Swarm Intelligence,
Nature's way to system engineering

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Road map

- Generalities and Nature’s examples
- Characteristics of Swarm Intelligence design
- Stigmergy and self-organization in insect societies
- The Ant Colony Optimization (ACO) metaheuristic

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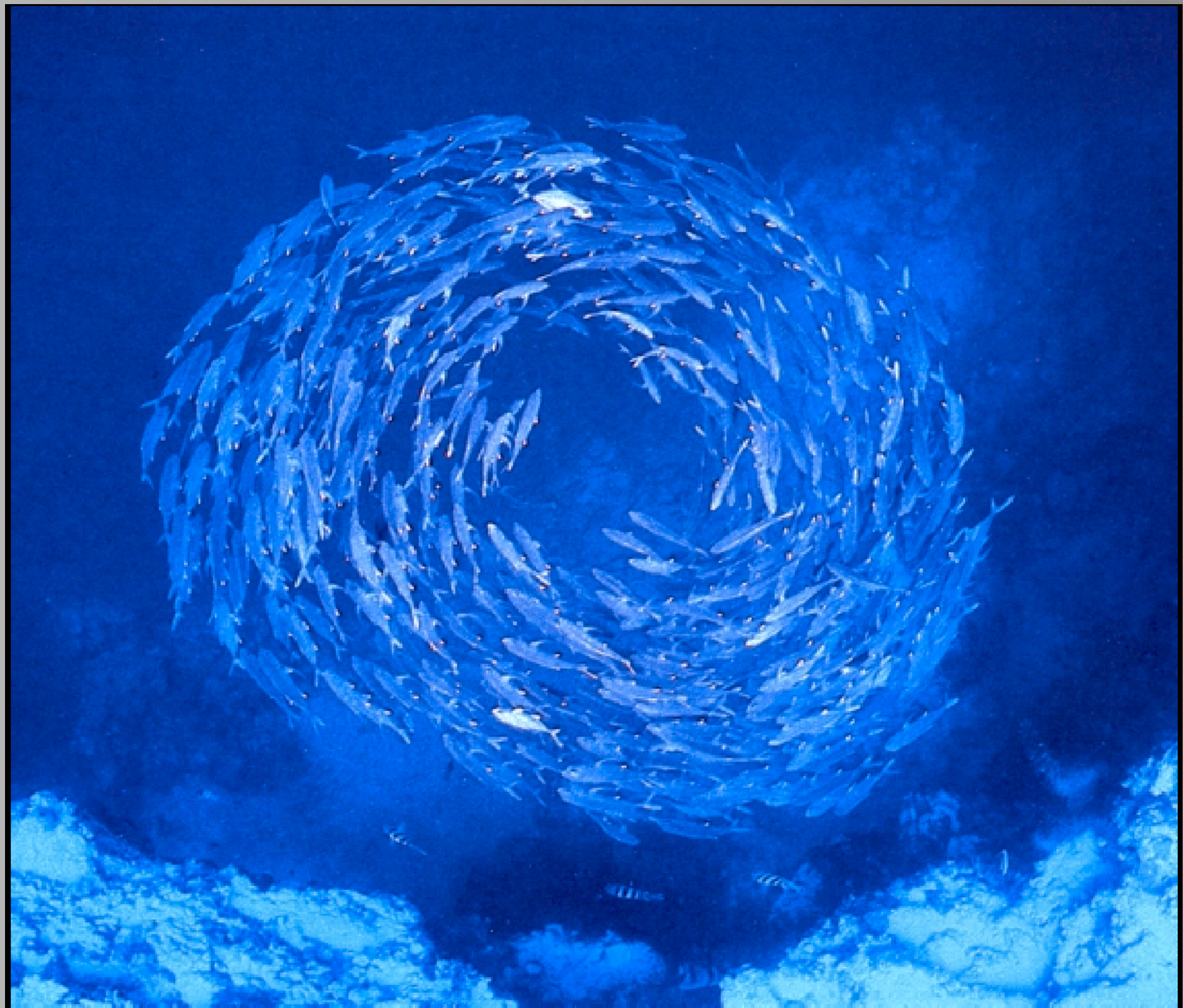
Swarm Intelligence: what’s this?

- A computational and behavioral metaphor for problem solving that originally took its inspiration from the Nature’s examples of collective behaviors (from the end of ’90s)
  - *Social insects (ants, termites, bees, wasps): nest building, foraging, assembly, sorting,. . .*
  - *Vertebrates: swarming, flocking, herding, schooling*
- *Any attempt to design algorithms or distributed problem-solving devices inspired by the collective behavior of social insects and other animal societies [Bonabeau, Dorigo and Theraulaz, 1999]*

- . . . however, we don’t really need to “stick” on examples from Nature, whose constraints and targets might differ profoundly from those of our environments of interest . . .

Nature's examples of SI



Fish schooling (©CORO, CalTech)

Nature's examples of SI (2)

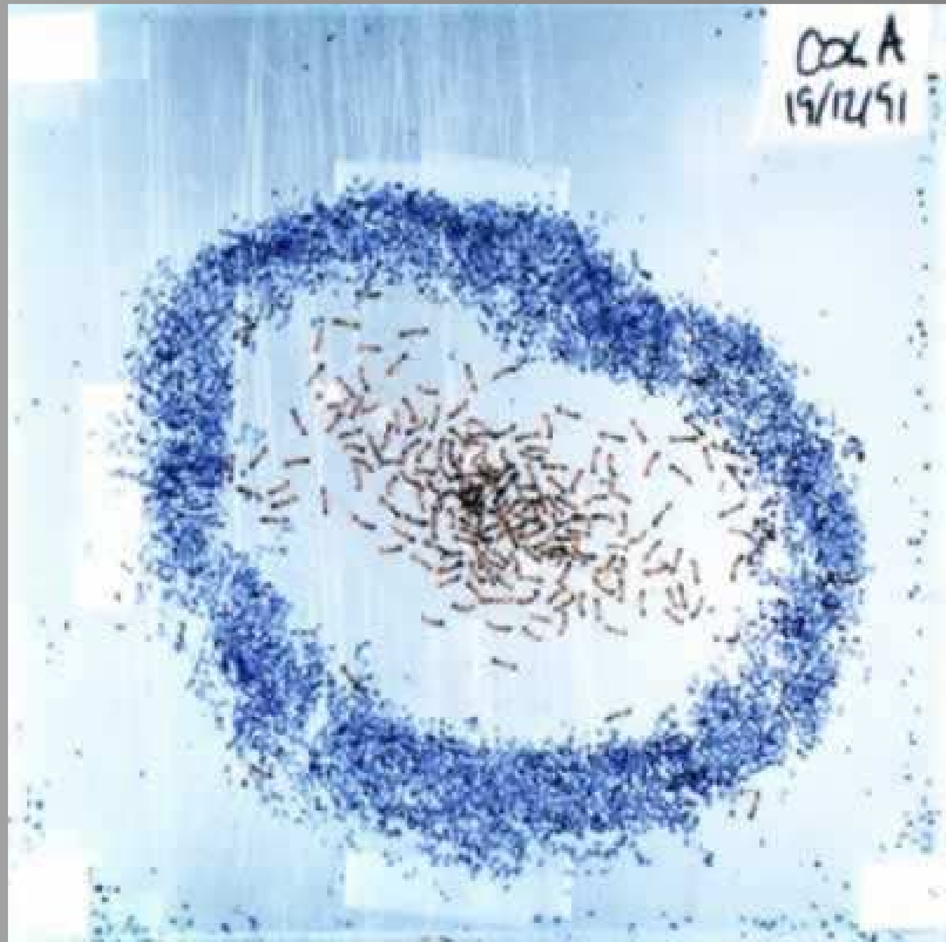
Birds flocking in V-formation (©CORO, Caltech)

