Swarm-Based Intelligence

Big effects from small interactions

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Revision

1. Work with Iterative Optimization Heuristics
2. Can use inspiration from natural phenomena
3. Population-based algorithms
4. No single best algorithm for all problems
5. Emergence, Complexity, Self-Organization

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Termites building their hills...

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Wasps building a nest...

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Bees attacking together…

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Ants foraging...

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Fish schooling to obtain safety in numbers…

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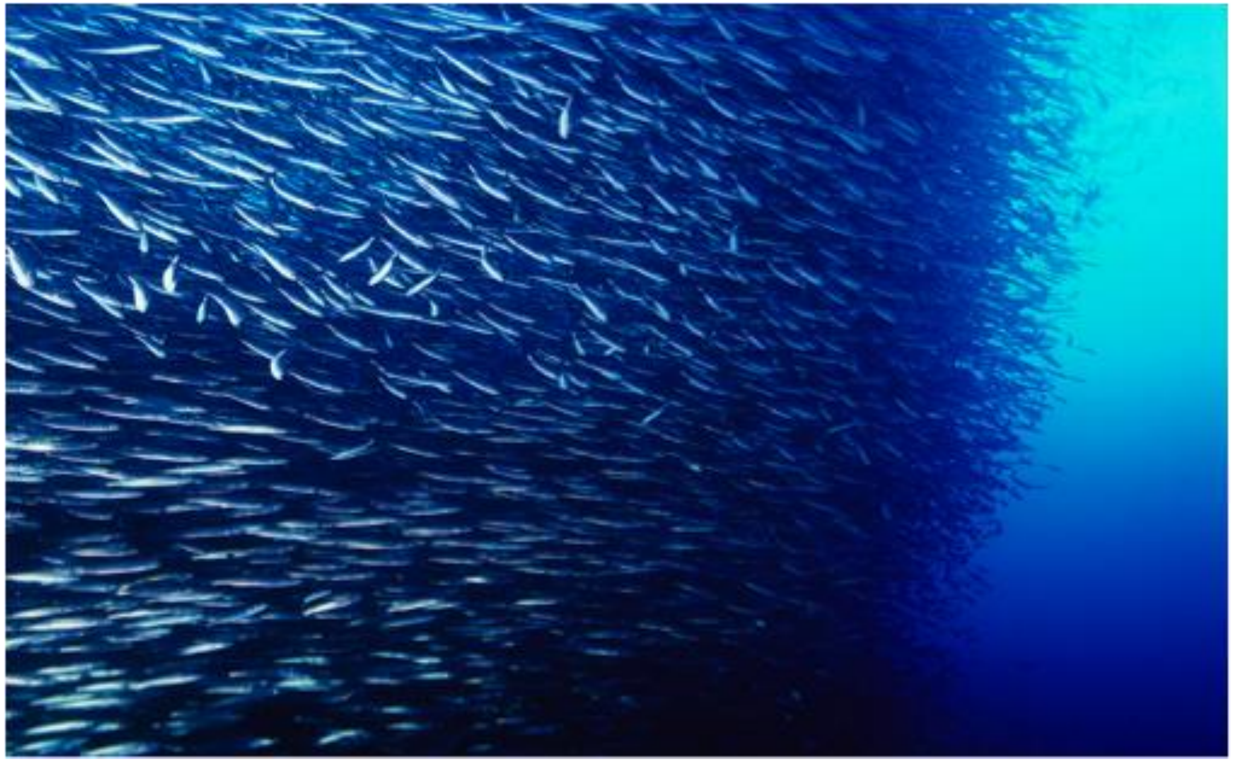

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Birds flocking for safety in numbers and increased foraging efficiency…

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Why do animals swarm?

- Defense against predators
- Enhanced predator detection
- Minimizing chance of capture
- Enhanced foraging success
- Better chances to find a mate
- Decrease of energy consumption
- …

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Some collective behaviors

- Nest building and maintaining
- Division of labor and adaptive task allocation
- Discovery of shortest paths between nest and food
- Clustering and sorting (e.g., dead bodies, eggs)
- Structure formation (e.g., deal with obstacles)
- Recruitment for foraging (tandem, group, mass)
- Cooperative transport (e.g., food)

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... and many more!


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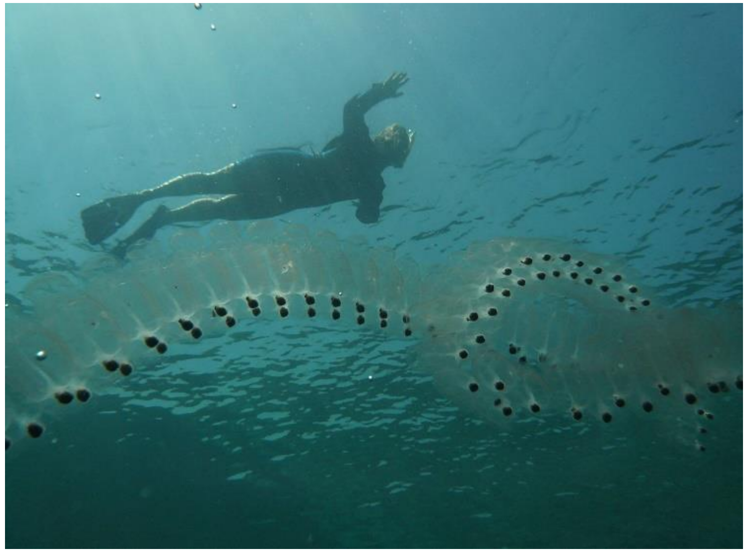
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Swarm Intelligence (SI)

- Originates from study of colonies, swarms, social organisms
- Collective intelligence
  - Arising from interactions
  - Individuals having simple behavioral intelligence
- Each individual
  - Communicates / behaves in a distributed way
  - With a certain information exchange protocol
- Inspiration for the design of multi-agent algorithms.

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Power of Swarm Intelligence

- Great inspiration for algorithm design:
  - Offer **solutions for various kinds of problems**
  - **Self-organized**, **decentralized control** → **robust** and **flexible** against changes of the environment
  - **System-level behaviors** appear to **transcend** the behavioral repertoire of the **single individual**

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Self-organization in Swarms

- Self-organization is the main driving force

"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]

How is Self-Organization Achieved?

- Communication is necessary:
  - **Point-to-point**:

    antennation, trophallaxis (food or liquid exchange), mandibular contact, direct visual contact, chemical contact, . . . unicast radio contact!

  - **Broadcast-like**: 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**: Individuals interact indirectly when one of them modifies the environment and the other responds to the new environment at a later time.

    This is called **stigmergy** (e.g., pheromone laying/following, post-it, web)

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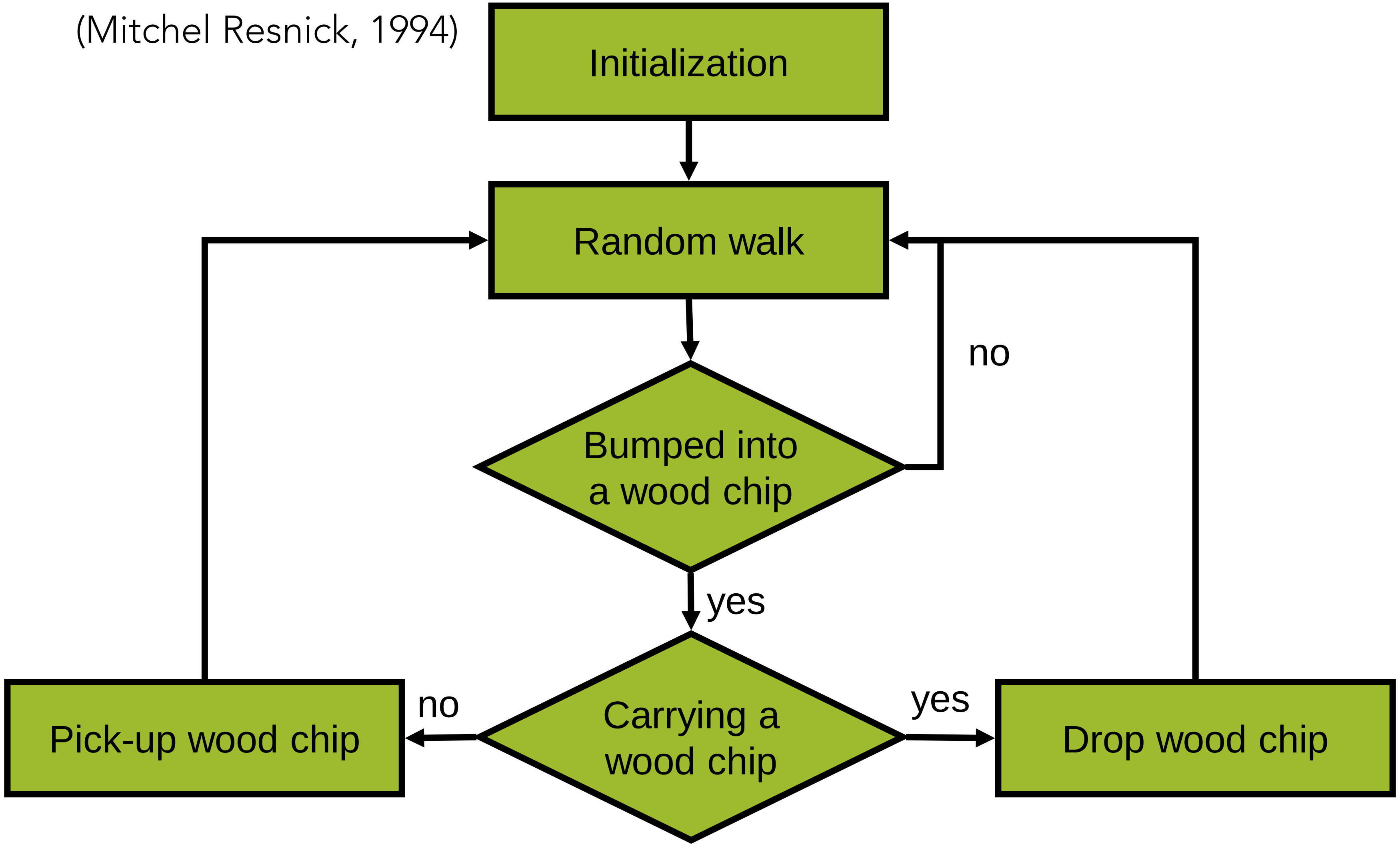
Self-Organization: Termite Simulation

