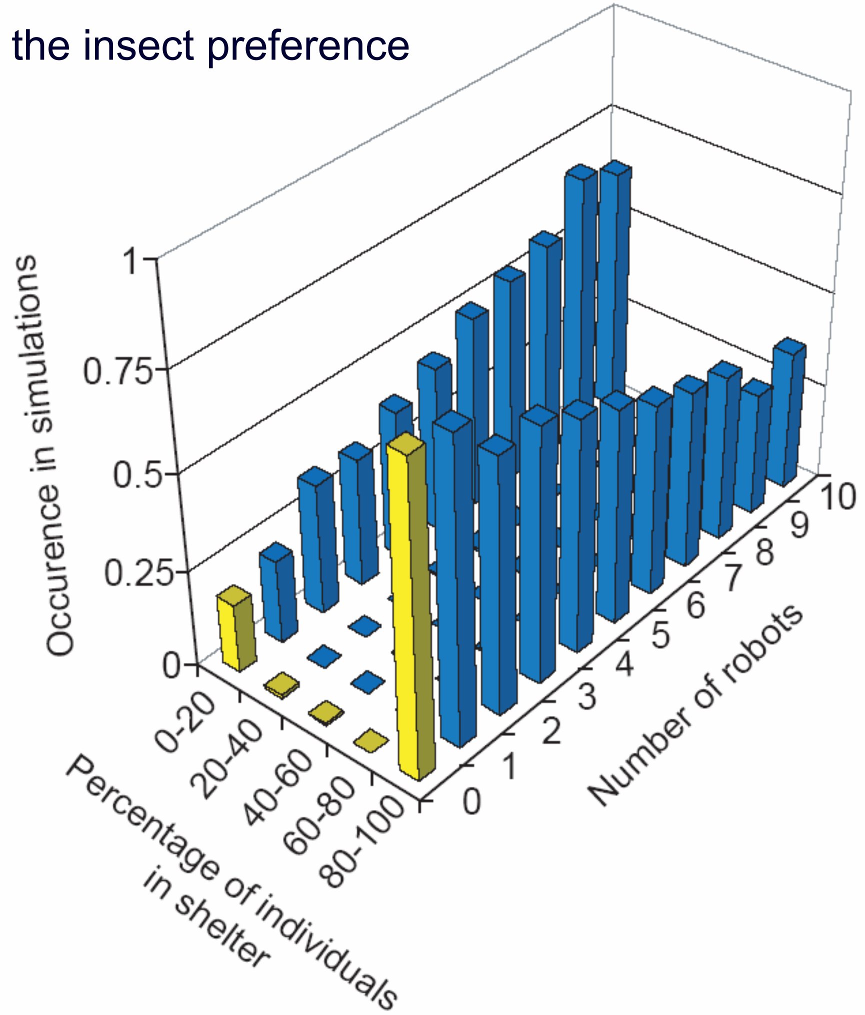
Modeling the collective choice of mixed groups: stochastic computer simulations

Two different shelters: the cockroaches prefer the dark one, the robots prefer the light one

The robots induce a change in the insect preference

20 cockroaches
β=1

Effect of robot number



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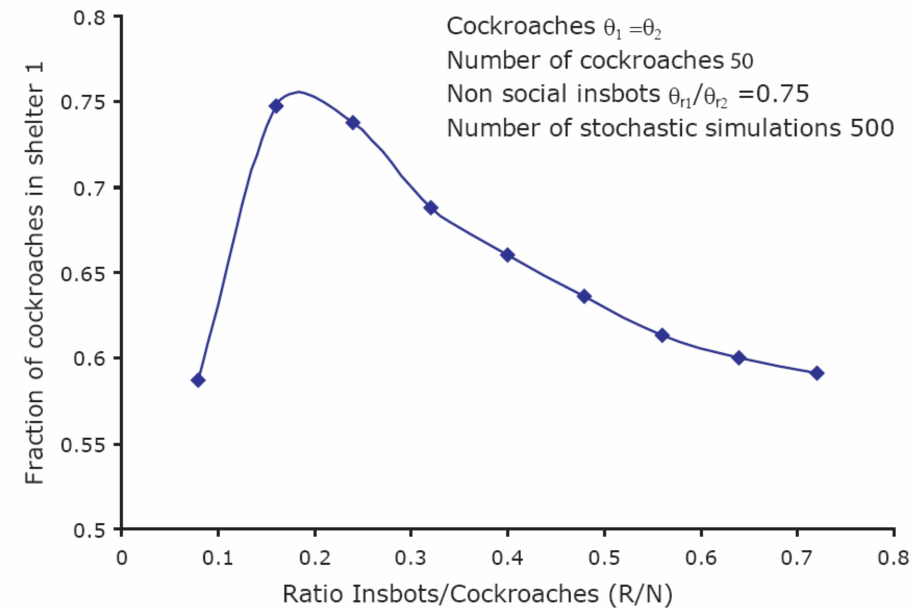
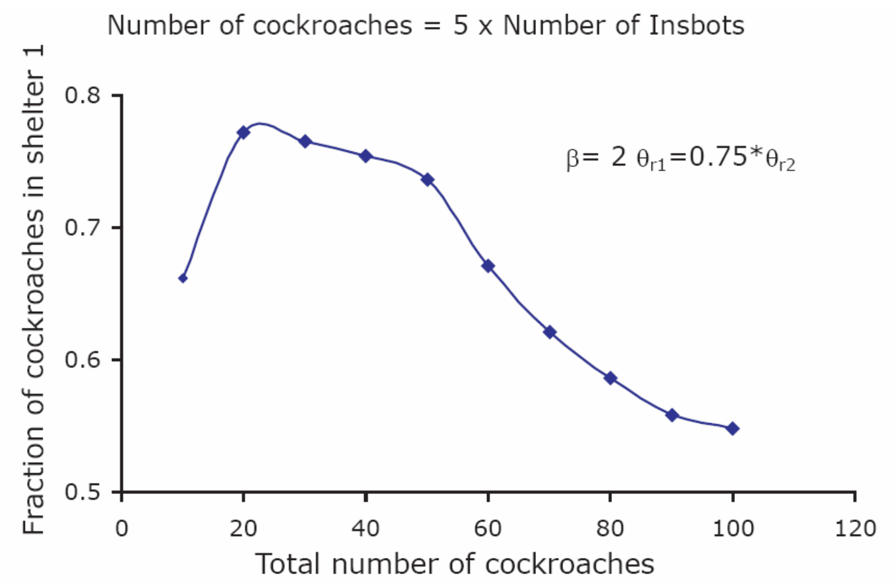
Modeling the collective choice of mixed groups: optimality and scalability (computer simulations)

Robot efficiency presents an optimum



Even at the optimal R/N, there is an optimal cockroach population size that maximizes the fraction of the insect population that is controlled by the robot



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Modulation (control) of the collective decision making in the example of shelter selection by cockroaches and autonomous robots

- Modulation trough the number of artificial agents and their nature.
- Role of the number of robots in regulating the choice

- Modulation through the behavioral rules and capacities of agents.

  - social among themselves or not

  - react to the insects or not

  - have preferences or not (for a specific shelter)

  - nature and intensity of the signals towards the insects (pheromone tagging, tactile interactions)

- Modulation of the environment

  - not used until now

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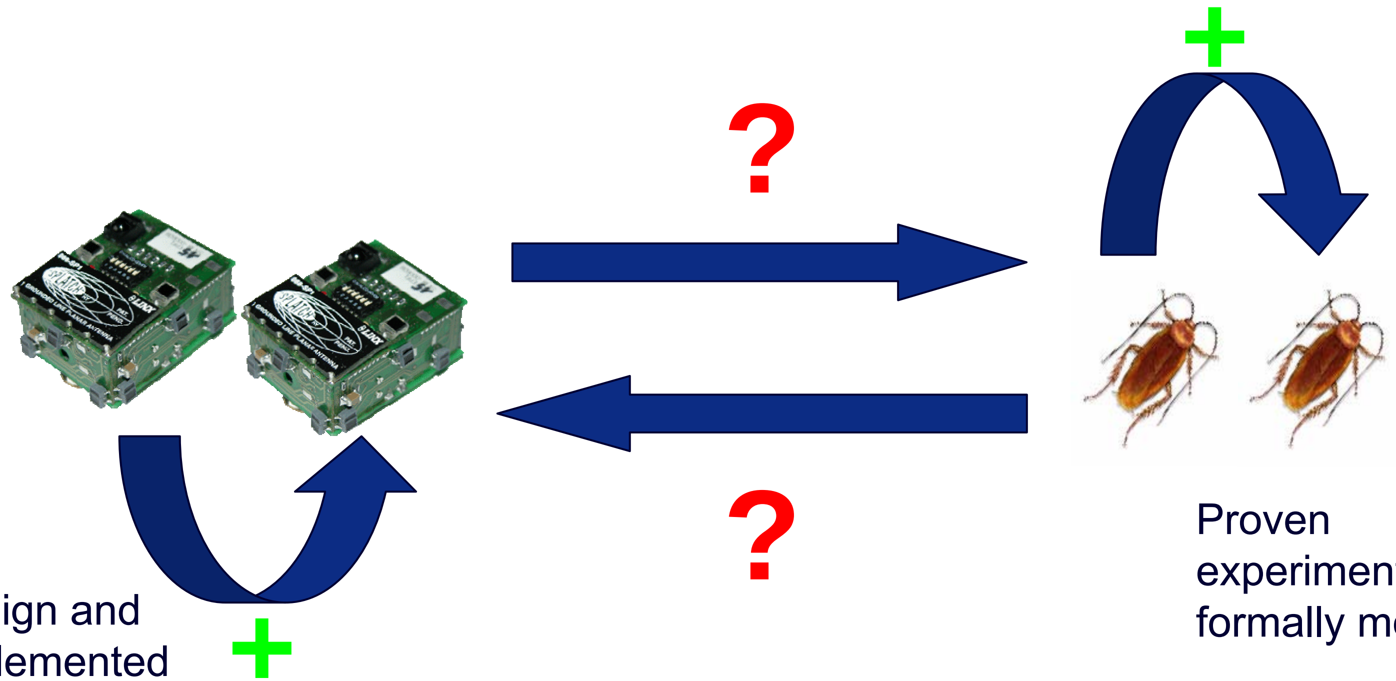
Collective decision making in mixed groups of robots and cockroaches

Building interactions and communication:

- ❖Perception of individual presence
- ❖Modulation of the behavior according to individual presence



Design and implemented (EPFL)

Proven experimentally and formally modeled

Caprari G., Colot A., Siegwart R., Halloy J. and Deneubourg, J.-L..Animal and Robot Mixed Societies- Building Cooperation Between Microrobots and Cockroaches. IEEE Robotics & Automation Magazine. Vol.12, No 2, June, pp 58-65. 2005.

