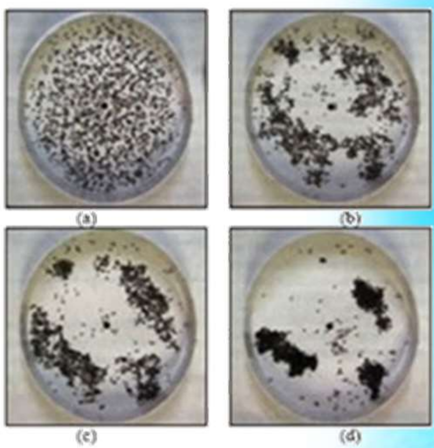
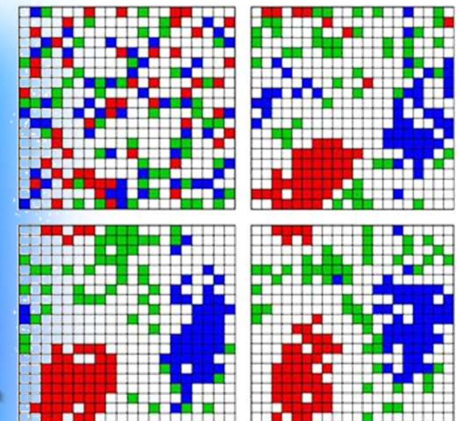
lecture 13





Collective Behavior

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Natural design principles

exploring similarities across nature

- self-similar structures
  - Trees, plants, clouds, mountains
    - morphogenesis
  - Mechanism
    - Iteration, recursion, feedback
- dynamical systems and unpredictability
  - From limited knowledge or inherent in nature?
  - Mechanism
    - Chaos, measurement
- self-organization, collective behavior, emergence
  - Complex behavior from collectives of many simple units or agents
    - cellular automata, dynamical networks, morphogenesis, swarms, brains, social systems
  - Mechanism
    - Parallelism, multiplicity, multi-solutions, redundancy
- evolution
  - Adaptation, learning, social evolution
  - Mechanism
    - Reproduction, transmission, variation, selection, Turing’s tape
- Collective behavior Behavior derived from many inseparable sources
    - Multi-level selection, swarm intelligence, immune system, anticipatory systems, brain-body-environment-culture, embodiment, epigenetics, culture
  - Mechanism
    - Network causality, odularity, control, hierarchy, connectivity, stigmergy, redundancy

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dumb agents, intelligent collective

- Bio-inspired methodology for solving distributed problems
  - biological examples
    - social insects
      - ants, termites, bees, wasps
    - swarming, flocking, herding behaviors in vertebrates.
- Collective behavior algorithms
  - Distributed or decentralized control
    - No central control or agent
  - Local communication among agents
  - Self-organization
    - Simple agents, complicated emergent behavior
  - Robust
    - To individual loss
  - Adaptive and Flexible
    - Capability to respond to perturbations

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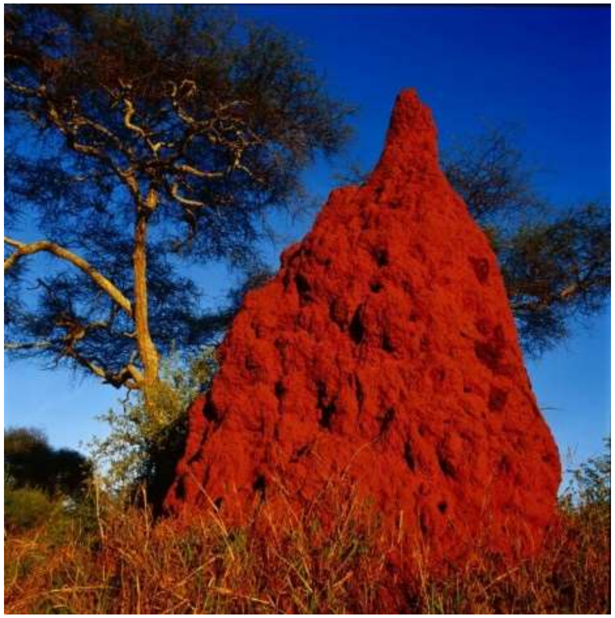
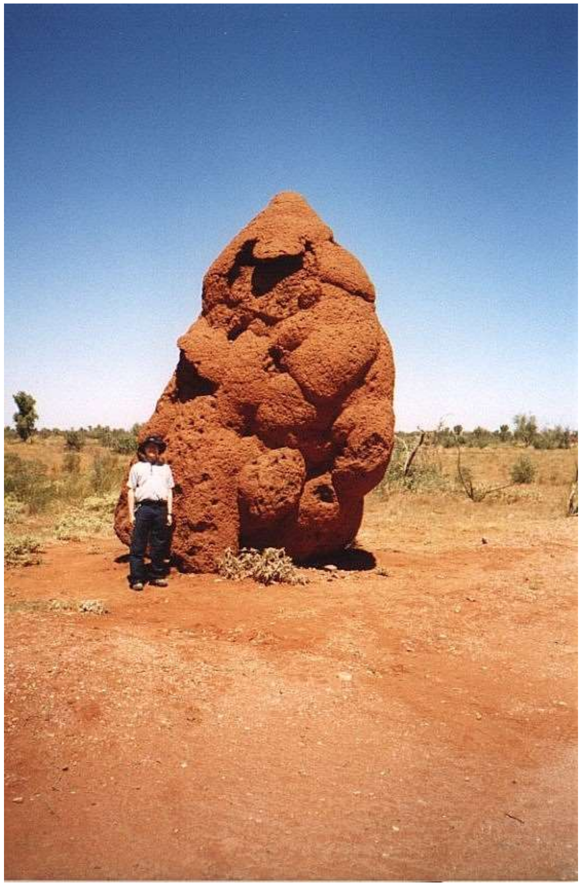
- stigma + ergon = mark + work
- Process of communication by changing environment
  - Pheromone trails
  - Nest Building
    - Termites use a simple rule:
      - Each agent scoops up a 'mudball' and covers it with pheromones
      - Others are attracted by pheromone and are therefore more likely to drop their own mudballs near their neighbors
- Introduced by Pierre-Paul Grassé in 1959
  - "Stimulation of workers by the performance they have achieved.“
    - Regulation of behavior (and constructions) is dependent on the behavior of others and the environment they build
    - Worker is guided by work
  - Used in optimization algorithms
  - Stigmergy: Ant colony algorithms
  - Flocking behavior: Particle Swarm Optimization



natural achievements



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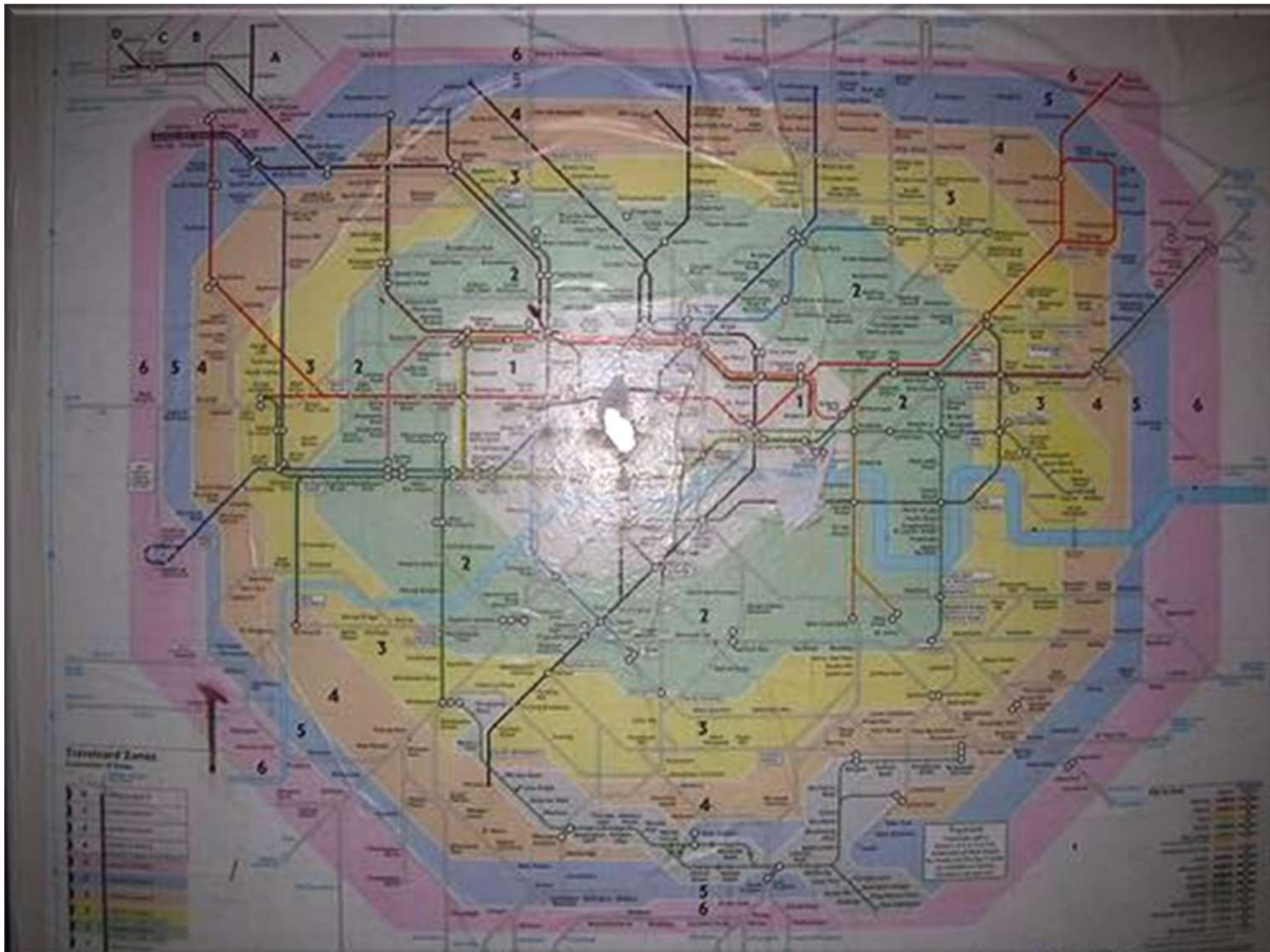
natural achievements