Nature's examples of SI (3)

Termites' nest (©Masson)

Nature’s examples of SI (4)

Ant chain (©S. Camazine)



Ant wall (©S. Camazine)

Nature’s examples of SI (5)

- Ants: leaf-cutting, breeding, chaining
- Ants: Food catering
- Bees: scout dance

What do all these behaviors have in common?

- Distributed society of autonomous individuals/agents
- Control is fully distributed among the agents
- Communications among the individuals are localized
- Stochastic agent decisions (partial/noisy view)
- System-level behaviors appear to transcend the behavioral repertoire of the single (minimalist) agent
- Interaction rules seem to be simple
- The overall response of the system features:
  - Robustness
  - Adaptivity
  - Scalability

Swarm Intelligence design means . . . ?

- Allocating computing resources to a (large?) number of minimalist units (swarm?)
- No centralized control (not at all?)
- Units interact in a simple and localized way
- Units do not need a representation of the global task
- Stochastic components are important
- . . . and let generate useful global behaviors by *self-organization*

Modular design shifting complexity from modules to protocols

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I had a dream . . .

. . . I can generate *complexity out of simplicity*: I can put all the previous ingredients in a pot, boil them down and get good, robust, adaptive, scalable algorithms for my problems!

. . . it reminds me of alchemists . . .

- Task complexity is a *conserved* variable

The dark side of SI design

- *Predictability is a problem in distributed bottom-up approaches*
- *Efficiency is another issue* (BTW, are ants efficient?)
- *What's the overall cost?* (self-organization is dissipative)
- *Loads of parameters to assign* (e.g., how many agents?)
- *Nature had millions of years to "design" effective systems by ontogenetic and phylogenetic evolution driven by selection, genetic recombination and random mutations*, but we have less time. . .

Self-organization: definitions

- *Self-organization consists of 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 [Bonabeau et al., 1997]*

- *More general: any dynamic system from which order emerges entirely as a result of the properties of individual elements in the system, and not from external pressures (e.g., Beńard cellular convection, Belousov-Zhabotinski reactions)*

- *In more abstract terms: self-organization is related to an increase of the statistical complexity of the causal states of the process [Shalizi, 2001]: when a number of units have reached organized coordination, it is necessary to retain more information about the inputs in order to make a statistically correct prediction*

Main forms of communication

- *Point-to-point*: antennation, trophallaxis (food or liquid exchange), mandibular contact, direct visual contact, chemical contact, . . . unicast radio contact!
- *Broadcast-like*: the signal propagates to some limited extent throughout the environment and/or is made available for a rather short time (e.g., use of lateral line in fishes to detect water waves, generic visual detection, actual radio broadcast
- *Indirect*: two individuals interact indirectly when one of them modifies the environment and the other responds asynchronously to the modified environment at a later time. This is called *stigmergy* [Grassé, 1959] (e.g., pheromone laying/following, post-it, web)

Algorithmic frameworks based on SI design

- *Ant Colony Optimization* (ACO) and *Particle Swarm Optimization* (PSO) are the most popular frameworks based on the original notion of SI (CA?)

- At the core of the design of ACO and PSO there is the specific way the agents communicate in the *spatial environment*. These two *optimization frameworks* focus on two different ways of distributing, accessing and using *information in the environment*

- ACO is based on stigmergy, while PSO uses broadcast-like communications

- In ACO and PSO agents are rather simple, since they *do not learn at individual level*

- The use of all the three forms of communication encompasses more general systems showing collective organized behaviors (*COIN, immune systems, cultural algorithms, neural systems, human organizations, mobile ad hoc networks*,. . .)

Collective robotics

- *Collective robotics* is attracting a lot of interest: groups of robots play soccer (RoboCup), unload cargo, patrol vast areas, cluster objects, self-assemble (Swarm-bots), and will maybe “soon” participate to war :-(. . .

  - Robot assembly to cross a gap

  - Robot assembly to transport a prey

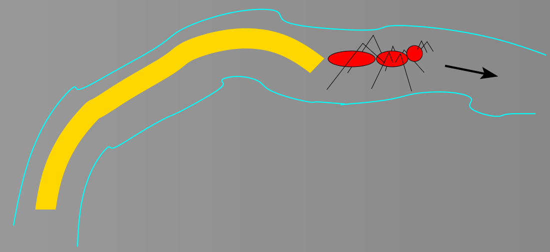
- Look at RoboCup (www.robocup.org) and Swarm-bots (www.swarm-bots.org)!

Stigmergy and Ant-inspired algorithms

- Stigmergy is at the core of most of all the amazing collective behaviors exhibited by the ant/termite colonies (nest building, division of labor, structure formation, cooperative transport)
- Grassé (1959) introduced this term to explain *nest building in termite societies*
- Goss, Aron, Deneubourg, and Pasteels (1989) showed how stigmergy allows *ant colonies to find shortest paths* between their nest and sources of food
- These mechanisms have been reverse engineered to give raise to a multitude of ant colony inspired algorithms based on stigmergic communication and control
- The *Ant Colony Optimization metaheuristic (ACO)* [Dorigo & Di Caro, 1999] is the most popular, general, and effective SI framework based on these principles