(Mitchel Resnick, 1994)



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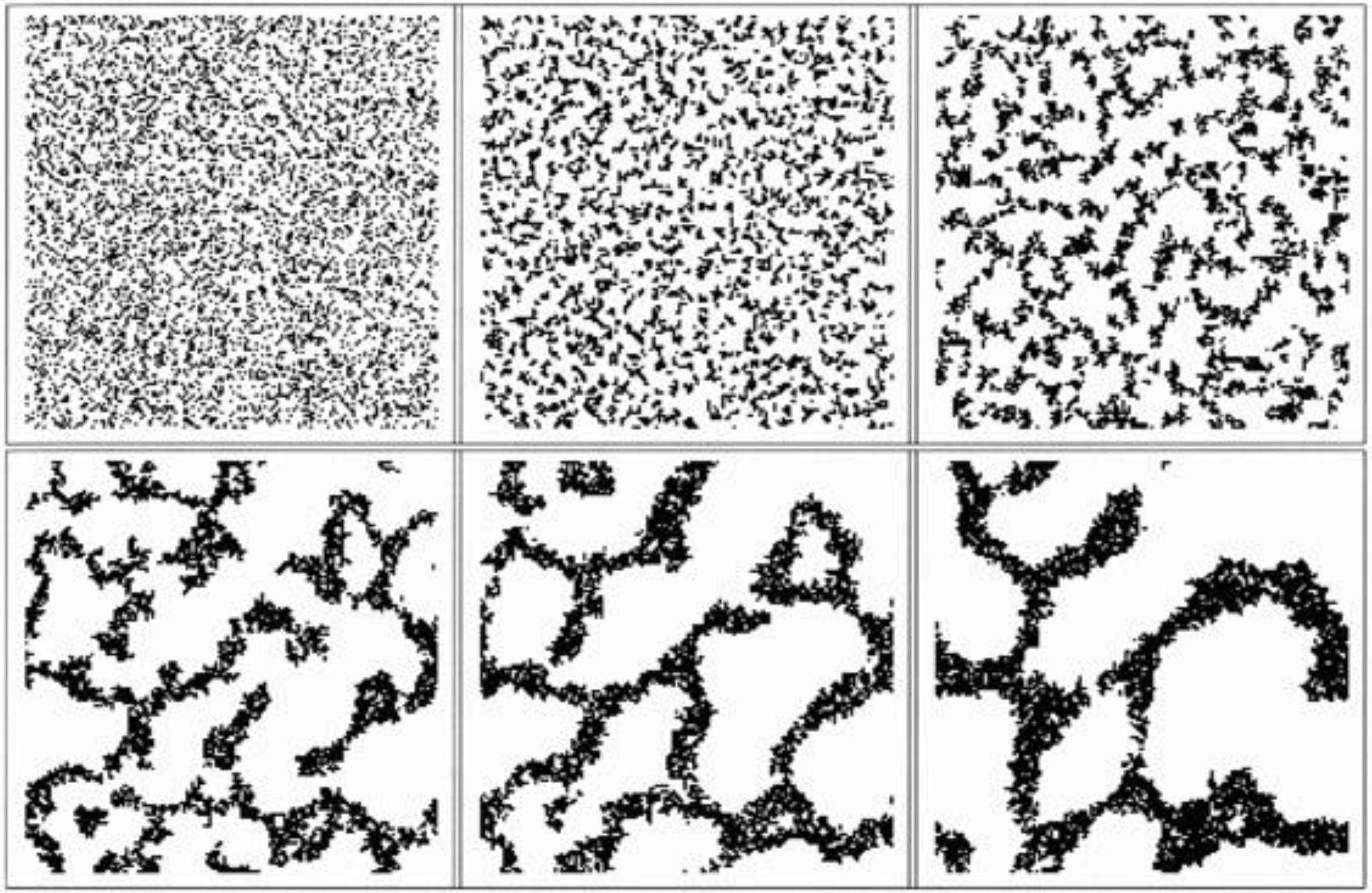
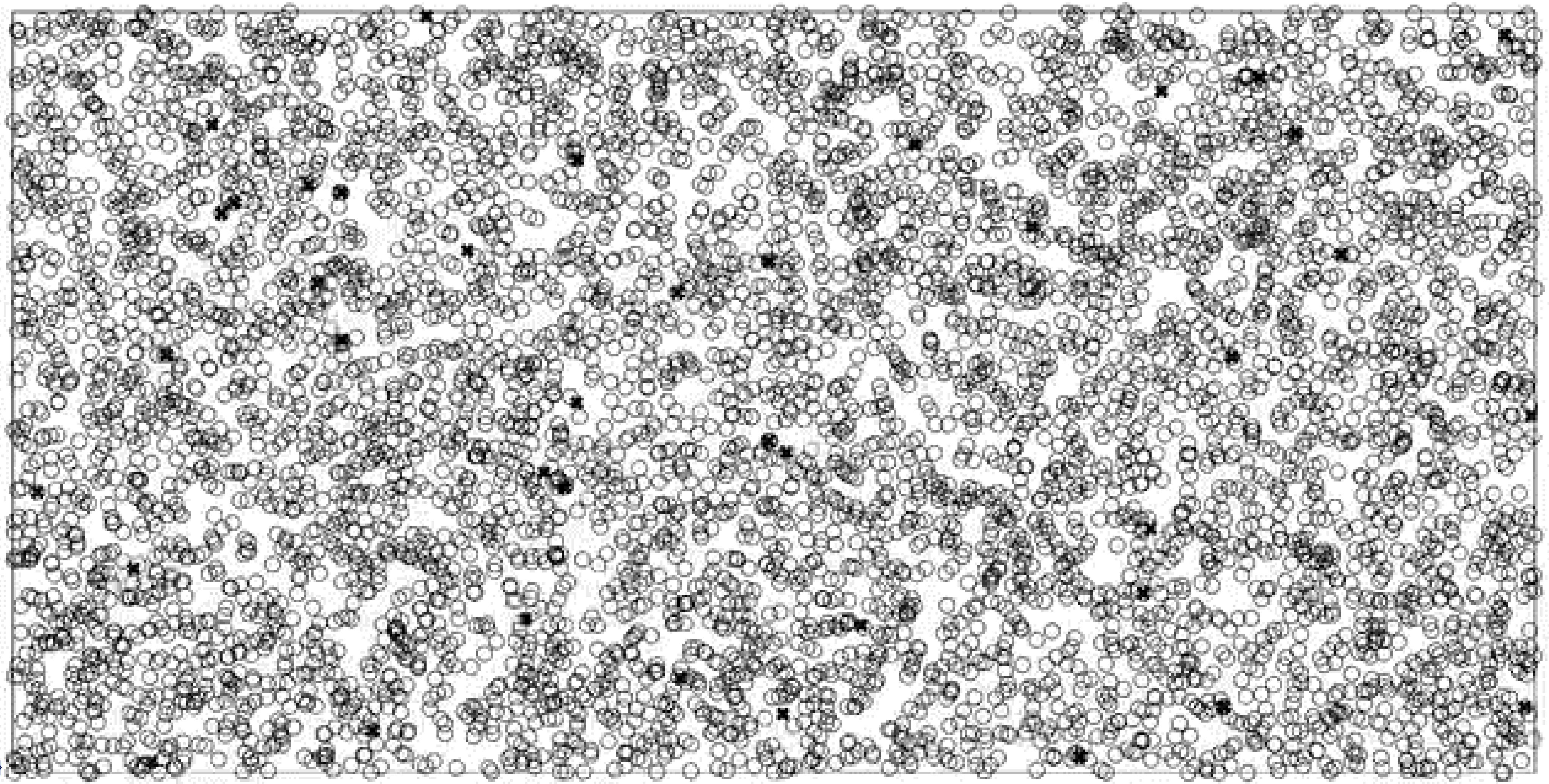
Self-Organization: Termite Simulation

(Mitchel Resnick, 1994)



Self-Organization: Termite Simulation



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Most Common Swarm-Based Algorithms

- Particle Swarm Optimization (PSO)
  - Based on model of the social behavior of bird flocks
  - Optimization technique for continuous optimization problems
- Ant Colony Optimization (ACO)
  - Based on a model of the social behavior of ant colonies
  - Meta-heuristic for combinatorial optimization problems (especially powerful in solving TSP-like problems)
- Many others exist, but we will not cover those

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Particle Swarm Optimization

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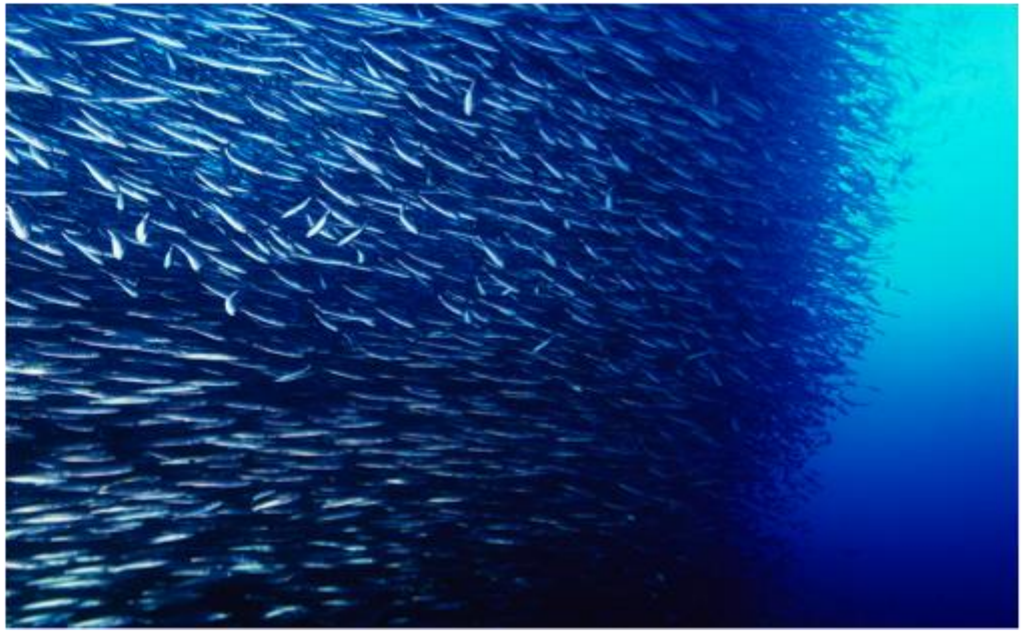
Particle Swarm Optimization

