DISTRIBUTED ALGORITHMS AND BIOLOGICAL SYSTEMS

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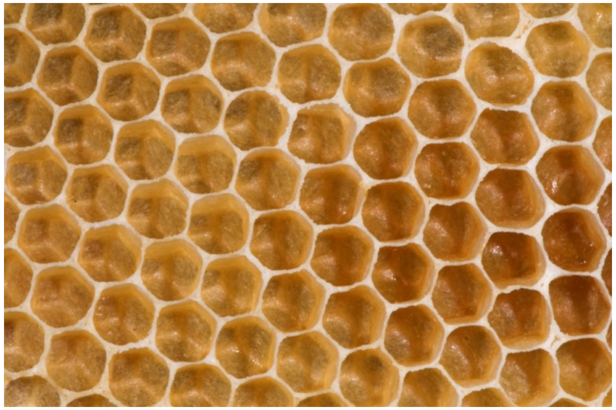
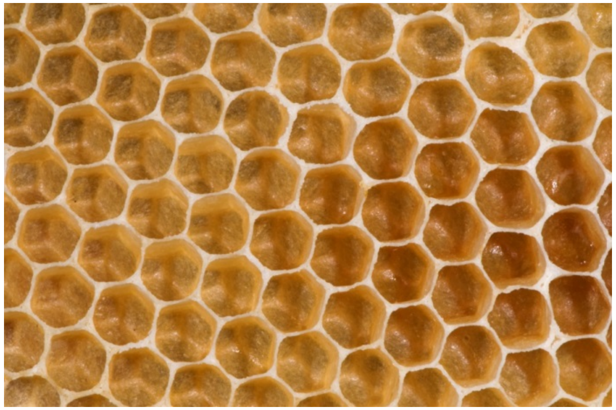


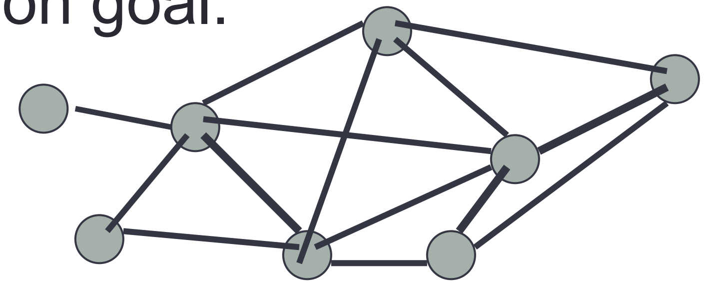
Distributed Algorithms + Biological Systems

- Distributed algorithms researchers have been considering biological systems for the past few years, looking for:
  - Biological problems and behaviors that they can model and study using distributed algorithms methods, and
  - Biological strategies that might be adapted for use in computer networks.
- This has yielded interesting distributed algorithms results.
- Q: But what can distributed algorithms contribute to the study of biological systems?
- This talk:
  - Overview fundamental ideas from the distributed algorithms research area, for biology researchers.
  - Consider how these might contribute to biology research.



What are distributed algorithms?

- Abstract models for systems consisting of many interacting components, working toward a common goal.



- Example systems:
  - Wired or wireless network of computers, communicating or managing data.
  - Robot swarm, searching an unknown terrain, cleaning up, gathering resources, …

What are distributed algorithms?

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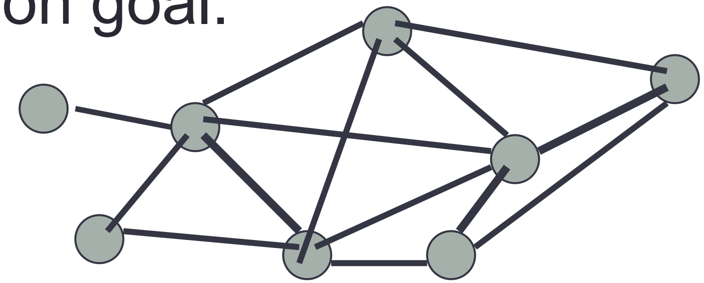
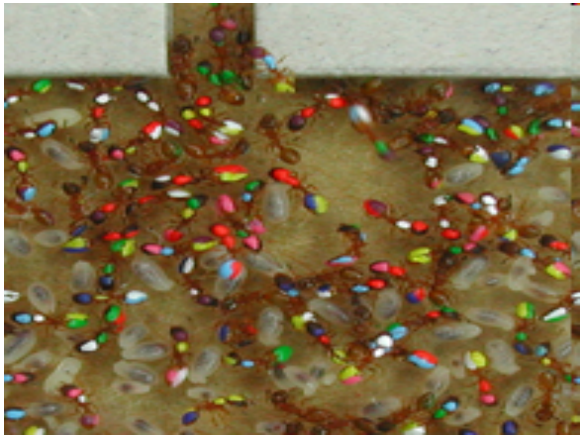


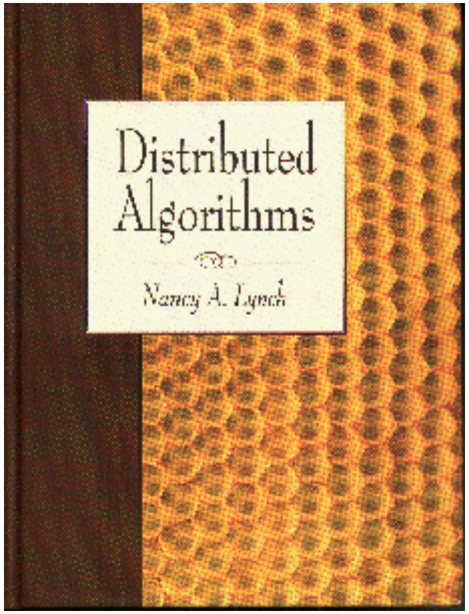
- Example systems:
  - Wired or wireless network of computers, communicating or managing data.
  - Robot swarm, searching an unknown terrain, cleaning up, gathering resources, …
  - Social insect colony, foraging, feeding, finding new nests, resisting predators,…

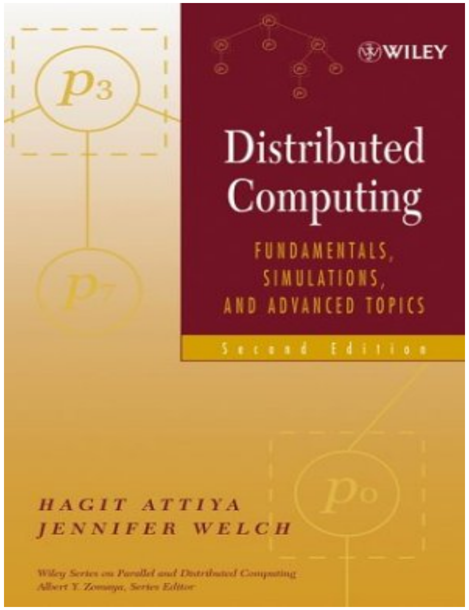


- Components generally interact directly with nearby components only, using local communication.

Distributed algorithms research

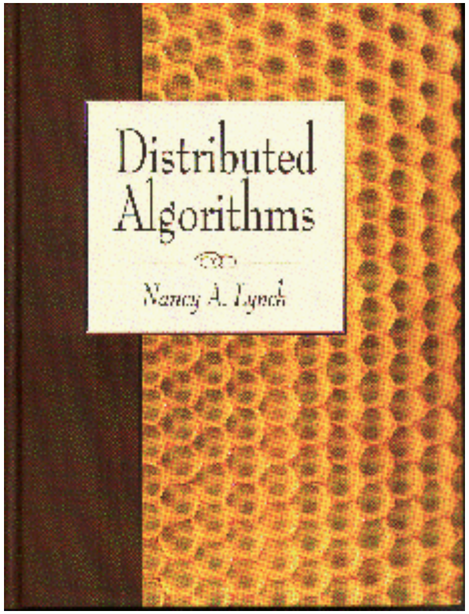
- Models for distributed system platforms.
- Problems to be solved.
- Algorithms, analysis.
- Lower bounds, impossibility results.
- Typical problems: Communication, consensus, data management, resource allocation, synchronization, counting,…
- Models:
  - Interacting automata.
  - Local communication: individual message-passing, local broadcast, or shared memory.
  - Metrics: Time, amount of communication, local storage.

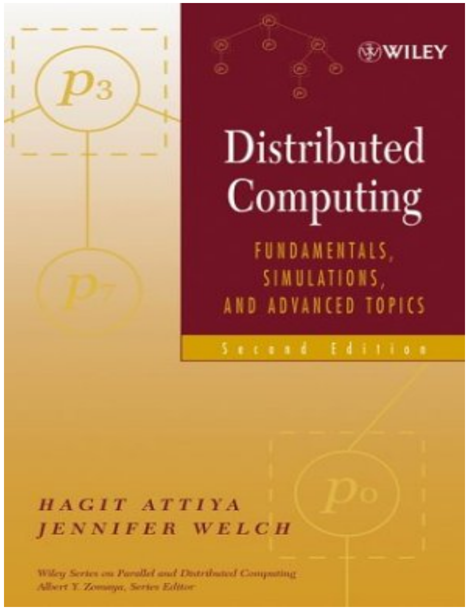




Algorithms

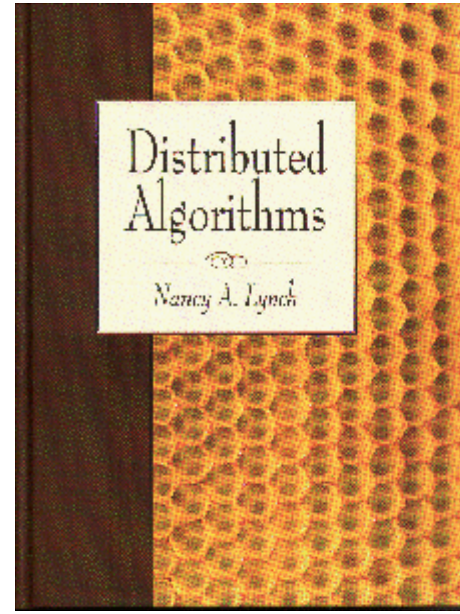
- Some based on simple rules, some use complex constructions.
- Designed to minimize costs, according to the cost metrics.
- Often designed to tolerate limited failures.
- Researchers analyze correctness, costs, and fault-tolerance.
- Try to “optimize”, according to the metrics.