Aimless bots

- Very simple Agents that primarily wander around randomly
  - Mitchell Resnick
- Rules
  - ***Wander*** aimlessly until bumping into a wood chip (Random walk)
    - If carrying a wood chip, drop it and *wander*
    - Else, pick chip up and *wander*

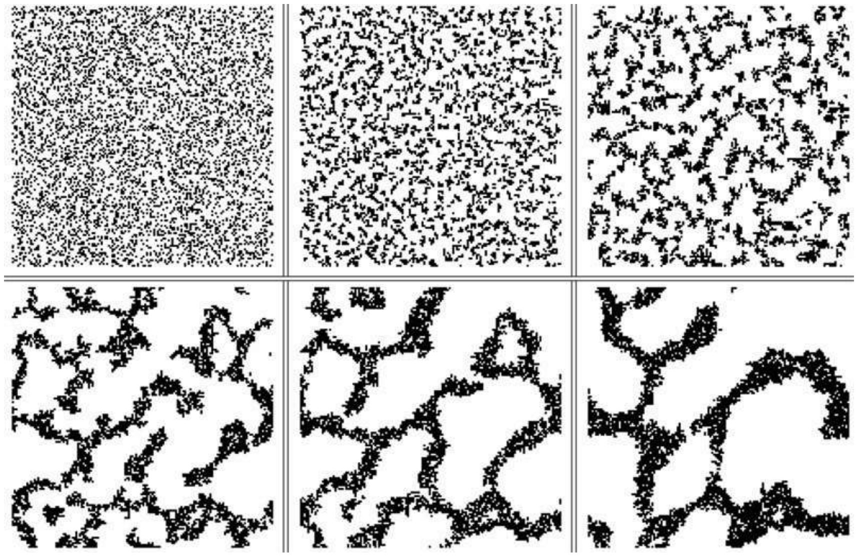


Figure by Gary Flake in *The Computational Beauty of Nature*.

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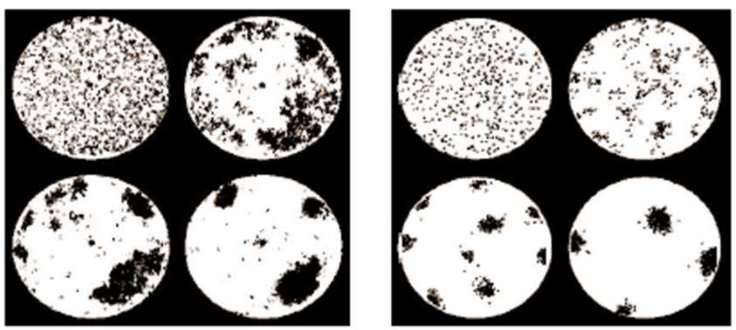
Probabilistic cleaning

- Very simple rules for colony clean up
  - ***Pick dead ant.*** if a dead ant is found pick it up (with probability inversely proportional to the quantity of dead ants in vicinity) and wander.
    - ***Drop dead ant***. If dead ants are found, drop ant (with probability proportional to the quantity of dead ants in vicinity) and wander.

Real and Simulated Ants Clustering



Real ants *Messor sancta* build clusters starting from randomly located corpses

Simulated ants build clusters starting from randomly located items

See Also: J. L. Deneubourg, S. Goss, N. Franks, A. Sendova-Franks, C. Detrain, L. Chretien. “The Dynamics of Collective Sorting Robot-Like Ants and Ant-Like Robots”. *From Animals to Animats: Proc. of the 1st Int. Conf. on Simulation of Adaptive Behaviour*. 356-363 (1990).

Figure by Marco Dorigo in *Real ants inspire ant algorithms*

Clustering by collective or swarm robots

- Becker et al Rules
  - **Move**: with no sensor activated move in straight line
  - **Obstacle avoidance**: if obstacle is found, turn with a random angle to avoid it and **move**.
  - **Pick up and drop**: Robots can pick up a number of objects (up to 3)
    - If shovel contains 3 or more objects, sensor is activated and objects are dropped. Robot backs up, chooses new angle and **moves**.
- Results in clustering
  - The probability of dropping items increases with quantity of items in vicinity

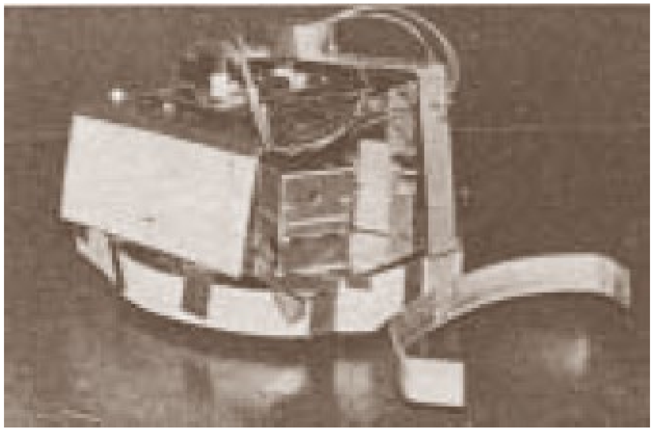


Figure from R Beckers, OE Holland, and JL Deneubourg [1994]. "From local actions to global tasks: Stigmergy and collective robotics". In *Artificial Life IV*.

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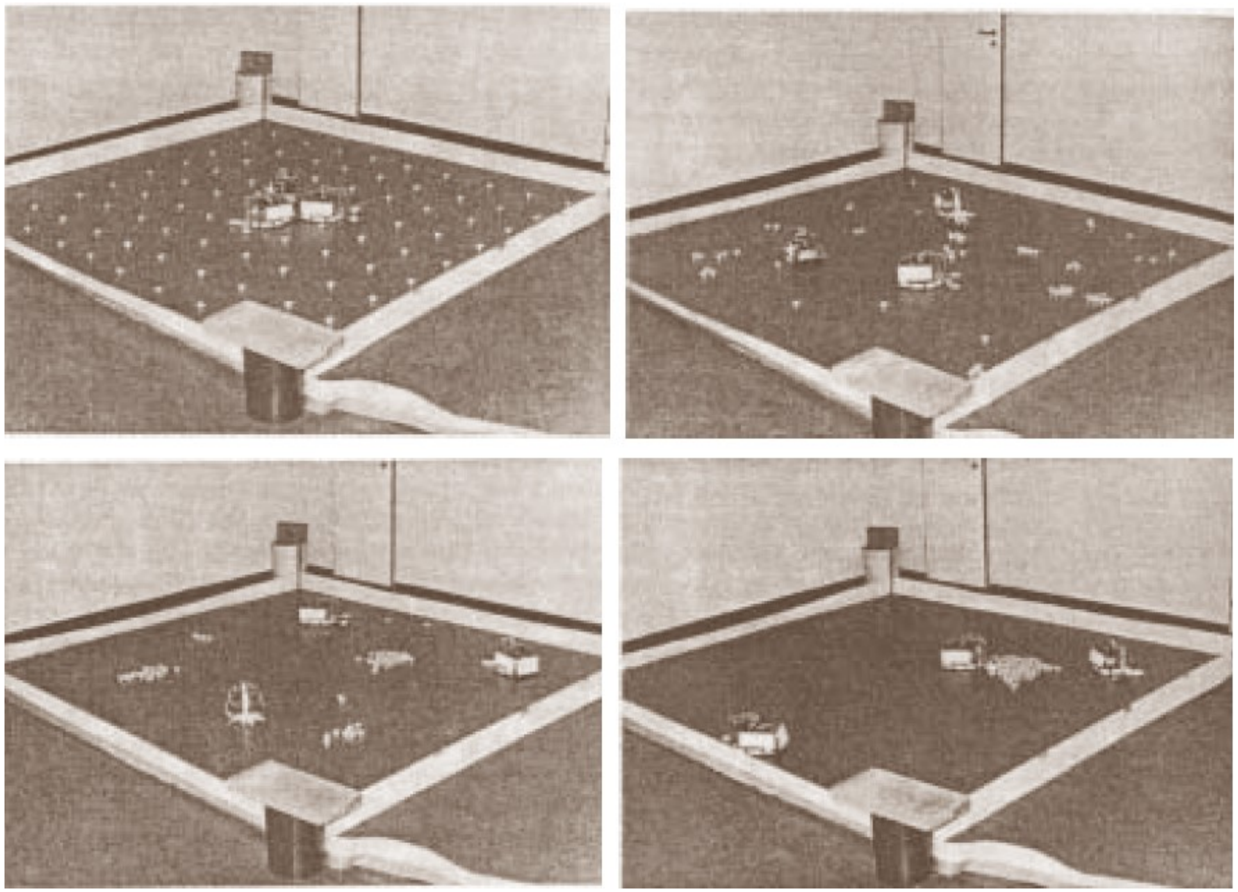
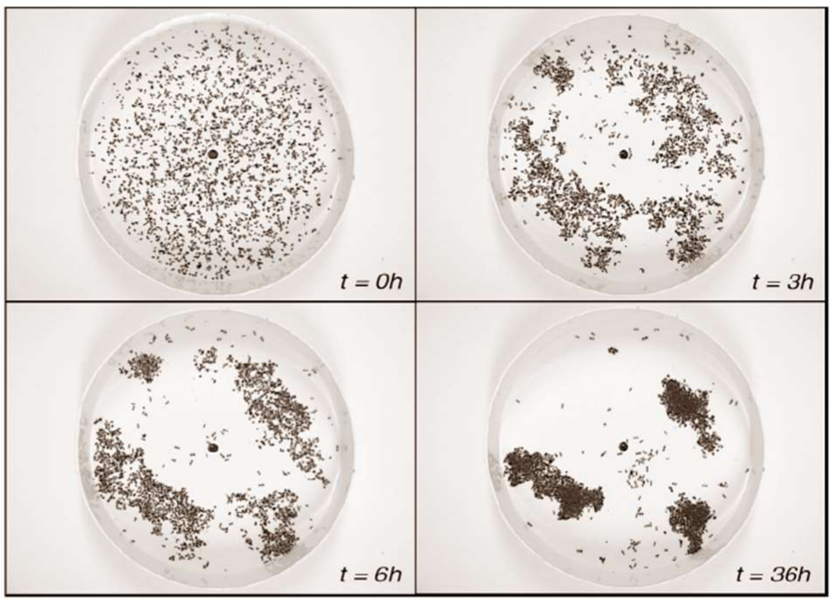