- Developed by Kennedy and Eberhart in 1995 [6]
- Population based optimization technique inspired by social behavior of bird flocking or fish schooling
- Individual swarm members can profit from the discoveries and previous experience of all other members of the school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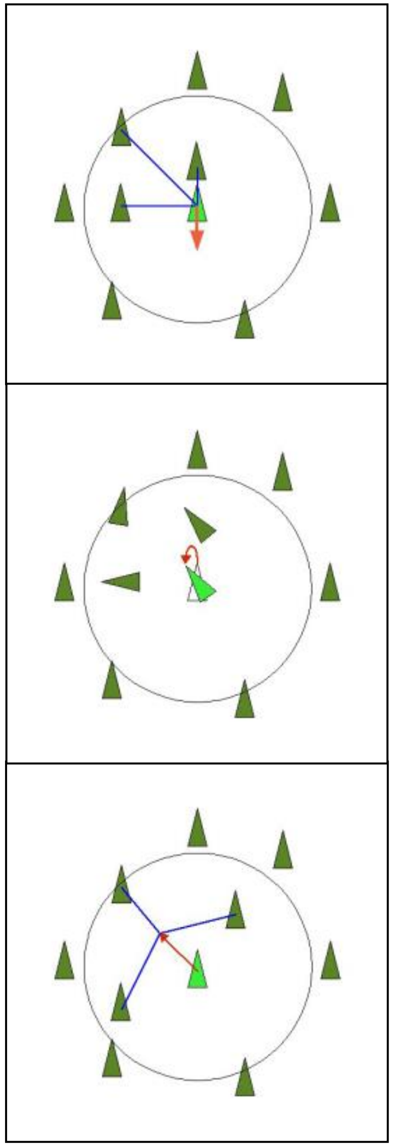
History - Boids

Note: BOIDS is not an optimization algorithm!



- Very simple simulation of the swarming behavior of bird-like objects (boids)
- Developed by Reynolds (1987), where the agents follow three simple rules:

→ **Separation**

Move away from neighbors if these are too close

→ **Alignment**

Steer towards the average heading of neighbors

→ **Cohesion**

Try to move toward the average position of neighbors

Boids in action

These simple rules yield surprisingly realistic swarm behavior

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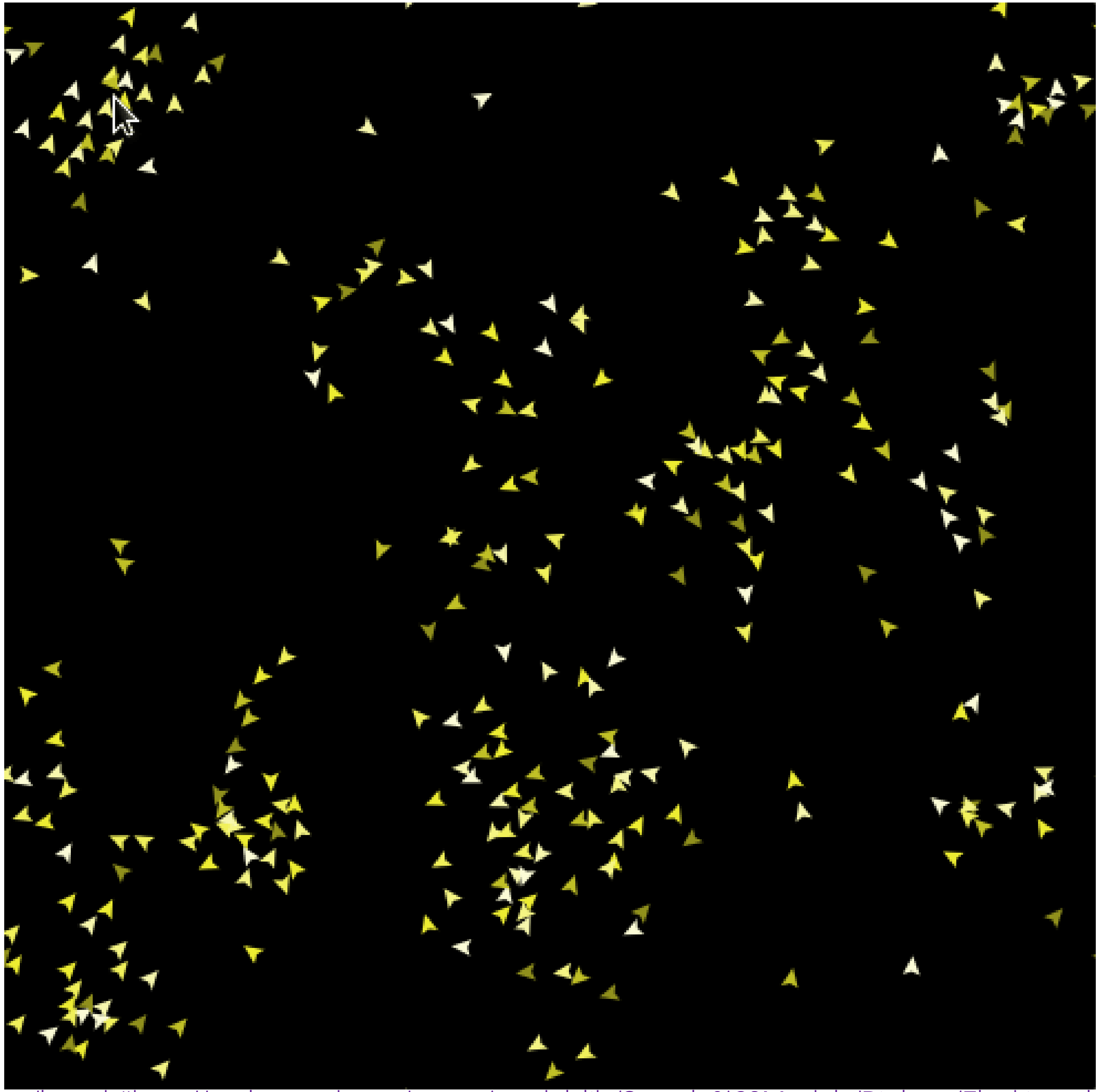


(see http://netlogoweb.org/launch#http://netlogoweb.org/assets/modelslib/Sample%20Models/Biology/Flocking.nlogo)

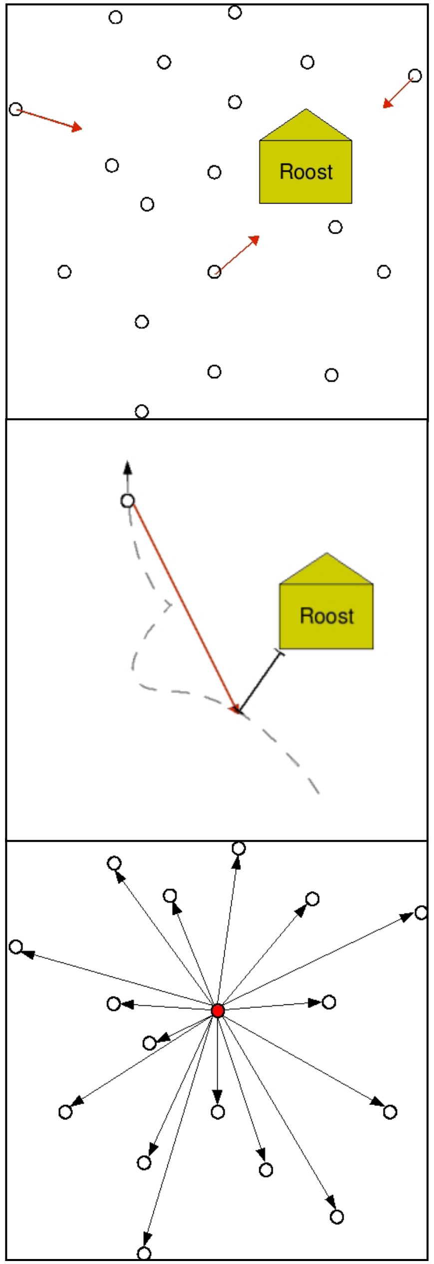
Extending Boids: Roosts

Kennedy and Eberhart included a ‘roost’ in a simplified Boids-like simulation such that each agent:

- Is attracted to the location of the roost,
- Remembers where it was closer to the roost,
- Shares information with its neighbors about its closest location to the roost

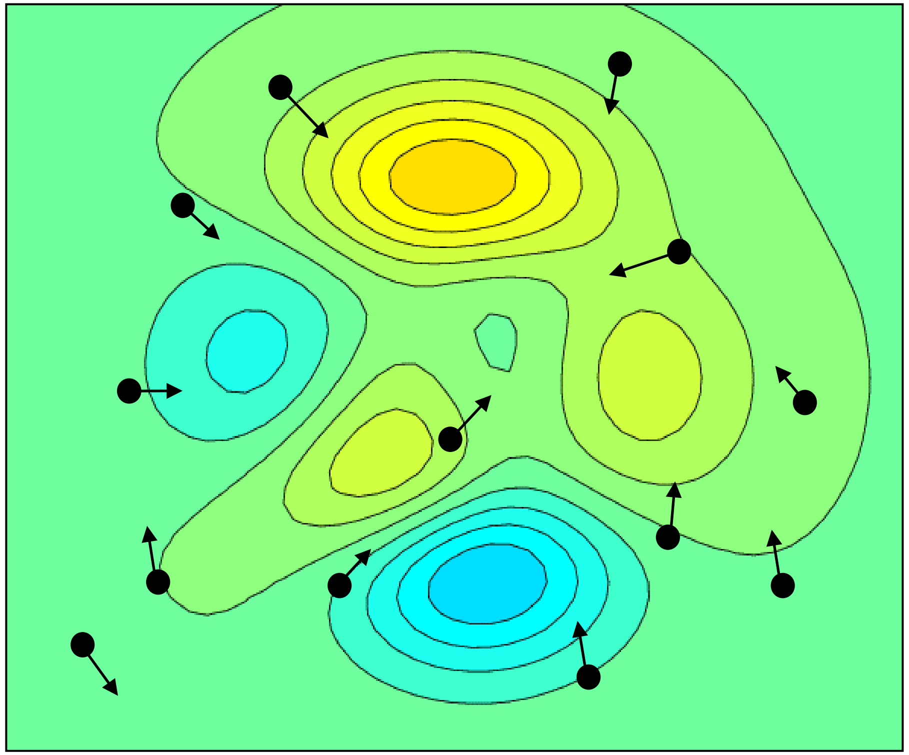
Eventually, all agents land on the roost.