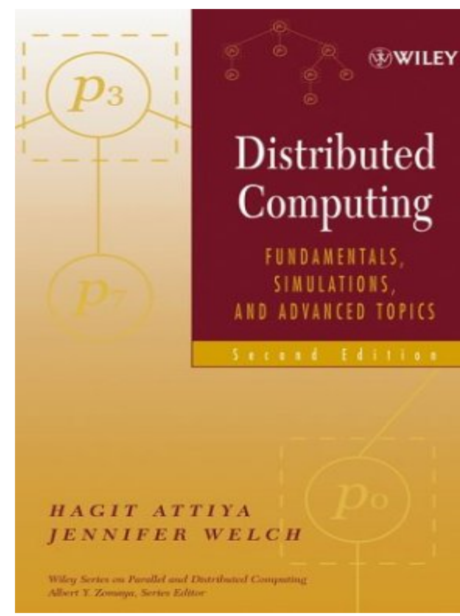




Lower bounds and other impossibility results

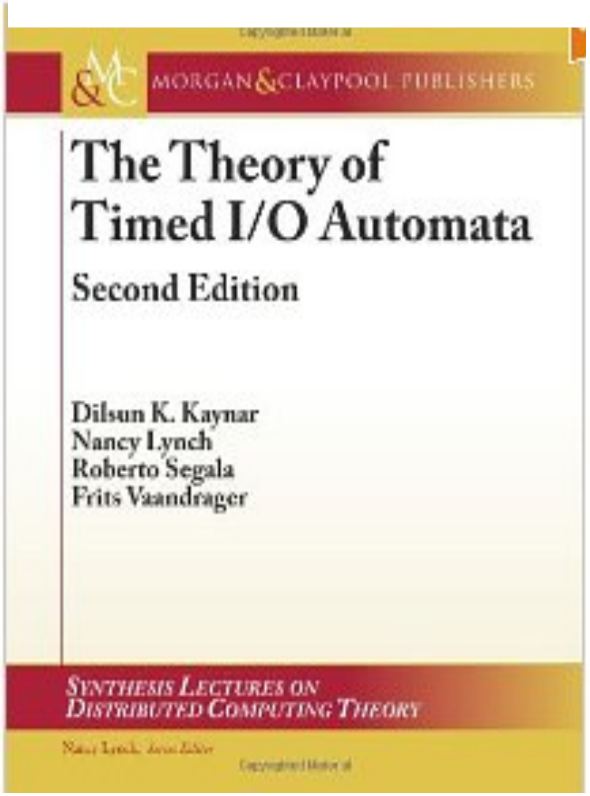
- Theorems that say that you can't solve a problem in a particular system model, or you can't solve it with a certain cost.
- Distributed computing theory includes hundreds of impossibility results.
  - Unlike sequential computing theory.
  - Because distributed platforms are hard to cope with: locality of knowledge and action impose strong limitations.





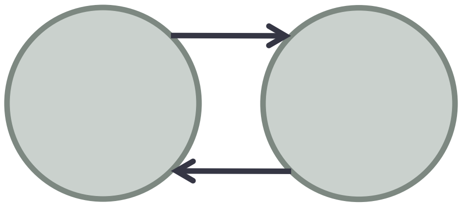
Formal modeling

- Distributed algorithms can be complicated:
  - Many components act concurrently.
  - May have different speeds, failures.
  - Local knowledge and action.
- In order to reason about them carefully, we need clear mathematical foundations.



Formal modeling

- Model systems using interacting automata.
  - Not finite-state automata, but more elaborate automata that may include complex states, timing information, probabilistic behavior, and both discrete and continuous state changes.
  - Support composition and abstraction.
  - Support rigorous analysis for correctness and costs.



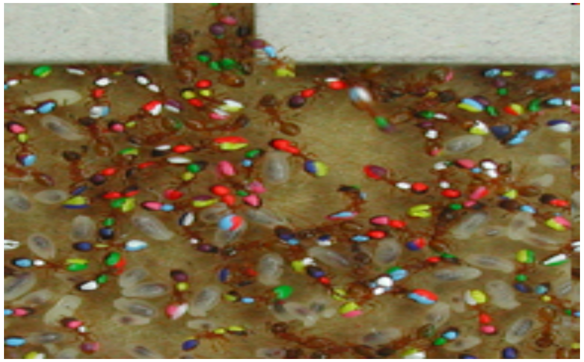
Key ideas

- Distinguish among:
  - The problems to be solved,
  - The platforms on which the problems must be solved, and
  - The algorithms that solve the problems on the platforms.
- Define cost metrics, such as time, local storage space, and amount of communication.
- Use the metrics to analyze and compare algorithms and prove lower bounds.

- Q: How could this approach help biology research?

Biology research

- Model a system of insects, or cells, using interacting automata.
- Define formally, separately:
  - The problems the systems solve (distinguishing cells, building structures, foraging, reaching consensus, task allocation, …),
  - The physical capabilities of the systems, and
  - The strategies (algorithms) that are used by the systems.
- Identify cost metrics (time, energy,…)
- Analyze and compare strategies.
- Prove inherent limitations.
- Use the results to:
  - Predict system behavior.
  - Explain why a biological system has evolved to have the structure and behavior it has.



The rest of the talk:

Two standard examples from distributed algorithms:

1. Leader election
2. Maximal independent set

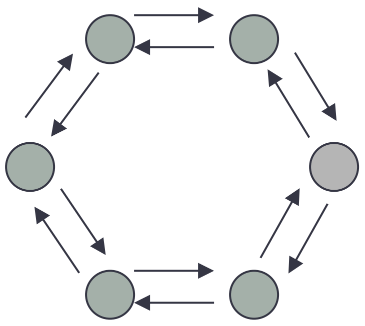
How one might apply distributed algorithm ideas in biology

Two preliminary biology-related examples:

3. Ant foraging
4. Ant task allocation

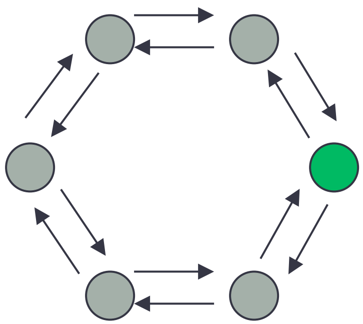
Saket: More biology-related examples

Example 1: Leader election



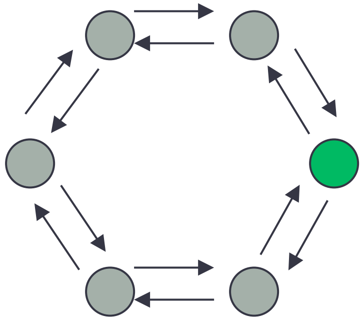
- Ring of processes.
- Computers, programs, robots, insects, cells,…
- Communicate with neighbors by sending “messages”, in synchronous rounds.

Example 1: Leader election



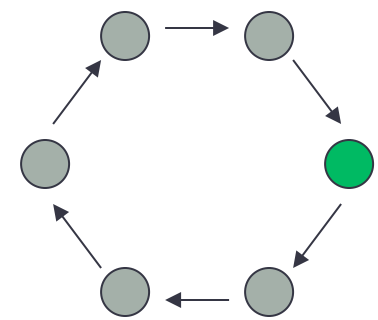
- Ring of processes.
- Computers, programs, robots, insects, cells,…
- Communicate with neighbors by sending "messages", in synchronous rounds.
- Problem: Exactly one process should (eventually) announce that it is the leader.
- Motivation:
  - A leader in a computer network or robot swarm could take charge of a computation, directing everyone else's activity.
  - A leader ant could choose a new nest.

Leader election



- Suppose that:
  - Processes start out identical.
  - The behavior of each process at each round is determined by its current state and incoming messages.
- Theorem: In this case, it's impossible for any distributed algorithm to elect a leader.
- Proof: By contradiction.
  - Suppose we have an algorithm that works.
  - All processes start out identical.
  - At round 1, they all do the same thing (send the same messages, make the same state changes), so they are again identical.
  - Same for round 2, etc.
  - Since the algorithm solves the problem, some process must eventually announce that it is the leader.
  - But then everyone does, contradiction.

If processes aren't identical:

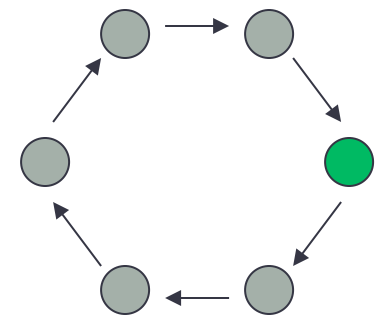


- E.g., they have unique ID numbers.

- Algorithm:
  - Send a message containing your ID clockwise.
  - When you receive an ID, compare it with your own ID.
  - If the incoming ID is:
    - Bigger, pass it on.
    - Smaller, discard it
    - Equal, announce that you are the leader.