Pheromone laying-attraction is the key

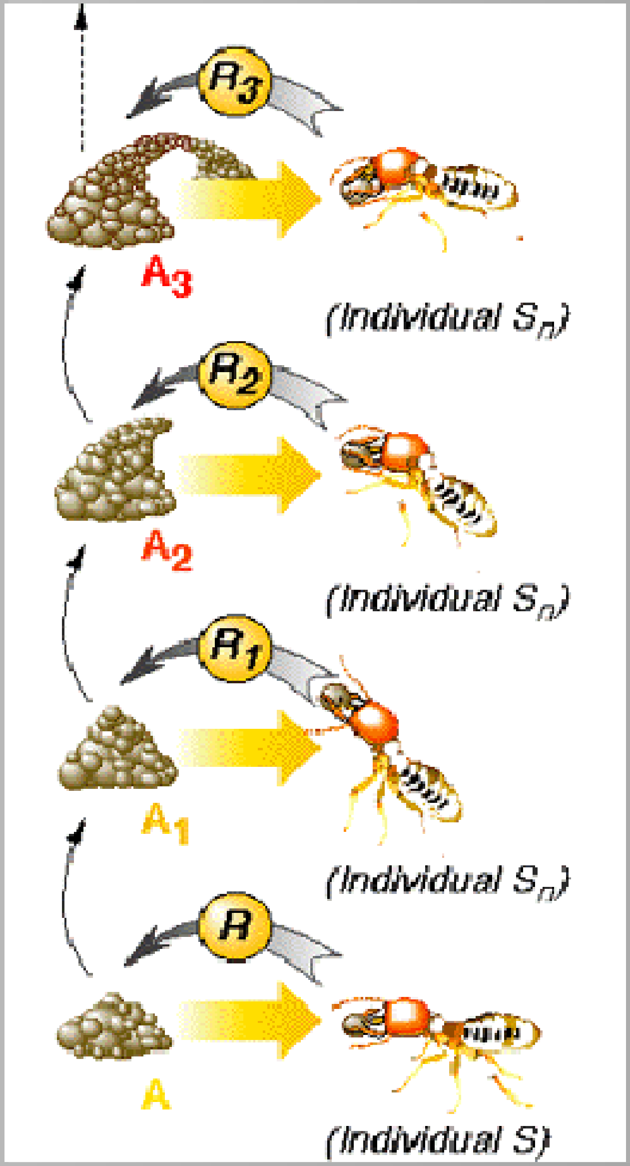
- While walking, the ants lay on the ground a volatile chemical substance, called *pheromone*



- Pheromone distribution *modifies the environment* (the way it is perceived) creating a sort of *attractive potential field* for the ants

- *This is useful for retracing the way back, for mass recruitment, for labor division and coordination, to find shortest paths. . .*

Termite nest building



- Grassé observed that insects are capable to respond to so called *significant stimuli* which activate a genetically encoded reaction. In turn, this reaction as new significant stimuli, generating a *recursive feedback* that can lead to a phase of a global coordination
- Stigmergy = incite to work

Stigmergy and stigmergic variables

- *Stigmergy* means any form of indirect communication among a set of possibly concurrent and distributed agents which happens through acts of local modification of the environment and local sensing of the outcomes of these modifications
- The local environment's variables whose value determine in turn the characteristics of the agents' response, are called *stigmergic variables*
- Stigmergic communication and the presence of stigmergic variables is expected (depending on parameter setting) to give raise to a *self-organized global behaviors*
- *Blackboard/post-it, style of asynchronous communication*

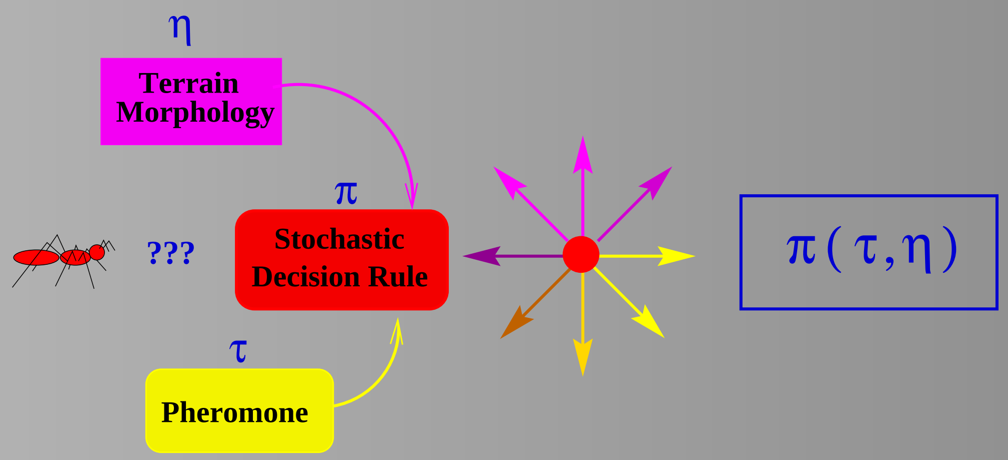
Examples of stigmergic variables

- *Leading to diverging behavior at the group level:*
  - The height of a pile of dirty dishes floating in the sink
  - Nest energy level in foraging robot activation [Krieger and Billeter, 1998]
  - Level of customer demand in adaptive allocation of pick-up postmen [Bonabeau et al., 1997]

- *Leading to converging behavior at the group level:*
  - Intensity of pheromone trails in ant foraging: shortest paths!