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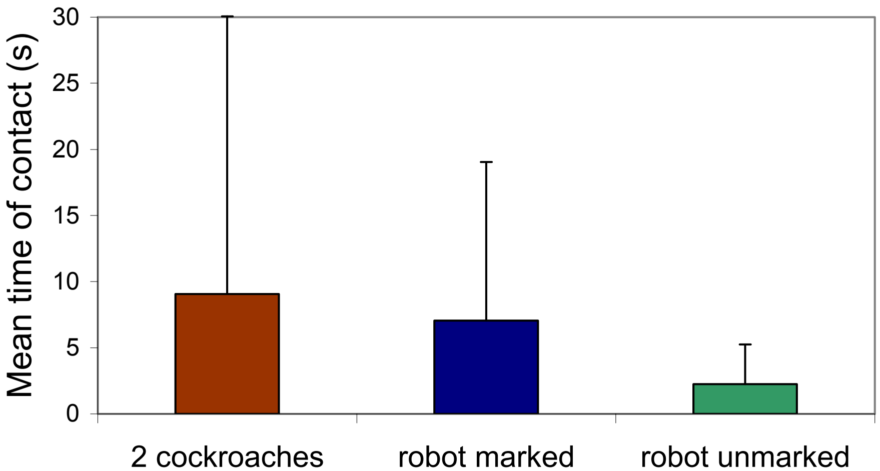
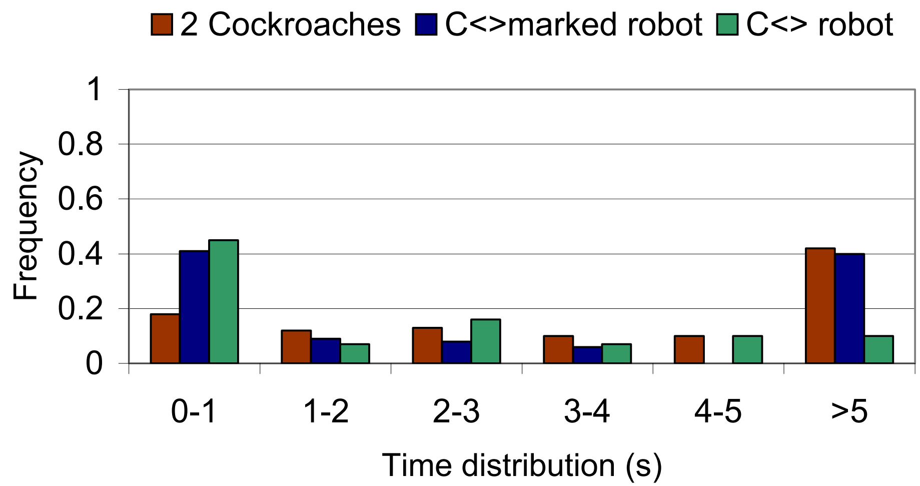
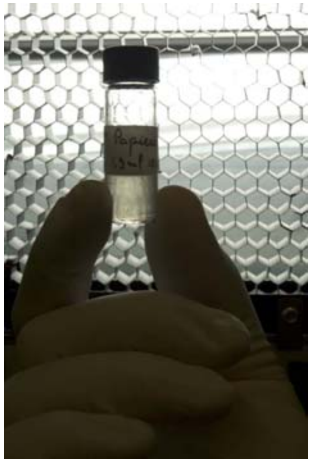
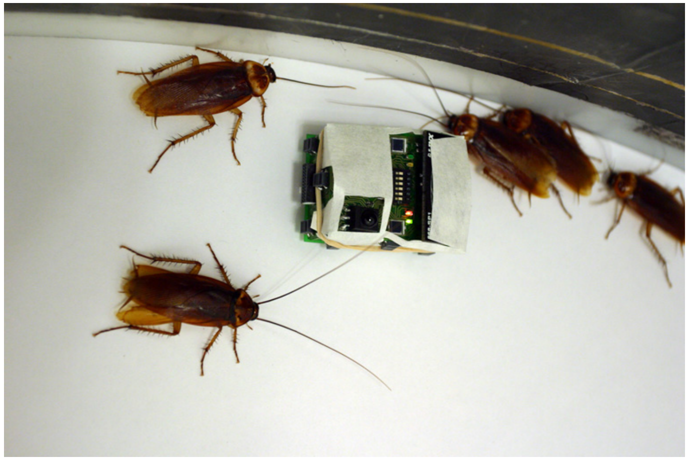
Collective decision making in mixed groups of robots and cockroaches









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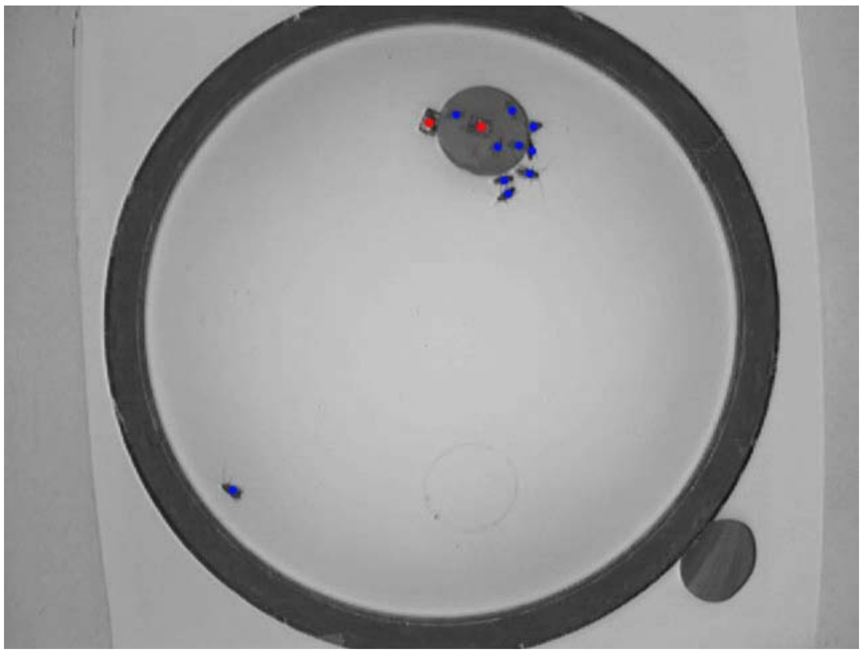
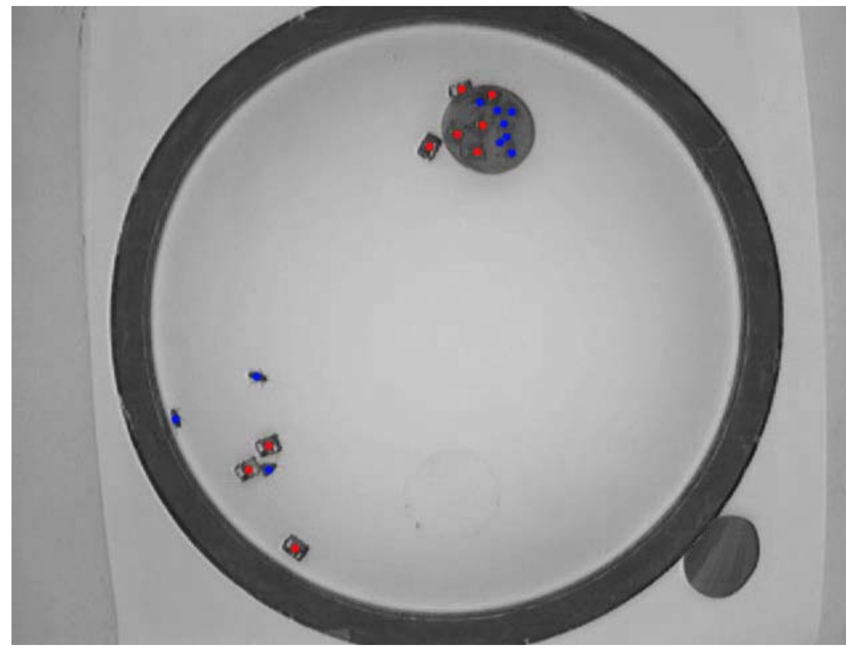
Collective decision making in mixed groups of robots and cockroaches

Interactions at the collective level: the machines are accepted





❖ Probability to rest increases with the number of neighbors
❖ Robots are found more often under the shelter containing most of the cockroaches
❖ Robots spend more time under shelter when cockroaches are present than alone

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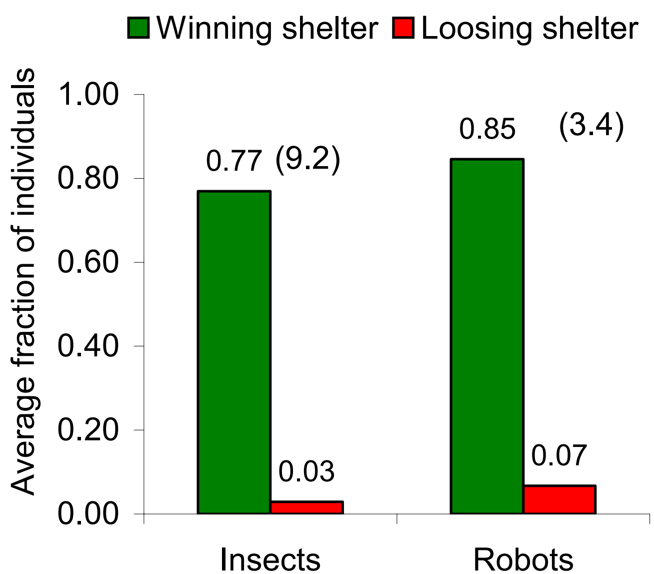
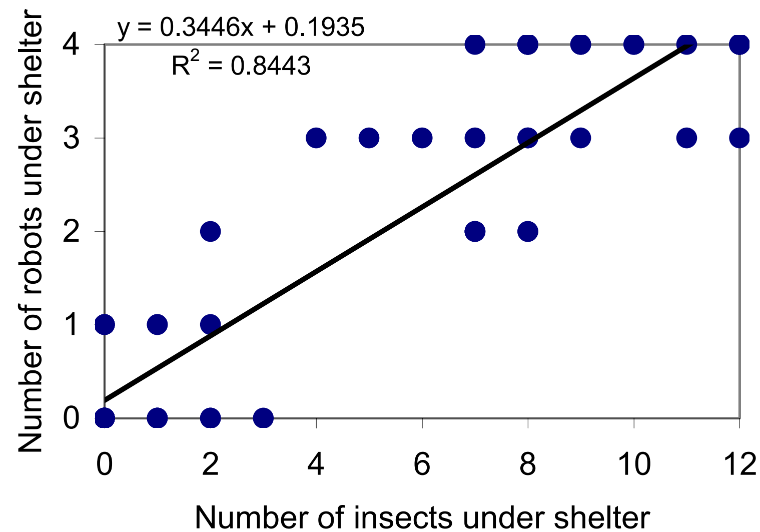
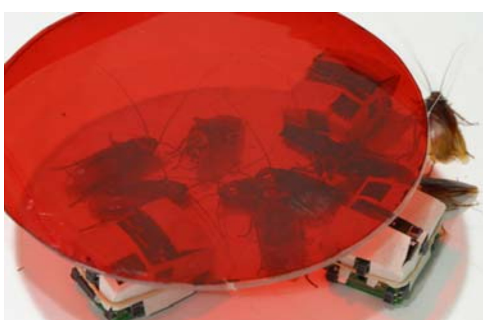
Collective decision making in mixed groups of robots and cockroaches: experimental demonstration