- Elects the process with the largest identifier.
- Takes $O(n)$ communication rounds, $O(n^2)$ messages.

If they are identical, but can make random choices:

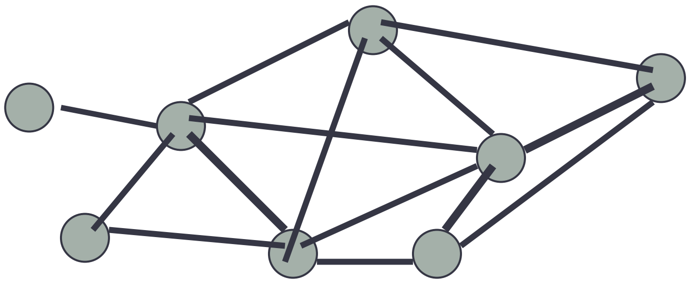


- No unique IDs.
- Assume they know n, the total number of processes.

- Algorithm:
  - Toss an unfair coin, with probability 1/n of heads.
  - If you toss heads, become a "leader candidate".
  - It's "pretty likely" that there is exactly one candidate.
  - The processes can verify this by passing messages around and seeing what they receive.
  - If they did not succeed, try again…

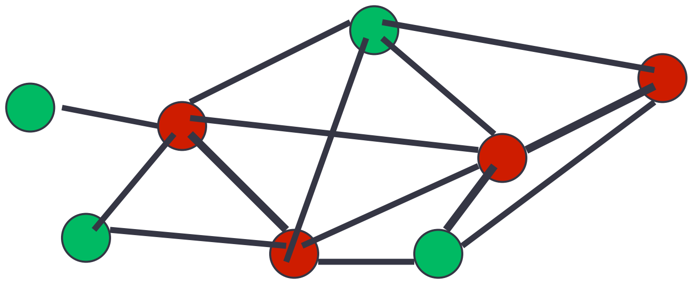
- Expected number of attempts is constant.

Example 2: Maximal Independent Set



- Assume a general graph network, with processes at the nodes:
- Problem: Select some of the processes, so that they form a Maximal Independent Set.
- Independent: No two neighbors are both in the set.
- Maximal: We can't add any more nodes without violating independence.
- Motivation:
  - Communication networks: Selected processes can take charge of communication, convey information to all the other processes.
  - Developmental biology: Distinguish cells in fruit fly's nervous system to become "Sensory Organ Precursor" cells.

Maximal Independent Set



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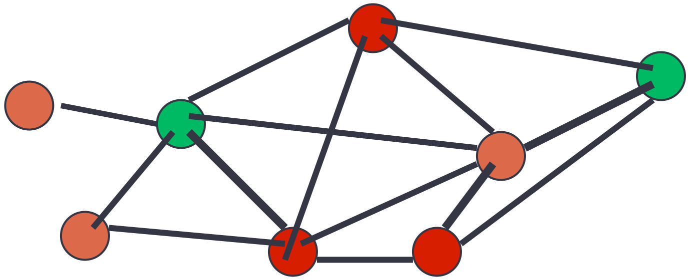
Maximal Independent Set



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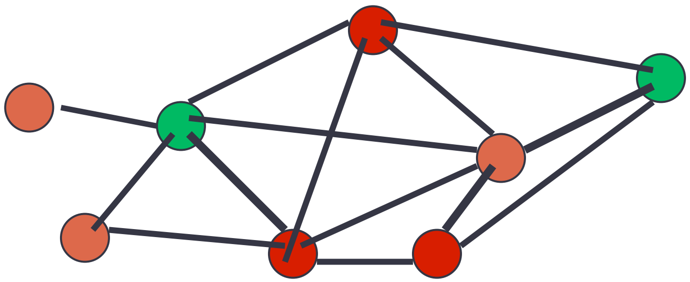
Distributed MIS problem

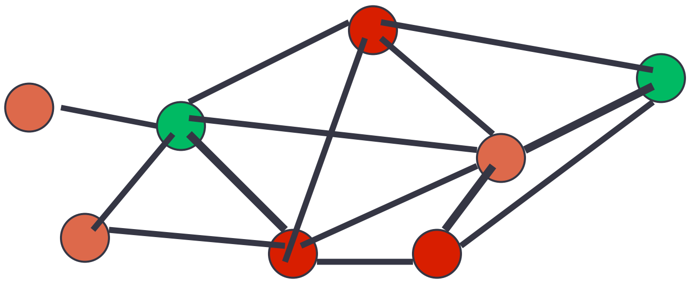
- Assume processes know a "good" upper bound on n.
- No IDs.



- Problem: Processes should cooperate in a distributed (message-passing) algorithm to compute an MIS of the graph.
- Processes in the MIS should output in and the others should output out.

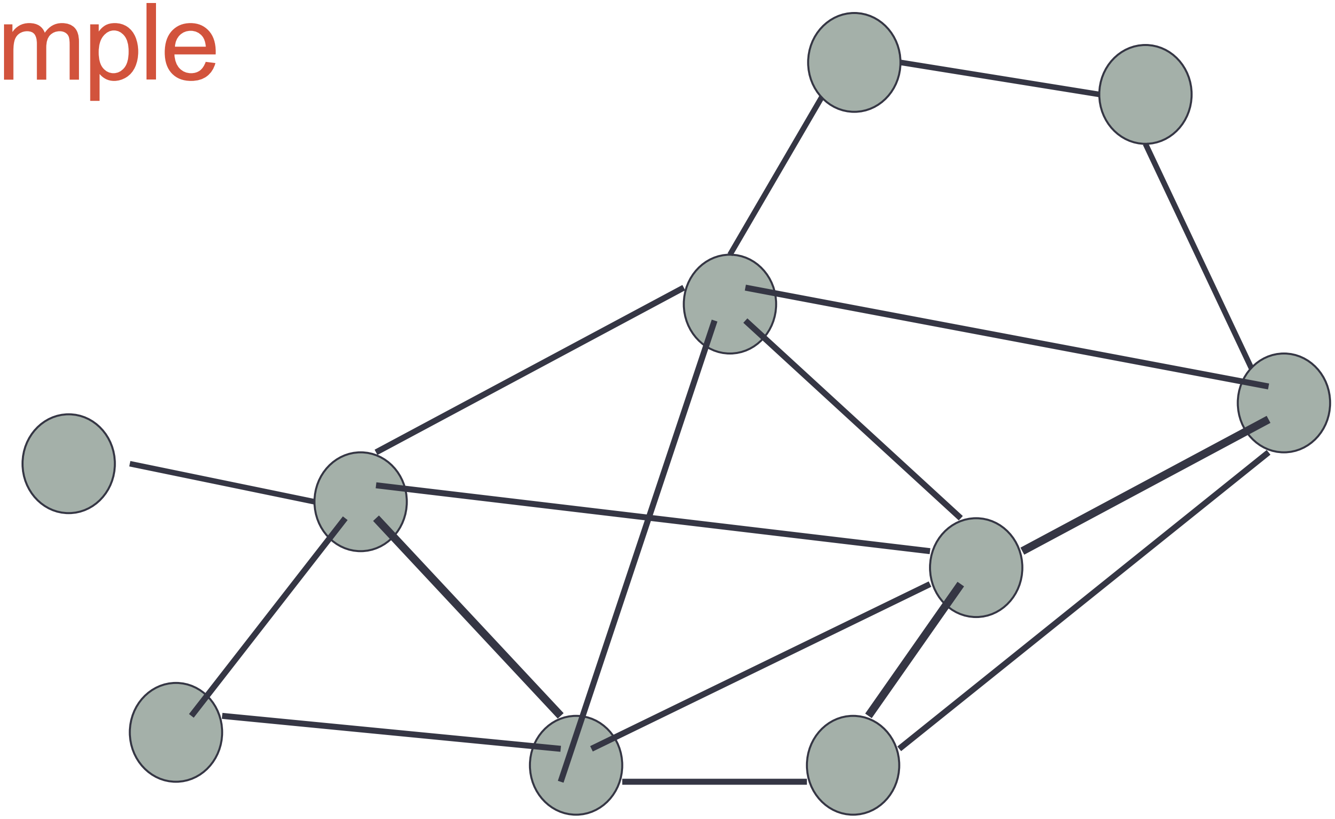
- Unsolvable by deterministic algorithms, in some graphs.
- Probabilistic algorithm:

Probabilistic MIS algorithm



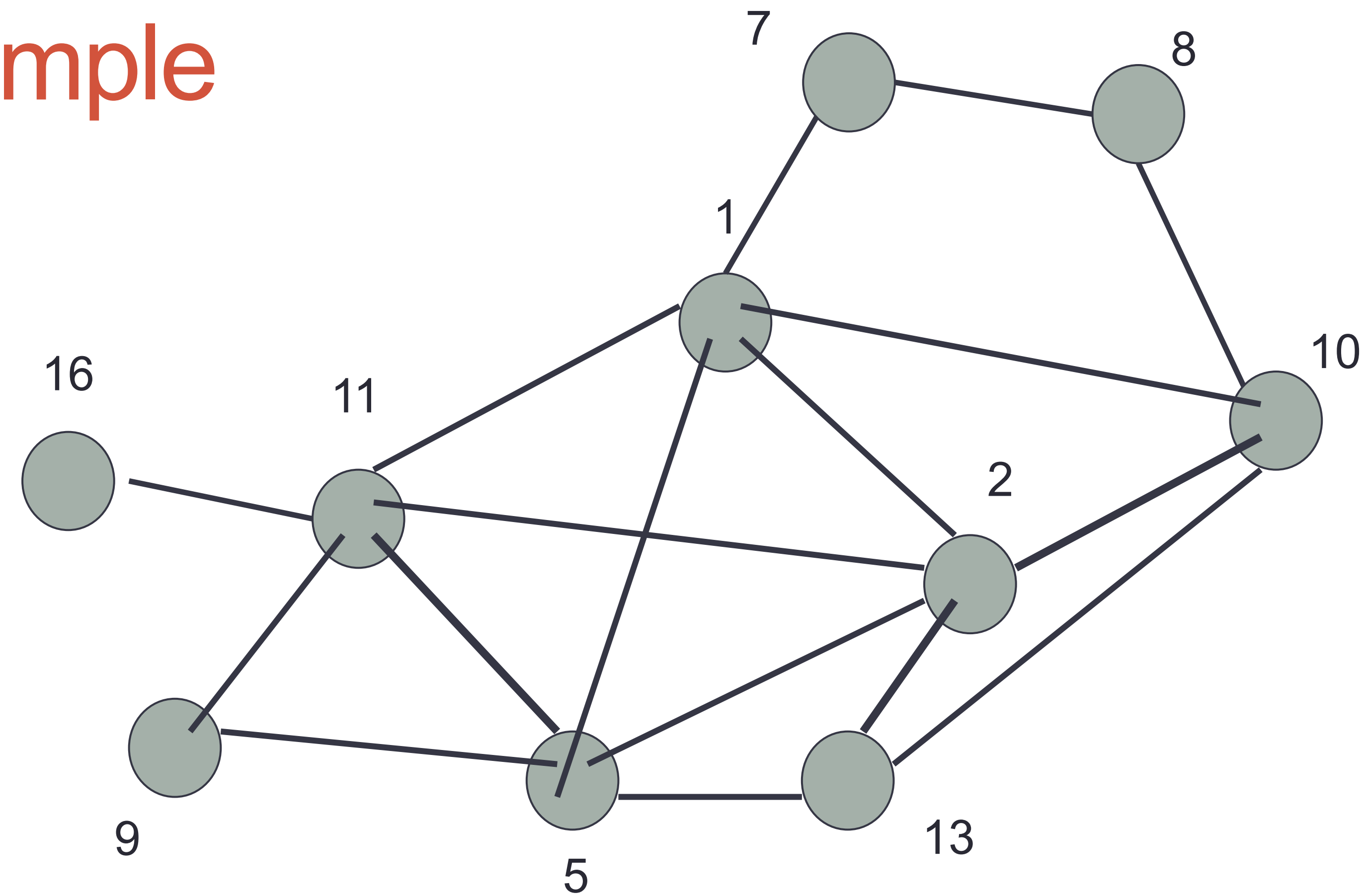
- Algorithm idea:
  - Each process chooses a random ID from 1 to N.
  - N should be large enough so it's likely that all IDs are distinct.
  - Neighbors exchange IDs.
  - If a process's ID is greater than all its neighbors' IDs, then the process declares itself in, and notifies its neighbors.
  - Anyone who hears a neighbor is in declares itself out, and notifies its neighbors.
  - Processes construct a reduced graph, omitting those who have already decided.
  - Repeat with the reduced graph, until no nodes remain.

Example



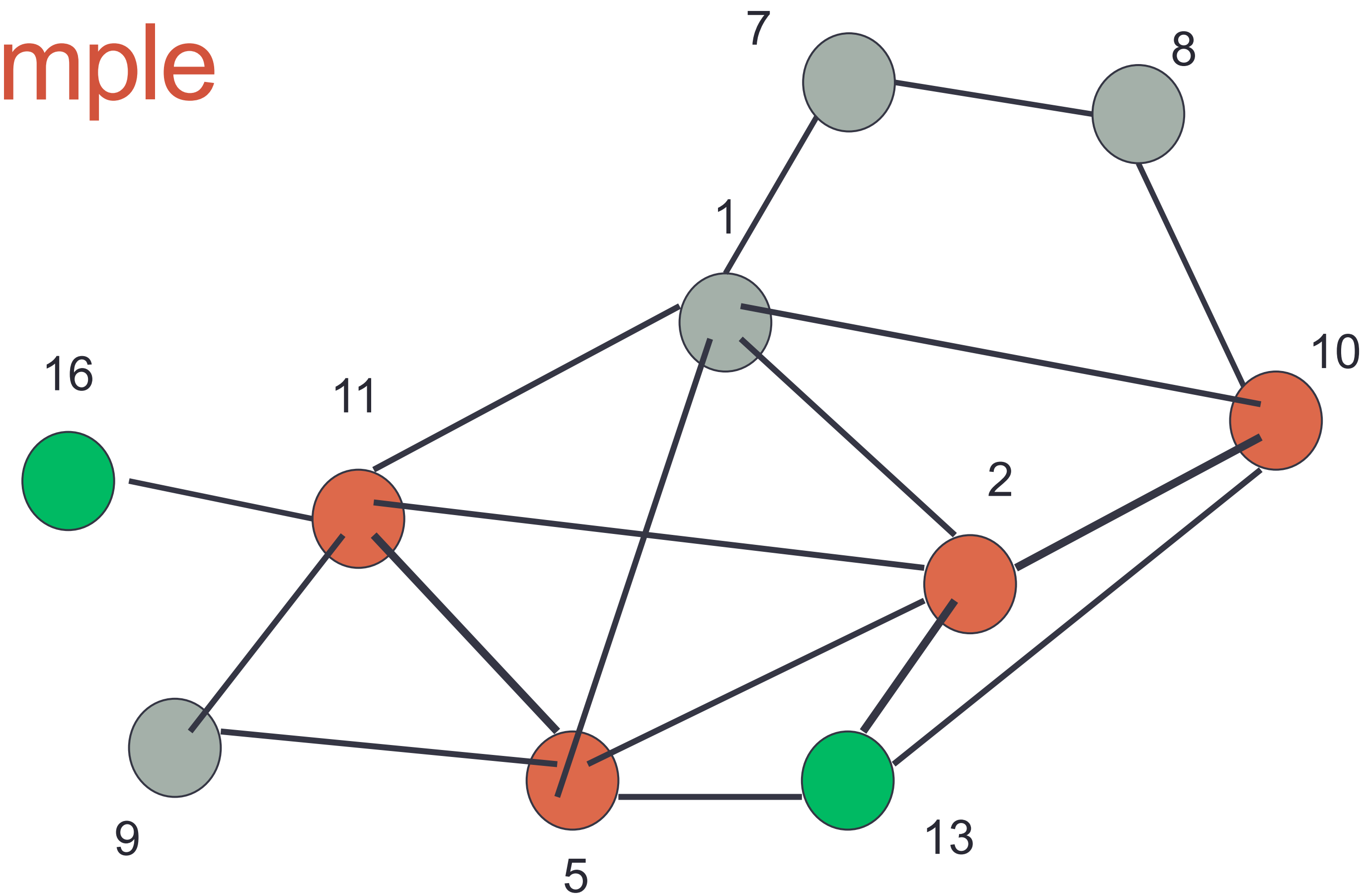
- All nodes start out identical.

Example



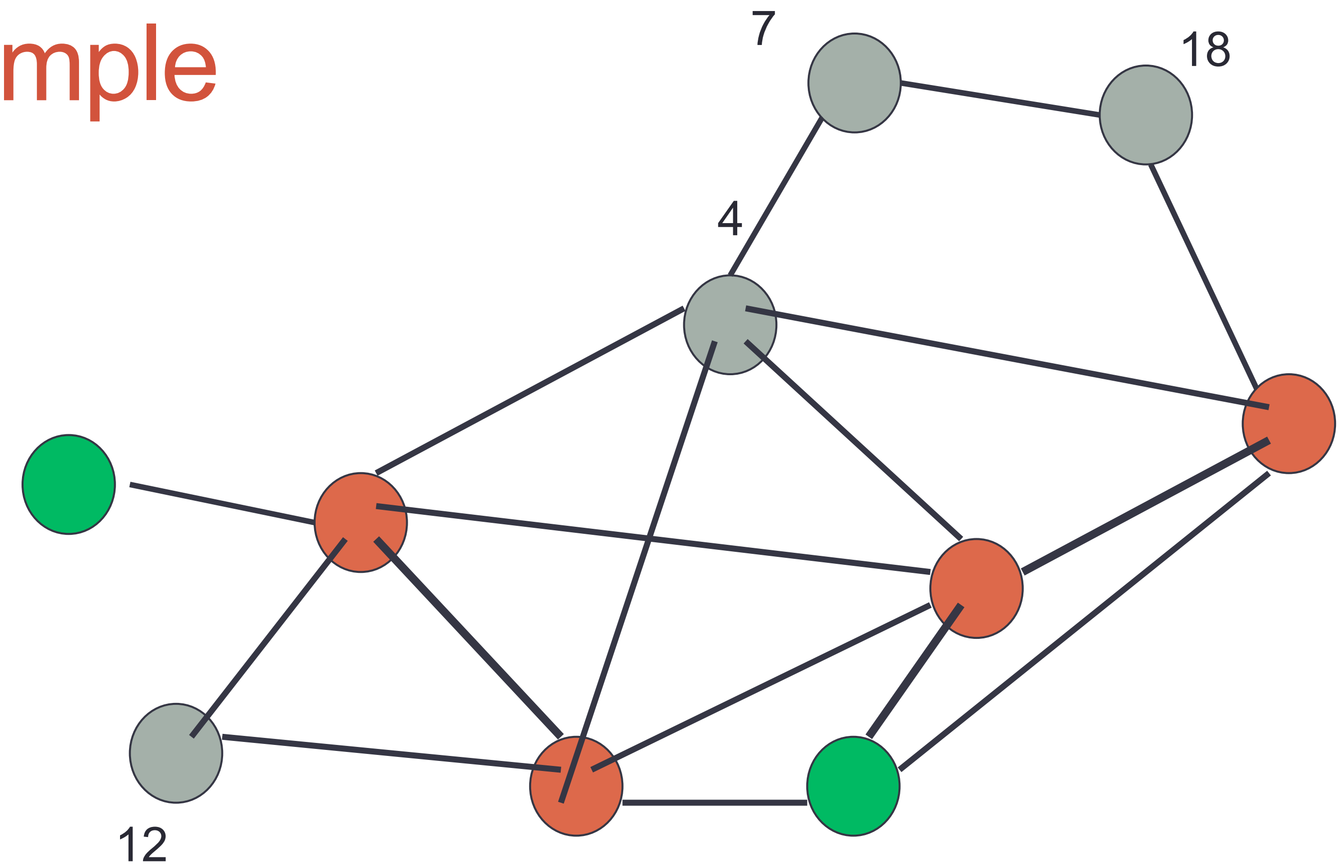
- Everyone chooses an ID.