What if the notion of distance to the roost is changed by an unknown function?



PSO - General concept

- **Swarm** of **particles**
- Each particle residing at a **position** in the search space
- **Fitness** of each particle = the quality of its position
- Particles fly over the search space with a certain **velocity**
- **Velocity** (both direction and speed) of each particle is influenced by its own best position found so far and the best solution that was found so far by its **neighbors**
- Eventually the swarm will **converge** to **optimal** positions



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PSO – Basic structure

The basic steps in the PSO algorithm are as follows:

Algorithm 2 Particle Swarm Optimization

Randomly initialize particles ($\mathbf{x}_i$) and their velocities ($\mathbf{v}_i$) in the search space
while termination criteria are not met **do**
    for each particle i **do**
        Evaluate the fitness y_i at current position $\mathbf{x}_i$
        if y_i is better than its personal best $pbest_i$ **then**
            update $\mathbf{p}_i$ and $pbest_i$
        end if
        if y_i is better than its global best $gbest_i$ **then**
            update $\mathbf{g}_i$ and $gbest_i$
        end if
    end for
    for each particle i **do**
        Update the velocity $\mathbf{v}_i$ based on $\mathbf{p}_i$, $\mathbf{g}_i$ and $\mathbf{v}_i$
        Update the position: $\mathbf{x}_i \leftarrow \mathbf{x}_i + \mathbf{v}_i$
    end for
end while

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Original PSO - Notation


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For each particle i:

- $\boldsymbol{x}_i$ is a vector denoting its position
- $\boldsymbol{v}_i$ is the vector denoting its velocity
- y_i denotes the fitness score of $\boldsymbol{x}_i$
- $\boldsymbol{p}_i$ is the best position that it has found so far
- $pbest_i$ denotes the fitness of $\boldsymbol{p}_i$
- $\boldsymbol{g}_i$ is the best position that has been found so far in its neighborhood
- $gbest_i$ denotes the fitness of $\boldsymbol{g}_i$

Velocity update:

- $\mathrm{U}(0,\boldsymbol{\phi}_i)$ is a random vector uniformly distributed in $[0,\boldsymbol{\phi}_i]$ generated at each generation for each particle
- $\boldsymbol{\phi}_1$ and $\boldsymbol{\phi}_2$ are the acceleration coefficients determining the scale of the forces in the direction of $\boldsymbol{p}_i$ and $\boldsymbol{g}_i$
- $\otimes$ denotes the element-wise multiplication operator

Velocity Update

$$\vec{v}_i \leftarrow \vec{v}_i + \mathcal{U}(0, \phi_1) \otimes (\vec{p}_i - \vec{x}_i) + \mathcal{U}(0, \phi_2) \otimes (\vec{g}_i - \vec{x}_i)$$

Momentum

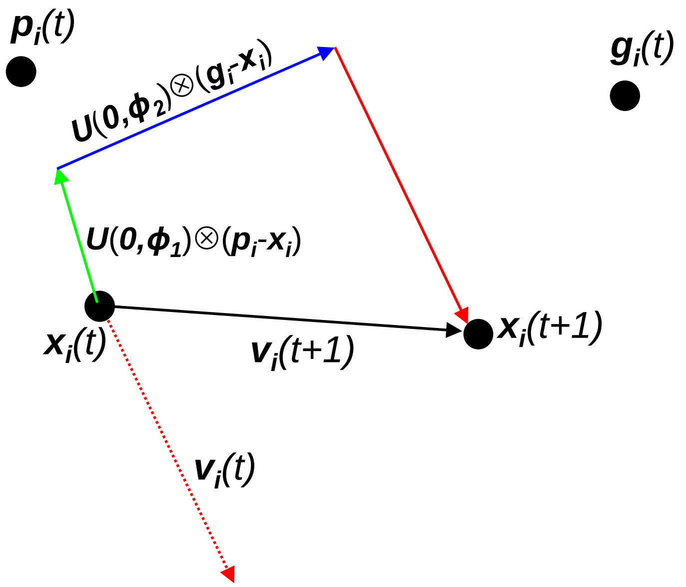
The force pulling the particle to continue its current direction

Cognitive component

The force emerging from the tendency to return to its own best solution found so far

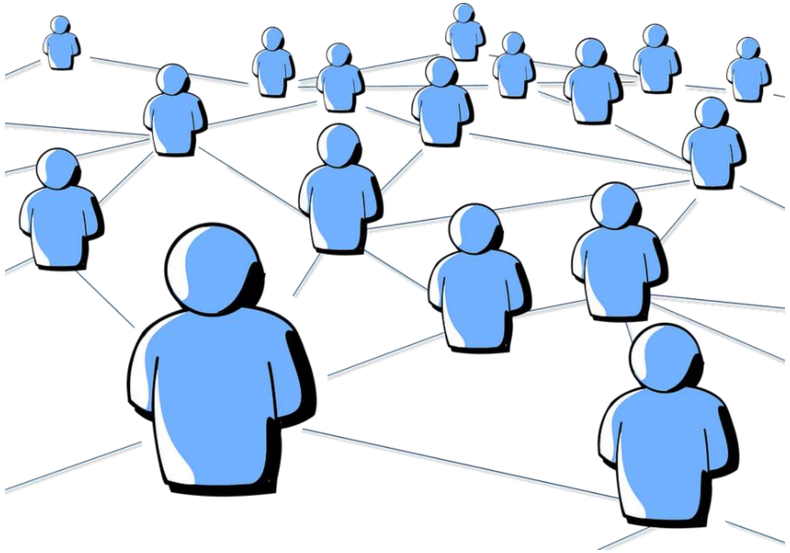
Social component

The force emerging from the attraction of the best solution found so far in its neighborhood



Social Component - Neighborhoods

- The neighborhood of each particle defines its communication structure (its social network)
- Two general types:



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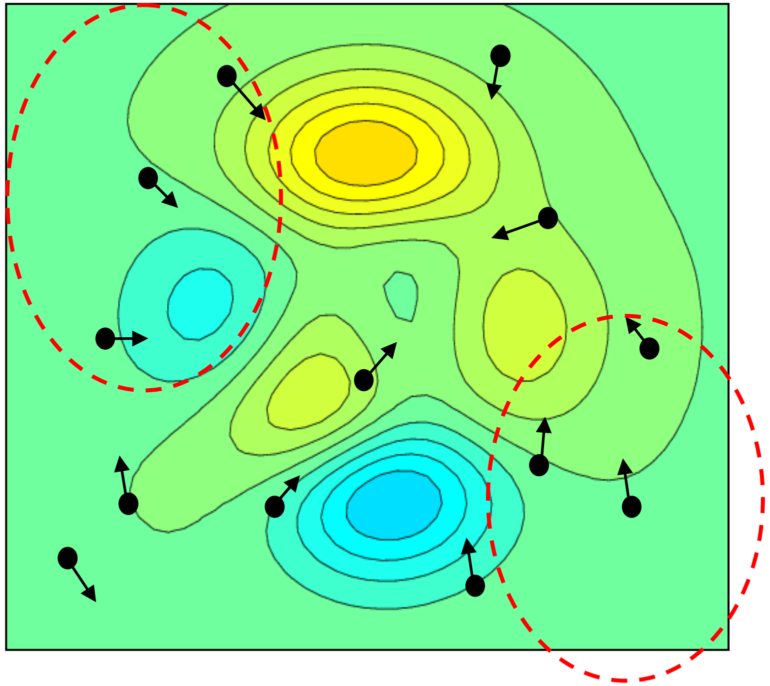
Geographical neighborhood topologies:

- Based on Euclidean proximity in the search space
- Close to the real-world paradigm but computationally expensive

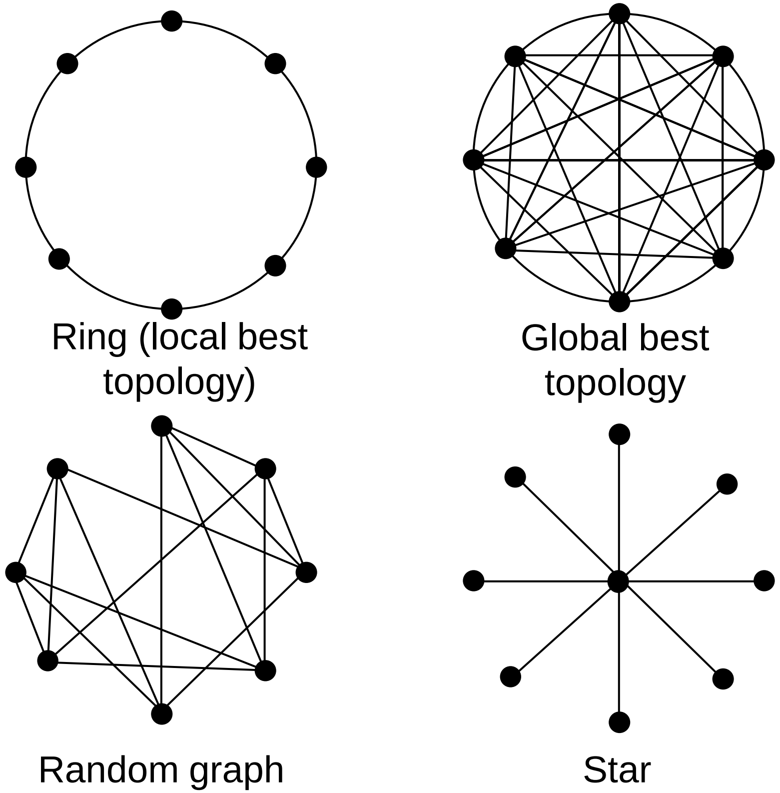
Communication network topologies:

- Communication networks are used based on some connection graph architecture (e.g. rings, stars, von Neumann networks and random graphs)
- Favored over geographical neighborhood because of better convergence properties and less computation involved

Neighborhood Topologies



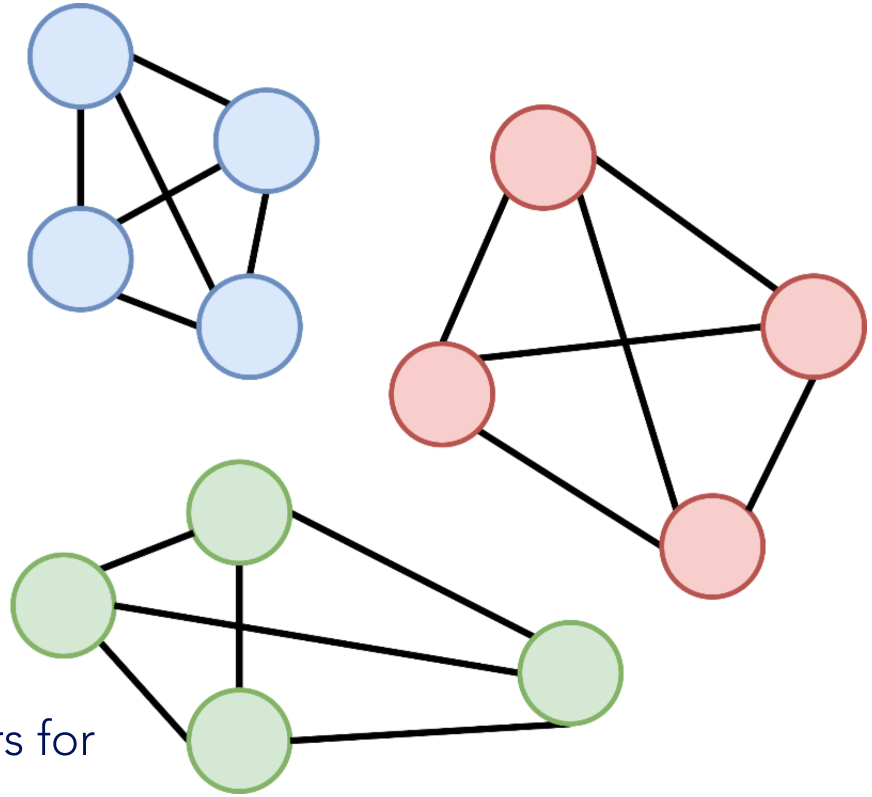
Geographical neighborhoods



Communication network topologies

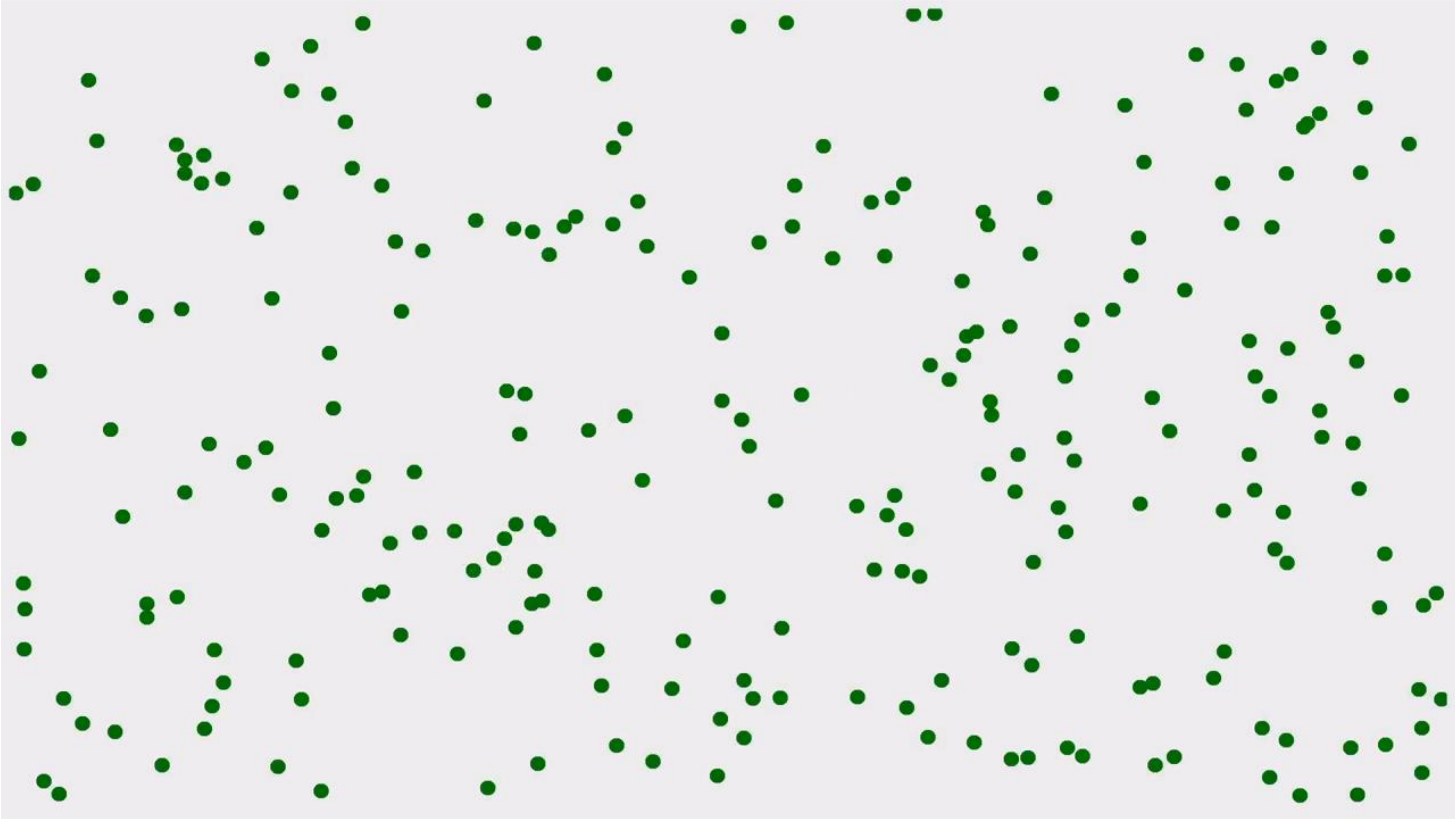
More on Neighborhood Topologies

- Also considered were:
  - Clustering topologies (islands)
  - Dynamic topologies
  - …

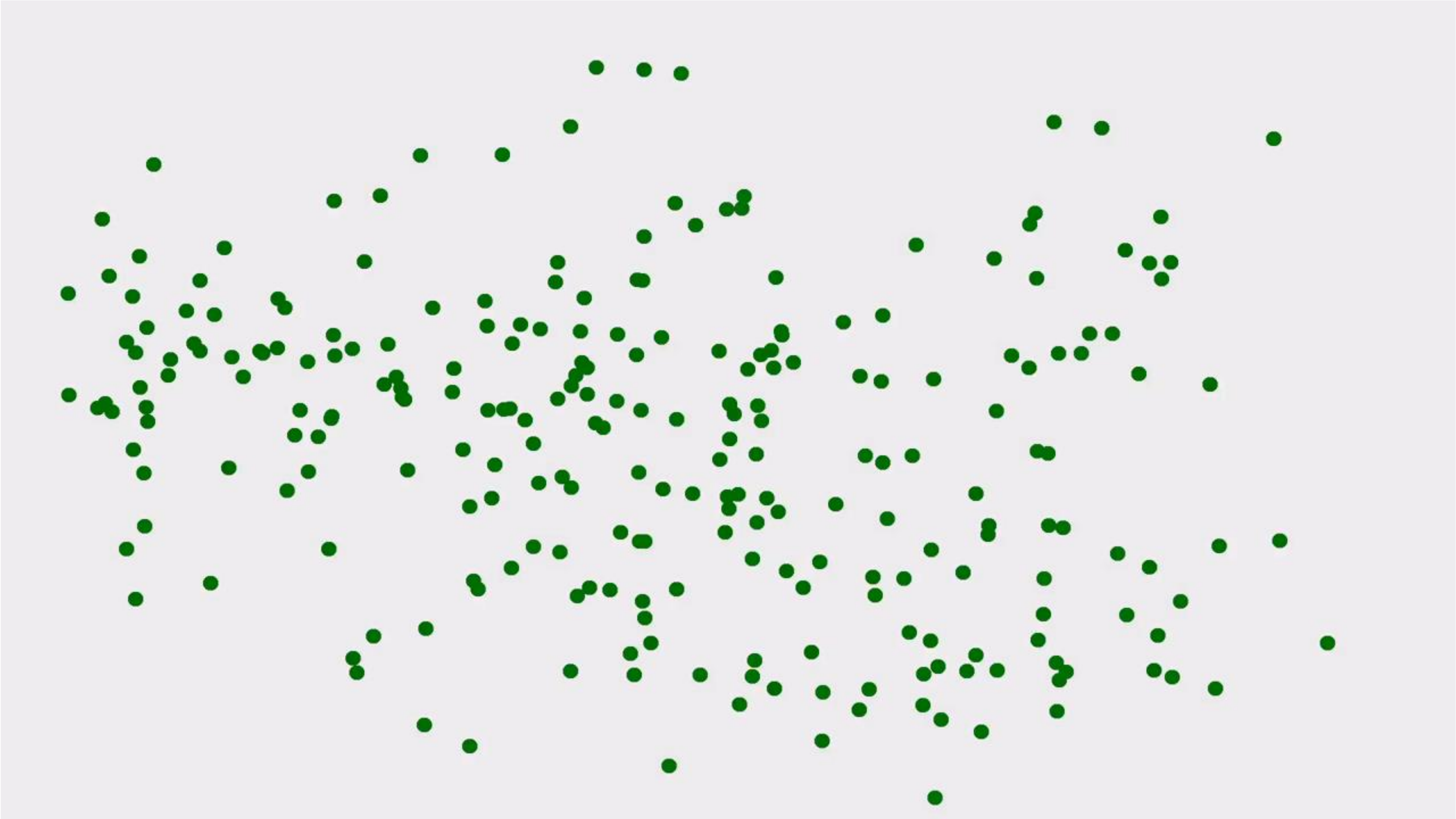


- No clear way of saying which topology is the best
- Exploration / exploitation
  - Some neighborhood topologies are better for local search others for global search
  - The lbest neighborhood topologies seems better for global search, gbest topologies seem better for local search