Shared collective decision between identical shelters
12 cockroaches & 4 robots; 30 tests (3H each)





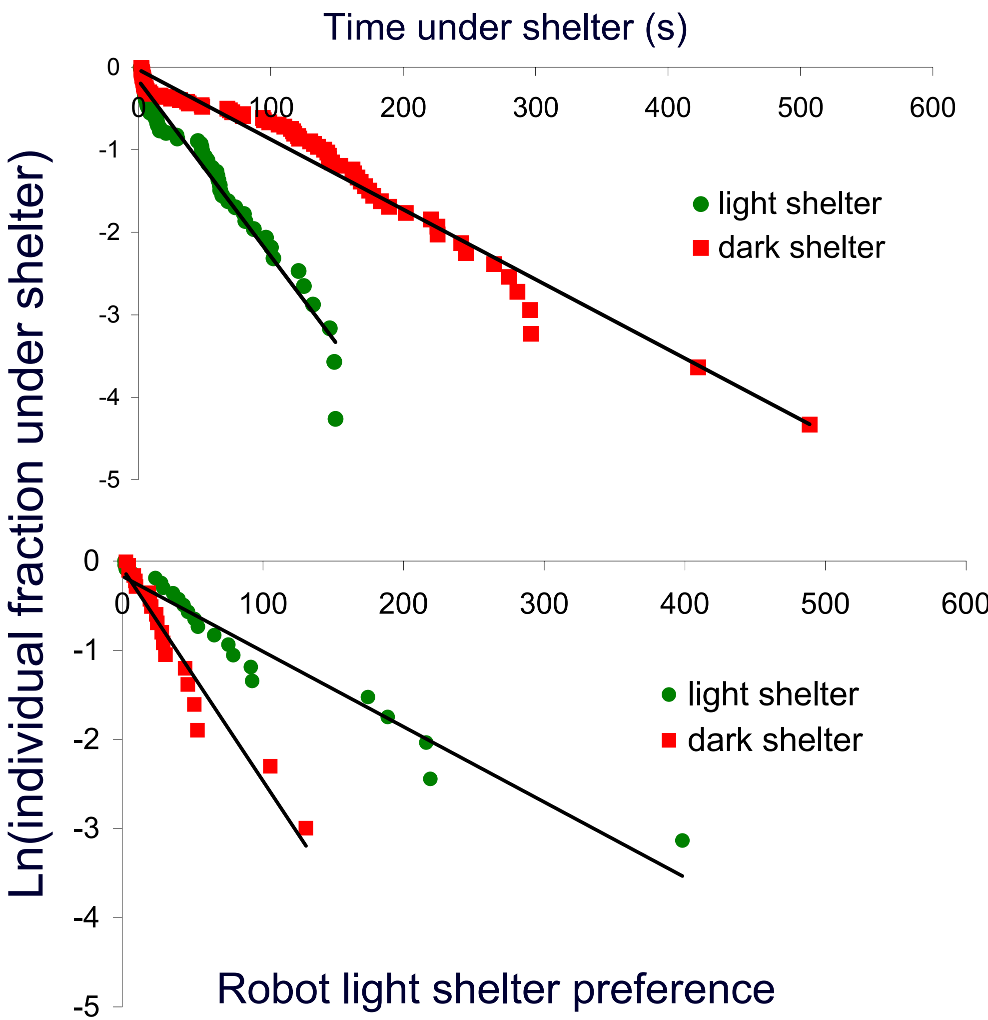
Correlation coefficient: 0.92
Robots are with insects



Clear choice in 25 out 30 tests

Saffre & Halloy, 2005

Collective decision making in mixed groups of robots and cockroaches



	Probability to leave without congeners (s^{-1})	
	Light shelter	Dark shelter
Cockroach	0.030	0.006
Dark shelter preference	0.021	0.008
Light shelter preference	0.008	0.024

Robots and insects can present opposite preference for shelters

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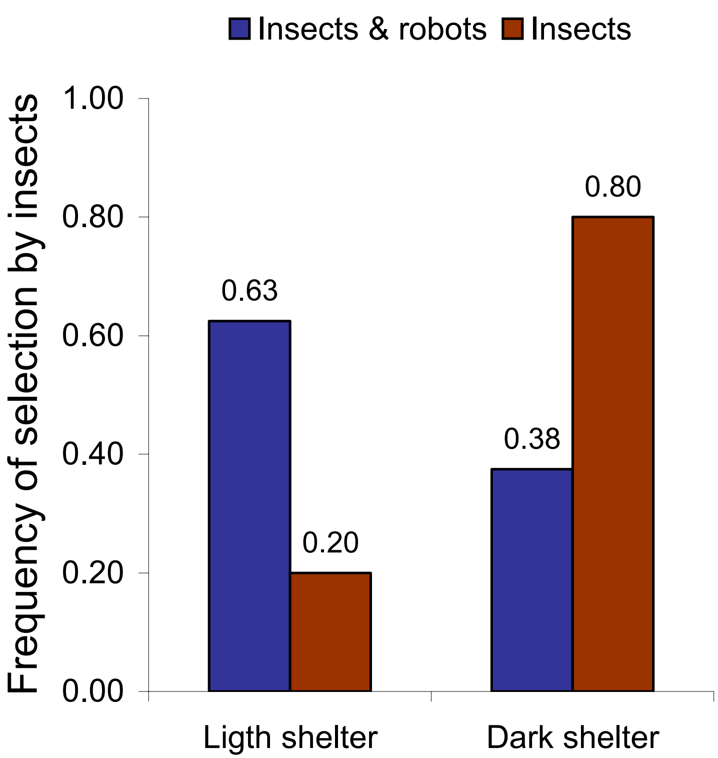
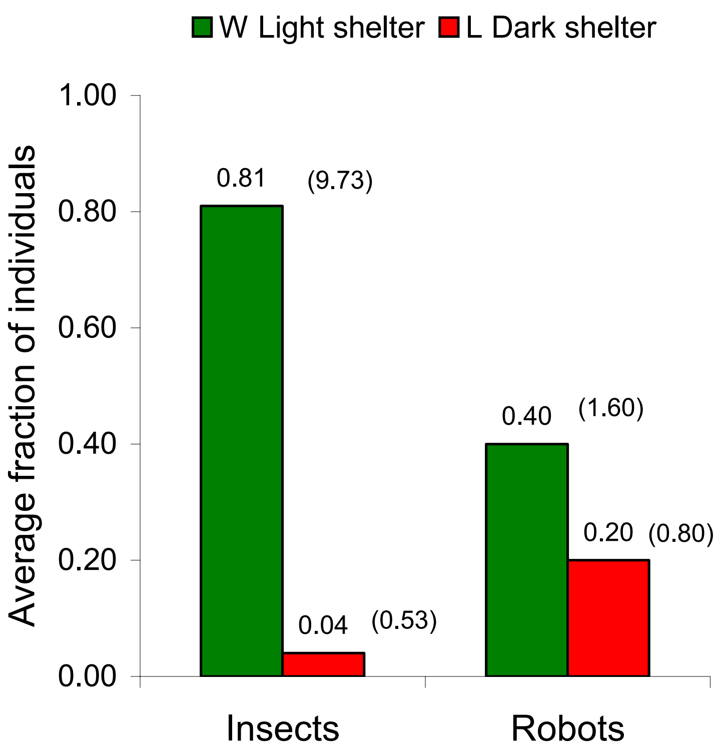
Collective decision making in mixed groups of robots and cockroaches

Control of collective decision induced by the robots: experimental demonstration
12 cockroaches & 4 robots 30 tests





Total test number	Clear choice	Light shelter	Dark shelter	
30.00	24.00	15.00	9.00	**Mixed groups**
30.00	20.00	4.00	16.00	**Insects only**

Saffre & Halloy, 2005

Collective decision making in mixed groups of robots and cockroaches

- Cockroaches perform group choice that is a form of self-organized collective decision. It emerges form the local interactions between individuals.
- Both machines and insects are capable, independently of each other, to perform such collective decision.
- The robots are accepted by the cockroaches groups and actively take part in the collective choice.
- Most of the time, they gather with the cockroaches under the same shelter.
- When the robots are programmed to have an opposite preference compared to insects, they are able to induce a change in the global pattern by reversing the collective shelter preference.
- The mixed group of robots and insects gather in the less preferred shelter by the insects.
- These experimental results demonstrate the existence of shared and controlled collective choice between machines and animals.

Saffre & Halloy, 2005

Conclusion

Dynamical modeling, at the abstract level, gives a general framework to formalize collective decision making in mixed groups of animal and machines.

The abstraction from a particular example allows exploring the generic features that lead to collective choice.

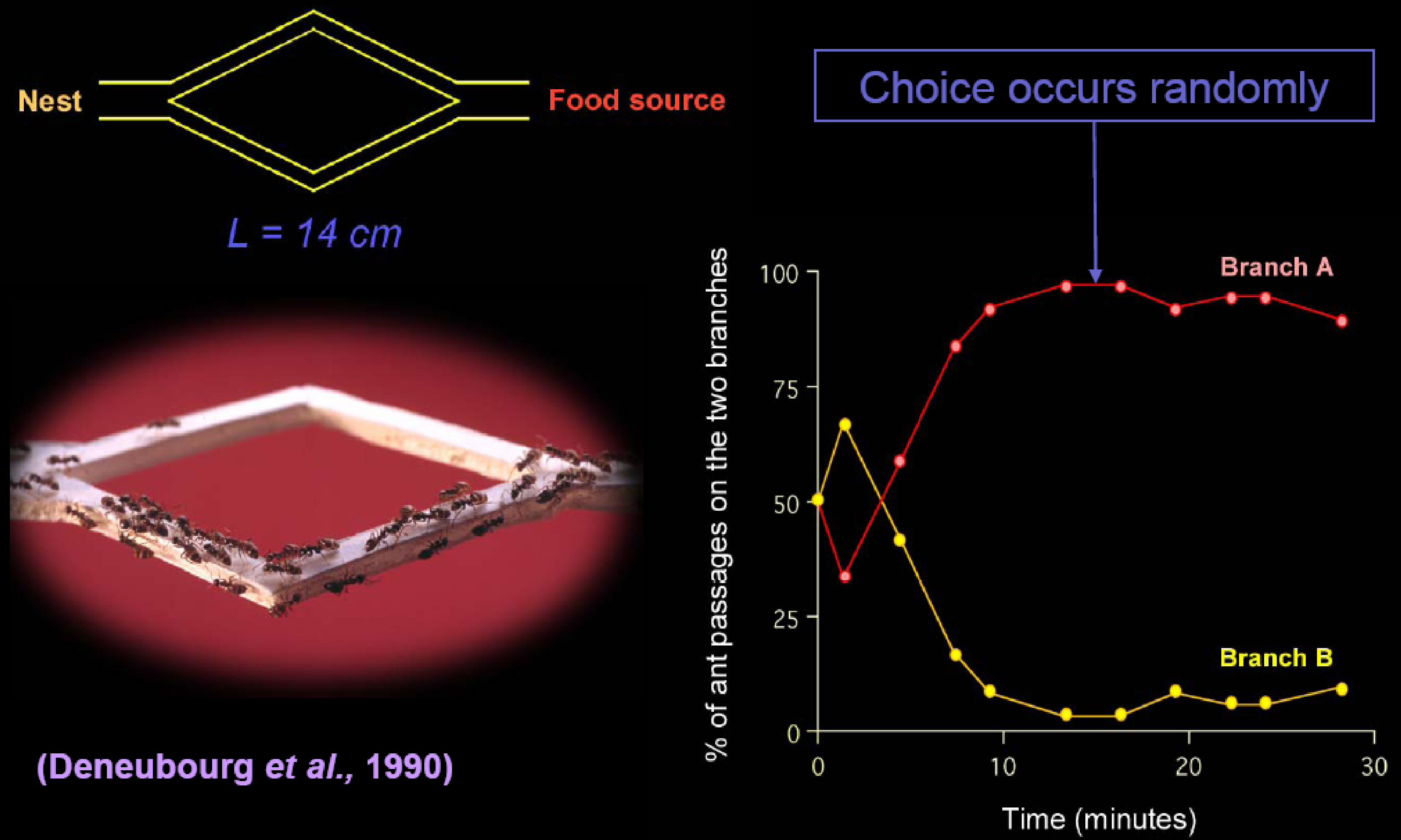
Care has to be taken in handling the high level hypothesis of the model.
When they are experimentally validated they gain the status of features or requirements for the artificial agent.
The design of the artificial agent has to lead to fulfill correctly these features.