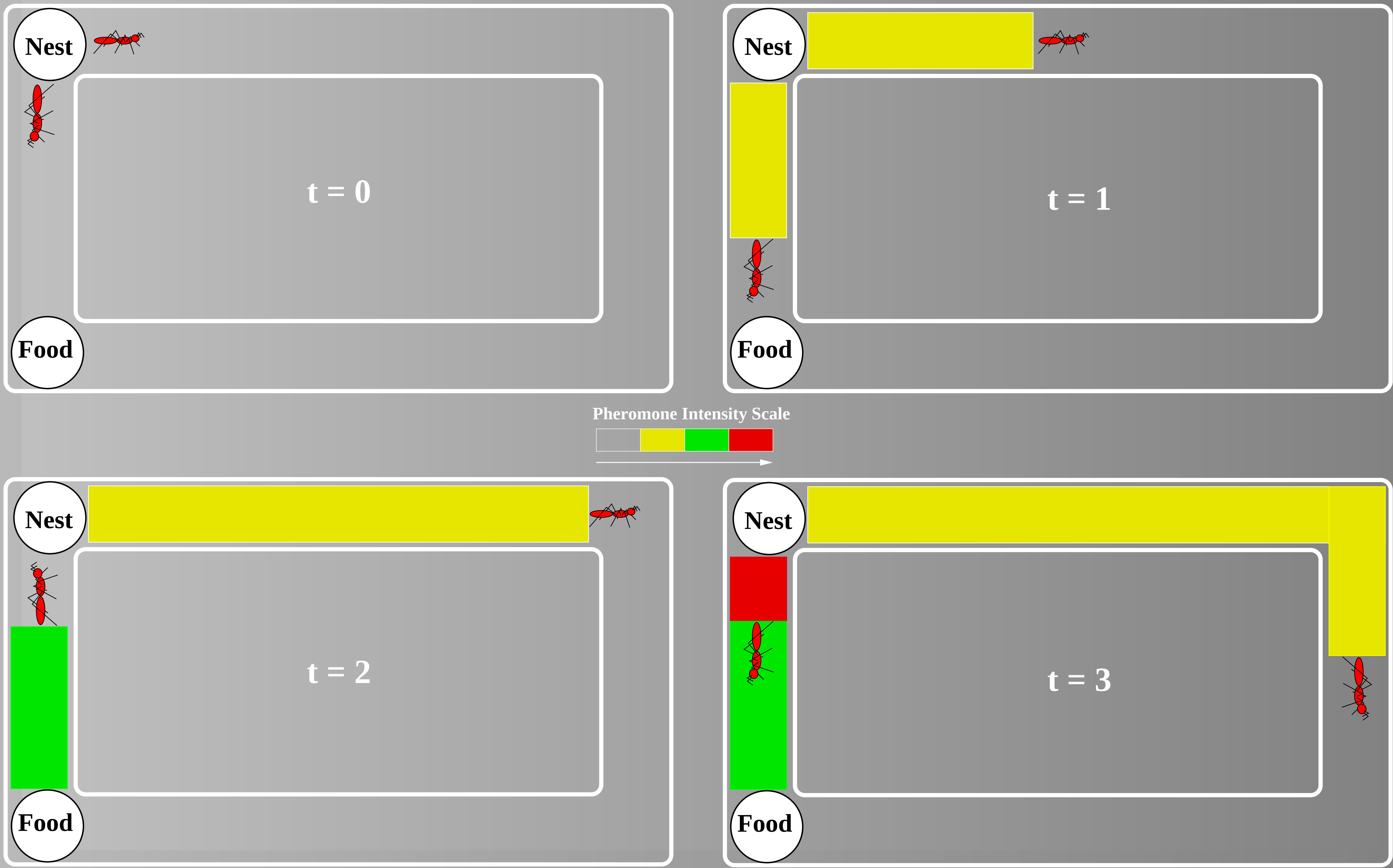
Shortest path behavior in ant colonies

- While walking, at each step a *routing decision* is issued. Directions locally marked by *higher pheromone intensity* are preferred according to some *probabilistic rule*:

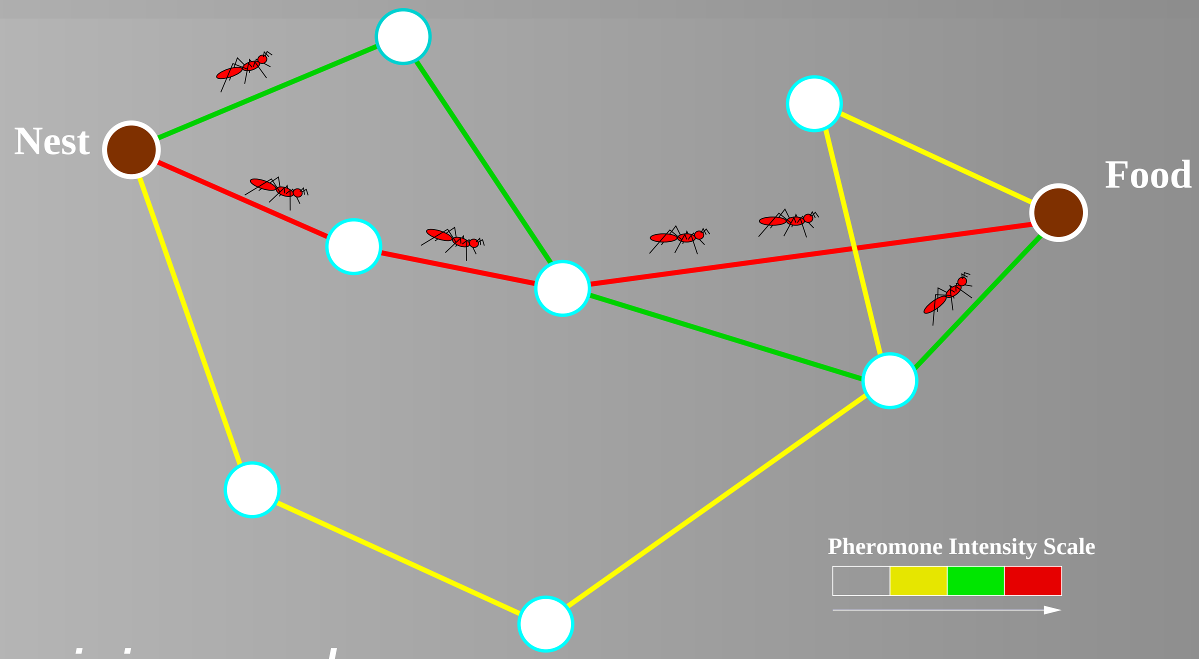


- This basic pheromone laying-following behavior is the main ingredient to allow the colony converge on the *shortest path* between the nest and a source of food

Ant colonies: Pheromone and shortest paths



Ant colonies in a more complex discrete world



- Multiple *decision nodes*
- A path is *constructed* through a *sequence of decisions*
- Decisions must be taken on the basis of local information only
- A traveling *cost* is associated to node *transitions*
- *Pheromone intensity locally encodes decision goodness as collectively estimated by the repeated path sampling*

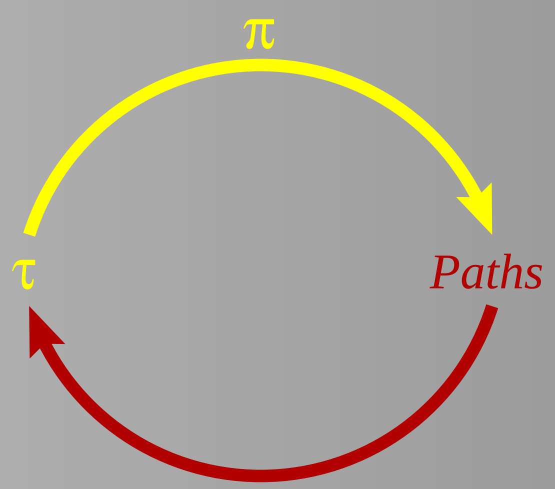
Ant colonies: Ingredients for shortest paths

- A number of concurrent autonomous (simple?) agents (ants)
- Forward-backward path following/sampling
- Multiple paths are tried out and implicitly evaluated
- Local laying and sensing of pheromone
- Stochastic step-by-step decisions biased by pheromone
- Positive feedback effect (local reinforcement of good decisions)
- Persistence / evaporation of the pheromone field
- Iteration over time of the path sampling actions
- Convergence onto the shortest path?

What pheromone represents in abstract terms?