ant clustering algorithm (ACA)

based on dead body cleaning

- Very simple rules for colony clean up
  - ***Pick dead ant.*** if a dead ant is found pick it up (with probability inversely proportional to the quantity of dead ants in vicinity) and wander.
    - ***Drop dead ant***. If dead ants are found, drop ant (with probability proportional to the quantity of dead ants in vicinity) and wander.



Data vector: $\boldsymbol{X}$

x_1	x_2	x_3	…	x_{n-1}	x_n

■ ■ ■

x_1	x_2	x_3	…	x_{n-1}	x_n

■ ■ ■

x_1	x_2	x_3	…	x_{n-1}	x_n

Cluster data (N samples) according to ant clean up rules

Lumer, E. D. and Faieta, B. 1994. Diversity and adaptation in populations of clustering ants. In *From Animals To Animats 3*, pp. 501-508.

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using thresholds

Clustering rules

- ***Pick data sample***
  If there are few similar
- ***Drop data sample.***
  If there are many similar

x_1	x_2	x_3	…	x_{n-1}	x_n

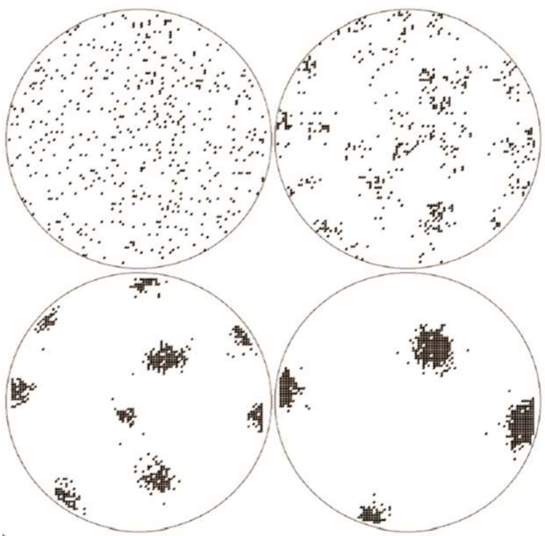
Probability of picking up (Threshold: k_1)

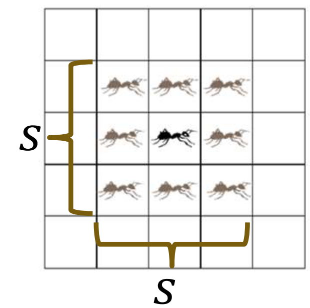
$$p_p(\mathbf{x}_i) = \left(\frac{k_1}{k_1 + f(\mathbf{x}_i)}\right)^2$$

Probability of dropping

$$p_d(\mathbf{x}_i) = \left(\frac{f(\mathbf{x}_i)}{k_2 + f(\mathbf{x}_i)}\right)^2$$

$$p_d(\mathbf{x}_i) = \begin{cases} 2f(\mathbf{x}_i) & \text{if } f(\mathbf{x}_i) < k_2 \\ 1 & \text{otherwise} \end{cases}$$





Neighborhood Similarity or density measure

$$f(\mathbf{x}_i) = \begin{cases} \frac{1}{s^2} \sum_{\mathbf{x}_j \in Neigh(s \times s)} \left(1 - \frac{D(\mathbf{x}_i, \mathbf{x}_j)}{\alpha}\right) & \text{if } f > 0 \\ 0 & \text{otherwise} \end{cases}$$

Discrimination factor: α

$$D(\mathbf{x}_i, \mathbf{x}_j) = \sqrt{\sum_{k=1}^{n} \left(x_{i,k} - x_{j,k}\right)^2}$$

Reduces dimensionality
No a priori number of clusters
Overshoots number of clusters

Improved with
Different moving speeds, Short-term memory, Behavioral switches
Cooling cycle for thresholds, progressive vision, pheromone reinforcement

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for multivariate data

Group n-dimensional data samples in 2-dimensional grid

Data vector: X_1

x_1	x_2	x_3	…	x_{n-1}	x_n

Data vector: X_2

$x_{2,1}$	$x_{2,2}$	$x_{2,3}$	…	$x_{2,n-1}$	$x_{2,n}$

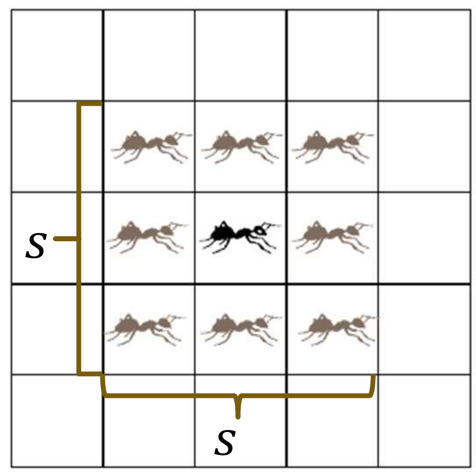
Distance between two data samples (in original multivariate space):

$$D(\mathbf{x}_i, \mathbf{x}_j) = \sqrt{\sum_{k=1}^{n} (x_{i,k} - x_{j,k})^2}$$

e.g. Euclidean

Ants see data points in a certain neighborhood

s^2: area of neighborhood (side s, radius 1)



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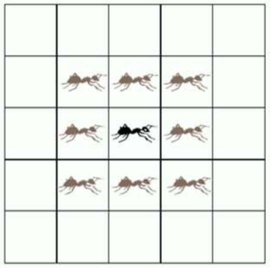
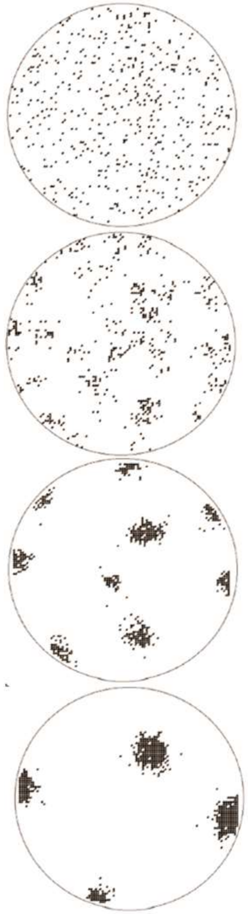
The workings

1. Project high-dimensional data items onto 2-dimensional grid randomly
2. Distribute N ants randomly on grid
3. repeat
   - For every ant i in colony
     - Compute neighborhood density $f(x_i)$
     - **If** ant i is unloaded and its cell is occupied with data item x_i then pick up x_i with probability $p_p(x_i)$
     - **Else if** ant i is loaded with x_i and its cell is empty drop x_i with probability $p_d\,(x_i)$
     - Move randomly to neighbor cell with no ant
4. Until maximum iterations