The framework allows making global prediction in well defined system and gives guidelines for the experiments.

However, it does not give specific clues about a particular lower level implementation neither in biological nor in artificial systems.

Saffre & Halloy, 2005

Path selection by ants

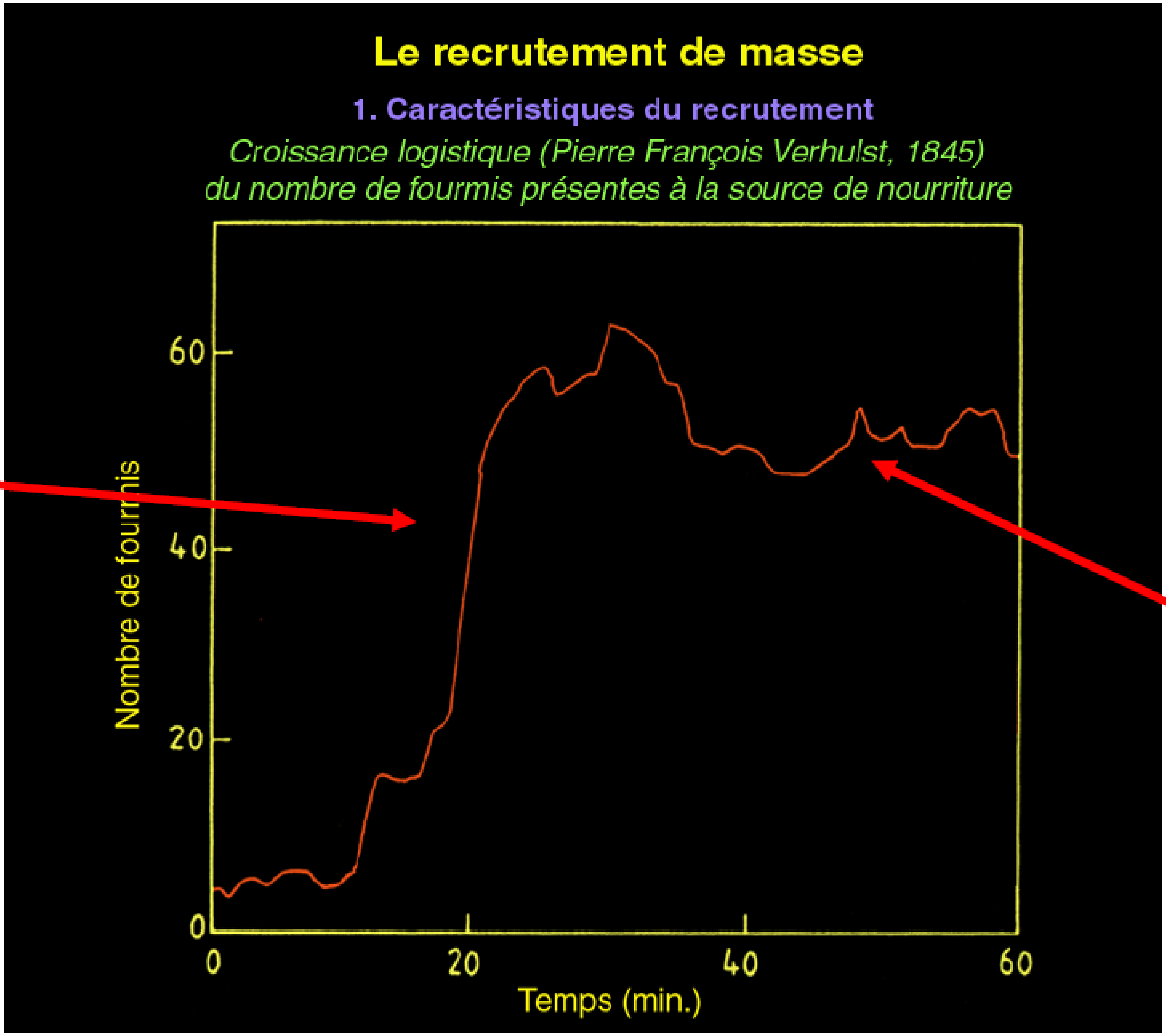


(Deneubourg *et al.*, 1990)

Saffre & Halloy, 2005

Path selection dynamics

Growing phase (positive feedback)



Saturation phase (negative feedback)

Pasteels, Deneubourg & Goss Experentia,1987

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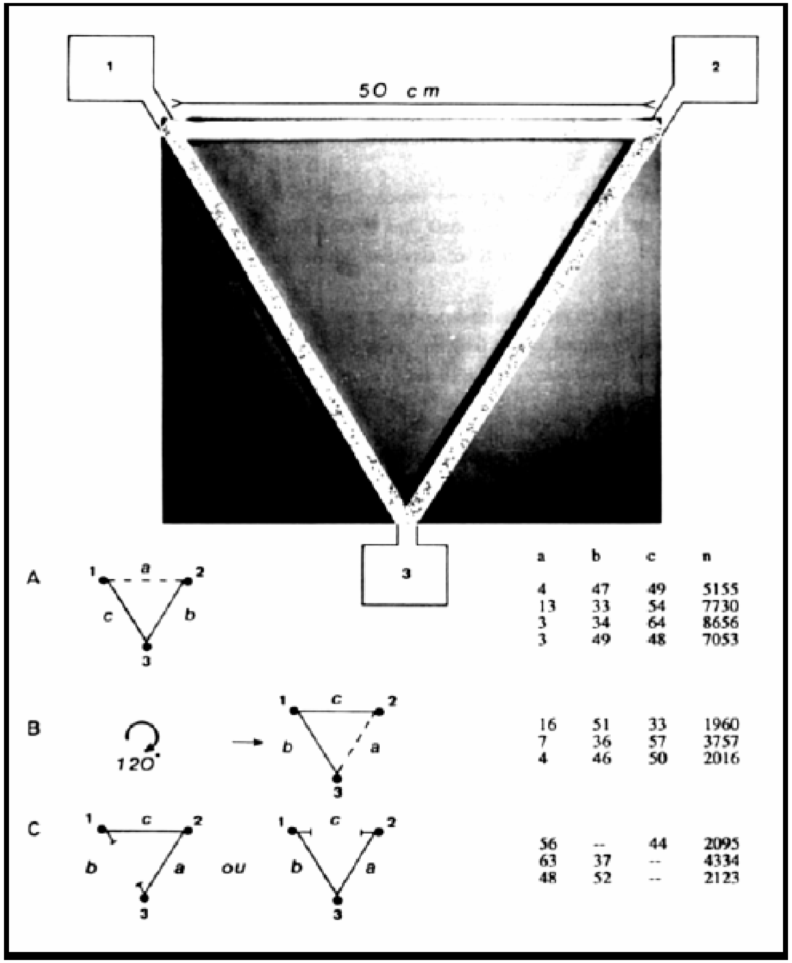
From ants to Ant Colony Optimization

The trail laying mechanism allows ants to solve more elaborate path networks like minimal spanning tree or edge interruptions.

Spin off idea to transpose the model as a heuristic optimization algorithm named Ant Colony Optimization (see books by M. Dorigo)



	a	b	c	n
A	4	47	49	5155
	13	33	54	7730
	3	34	64	8656
	3	49	48	7053
B	16	51	33	1960
	7	36	57	3757
	4	46	50	2016
C	56	--	44	2095
	63	37	--	4334
	48	52	--	2123

Experimental results for a triangular network (3 nest super-colony) with *Linepithema humile* (Argentine ants) [Aron, Deneubourg, Goss, Pasteels, 1991]

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Saffre & Halloy, 2005

Model for trail recruitment

$$P_l = \frac{(k_i + C_l)^n}{\sum_{l=1}^{s}(k_l + C_l)^n}$$

$$P_{il} = \frac{(1 + \sum_{j=1}^{g} \beta_{jl} c_{il})^n}{\sum_{i=1}^{s}(1 + \beta_{jl} c_{il})^n}$$

P: probability of trail laying
C: pheromone concentration proportional to number of individual
n steepness of threshold response

- 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

$$\frac{dC_{il}}{dt} = q\phi P_{il} - \nu C_{il} \longrightarrow \frac{dC_{il}}{dt} = \Phi P_{il} - C_{il}$$

$$\left[\Phi = \frac{q\phi}{\nu}\right]$$

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Beckers, Deneubourg & Goss Journal of Theoretical Biology, 1992

J. Millor, J.M. Amé, J. Halloy and J.L. Deneubourg JTB 2005

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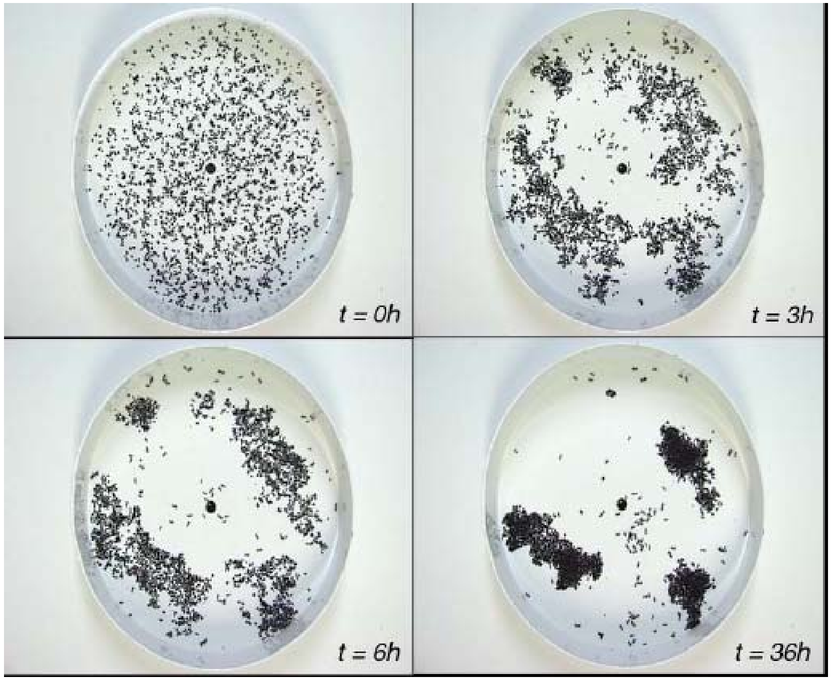
Saffre & Halloy, 2005