- *Distributed, dynamic, and collective memory of the colony*
- *Learned goodness of a local move (routing choice)*
- Circular relationship: pheromone trails modify environment $\longrightarrow$ locally bias ants decisions $\longrightarrow$ modify environment

Pheromone distribution biases path construction



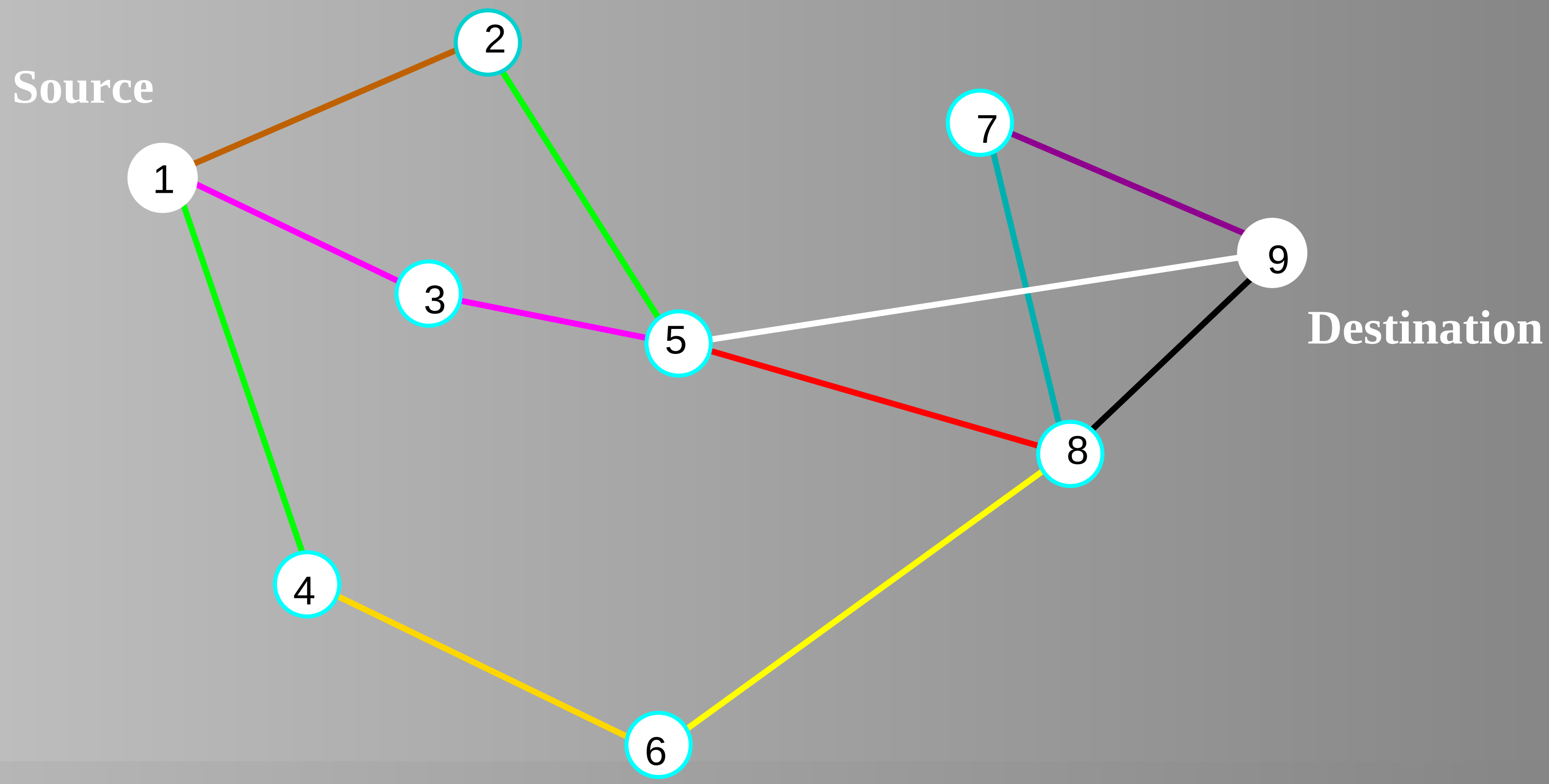
Outcomes of path construction are used to modify pheromone distribution

A meta-strategy for shortest path problems

- By reverse engineering ant colonies' shortest path behavior we get an effective metaheuristic, *ACO*, based on repeated path sampling and distributed/collective decision learning through reinforcements, *to solve shortest path problems* . . .
- . . . in a possibly *fully distributed and adaptive way*
- . . . and we know that shortest paths are a very general model for *combinatorial optimization and decision problems!*

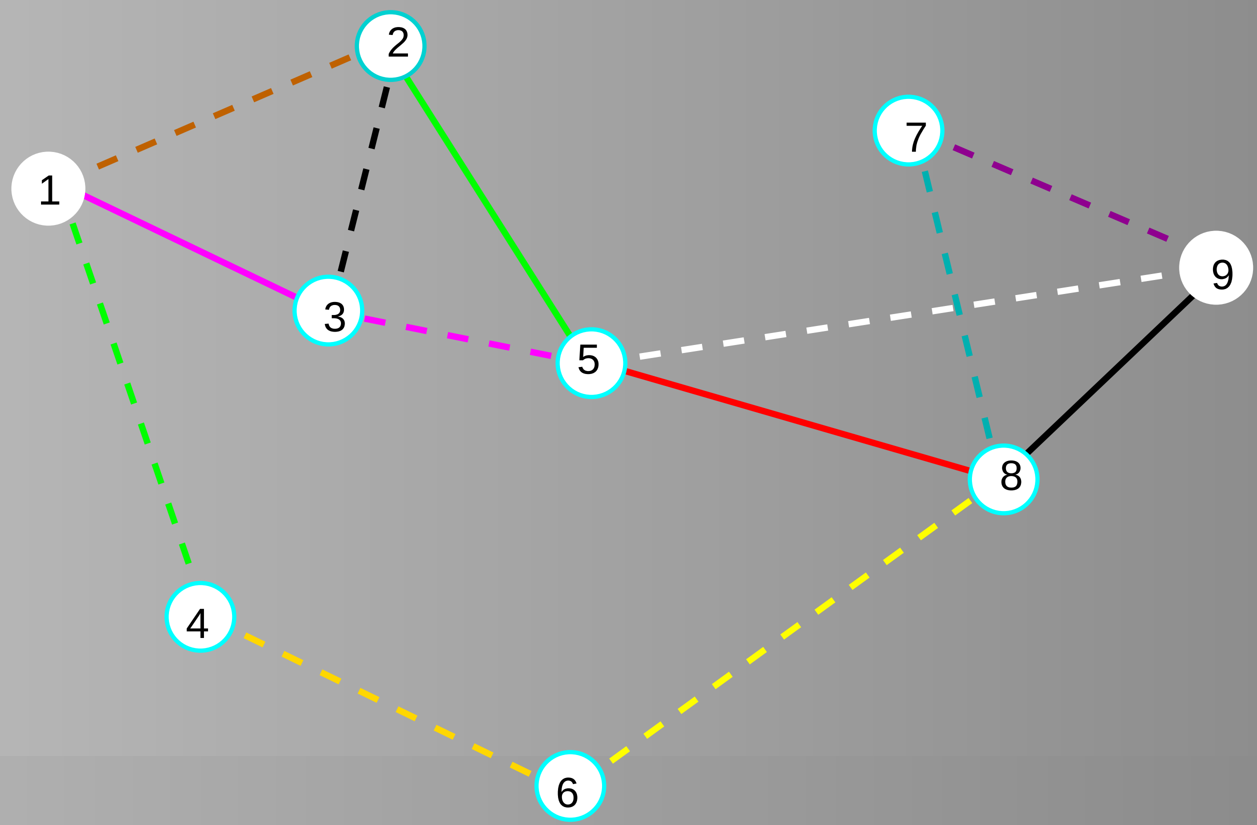
Examples of combinatorial problems (1)