Lbest PSO

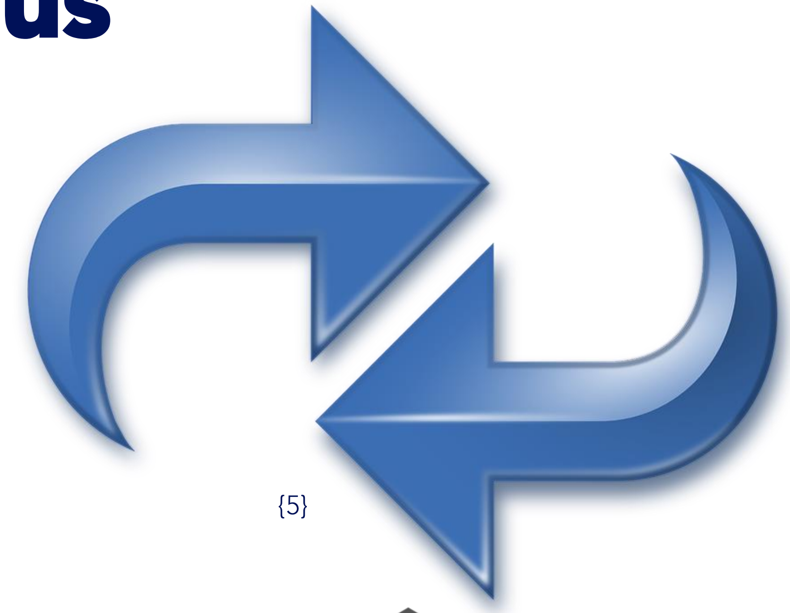


Gbest PSO



Synchronous versus Asynchronous

- Synchronous updates
  - Personal best and neighborhood bests updated separately from position and velocity vectors
  - Slower, but 'perfect' feedback about best positions
  - Better for gbest PSO (exploitation)
- Asynchronous updates
  - New best positions updated after each particle position update
  - Immediate, but imperfect, feedback about best regions of the search space
  - Better for lbest PSO (exploration)



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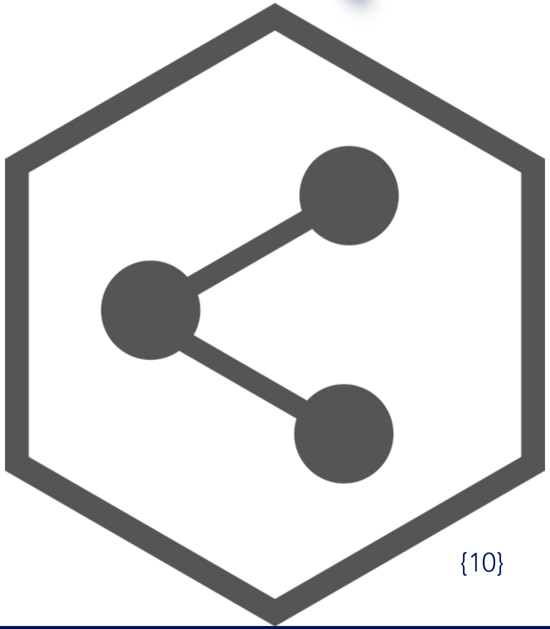

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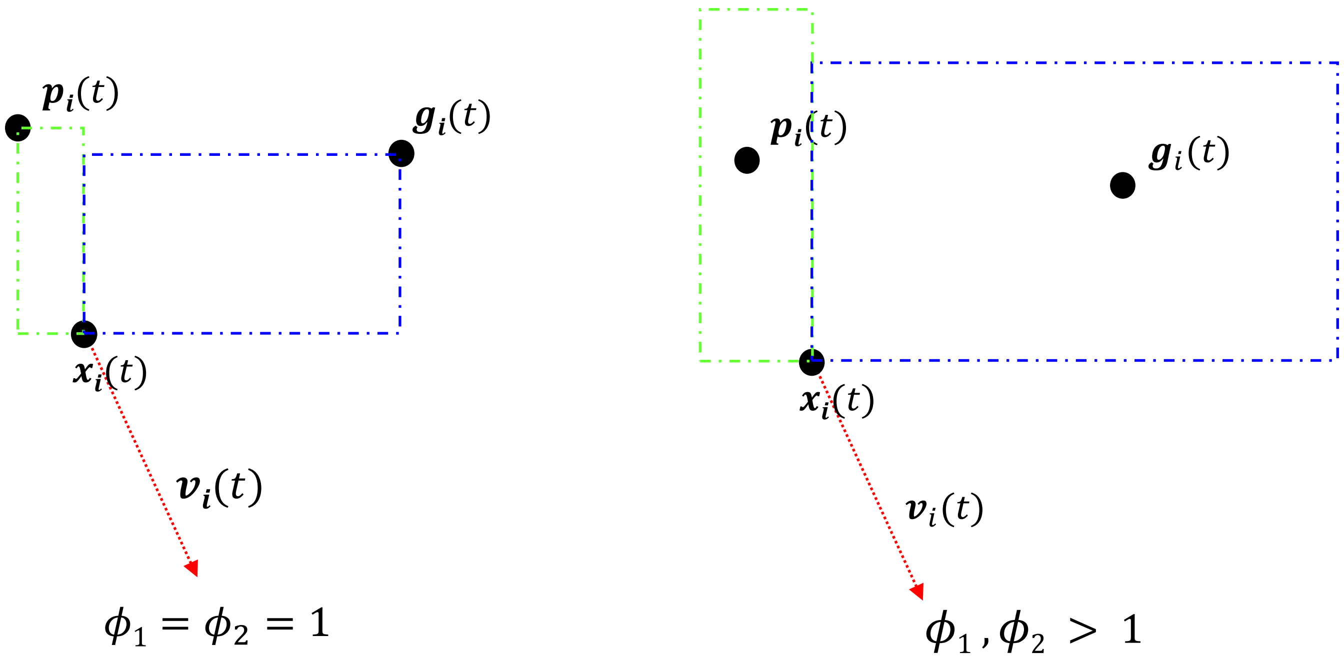
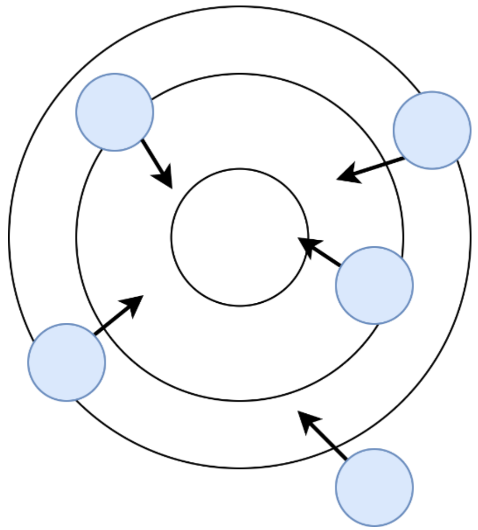
Acceleration Coefficients

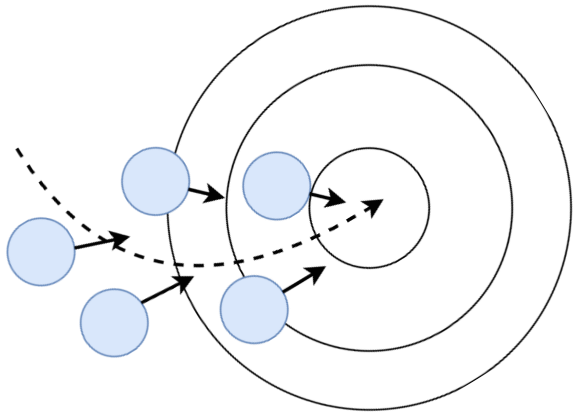
- The boxes show the distribution of the random vectors of the attracting forces of the local best and global best
- The acceleration coefficients determine the scale distribution of the random cognitive component vector and the social component vector



Acceleration Coefficients – Insights

$\phi_1 > 0, \phi_2 = 0$	particles are independent hill-climbers
$\phi_1 = 0, \phi_2 > 0$	swarm is one stochastic hill-climber
$\phi_1 = \phi_2 > 0$	particles are attracted to the average of $\boldsymbol{p}_i$ and $\boldsymbol{g}_i$
$\phi_2 > \phi_1$	more beneficial for unimodal problems
$\phi_1 > \phi_2$	more beneficial for multimodal problems
low ϕ_1, ϕ_2	smooth particle trajectories
high ϕ_1, ϕ_2	more acceleration, abrupt movements

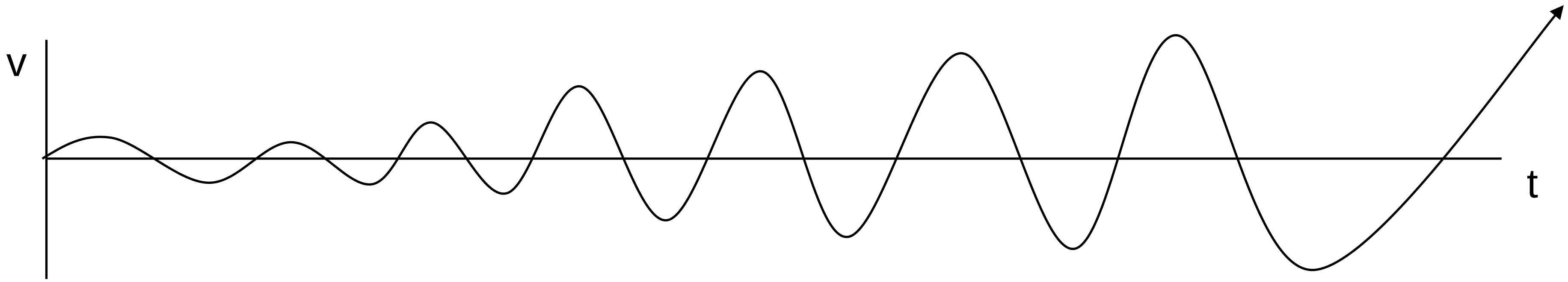




Adaptive acceleration coefficients have also been proposed. For example to have ϕ_1 and ϕ_2 decreased over time