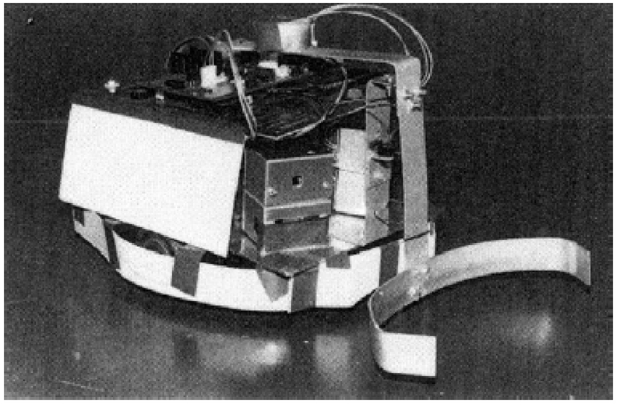
Sorting and clustering by ants

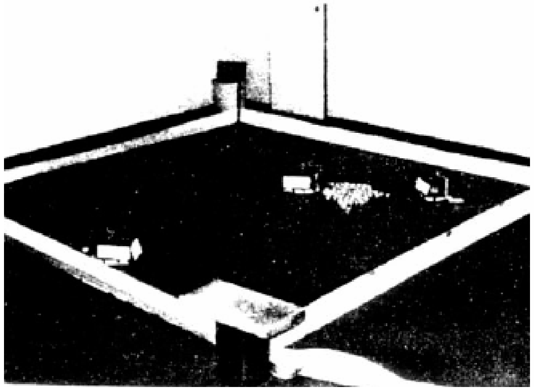


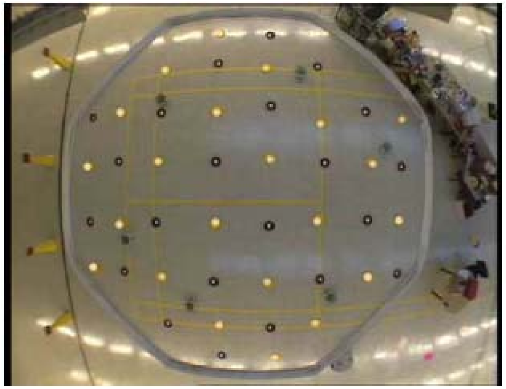
J.L. Deneubourg, S. Goss, N. Franks, A. Sendova-Franks, C. Detrain & L. Chrétien (1991). The dynamics of collective sorting robot-like ants and ant-like robots. In From Animals to Animats, Eds. J.-A. Meyer & S. Wilson. MIT Press, Cambridge (Mass.), 356-365.

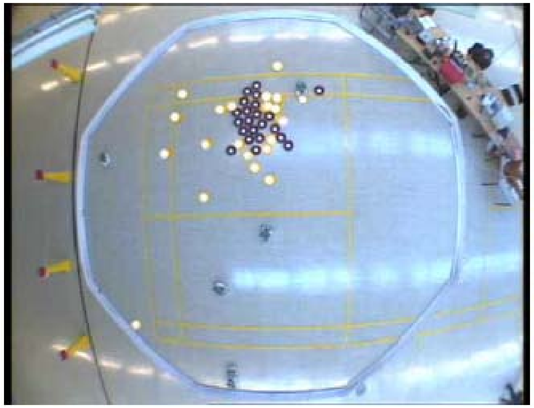
Saffre & Halloy, 2005

Sorting & clustering spin off in collective robotics









R. Beckers, O.E. Holland & J.L.Deneubourg (1994). From local actions to global tasks: stigmergy and collective robotics. In Proceedings of ALIFE IV, Eds R.A. Brooks & P. Maes, MIT Press, Cambridge (Mass).

Holland, Melhuish (1999) Stigmergy, Self-Organization, and Sorting in Collective Robotics, Artificial Life.

Saffre & Halloy, 2005

Universal differentiation or task allocation regulatory modules I

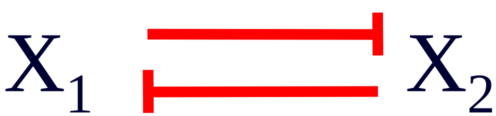
X_i : state variable of agent i

Negative feedback

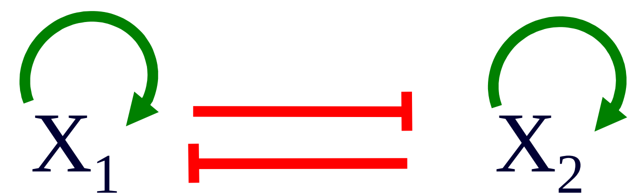
Positive feedback

I. Cross inhibitions

I.a



I.b



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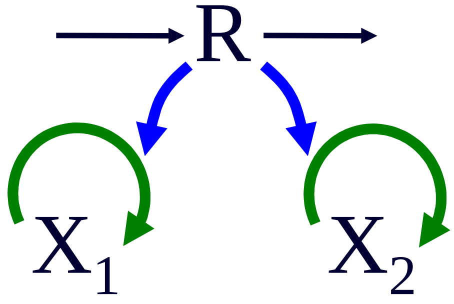
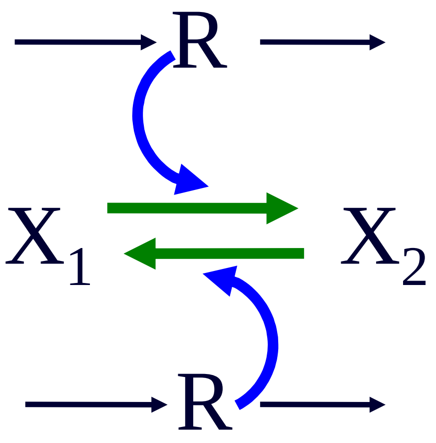
Universal differentiation or task allocation regulatory modules II

II. Resource competition

II.a



II.b



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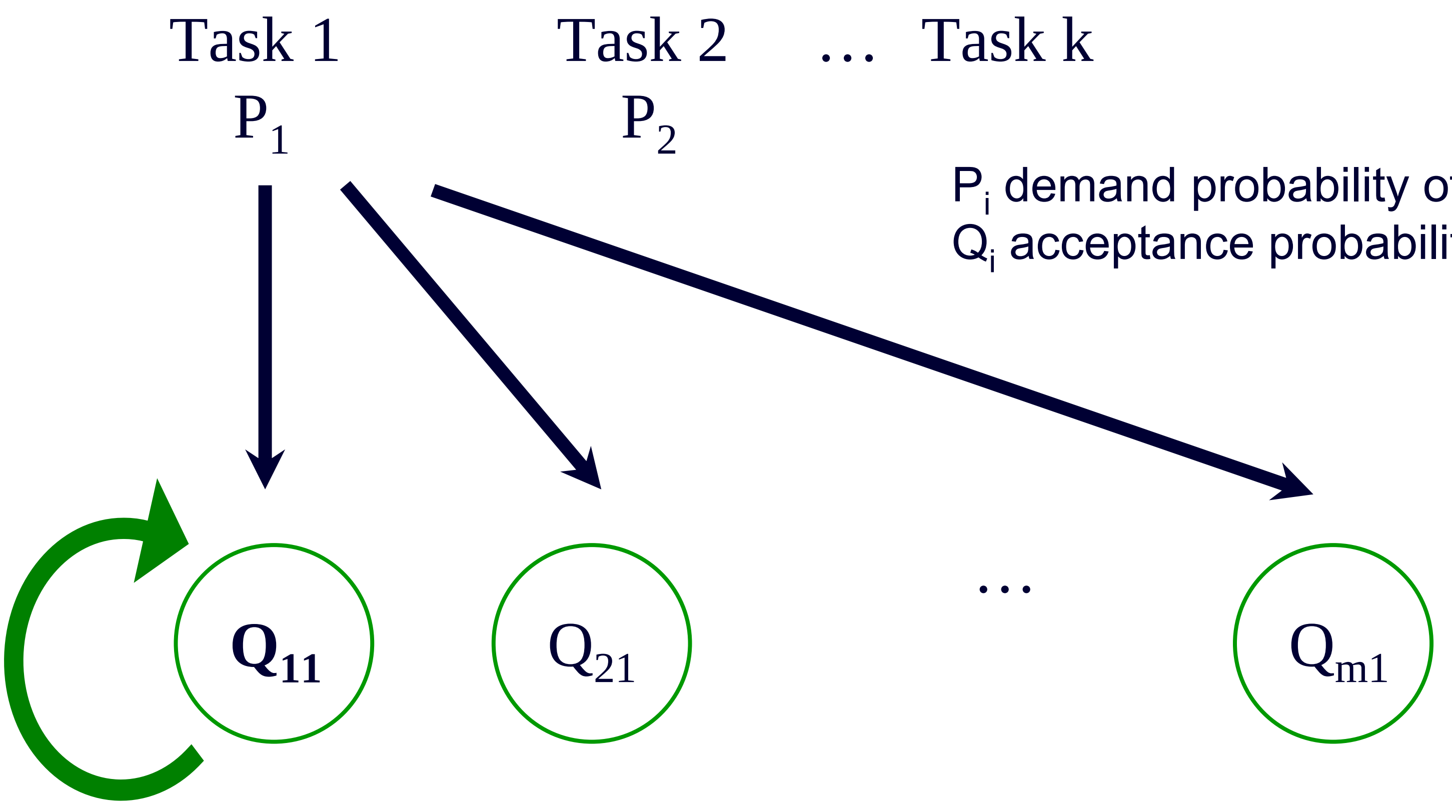
Example of task allocation based on mechanism II.a