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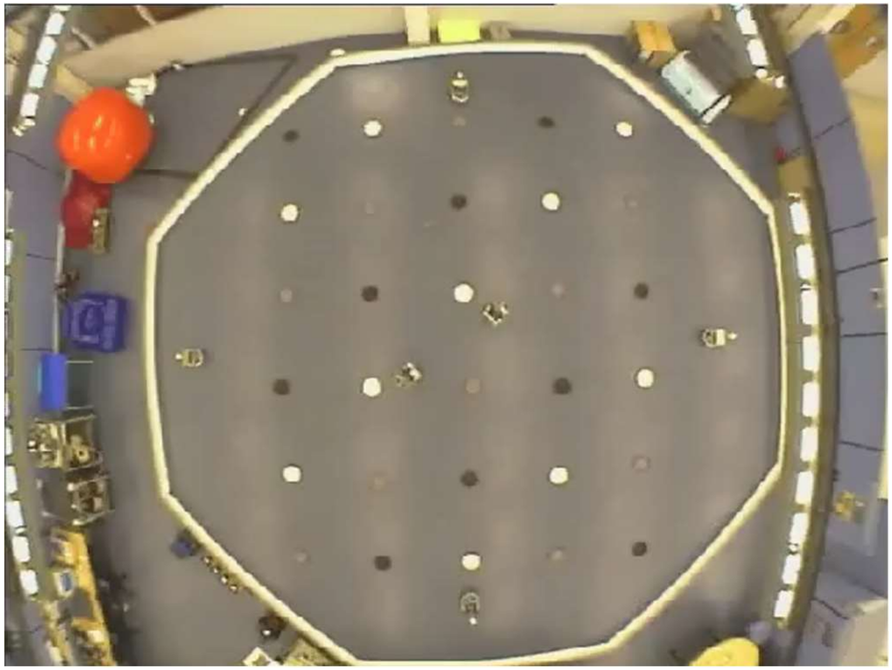
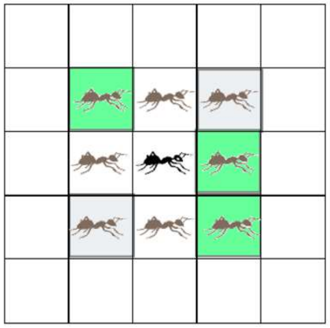
Inspired by brood sorting

Same principle as Clustering
- ***Pick data sample of type t***
  If there are few of type *t*
- ***Drop data sample of type t***
  If there are many of type *t*

$$p_p(\mathbf{x}_i \mid t) = \left(\frac{k_1}{k_1 + f_t(\mathbf{x}_i)} \right)^2$$

Probability of picking up item of type t





$$p_d(\mathbf{x}_i \mid t) = \left(\frac{f_t(\mathbf{x}_i)}{k_2 + f_t(\mathbf{x}_i)} \right)^2$$

Probability of dropping item of type *t*

$$f_t(\mathbf{x}_i) = \begin{cases} \frac{1}{s^2} \sum_{\mathbf{x}_j \in Neigh_t(s \times s)} \left(1 - \frac{D(\mathbf{x}_i, \mathbf{x}_j)}{\alpha} \right) & \text{if } f > 0 \\ 0 & \text{otherwise} \end{cases}$$

Neighborhood density of type *t*

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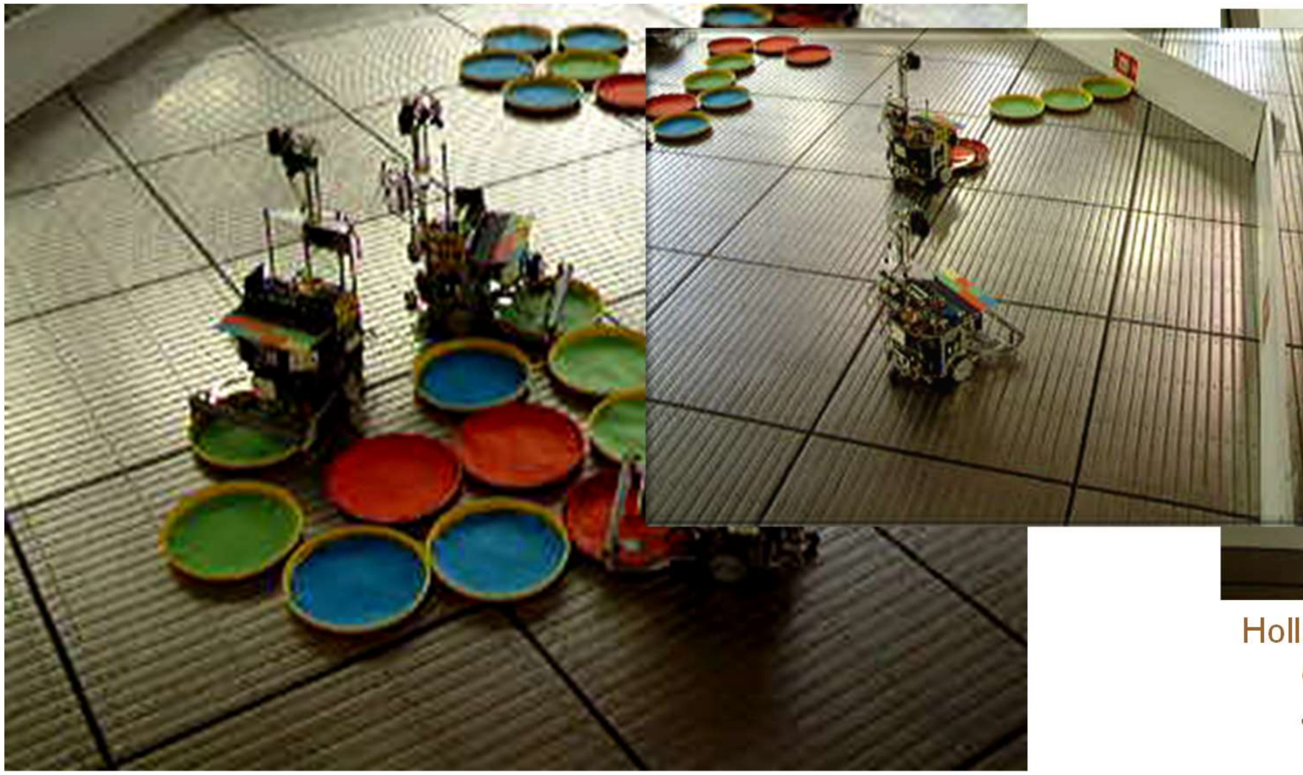
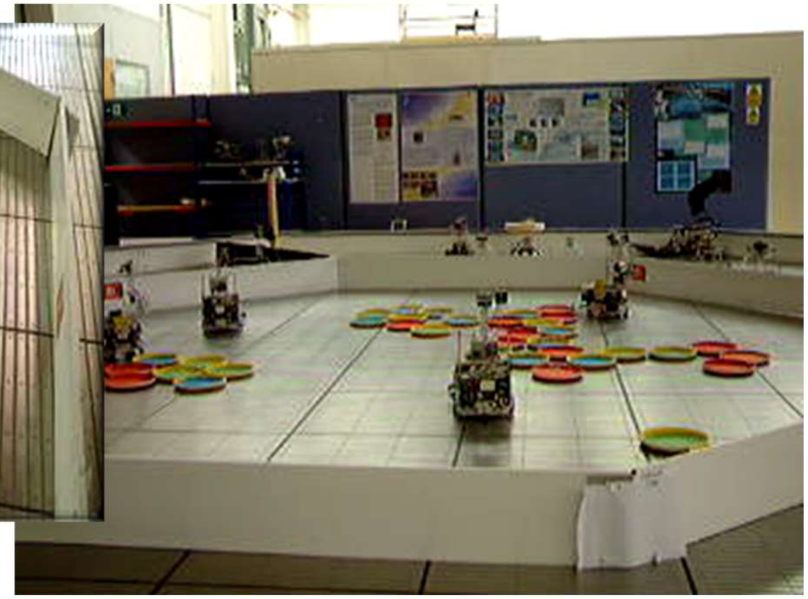
based on ant algorithm





Holland O. & Melhuish C. (1999) “Stigmergy, Self-organisation, and Sorting in Collective Robotics” *Journal of Adaptive Behaviour* . 5(2).

See Also: J. L. Deneubourg, S. Goss, N. Franks, A. Sendova-Franks, C. Detrain, L. Chretien. “The Dynamics of Collective Sorting Robot-Like Ants and Ant-Like Robots”. *From Animals to Animats: Proc. of the 1st Int. Conf. on Simulation of Adaptive Behaviour*. 356-363 (1990).

Bristol Robotics Laboratory.

Artificial ecosystems

- Automata with diverse characteristics
  - Bugs have an identity separate from the world
    - Bug: data structure and set of rules
    - World: Arena for information exchange plus set of rules

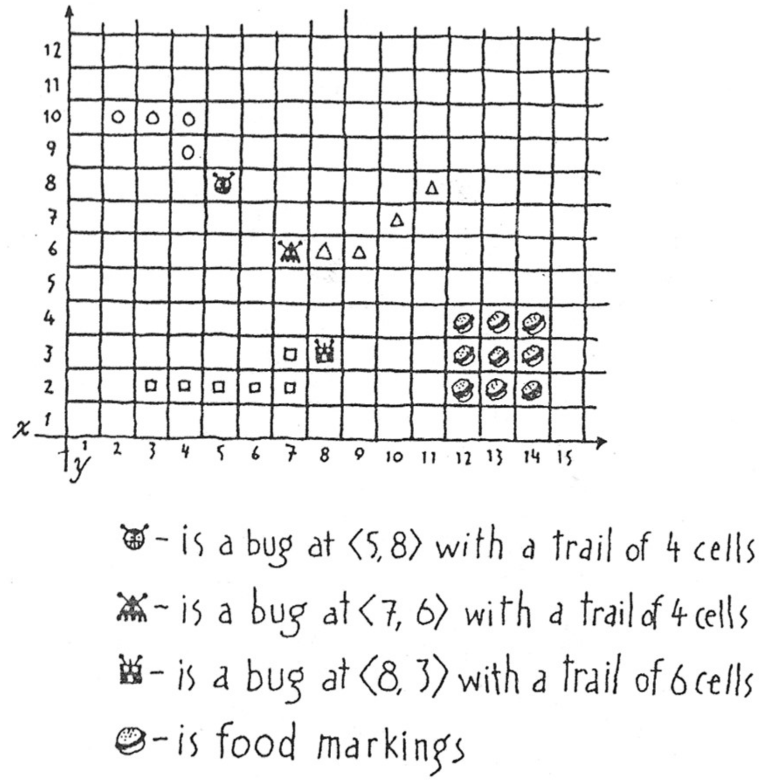


Figure by Rudy Rucker in *Artificial Life Lab*.