Example



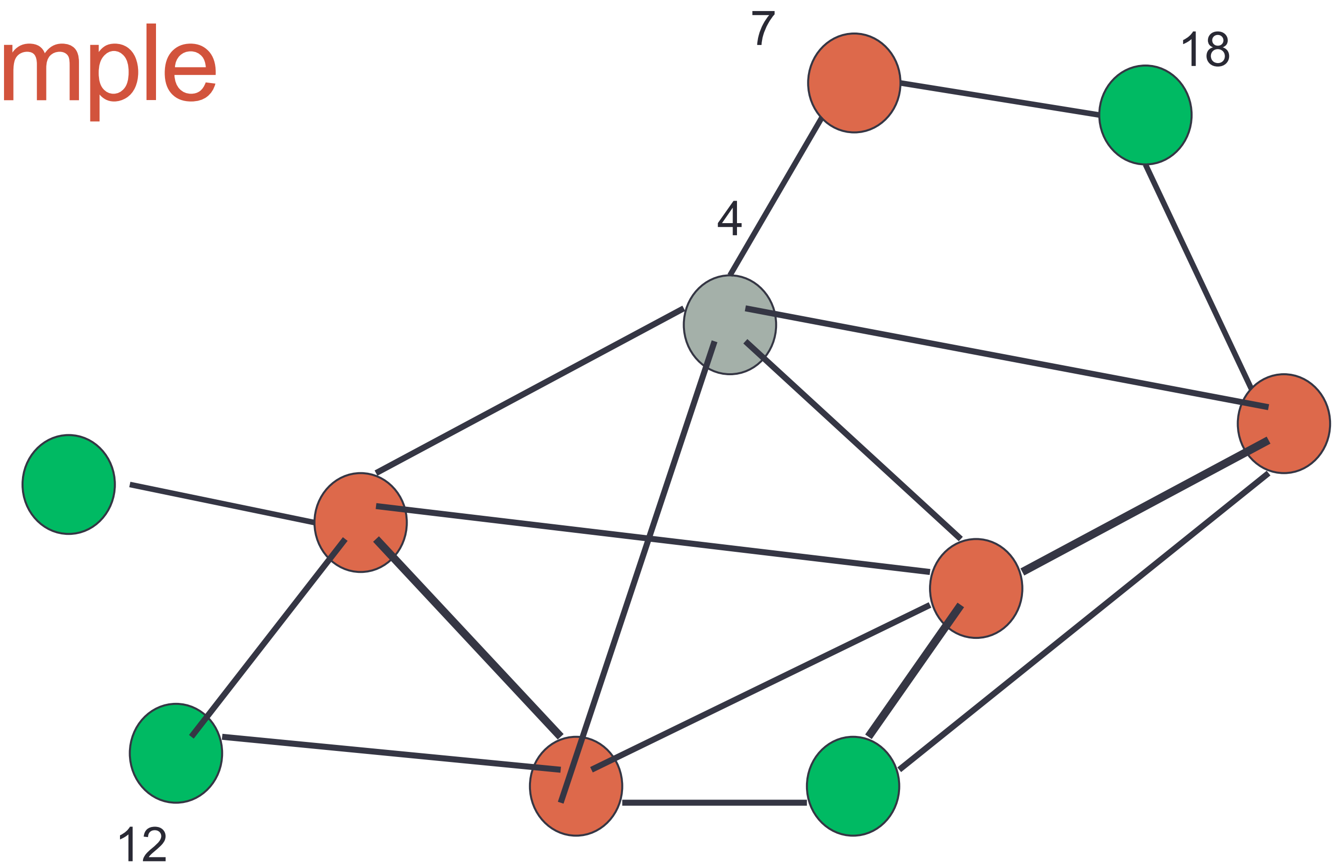
- Processes that chose 16 and 13 are in.
- Processes that chose 11, 5, 2, and 10 are out.

Example



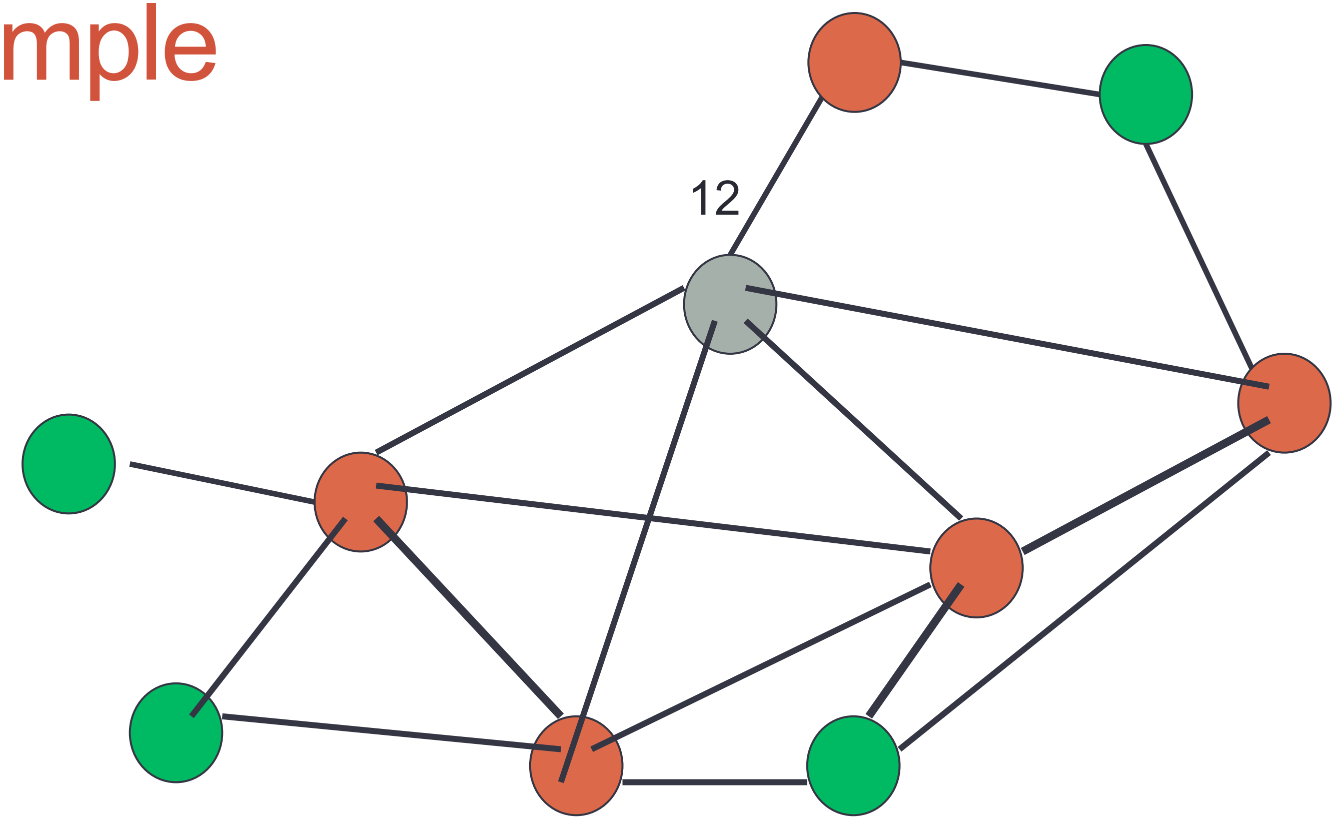
- Undecided (gray) processes choose new IDs.

Example



- Processes that chose 12 and 18 are in.
- Process that chose 7 is out.