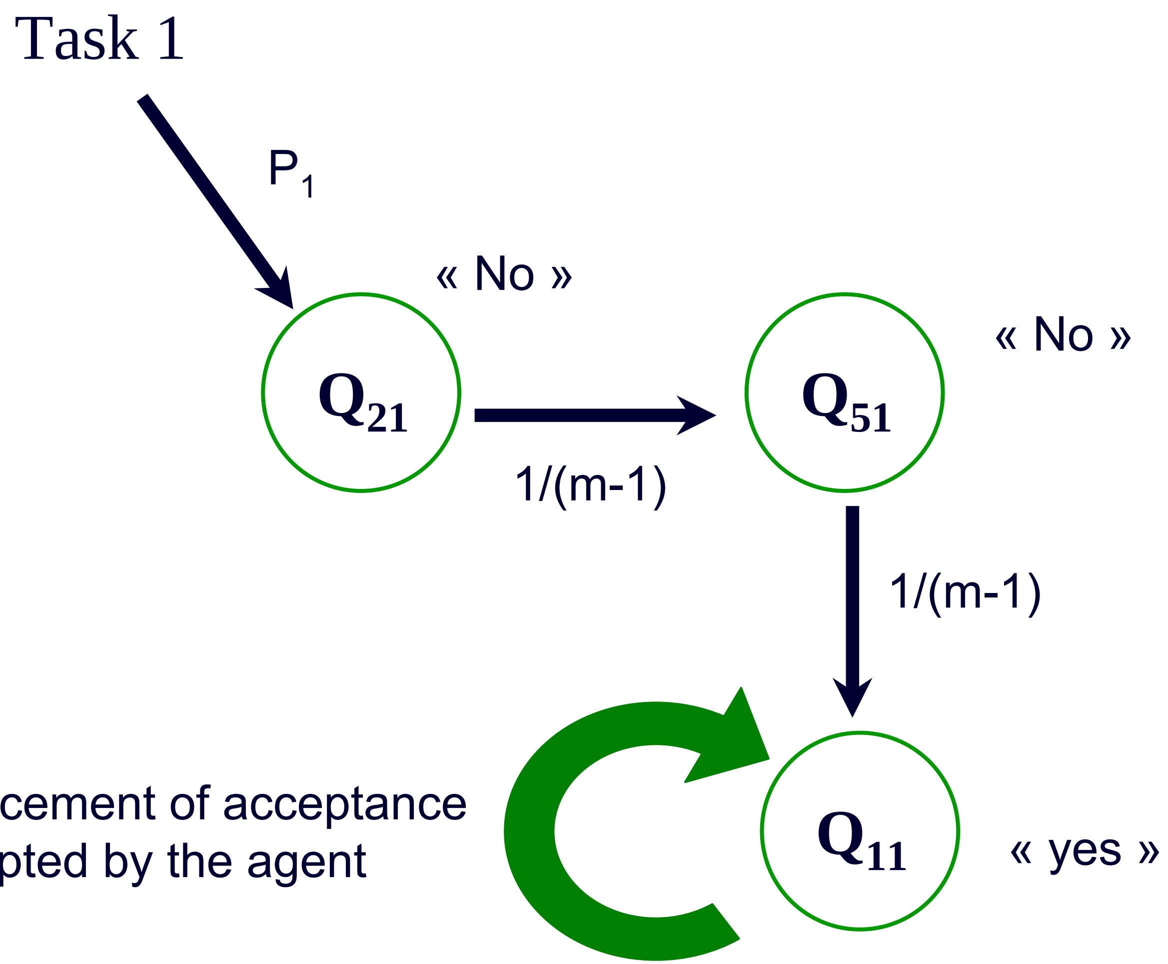
P_i demand probability of task i
Q_i acceptance probability of task i

Individual

Reinforcement of acceptance
if accepted by the agent
(positive feedback)

Saffre & Halloy, 2005

Example of task allocation based on mechanism II.a



Reinforcement of acceptance
if accepted by the agent

Saffre & Halloy, 2005

Probability to perform task j (individual i)

$$Q_{ij} = \frac{A_{ij}^{l}}{\sum_{i=1}^{m} A_{ij}^{l}}$$

l=2
j=10
m=individual number

IF individual i performs task j then A_{ij} increases

$$A_{ij} \rightarrow A_{ij} + F(A_{ij})$$

α=0.5

$$F(A_{ij}) = \alpha A_{ij}$$

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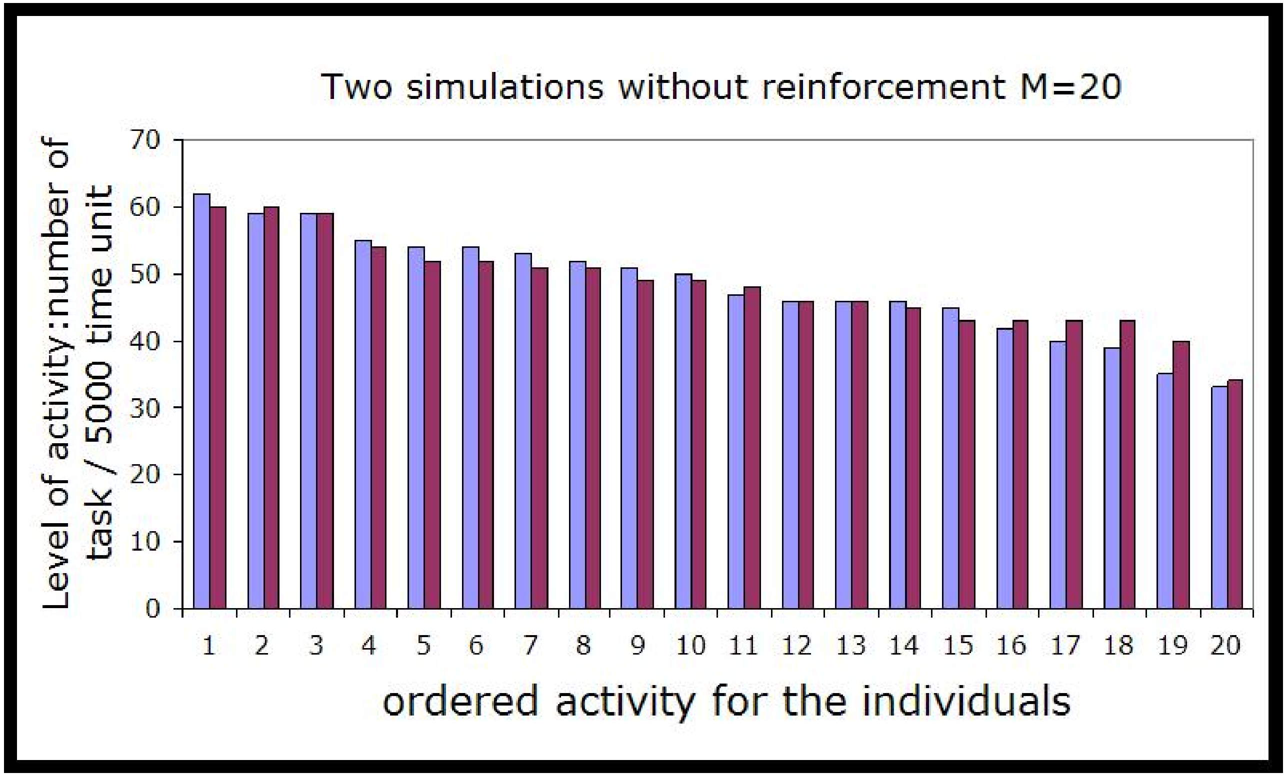
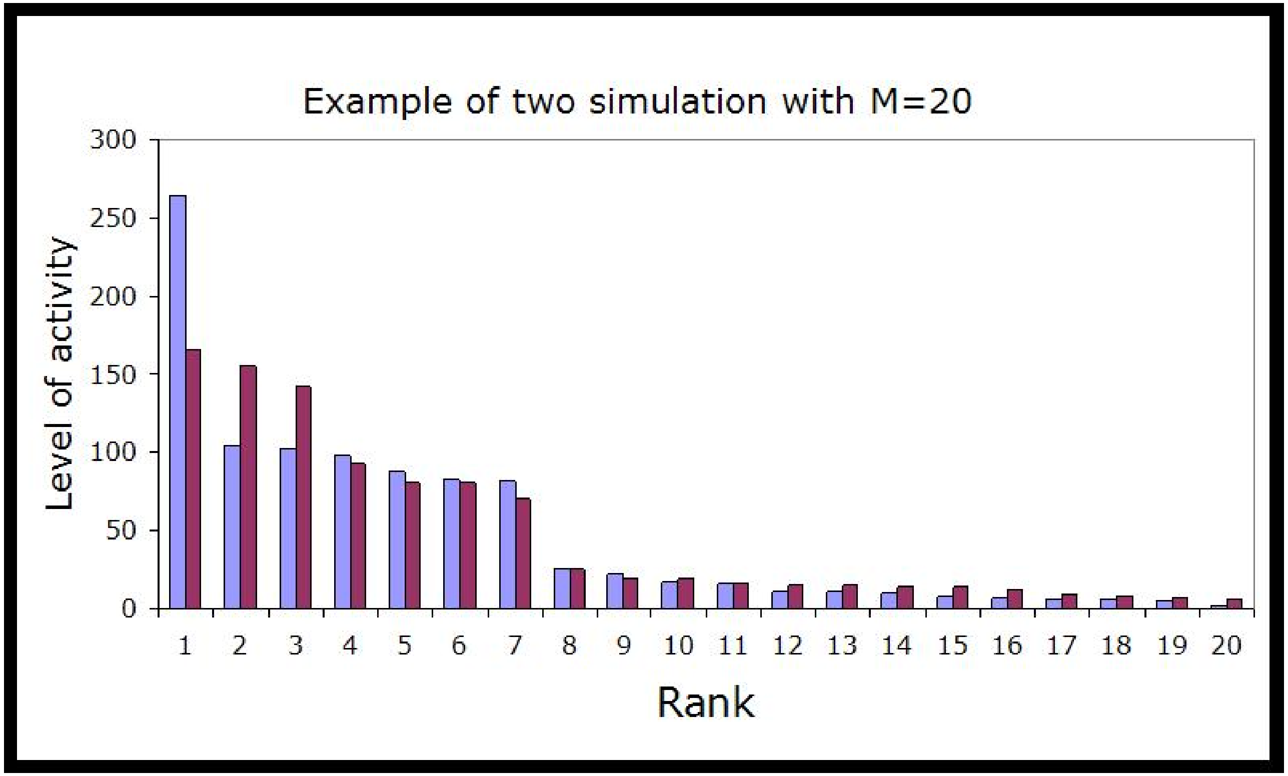
Reference state without reinforcement $l=0$:
binomial distribution of tasks among individuals