- *Shortest path (SPP)*: $C = \{\text{graph nodes}\}$
- Ex. Sequential decision processes (capacited graph)



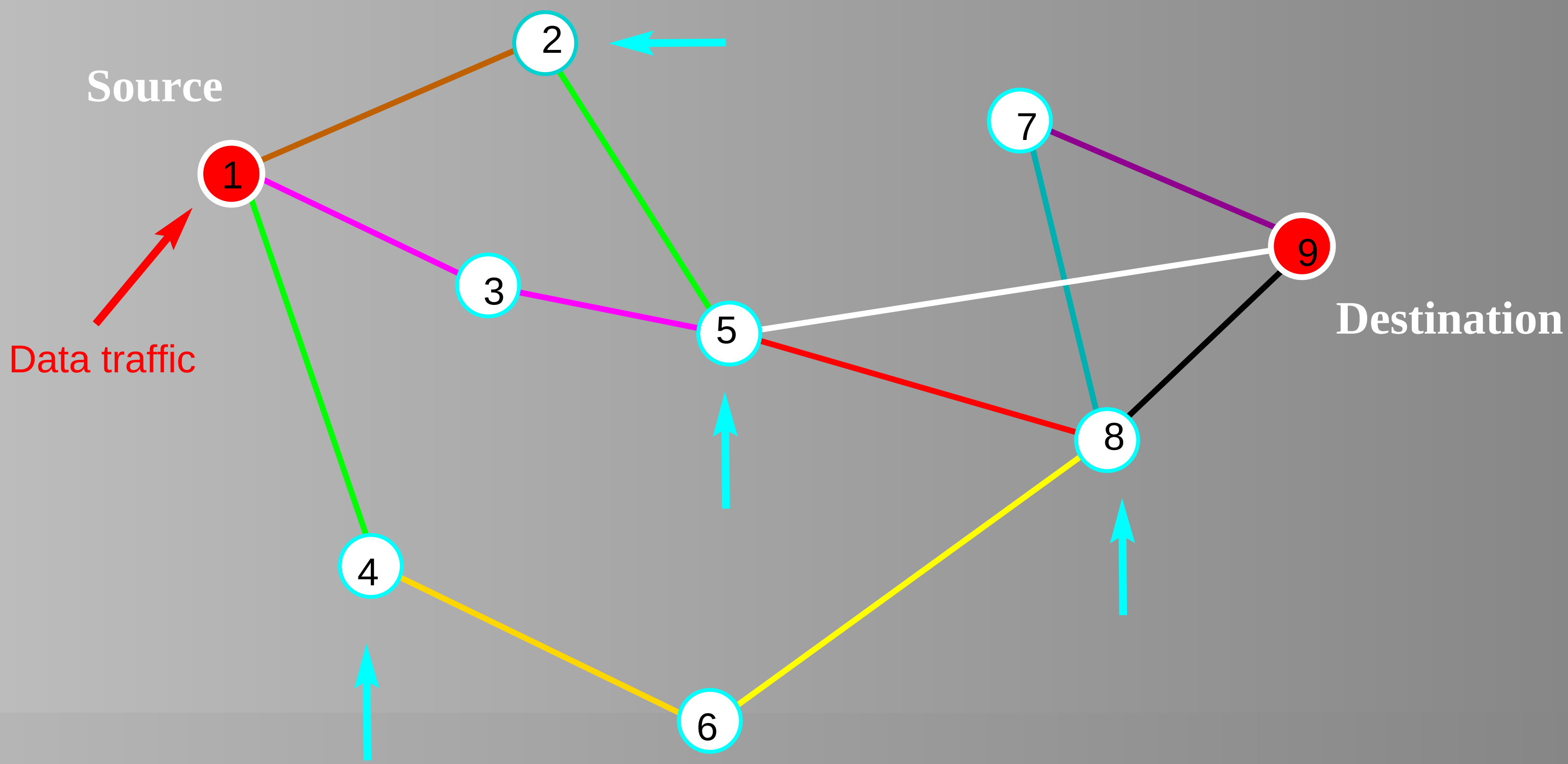
Examples of combinatorial problems (2)

- *Traveling salesman problem (TSP)*: $C = \{\text{cities to visit}\}$
- Ex. Goods delivery
- Constrained shortest path



Examples of combinatorial problems (3)

- *Data routing*: $C = \{\text{network nodes}\}$
- Shortest path + Multiple traffic flows to route simultaneously
- Telecommunication networks



Then, how do we deal with these problems?

- *SPP:* very efficient algorithms are available (label setting / correcting methods)

- *TSP:* for NP-hard problems optimal algorithms are computationally inefficient or totally unfeasible
  $\longrightarrow$ *Heuristic algorithms for good solutions in practice*

- *Routing:* there are optimal distributed algorithms for shortest paths and traffic flows allocation, but:
  - non-stationarities in traffic and topology, uncertainties, QoS constraints are the norm not the exception!
  - *Optimized solutions require full adaptivity and fully distributed behaviors* ($\longrightarrow$ Traffic Engineering)