Example



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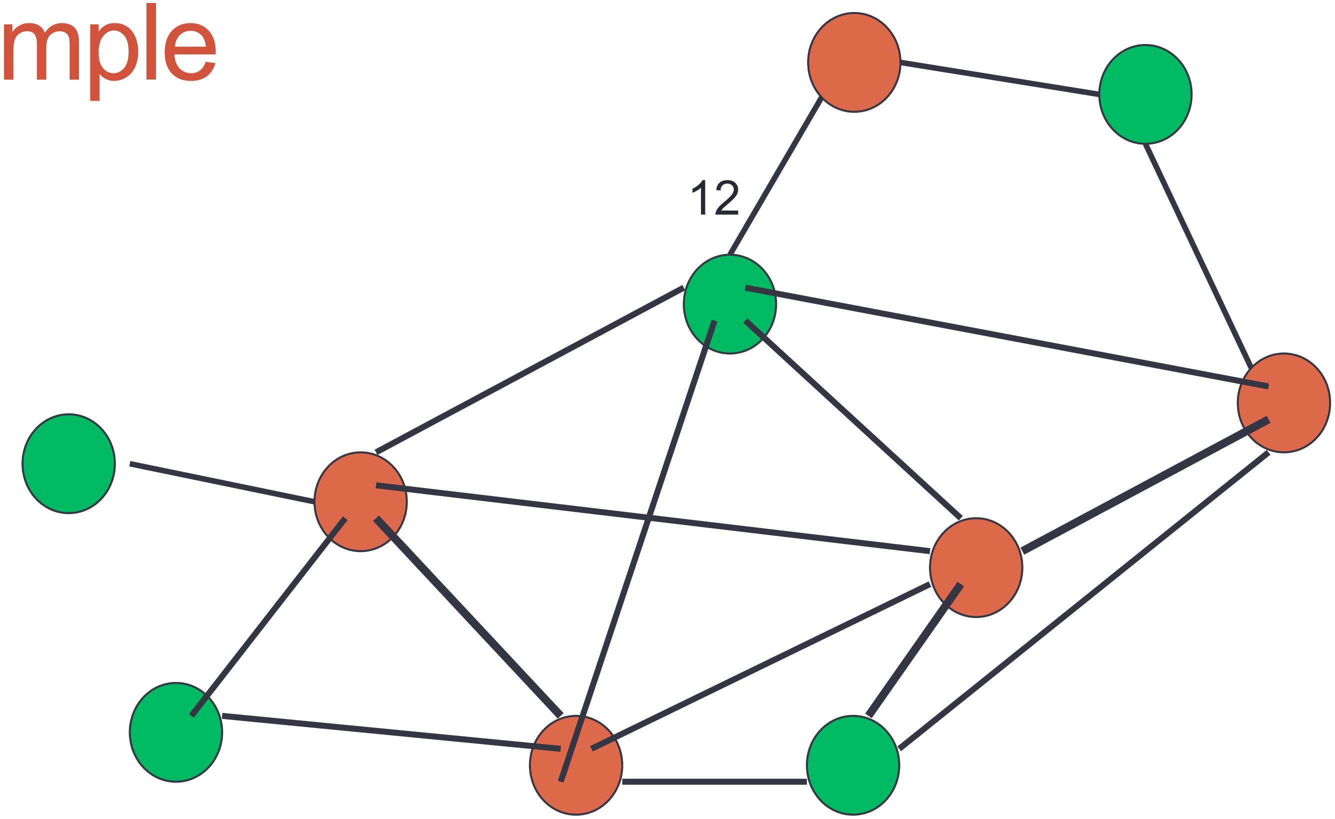


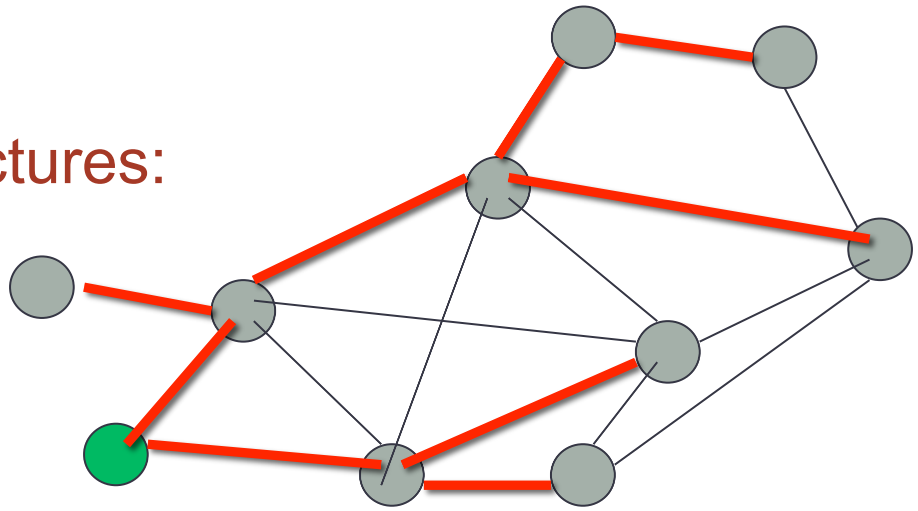
- It's in.

Properties of the algorithm

- If it ever finishes, it produces a Maximal Independent Set.
- It eventually finishes (with probability 1).
- The expected number of rounds until it finishes is $O(\log n)$.

More examples

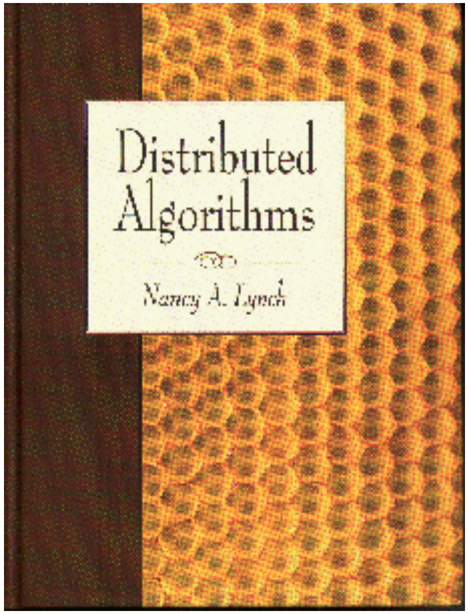
- Building spanning trees that minimize various network cost measures.
- Motivation:
  - Communication networks: Use the tree for sending messages from the leader to everyone else.
  - Slime molds: Build a system of tubes that can transport nutrients from several food sources.
- Building other network structures:
  - Routes
  - Clusters with leaders.
  - …

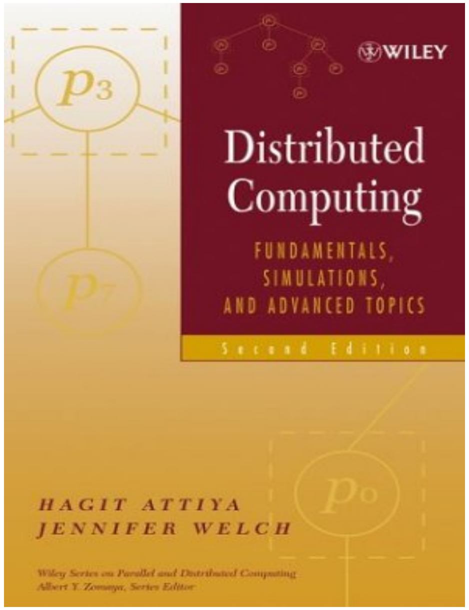


More examples

- Reaching consensus, in the presence of faulty components (stopping, Byzantine).
- Motivation:
  - Agree on aircraft altimeter readings.
  - Agree on processing of data transactions.
  - Ants: Agree on a new nest location.

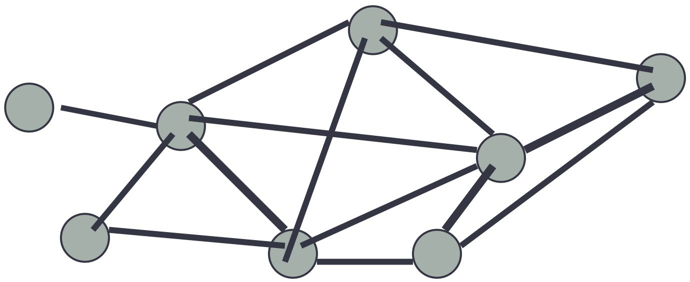
- Communication
- Resource allocation
- Task allocation
- Synchronization
- Data management
- Failure detection
- …





Recent Work: Dynamic Networks

- Most of distributed computing theory deals with fixed, wired networks.

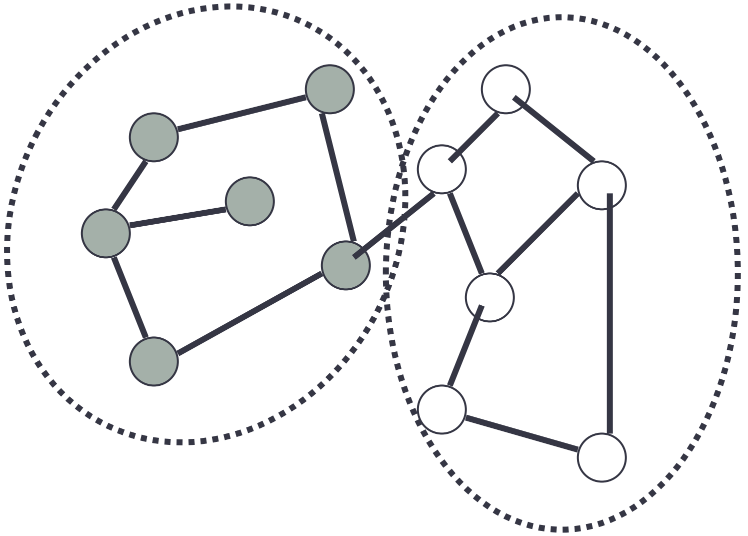


- Now researchers are also studying dynamic networks, which change while they are operating.
- E.g. wireless networks, robot swarms.
- Participants may join, leave, fail, and recover.
- May move around (mobile systems).

Computing in Dynamic Graph Networks

- Network is a graph that changes arbitrarily from round to round (but it's always connected).
- At each round, each process sends a message, which is received by all of its neighbors at that round.