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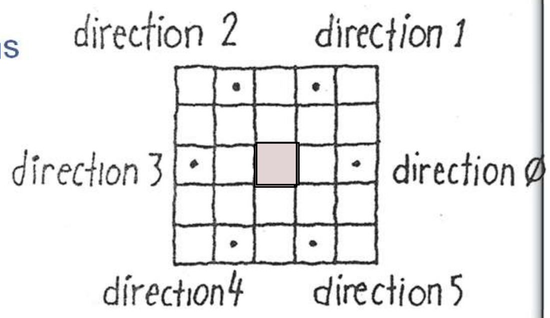
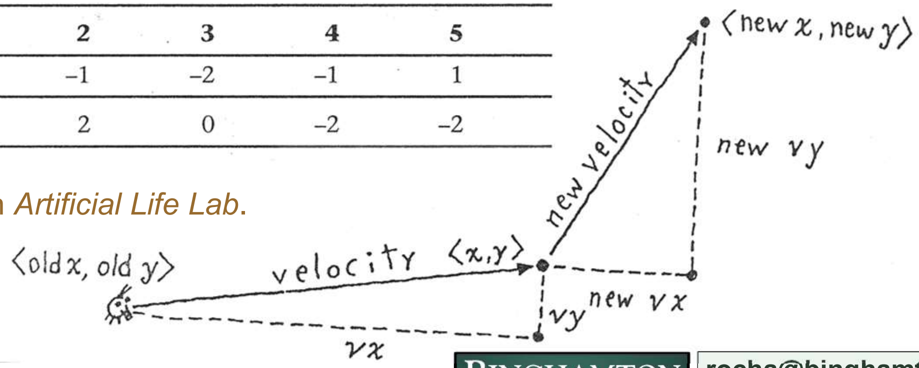
- Automata with diverse characteristics
  - Bugs have an identity separate from the world
    - Bug: data structure and set of rules
    - World: Arena for information exchange plus set of rules
- Typical bug implementation
  - ID#
  - Transition tables, rules of operations
  - Position in world
  - Fitness value
  - State (e.g. mood)
  - Velocity
    - Speed and direction
  - Group membership



	0	1	2	3	4	5
Change in X	2	1	–1	–2	–1	1
Change in Y	0	2	2	0	–2	–2

Figures by Rudy Rucker in *Artificial Life Lab*.



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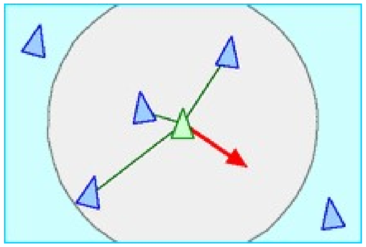
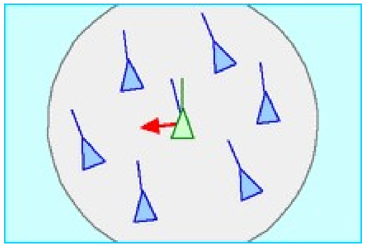
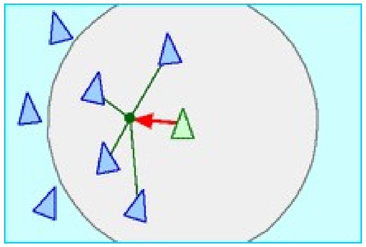
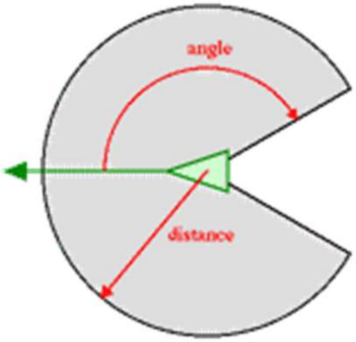
simple rules, complex behavior

- Boids by Craig Reynolds (1986)
  - 3 Steering behaviors
    - **Alignment**: move towards the average heading of local flockmates
      - Adjust velocity direction according to others in vicinity
    - **Separation**: steer to avoid crowding local flockmates
      - Maintain minimum distance to others (adjusting speed)
    - **Cohesion**: steer to move toward the average position of local flockmates
      - Adjust velocity direction according to others in vicinity
  - Each boid sees only flockmates within a certain small neighborhood around itself.
  - http://www.red3d.com/cwr/boids/









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simple rules, complex behavior

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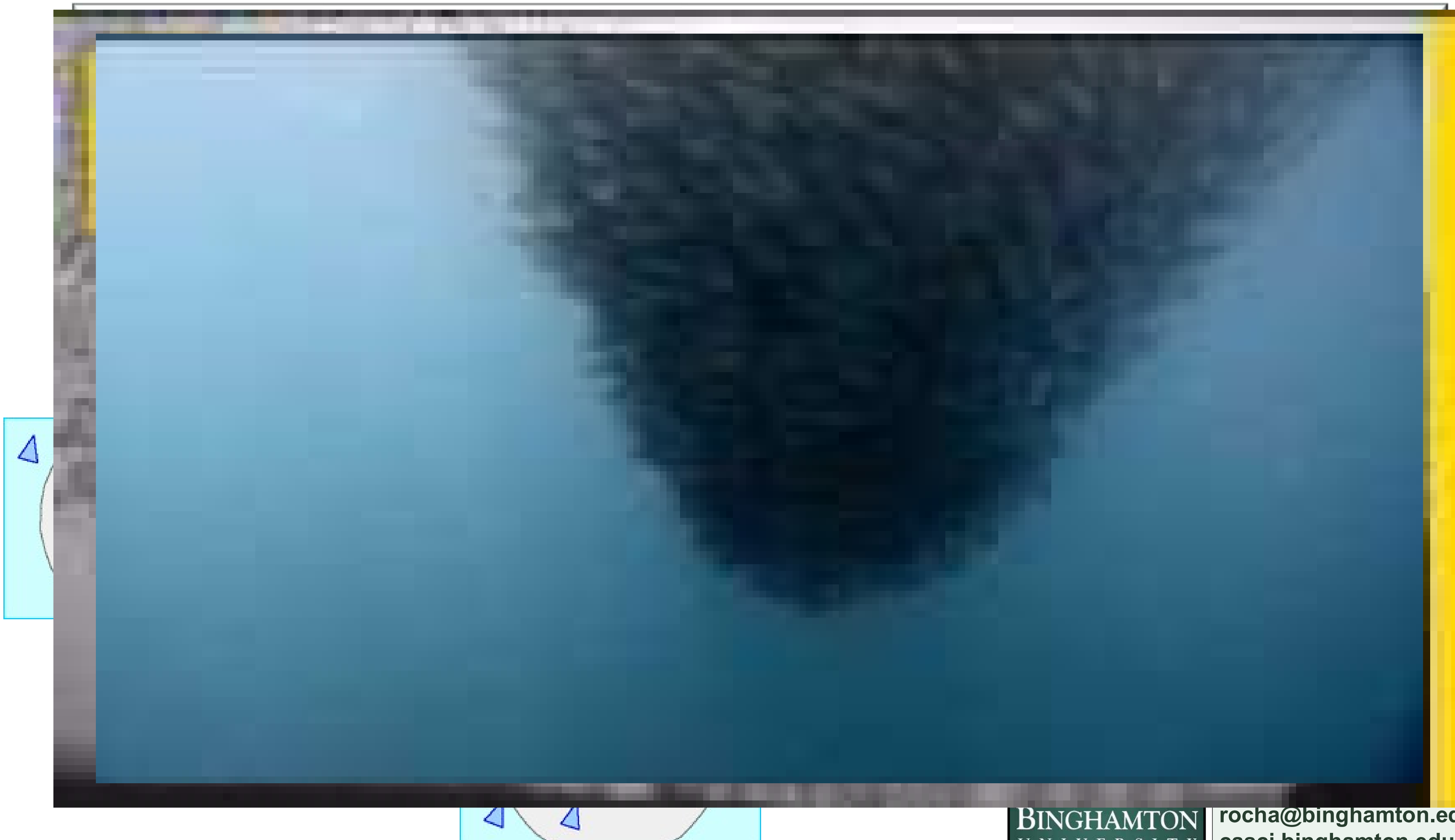