Original PSO - Problems

- The acceleration coefficients should be set sufficiently high
- Higher acceleration coefficients result in less stable systems in which the velocity has a tendency to explode



- To fix this, the velocity $\boldsymbol{v}_i$ is usually kept within the range $[\boldsymbol{v}_{max,} -\boldsymbol{v}_{max}]$
- However, limiting the velocity does not necessarily prevent particles from leaving the search space, nor does it help to guarantee convergence

Inertia weighted PSO

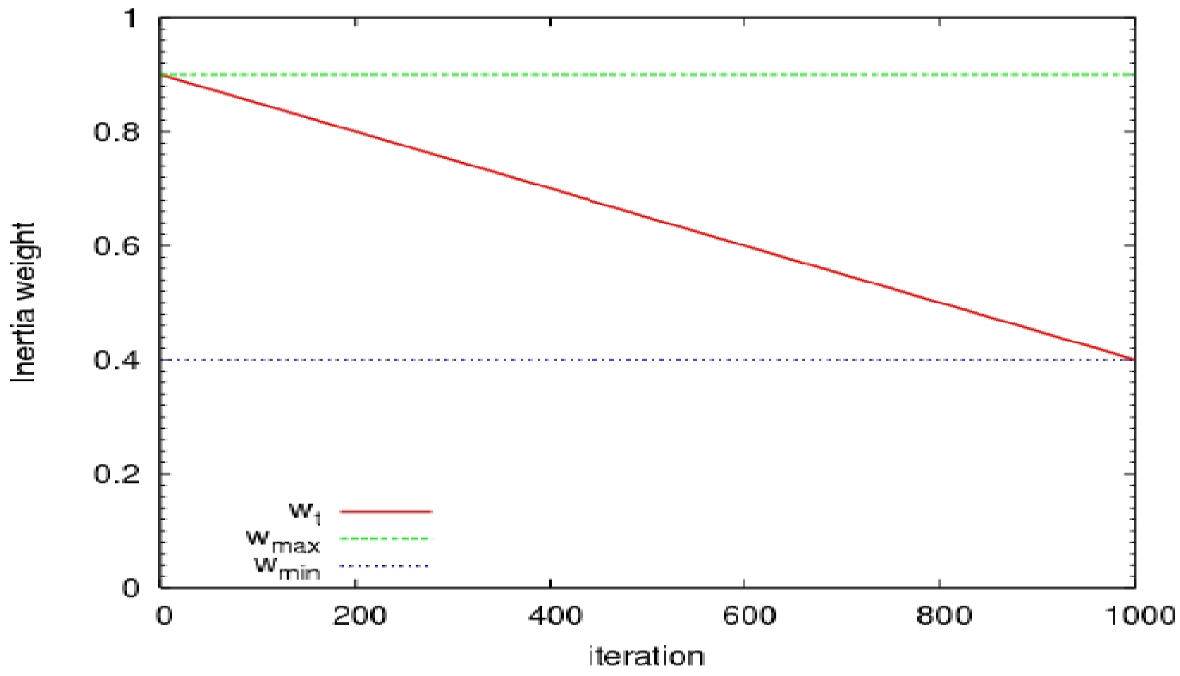
- An **inertia weight** ω was introduced to control the velocity explosion:

$$\vec{\boldsymbol{v}}_i \leftarrow \omega \cdot \vec{\boldsymbol{v}}_i + \boldsymbol{\mathcal{U}}(0, \phi_1) \otimes (\vec{\boldsymbol{p}}_i - \vec{\boldsymbol{x}}_i) + \boldsymbol{\mathcal{U}}(0, \phi_2) \otimes (\vec{\boldsymbol{g}}_i - \vec{\boldsymbol{x}}_i)$$

- If ω, ϕ_1 and ϕ_2 are set correctly, this update rule allows for convergence without the use of v_{max}
- The inertia weight can be used to control the balance between exploration and exploitation:
  - ω ≥ 1: velocities increase over time, swarm diverges
  - 0 < ω < 1: particles decelerate, convergence depends ϕ_1 and ϕ_2
- Rule-of-thumb settings: ω = 0.7298 and $\phi_1 = \phi_2 = 1.49618$

Time Decreasing Inertia Weight

- Eberhart and Shi [1] suggested to decrease ω over time (typically from 0.9 to 0.4) and thereby gradually changing from an exploration to exploitation



- Other schemes for a dynamically changing inertia weight are also possible and have also been tried
- Comparable to cooling scheme from Simulated Annealing

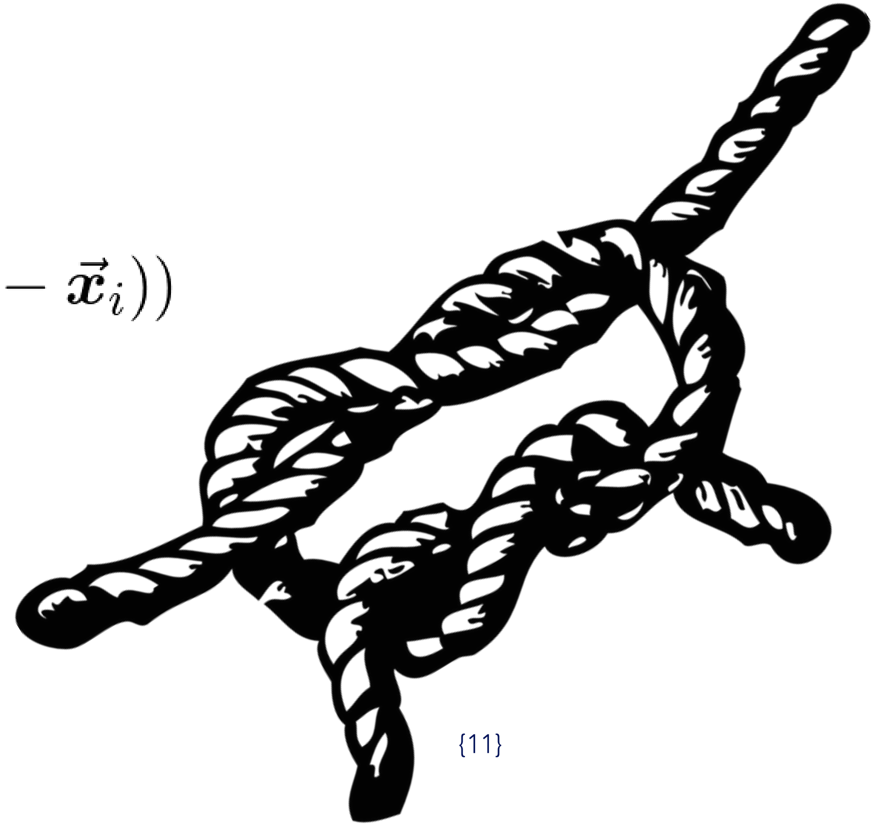
Constricted Coefficients PSO

- Take away some 'guesswork' for setting ω, ϕ_1 and ϕ_2
- An elegant method for preventing explosion, ensuring convergence and eliminating the parameter v_{max}

- The constriction coefficient [2] was introduced as:

$$\vec{\boldsymbol{v}}_i \leftarrow \chi \cdot (\vec{\boldsymbol{v}}_i + \boldsymbol{\mathcal{U}}(0, \phi_1) \otimes (\vec{\boldsymbol{p}}_i - \vec{\boldsymbol{x}}_i) + \boldsymbol{\mathcal{U}}(0, \phi_2) \otimes (\vec{\boldsymbol{g}}_i - \vec{\boldsymbol{x}}_i))$$

With $\phi = \phi_1 + \phi_2 > 4$ and $\chi = \dfrac{2}{\phi + \sqrt{\phi^2 - 4\phi}}$



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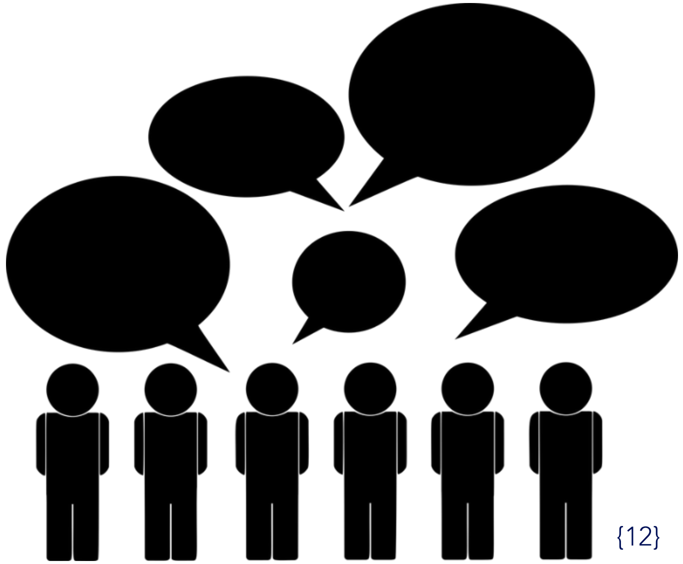
Fully Informed Particle Swarms (FIPS)

- Each particle is affected by **all** of its K neighbors
- The velocity update in FIPS [3] is:

$$\vec{\boldsymbol{v}}_i \leftarrow \chi \cdot \left(\vec{\boldsymbol{v}}_i + \frac{1}{K_i} \sum_{n=1}^{K_i} \boldsymbol{\mathcal{U}}(0, \phi) \otimes (\vec{\boldsymbol{p}}_{nbr_n} - \vec{\boldsymbol{x}}_i) \right)$$

$$\vec{\boldsymbol{x}}_i \leftarrow \vec{\boldsymbol{x}}_i + \vec{\boldsymbol{v}}_i$$