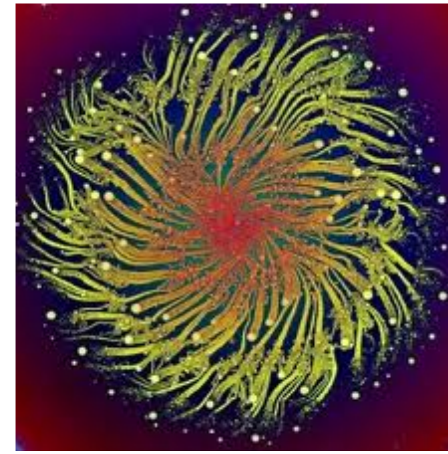
- Problems:
  - Global message broadcast,
  - Determining the minimum input.
  - Counting the total number of nodes.
  - Consensus
  - Clock synchronization



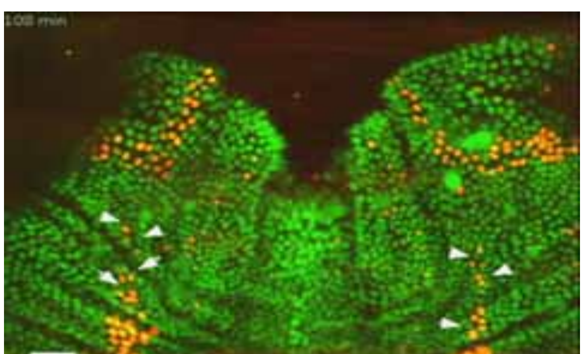
Robot Coordination Algorithms

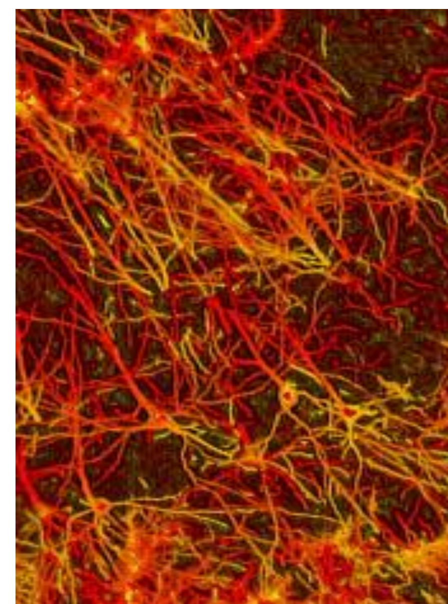
- A swarm of cooperating robots, engaged in:
  - Search and rescue
  - Exploration
- Robots communicate, learn about their environment, perform coordinated activities.
- Problems:
  - Keep the swarm connected for communication.
  - Achieve “flocking” behavior.
  - Map an unknown environment.
  - Determine global coordinates, working from local sensor readings.

Biological Systems as Distributed Algorithms

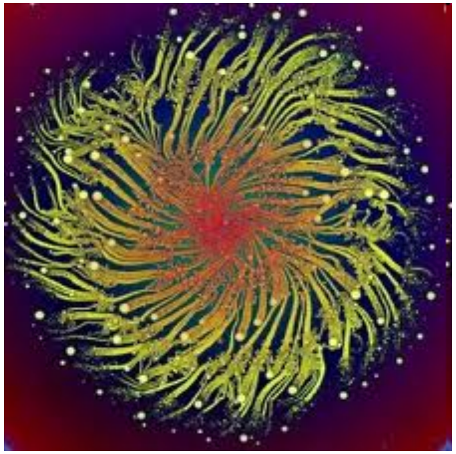


- Biological systems consist of many components, interacting with nearby components to achieve common goals.
- Colonies of bacteria, bugs, birds, fish,…
- Cells within a developing organism.
- Brain networks.

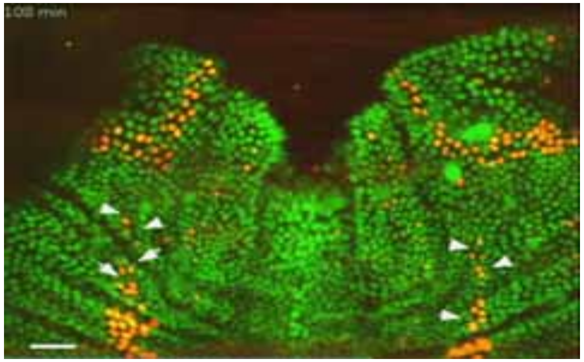


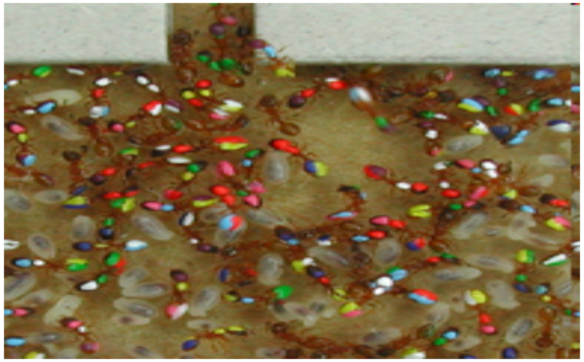


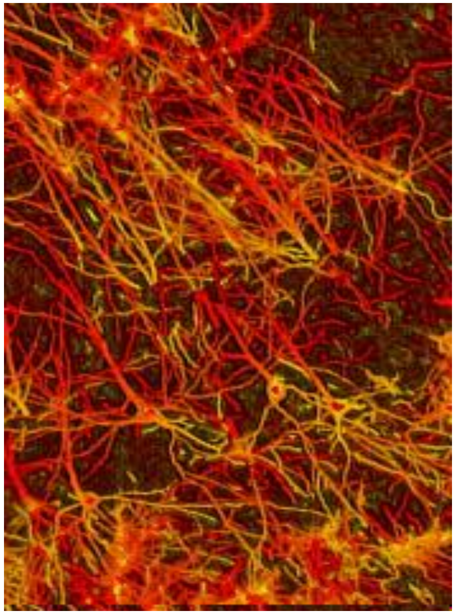
Biological Systems as Distributed Algorithms



- They are special kinds of distributed algorithms:
  - Use simple chemical “messages”.
  - Components have simple “state”, follow simple rules.
  - Flexible, robust, adaptive.

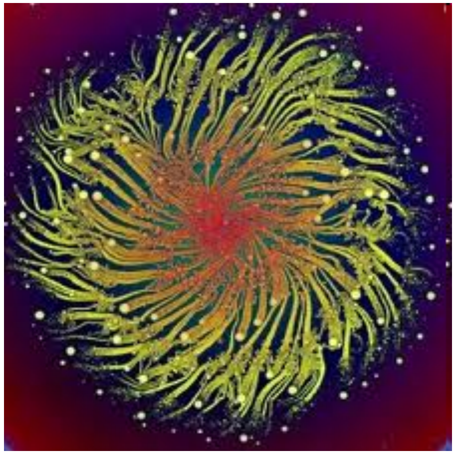


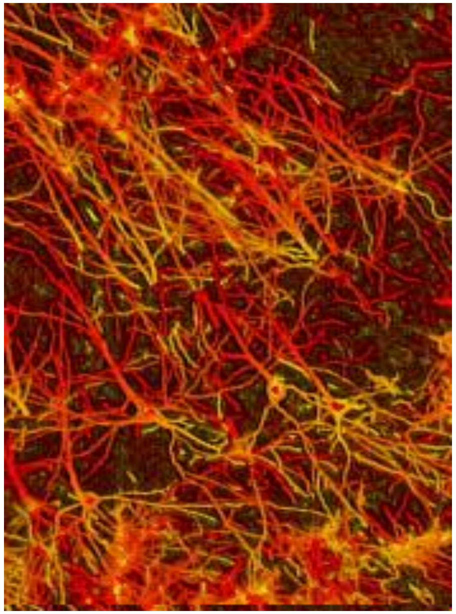


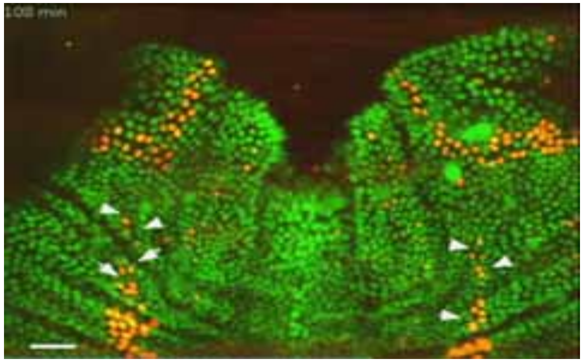


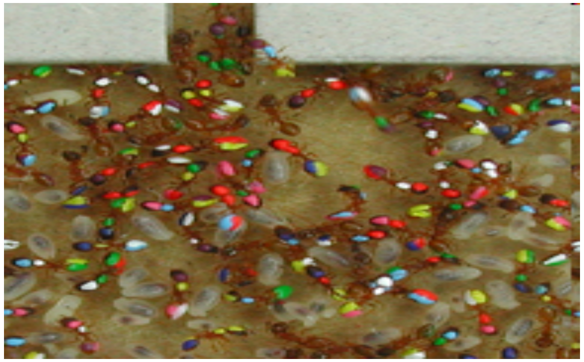
Problems

- Leader election: Ants choose a queen.
- Maximal Independent Set: In fruit fly development, some cells become sensory organs.
- Building communication structures:
  - Slime molds build tubes to connect to food.
  - Brain cells form circuits to establish memories.