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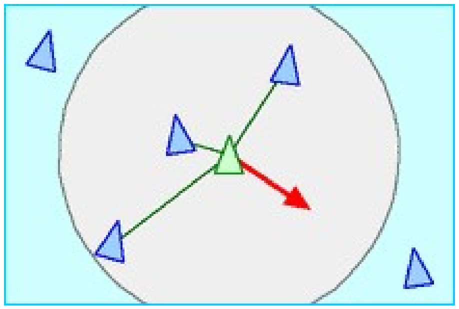
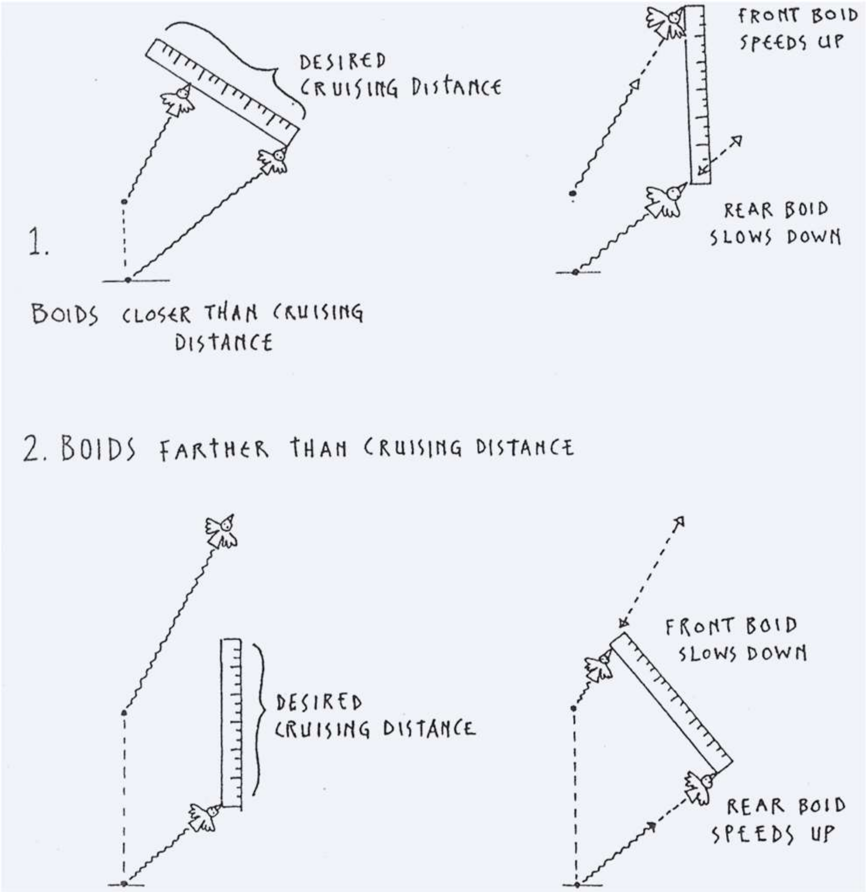
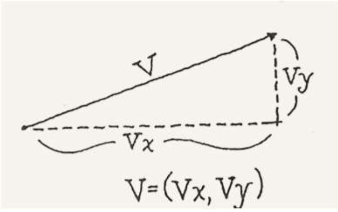
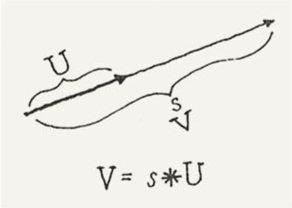
Separation: maintain minimum distance adjusting speed









Separation: move (speed up or slow down) move to avoid crowding and attain desired cruising distance with local flockmates

Figures by Rudy Rucker in *Artificial Life Lab*.

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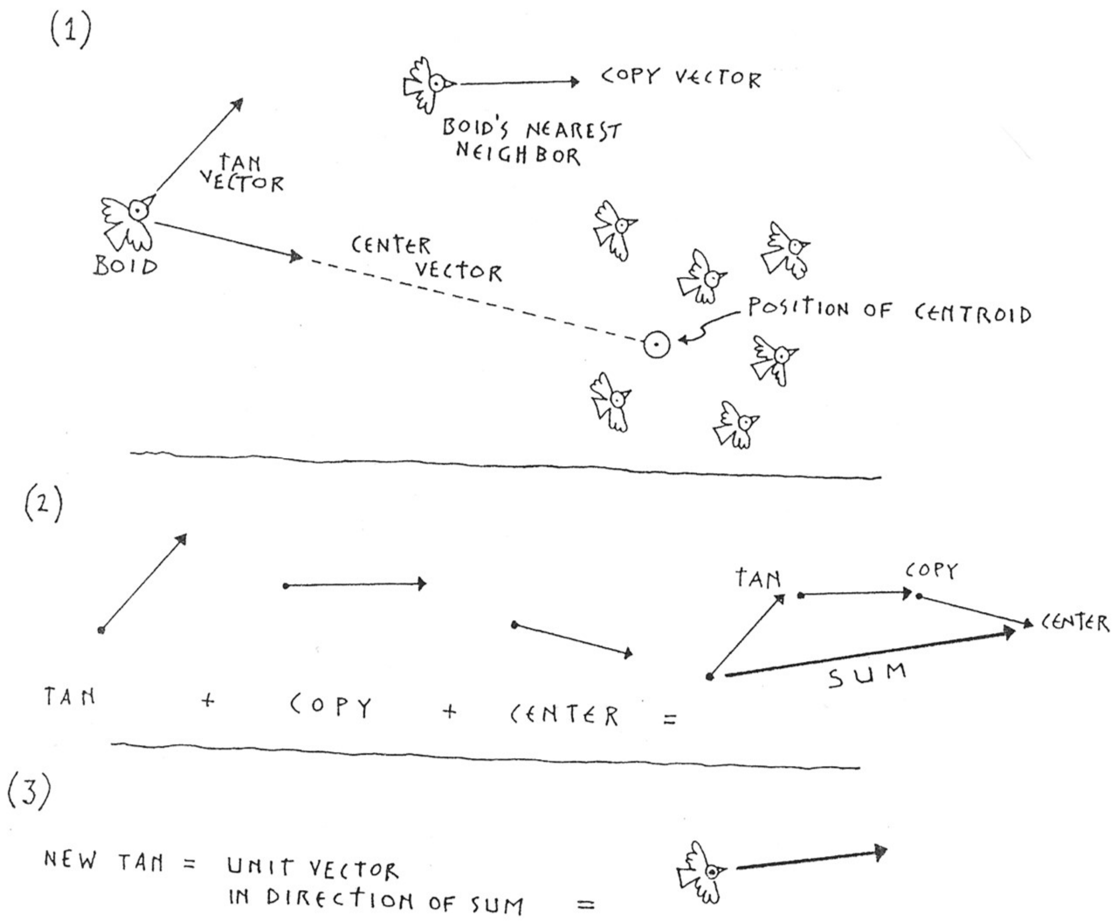
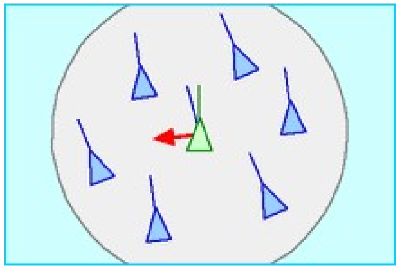
velocity vector update





Alignment: steer towards the average heading of local flockmates

Cohesion: steer to move toward the average position of local flockmates

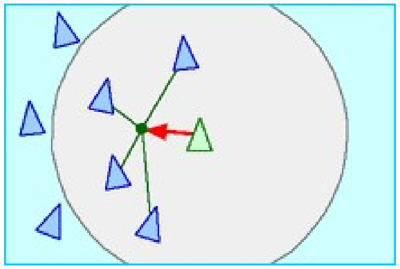


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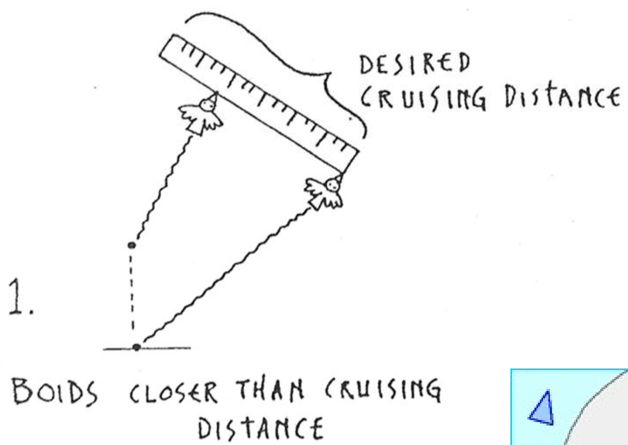
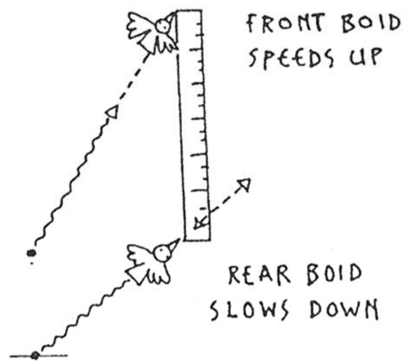
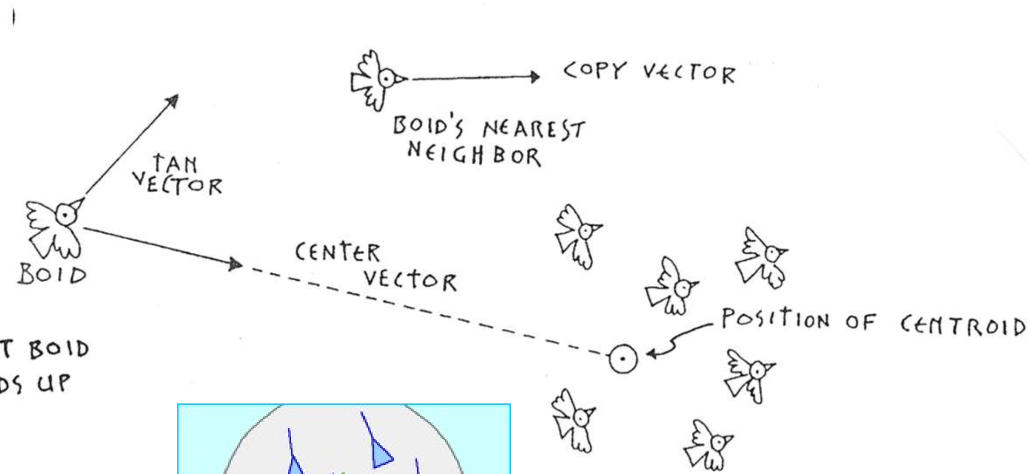
Figure by Rudy Rucker in *Artificial Life Lab*.