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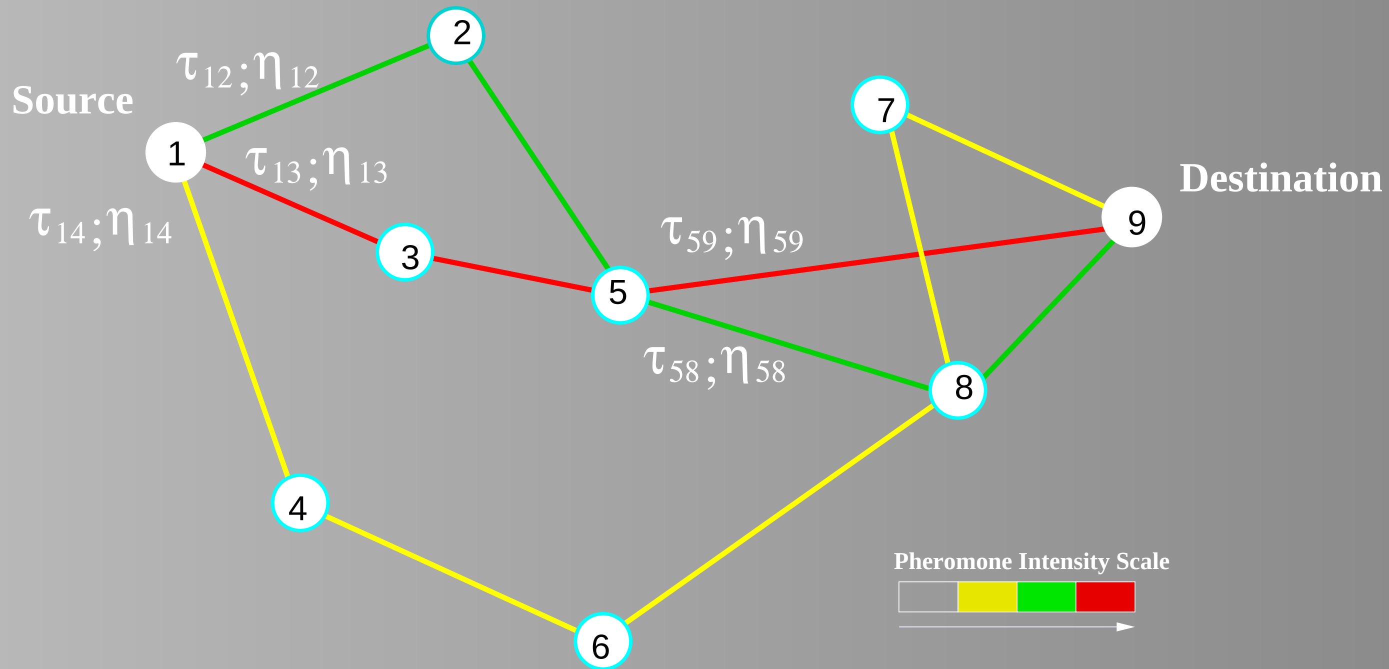
ACO: general architecture

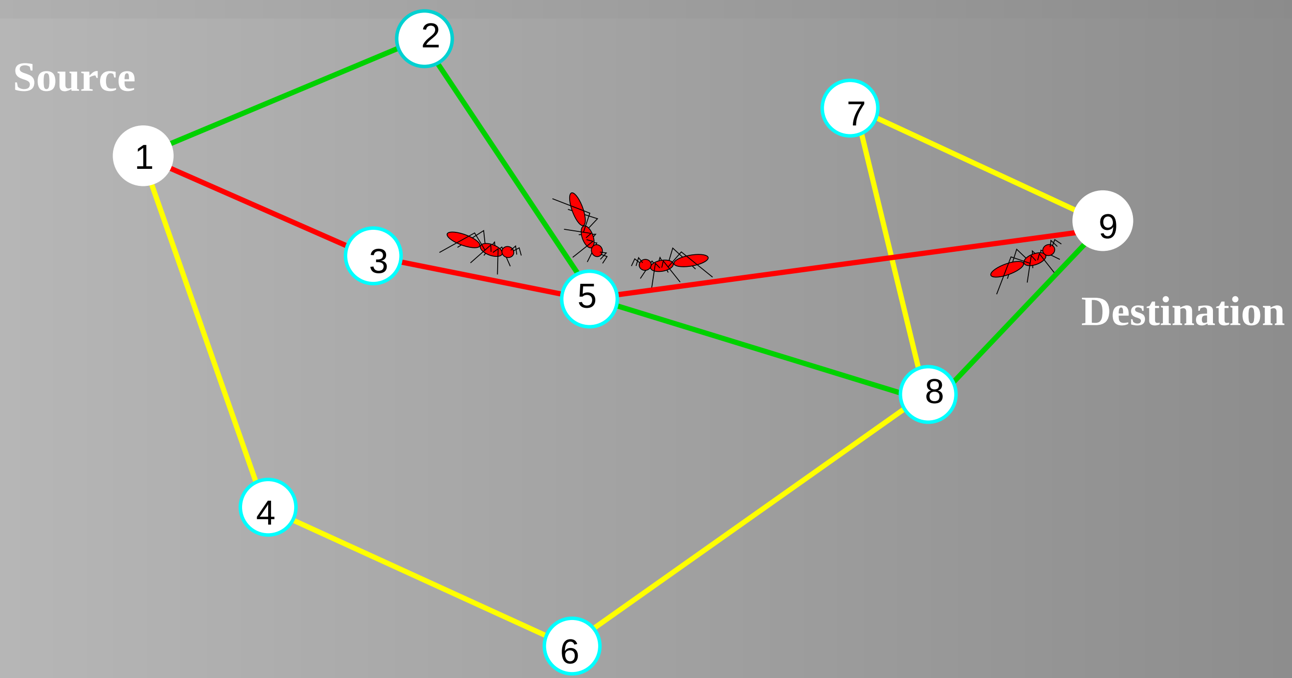
```
procedure ACO_metaheuristic()
  while (¬ stopping_criterion)
     schedule_activities
       ant_agents_construct_solutions_using_pheromone();
       pheromone_updating();
       daemon_actions();      /* OPTIONAL */
     end schedule_activities
  end while
return best_solution_generated;
```

ACO: From natural to artificial ant colonies(1)



- Each node i holds an *array of pheromone variables:*
  $\vec{\tau}_i = [\tau_{ij}] \in \mathbf{R}, \forall j \in \mathcal{N}(i)$ $\longrightarrow$ Learned through path sampling
- and an equivalent array of *heuristic variables:*
  $\vec{\eta}_i = [\eta_{ij}] \in \mathbf{R}, \forall j \in \mathcal{N}(i)$ $\longrightarrow$ Resulting from other sources $\uparrow$
- $\tau_{ij} = q(j|i)$: estimated *quality/goodness/utility* of moving to next node j conditionally to the fact of being in i

ACO: From natural to artificial ant colonies(2)



- Each ant is an *autonomous agent that constructs a path* $\mathcal{P}_{1\rightarrow 9}$ $\rightarrow$ proposes a solution to the problem
- There might be one or more ants *concurrently active* at the same time. Ants do not need synchronization
- Next hops are selected through a *stochastic decision policy*

$$\pi_\epsilon(i;\ \vec{\tau}_i, \vec{\eta}_i)$$

ACO: Ant-routing table and decision policy

- The values of τ_i and η_i at each node i must be combined and given a relative weight in order to assign a precise goodness value to each locally available next hop $j \in \mathcal{N}(i)$:

$$\mathcal{A}_i(j) = f_\tau(\boldsymbol{\tau}_i, j) \circ f_\eta(\boldsymbol{\eta}_i, j)$$

- $\mathcal{A}_i(j)$ is called the *(Ant-routing table)*: it summarizes all the information locally available to make next hop selection.