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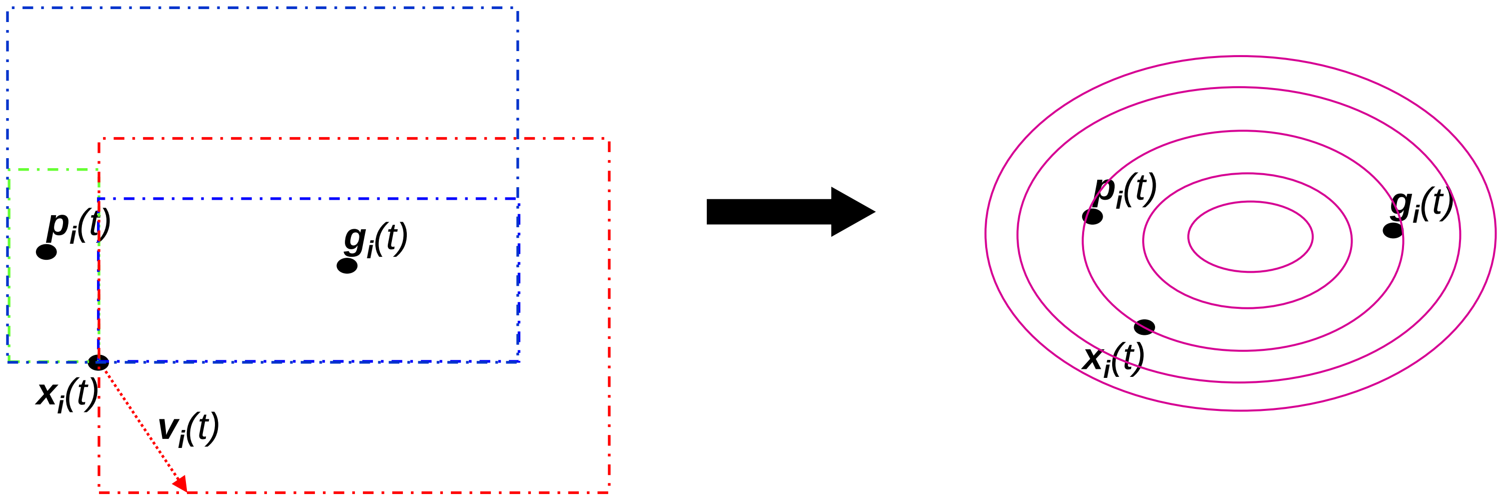
- FIPS outperforms the canonical PSO's on most test-problems
- The performance of FIPS is generally more dependent on the neighbourhood topology (global best neighborhood topology is recommended)

Bare Bones PSO

- Eliminate the velocity update of the particles (with all of its tricky parameter tuning)
- Move particles according to a probability distribution rather than through the addition of velocity [4]

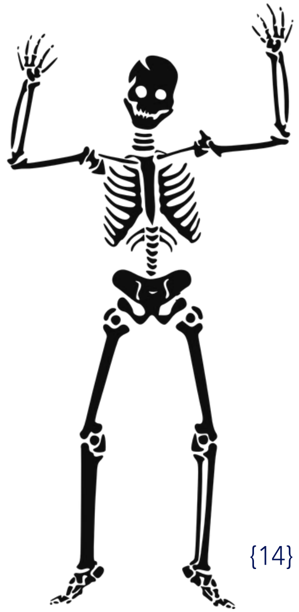


Bare Bones PSO

- Replace the particle update rule with a Gaussian distribution of mean $(p_i + g_i)/2$ and standard deviation $|p_i - g_i|$
- The position update rule in the jth component of the ith particle is:

$$x_{ij} = \mathcal{N}(\mu_{ij}, \sigma_{ij}), \text{ with } \mu_{ij} = \frac{p_{ij} + g_{ij}}{2} \text{ and } \sigma_{ij} = |p_{ij} - g_{ij}|$$

- Works fairly well, but the Gaussian distribution does not seem to be the best probability distribution (also the Lévy distribution has been tried)



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Binary / discrete PSO

- A simple modification for binary search spaces [5]
- Velocity remains continuous using the original update rule
- Positions are updated using the velocity as a probability threshold to determine whether the *j*th component of the *i*th particle is a zero or a one

$$x_{ij} = \begin{cases} 1 & \text{if } \tau < s(v_{ij}) \\ 0 & \text{otherwise} \end{cases}, \quad \text{with } s(v_{ij}) = \frac{1}{1 + \exp\left(-v_{ij}\right)}$$

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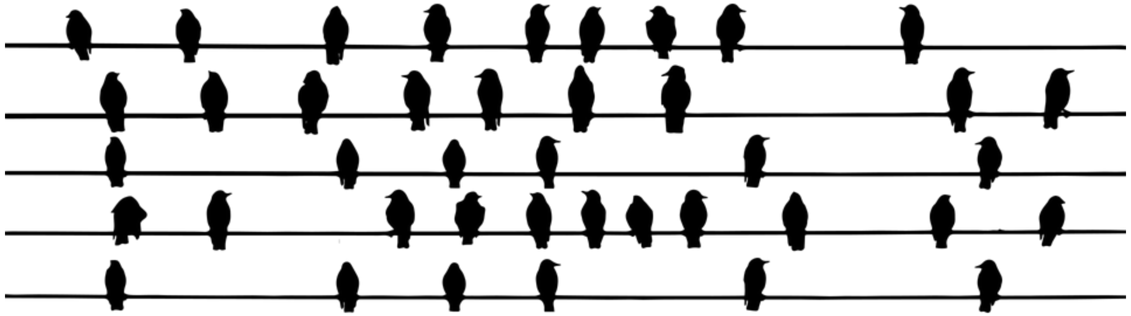

Summary

- Inspired by Boids-simulation
- Swarm-based algorithm for continuous optimization
- Velocity update in 3 components: inertia, cognitive and social
- Social component decided by neighbourhood topology (communication network)
- Acceleration coefficients have a large effect on the behaviour of the swarm
- Many variants of PSO exist

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Questions?

email them to NACO-TA@liacs.leidenuniv.nl
or
post them in Brightspace

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References

- [1] Eberhart, R. C. Shi, Y., 'Comparing inertia weights and constriction factors in particle swarm optimization', vol. 1, pp. 84-88 vol.1 (2000).
- [2] Clerc, M. Kennedy, J., 'The particle swarm - explosion, stability, and convergence in a multidimensional complex space', *EvolutionaryComputation, IEEE Transactions on* , vol. 6, no. 1, 58-73 (2002).
- [3] R. Mendes, J. Kennedy, and J. Neves, "The fully informed particle swarm: Simpler, maybe better," IEEE Trans. Evol. Comput., vol. 8, pp.204–210, June 2004.
- [4] Kennedy, J.: Bare bones particle swarms. In Proc. of the Swarm Intelligence Symposium (SIS 2003), 2003.
- [5] J. Kennedy and R. Eberhart. A discrete binary version of the particle swarm algorithm. In Proceedings of the IEEE International Conference on Systems, Man and Cybernetics, 4104-4108, IEEE Press, 1997
- [6] Kennedy, J. and Eberhart, R.: Particle Swarm Optimization. In Proceedings of the Fourth IEEE International Conference on Neural Networks, Perth, Australia. IEEE Service Center(1995) 1942-1948.
- Reynolds, C.W.: Flocks, herds and schools: a distributed behavioral model. Computer Graphics, 21(4), p.25-34, 1987.
- Riccardo Poli, James Kennedy, Tim Blackwell: Particle swarm optimization. Swarm Intelligence 1(1): 33-57 (2007)

Figure Sources – Swarm Intelligence

{1} https://en.wikipedia.org/wiki/Shoaling_and_schooling#/media/File:Large_fish_school.png
{2} https://upload.wikimedia.org/wikipedia/commons/thumb/9/95/Red-billed_quelea_flocking_at_waterhole.jpg/1200px-Red-billed_quelea_flocking_at_waterhole.jpg
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Figure and Video Sources PSO - I

- {1} https://commons.wikimedia.org/wiki/File:Polistes_nest_2_sjh.JPG
- {2} https://commons.wikimedia.org/wiki/File:Honeybee_thermal_defence01.jpg
- {3} https://upload.wikimedia.org/wikipedia/commons/thumb/9/95/Red-billed_quelea_flocking_at_waterhole.jpg/1200px-Red-billed_quelea_flocking_at_waterhole.jpg
- {4} https://pixabay.com/photos/black-headed-gulls-swarm-1731511/
- {5} https://pixabay.com/photos/termite-hill-ants-landscape-695209/
- {6} https://www.pexels.com/nl-nl/foto/beesten-dieren-dieren-in-het-wild-h2o-2289409/
- {7} https://en.wikipedia.org/wiki/Bait_ball#/media/File:Large_fish_school.png
- {8} https://en.wikipedia.org/wiki/Flock_%28birds%29#/media/File:Starling_flock_with_nearby_predator.jpg
- {9} https://pixabay.com/photos/birds-flock-wings-flying-sky-691274/
- {10} https://vimeo.com/78329987
- {11} https://en.wikipedia.org/wiki/Ant_colony_optimization_algorithms#/media/File:Safari_ants.jpg
- {12} https://pixabay.com/photos/formation-migratory-birds-geese-508038/
- {13} https://pixabay.com/photos/dolphins-fish-mammals-delphinidae-380034/
- {14} https://pixabay.com/photos/dna-3d-biology-genetic-research-5297378/
- {15} https://pixabay.com/photos/lightbulb-concept-cork-bulletin-2692247/

Figure Sources PSO - II

- {16} https://pixabay.com/photos/honey-bees-beehive-honey-bees-326337/
- {17} https://pixabay.com/photos/koi-carp-fish-water-swarm-feeding-3731172/
- {18} https://en.wikipedia.org/wiki/Swarm_behaviour#/media/File:Rail_Bridge_Swarm_of_Starlings._-_geograph.org.uk_-_124591.jpg
- {19} https://en.wikipedia.org/wiki/Swarm_behaviour#/media/File:Salp.jpg
- {20} https://pixabay.com/photos/flock-of-birds-swarm-starling-rome-591334/
- {21} https://pixabay.com/photos/dolphins-water-smooth-calm-ocean-945410/
- {22} https://en.wikipedia.org/wiki/Termite#/media/File:Coptotermes_formosanus_shiraki_USGov_k8204-7.jpg
- {23} https://pixabay.com/photos/apiary-bee-beehive-beekeeping-1867537/