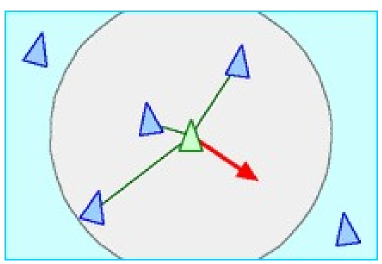
Boids

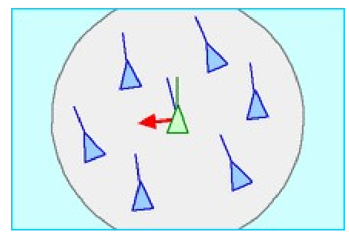
- Boids by Craig Reynolds (1986)
  - 3 Steering behaviors
    - **Separation**: move (speed up or slow down)
      - to avoid crowding and attain desired cruising distance with local flockmates
    - **Alignment**: steer towards the average heading of local flockmates
      - Adjust velocity according to others in vicinity
    - **Cohesion**: steer to move toward the average position of local flockmates

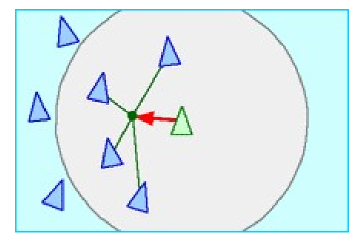












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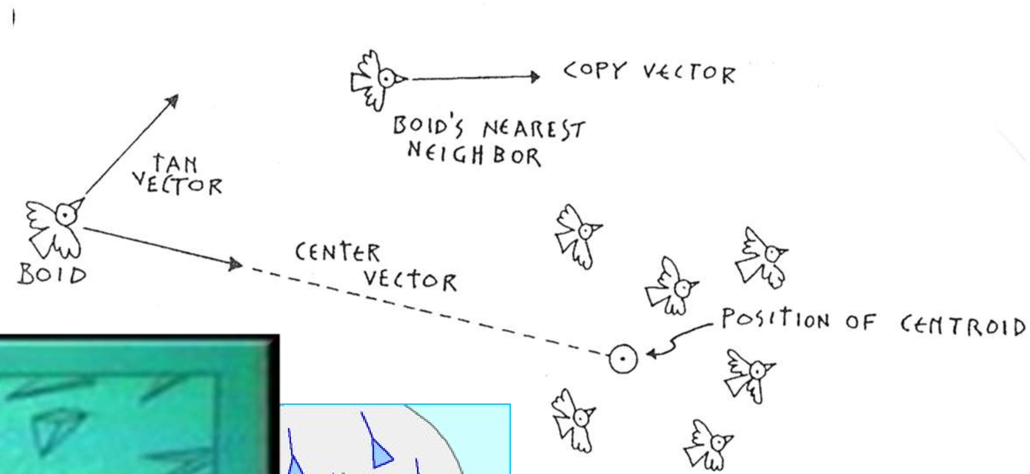
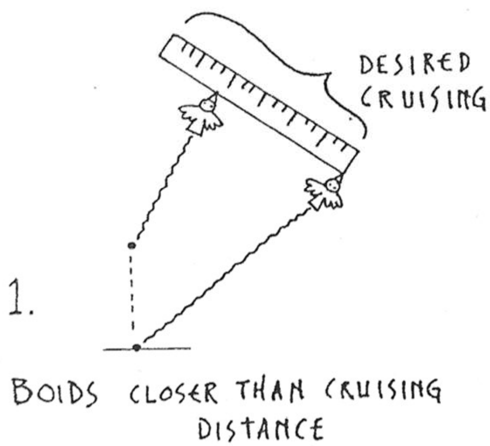
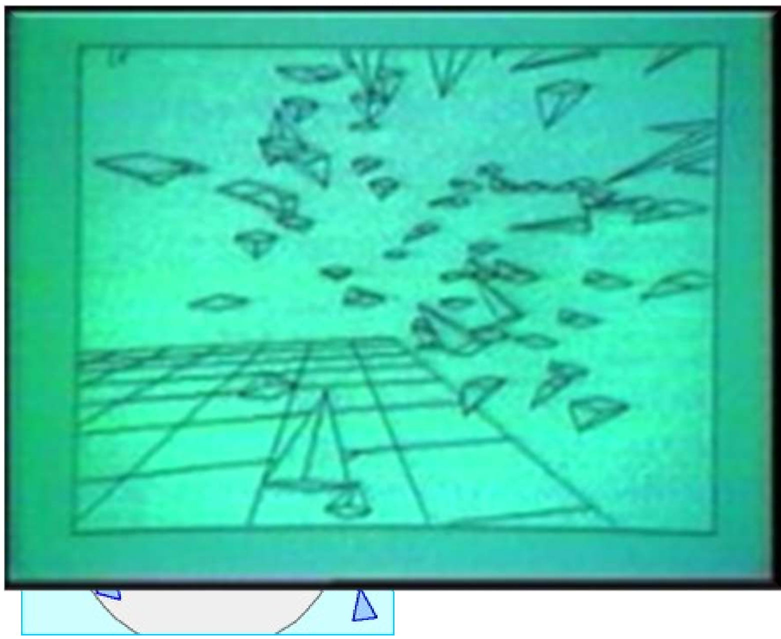
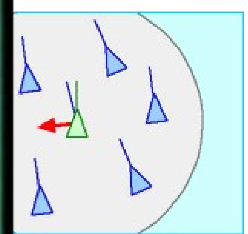
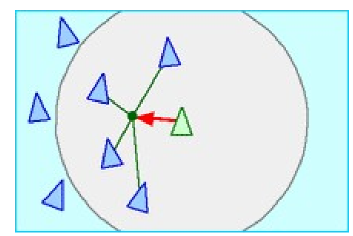
  - 3 Steering behaviors
    - **Separation**: move (speed up or slow down)
      - to avoid crowding and attain desired cruising distance with local flockmates
    - **Alignment**: steer towards the average heading of local flockmates
      - Adjust velocity according to others in vicinity
    - **Cohesion**: steer to move toward the average position of local flockmates











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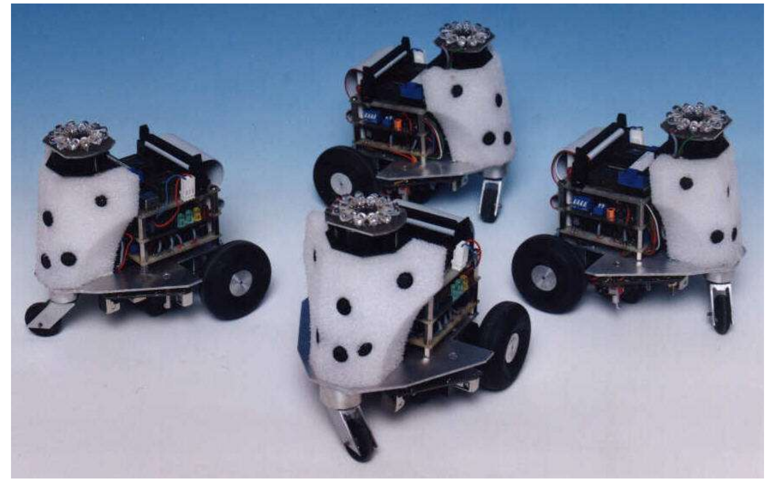
classics

- Batman Returns
  - to simulate bats and penquins
- Cliffhanger
  - Simulation of bats
- Jurassic Park
  - Simulation of gallamunus herd
- The Lion King
  - Scene of wildbeast stampede
- Jumanji
  - Stampede of zoo animals
- Star Trek Voyager "Elogium“
  - Simulation a swarm of space creatures

based on boids



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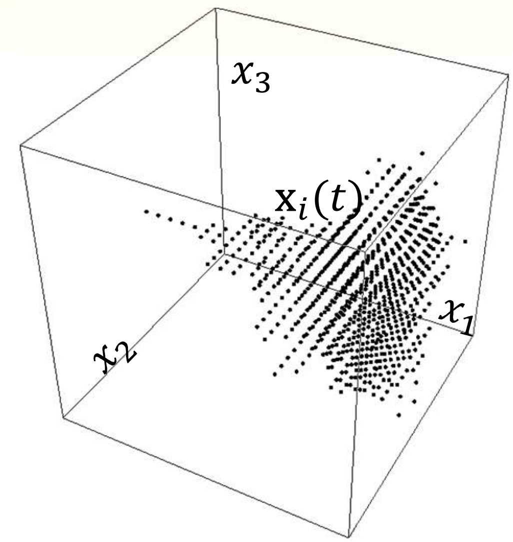
social flocking