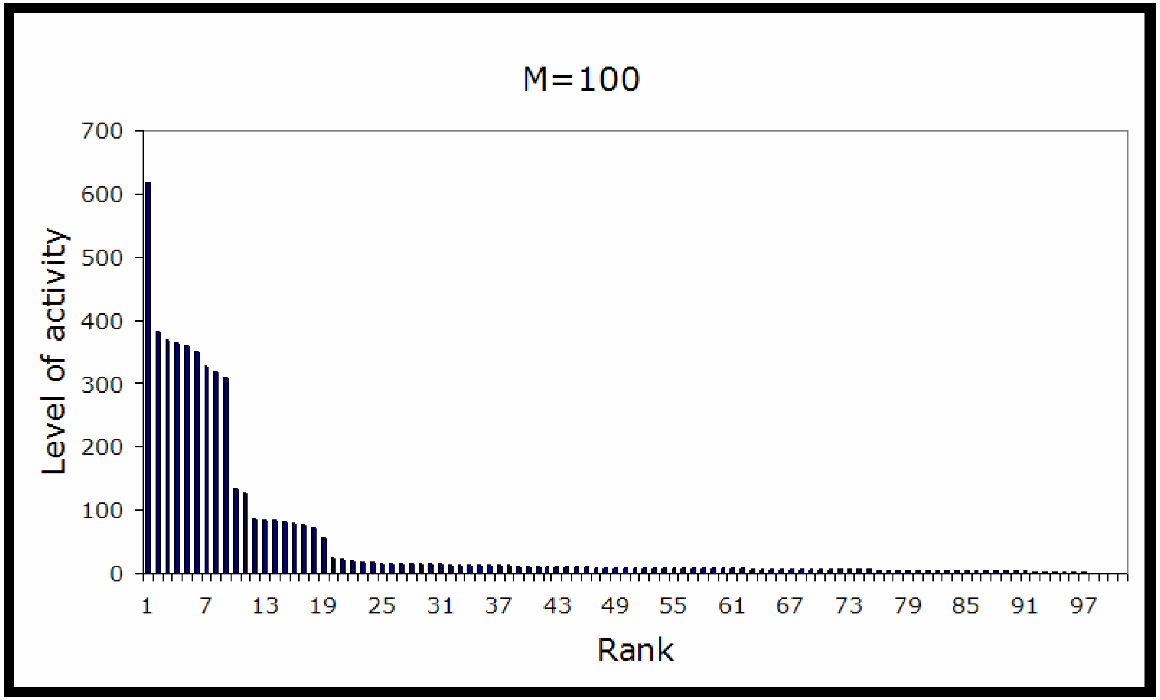


Saffre & Halloy, 2005

With reinforcement $l=2$:
Three clusters of specialized agents emerge

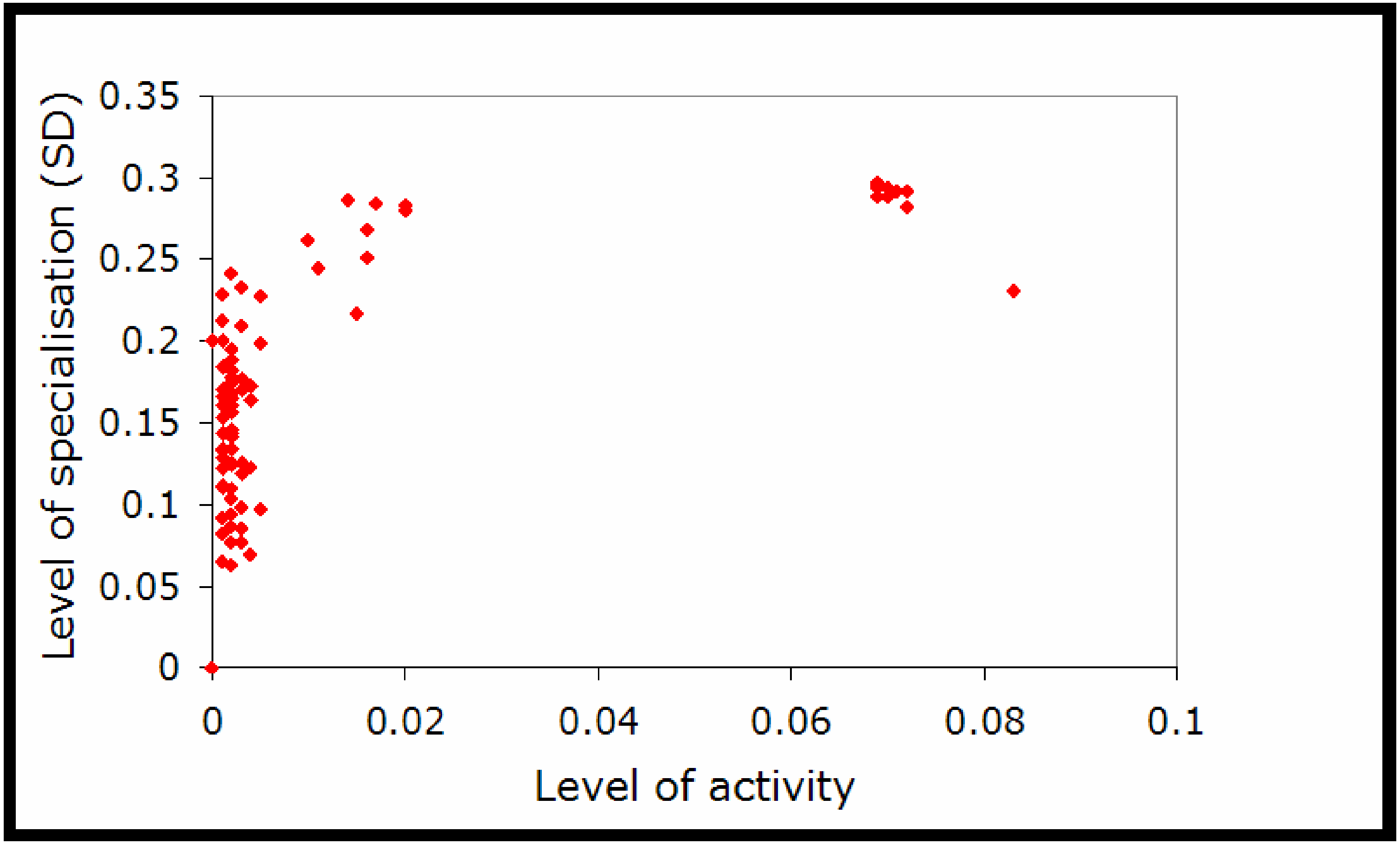


Saffre & Halloy, 2005



Increasing the number of agent
Increases the number of low activity nodes
However, the remaining inactive individuals remain available in case of new tasks appearing

Saffre & Halloy, 2005



Non specialized agents
With low activity

Low specialized agents
with low activity

Highly specialized agents
with high activity

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Saffre & Halloy, 2005

Results with such basic generic rules

- Two constraints at the individual level:
- Tasks are « consumed » hence not available
- The time spent to perform task is not spend to do other tasks

- Initial conditions
- The emergent state are independent of the initial conditions

- Size of specialist clusters remain constant.
- Even with some individuals predisposed for specific tasks

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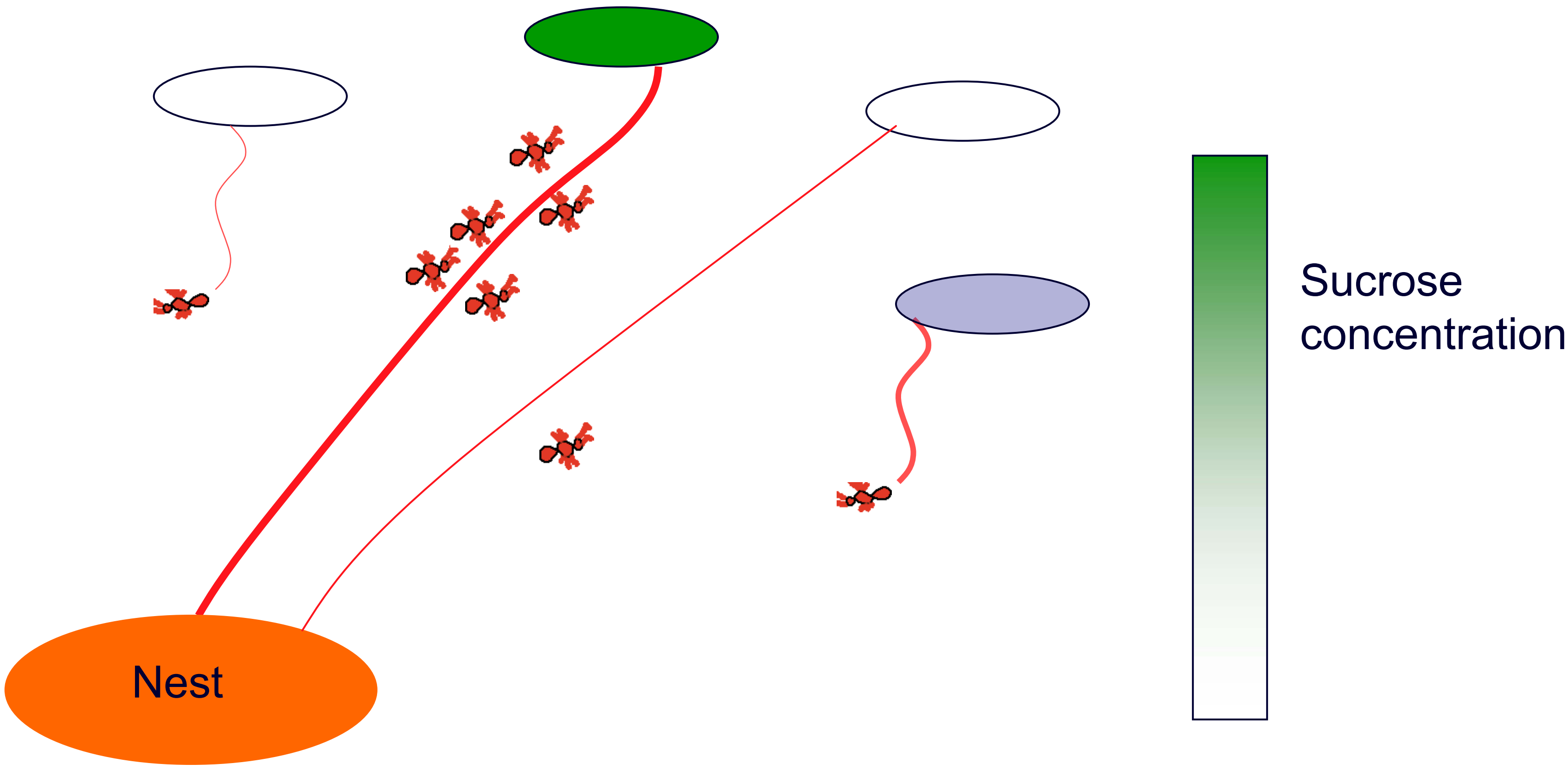
Saffre & Halloy, 2005

Role of randomness!