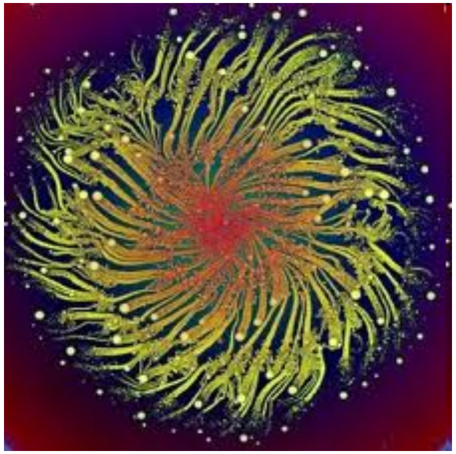


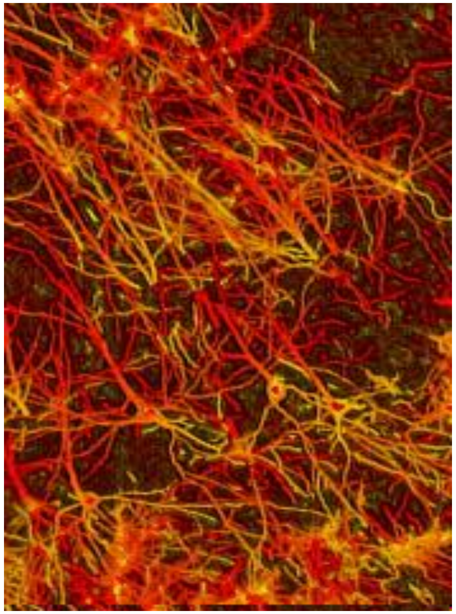


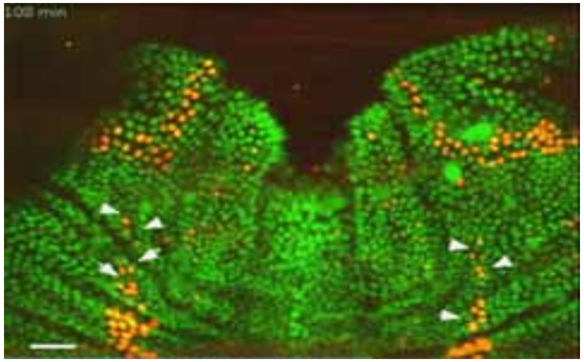


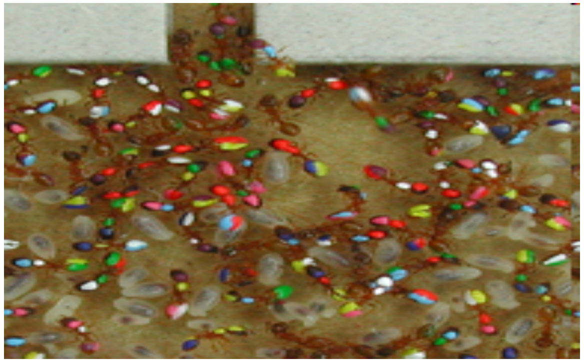
More problems

- Consensus: Bees agree on location of a new hive.
- Reliable local communication: Cells use chemical signals.
- Robot swarm coordination: Birds, fish, bacteria travel in flocks / schools / colonies.

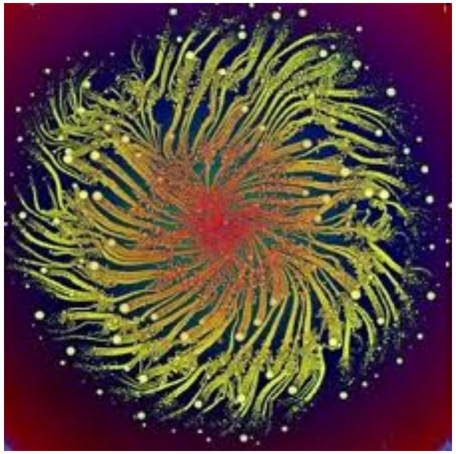




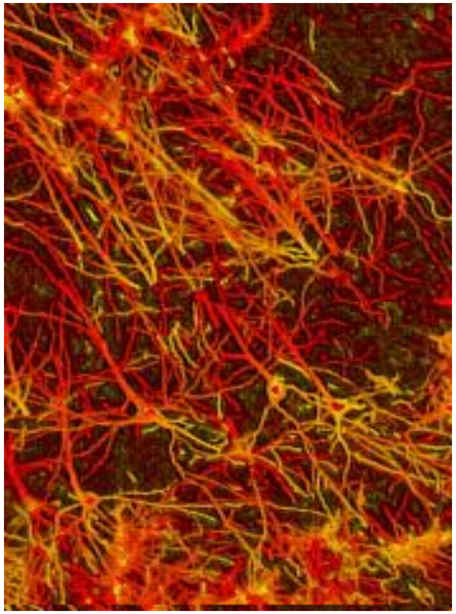




Biological Systems as Distributed Algorithms



- So, we can study biological systems as distributed algorithms.
- Define models, problem statements.
- Devise algorithms.
- Prove impossibility results.
- Goals:
    - Use distributed algorithms to understand biological system behavior.
    - Use biological systems to inspire new distributed algorithms.

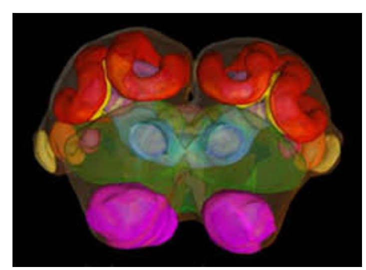


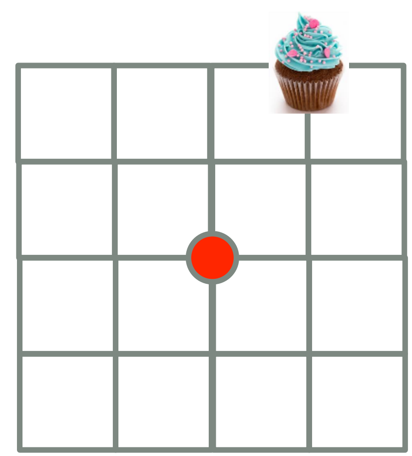
Biology-related examples:

3. Ant foraging
4. Ant task allocation

Example 3: Ant Foraging

- [Lenzen, Lynch, Newport, Radeva, PODC 2014]
- n ants exploring a 2-dimensional grid for food, hidden within distance D of the nest.
- No communication.
- Ants can return to the nest at any time.
- In terms of D and n, we get an upper bound on the expected time for some ant to find the food.
- We use an algorithm similar to [Feinerman, Korman].
- But we assume strict bounds on:
  - The size of an ant's memory.
  - The fineness of probabilities used in an ant's random choices.

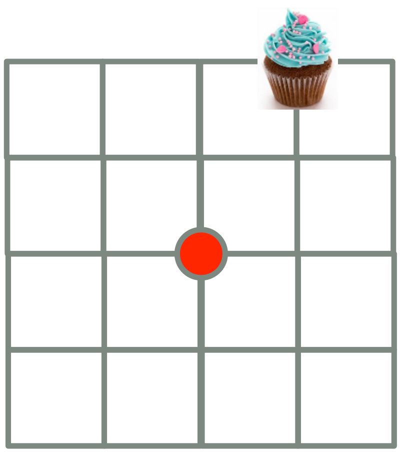




Ant Foraging

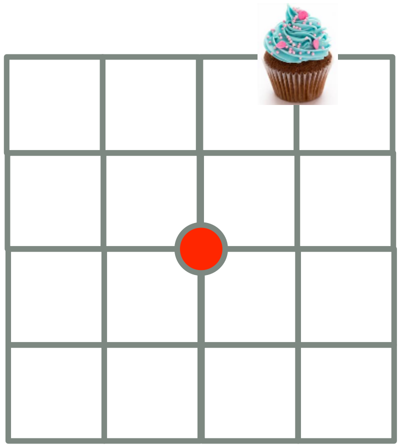
- Algorithm (for each ant):
  - Multi-phase
  - In successive phases, search to successively greater distances.
  - Distances are determined by random choices, using smaller probabilities at later phases.
- Expected time for some ant to find the food is (roughly) $O(D^2/n + D)$.

- Even in the "nonuniform" case, where ants don't have a good estimate of D.
- Analysis methods: Basic conditional probability analysis, Chernoff bounds.



Ant Foraging

- Assuming slightly smaller bounds on ant memory size and fineness of probabilities, we get:
- Lower bound: There is a food placement such that, with high probability, the time for the first ant to find the food is (roughly) $\Omega(D^2)$.
- Proof methods:
  - Model movement of an ant through its state space as a Markov chain.
  - Enhance this chain with information about the ant's movement in the grid.
  - Use properties of the enhanced Markov chain to analyze probabilities of reaching various locations in the grid within certain amounts of time.



Example 4: Ant Task Allocation

- [Cornejo, Dornhaus, Lynch, Nagpal 2014]
- n ants allocate themselves among a fixed set of tasks (foraging for food, feeding larvae, cleaning the nest…)
- No communication.
- Obtain information from the environment about tasks' current energy requirements.
- Try to minimize sum of squares of energy deficits for all tasks.
- Special case we've studied:
  - All ants are identical.
  - Synchronous rounds of decision-making.
  - Simple binary info (deficit/surplus for each task).

Ant Task Allocation

- Algorithm:
  - Probabilistic decisions, based on deficit/surplus info.
  - States: Resting, Reserve1, Reserve2, TempWorker, CoreWorker.
  - Worker ants work on tasks; others are idle.
    - Temps are more biased towards becoming idle.
    - Reserves are biased towards the task they last worked on.
  - Detailed state transition rules, task assignment rules.

- Theorem: In a period of length $\Theta(\log n)$ with unchanging demand, with high probability, the ants converge to a fixed allocation that satisfies all demands.
- Proof: Analyzes how oscillations get dampened.

Limited ant memory size…