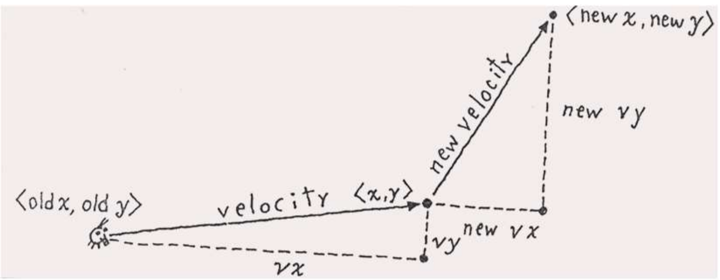
- Search by flocking
  - Social flocks looking for good positions
    - Metaphor: food, resources
- Agents flock according to social knowledge of
  - Their best position so far
  - The best position of the swarm or local neighbors
    - Not necessarily neighbors in search space but in some social structure (e.g. one dimensional lattice)
- Algorithm
  - Generate a random population of *particles*
    - $\mathbf{x}_i(t)$ --- vector of variables (similar to genotypes)
  - The position of agent i is $\mathbf{x}_i$ moving with velocity vector $\mathbf{v}_i$
    - $\mathbf{x}_i(t+1) = \mathbf{x}_i(t) + \mathbf{v}_i(t+1)$
  - Velocity update rule
    - w : inertia constant
    - c_1 and c_2 : constants
    - r_1 and r_2 : random values in [0,1]



$$\mathbf{v}(t+1) = w.\mathbf{v}(t) + c_1.r_1\left(\hat{\mathbf{x}} - \mathbf{x}(t)\right) + c_2.r_2\left(\hat{\mathbf{x}}_s - \mathbf{x}(t)\right)$$

Agent best so far (cognitive term)

Swarm best (social term)



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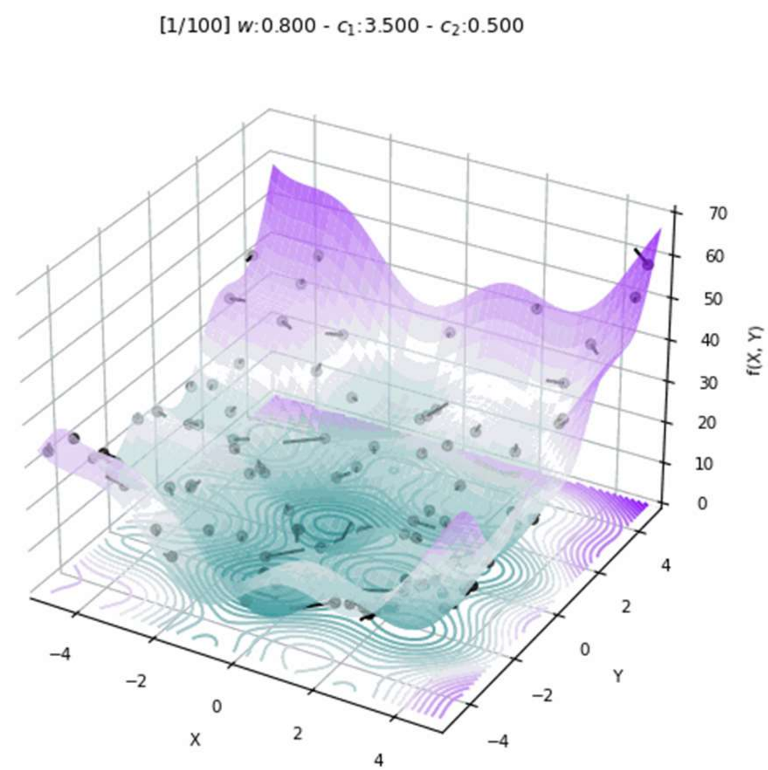
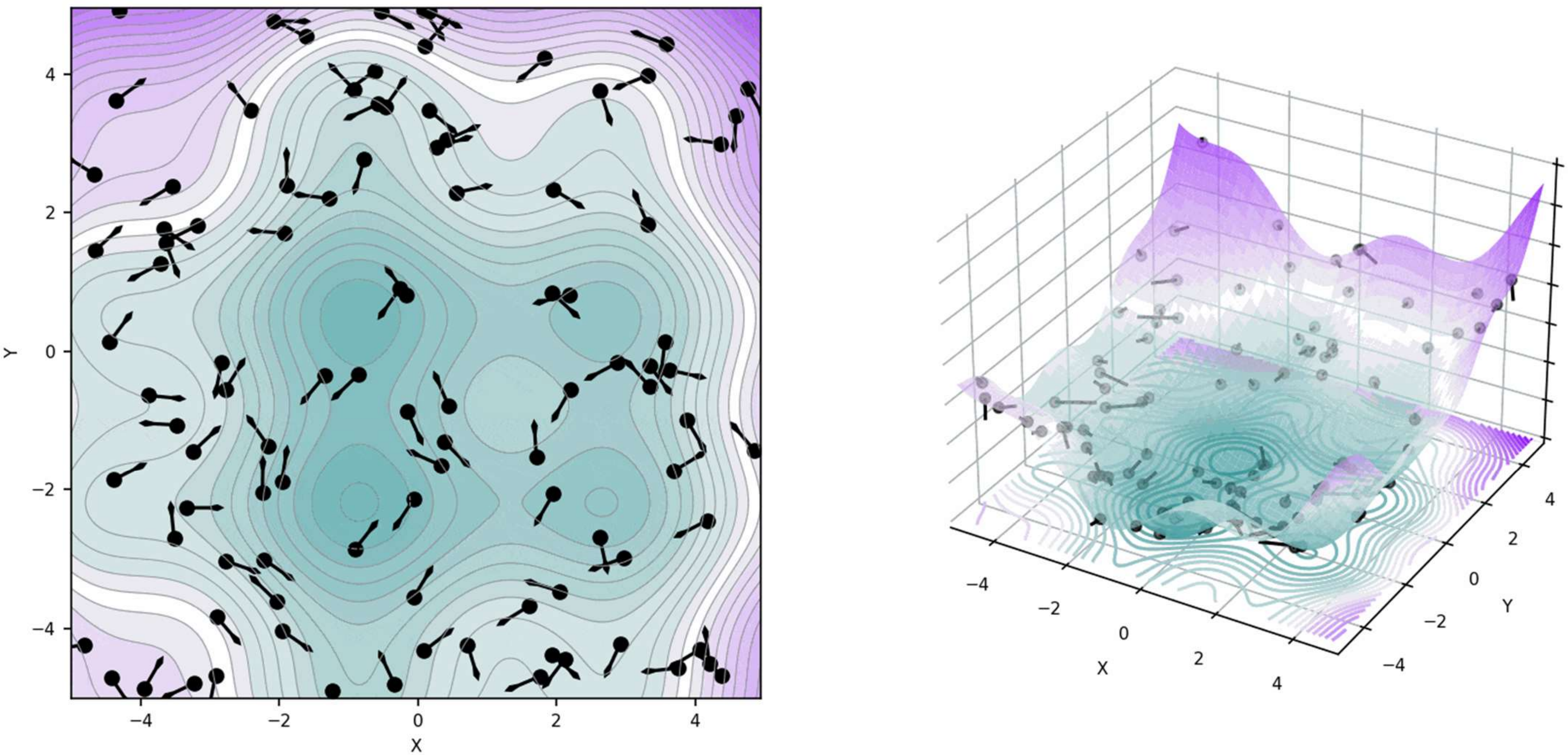
The workings

1. Generate random population of particles in search space
2. Generate random velocity vectors for each particle
3. Repeat (t++)
   - For every particle i in population
     - If $f\left(\mathbf{x}_i(t)\right) > f\left(\hat{\mathbf{x}}_i\right)$ then $\hat{\mathbf{x}}_i = \mathbf{x}_i(t)$
     - Compute $\hat{\mathbf{x}}_s$
     - $\mathbf{v}_i(t+1) = w.\mathbf{v}_i(t) + c_1.r_1(\hat{\mathbf{x}} - \mathbf{x}_i(t)) + c_2.r_2(\hat{\mathbf{x}}_s - \mathbf{x}_i(t))$
     - $\mathbf{x}_i(t+1) = \mathbf{x}_i(t) + \mathbf{v}_i(t+1)$
4. Until maximum iterations



Axel Thevenot [2020]. “Particle Swarm Optimization (PSO) Visually Explained”. *Towards Data Science*.

[1/100] w:0.800 - c_1:3.500 - c_2:0.500



readings

- Class Book
  - Floreano, D. and C. Mattiussi [2008]. *Bio-Inspired Artificial Intelligence: Theories, Methods, and Technologies*. MIT Press.
    - **Chapter 7**
- Lecture notes
  - Chapter 1: What is Life?
  - Chapter 2: The logical Mechanisms of Life
  - Chapter 3: Formalizing and Modeling the World
  - Chapter 4: Self-Organization and Emergent Complex Behavior
  - Chapter 5: Reality is Stranger than Fiction
  - Chapter 6: Von Neumann and Natural Selection
  - Chapter 7: Modeling Evolutionary Systems
    - posted online @ casci.binghamton.edu/academics/i-bic
- Papers and other materials
  - Optional
    - Nunes de Castro, Leandro [2006]. *Fundamentals of Natural Computing: Basic Concepts, Algorithms, and Applications*. Chapman & Hall.
      - Chapter 5, 7.7, 8.3.1, 8.3.6,