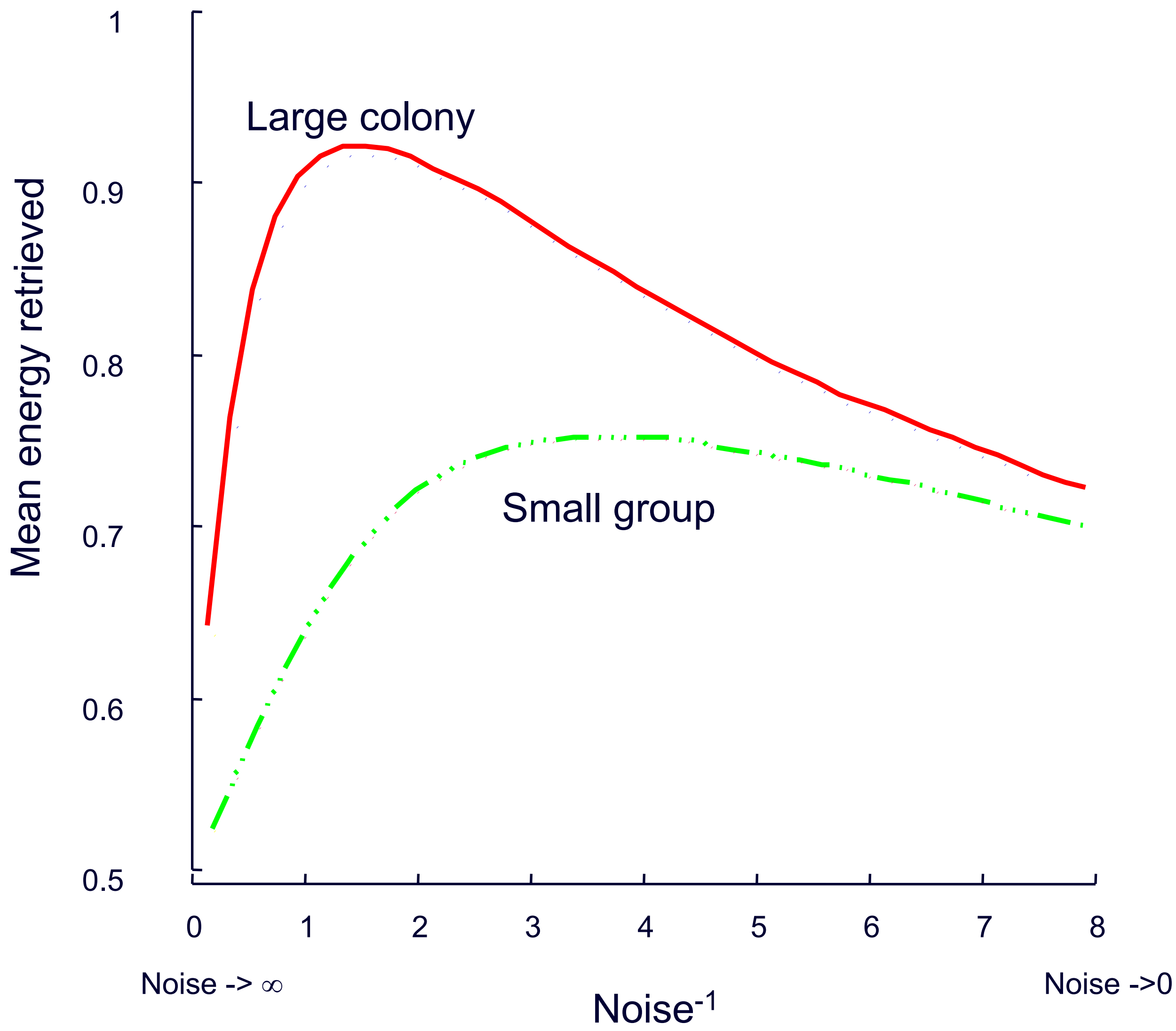
Foraging & trail recruitment -> optimal randomness



Trail laying intensity ≈ a (sucrose concentration)$^{0.5}$
Noise of communication decreases with the trail laying intensity

Saffre & Halloy, 2005

Existence of an **intrinsic optimal level of noise** that produces the efficiency of the collective choice between multiple sources



Deneubourg, Pasteels & Verhaeghe, 1983; Deneubourg, Nicolis & Detrain, 2004

Saffre & Halloy, 2005

Take-away message 1

- The purpose of the individual behavioral pattern is not found at the individual but at the collective level. The mechanism is at the individual level taking into account the interactions; the purpose lies at the collective level.
- In order to produce collective intelligence the systems must present some nonlinear properties coupled with positive or negative feedback mechanisms. One of the main roles of a positive feedback is to amplify random fluctuations to obtain a fast, nonlinear response of the system. To put it simply, innovation or efficient solutions are discovered by random fluctuations and selected by non-linear positive feedbacks.
- Randomness is an essential counterintuitive ingredient because in a classical engineering approach it is considered as a nuisance. In the context of collective intelligence, individual actions include a level of *intrinsic* randomness. Like moving randomly or behaving in a probabilistic way. The behavior of each individual becomes then less predictable or even unpredictable. Nevertheless, collective intelligence can be predicted with accuracy or even produced systematically in artificial systems
- Distributing the team within the environment of the problem to be solved and introducing the positive feed-backs interactions between the units allows the amplification of localized information found by one or a few of the units. Thus, thanks to this type of coordination, the team reaction to these local signals is the solution to the problem. While no individual is “aware” of all the possible alternatives, and no individual possess an explicitly programmed solution, all together they reach an “unconscious” decision.

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Take-away message 2

- The modeling framework briefly presented here does not mean that the individuals are simple. This is a common misunderstanding of this modeling framework. Even insects are sophisticated animals that have capabilities way beyond any available technology. The emergence of such collective problem solving in animal population is also based on sophisticated individual capabilities.
- However, while reviewing the hypothesis underlying such models, we notice that none of them is specific to animal species or even biology. Any system, including artificial ones, that fulfills these hypotheses will produce such emergent cooperative behavior.

Saffre & Halloy, 2005

Designing artificial complex systems

- We need to identify artificial systems (groups of machines and software) where the known regulatory modules can be applied to produce robust, optimal and autonomous behaviors
- We need to translate, mutatis mutandis, those rules into practical algorithms.
- It also corresponds to the transition from different level of description like for example, from physiology to behavior or from hardware to software.
- In natural systems, the balance between fully distributed and centralized control is usually determined by the task that the system is accomplishing as a whole and the capabilities of its constituents. Similarly, the purpose of an artificial system and the capabilities of individual units should preside to design choice.

Saffre & Halloy, 2005

Research issues…many!

- In artificial system the question remains to identify and design the correct level of individual complexity and the relevant signal that coupled with the appropriate nonlinear inter-agents interactions will produce cooperation and solve a specific real case. This question is an open field of research and there is no systematic way to tackle it with our present knowledge. The specific task to be performed and its complexity leads to a choice of appropriate individual and collective capabilities. An open question is to find a link between the task complexity and the complexity of individuals and communication systems needed to perform it.
- Another important issue arising in artificial systems is that they have to be designed from scratch including all level of description from low level hardware and software up to the high level feedback rules of interactions between agents. Again there is no systematic way to achieve this. The question of navigating formally and systematically between such levels of description remains an important topic for research.

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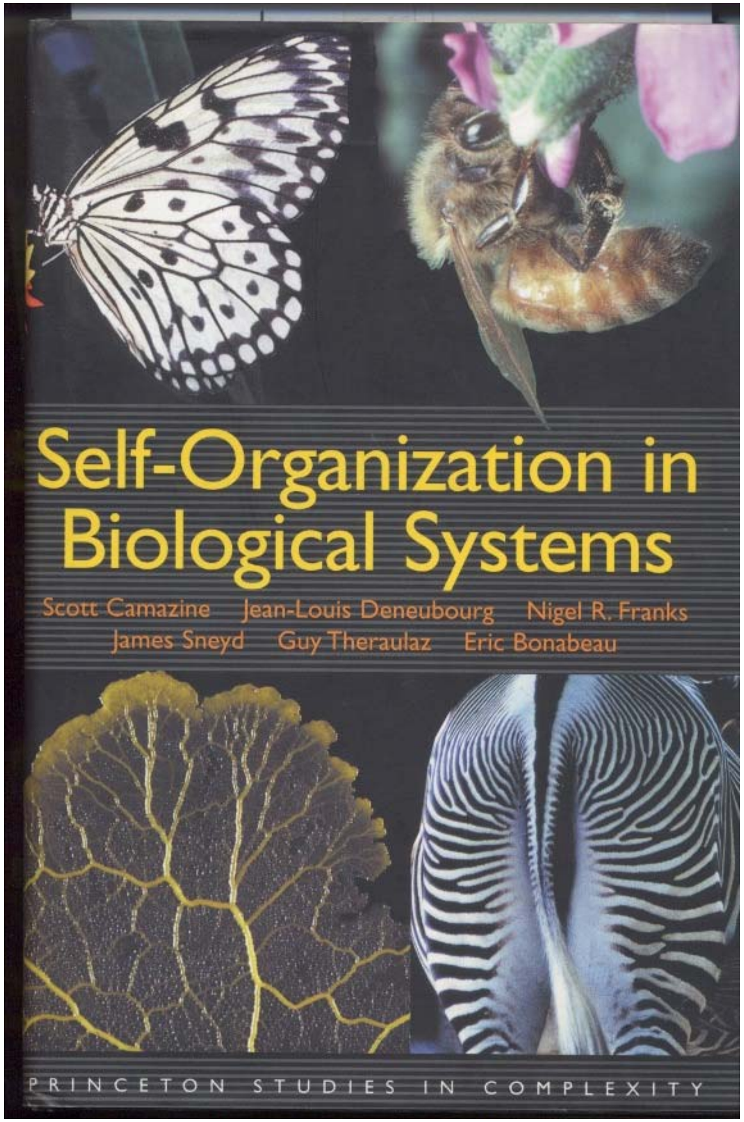
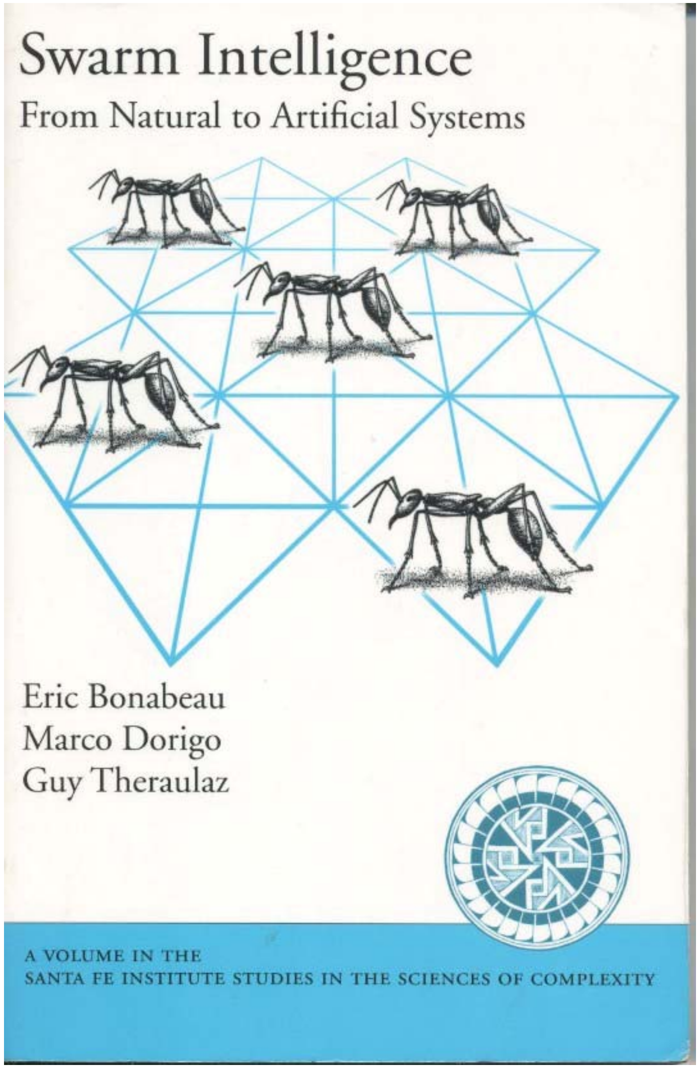
Saffre & Halloy, 2005

Research issues…many!

- How to “travel” between the different level of descriptions: from the abstract layer to the actual implementation layers (opposite directions in natural vs. artificial systems) ?
- What happens when several self-organized behavioral modules are connected?
- How the cascades of complexity emerges?
- What kind of scalability corresponds to each building bloc?
- What is the link between population size and organizational structures?
- In IT autonomous “behaviors” are looked for. When do we start to test in real (simple) cases what we know about emergent behaviors in tested natural systems?

Further reading





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Saffre & Halloy, 2005

Further reading