  Examples: $\tau_{ij}^{\alpha} \cdot \eta_{ij}^{\beta}, \quad \alpha\tau_{ij} + (1-\alpha)\eta_{ij}$

- $\mathcal{A}_i(j)$ values are used by π_ϵ to take a probabilistic decision:
  - *Example - Random-proportional:* $p_{ij} = \dfrac{\mathcal{A}_i(j)}{\sum_{k \in \mathcal{N}(i)} \mathcal{A}_i(k)}$
  - *Example - ϵ-greedy:*

$$\begin{cases} \textit{if } p_b > p_u: & p_{ij} = 1 \textit{ if } j = \arg\max \mathcal{A}_i(j),\ 0 \textit{ otherwise} \\ \textit{else}: & p_{ij} = 1/|\mathcal{N}(i)|,\ \forall j \in \mathcal{N}(i) \end{cases}$$

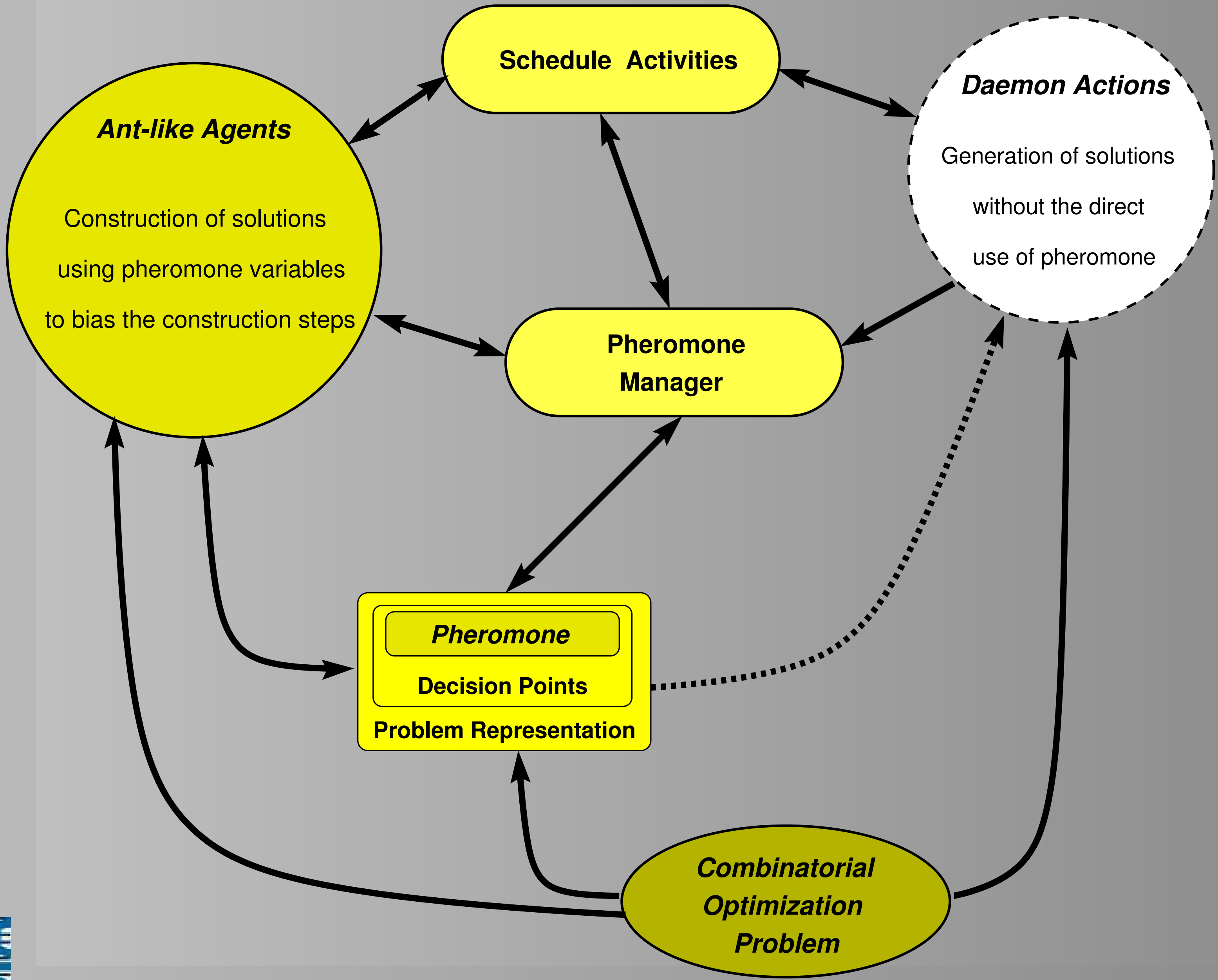
Pheromone updating

- Ants update pheromone *online step-by-step* $\longrightarrow$ Implicit path evaluation based on on traveling time and rate of updates
- Ant's way is inefficient and risky
- The right way is *online delayed* + *pheromone manager filter*:
  - *Complete the path*
  - *Evaluate*
  - *"Retrace" and assign credit / reinforce the goodness value of the decision (pheromone variables) that built the path*
  - *Total path cost can be safely used as reinforcement signal*

    Example TSP: $s = (c_1, c_3, c_5, c_7, c_9), \quad J(s) = L$

    $$\tau_{13} \leftarrow \tau_{13} + 1/L, \quad \tau_{35} \leftarrow \tau_{35} + 1/L, \ldots$$
- Online step-by-step decrease for exploration (e.g., ACS)
- If states: online step-by-step + bootstrapping is ok
- *Offline*: *daemon*, *evaporation*: $\tau_{ij} \leftarrow \rho\tau_{ij}, \ \rho \in [0, 1]$,

ACO's logical diagram can help to understand



Designing an ACO algorithm

- Representation of the problem $\longrightarrow$ pheromone model $\vec{\tau}$
- Heuristic variables $\vec{\eta}$
- Ant-routing table $\mathcal{A}$
- Stochastic decision policy π_ϵ
- Solution evaluation $J(s)$
- Policies for pheromone updating
- Scheduling of the ants
- Daemon components
- Pheromone initialization, constants, $\ldots$

Applications and performance

- *Traveling salesman:* state-of-the-art / good performance
- *Quadratic assignment:* good / state-of-the-art
- *Scheduling:* state-of-the-art / good performance
- *Vehicle routing:* state-of-the-art / good performance
- *Sequential ordering:* state-of-the-art performance
- *Shortest common supersequence:* good results
- *Graph coloring and frequency assignment:* good results
- *Bin packing:* state-of-the-art performance
- *Constraint satisfaction:* good performance
- *Multi-knapsack:* poor performance
- *Timetabling:* good performance
- *Optical network routing:* promising performance
- *Set covering and partitioning:* good performance
- *Parallel implementations and models:* good parallelization efficiency
- *Routing in telecommunications networks:* state-of-the-art performance

The end

Thanks for listening!

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