Collective Systems

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Collective Systems

Emergent Collective Behavior

- Some animal societies display coordinated and purposeful navigation of several individuals (from tens to thousands)
- Each individual uses only local information about the presence of other individuals and of the environment
- There is typically no pre-defined group leader

Emergent Collective Behavior

- In some cases, there is a leader and more restrictive rules on relative motion, but individuals still use local information to decide how to move

Autonomous Agent

- A unit that:
  - Interacts with its environment (which probably consists of other agents)
  - Acts independently from all other agents in that they don't take commands from a seen or unseen leader
  - Doesn't have an idea of the global plan it's supposed to be following

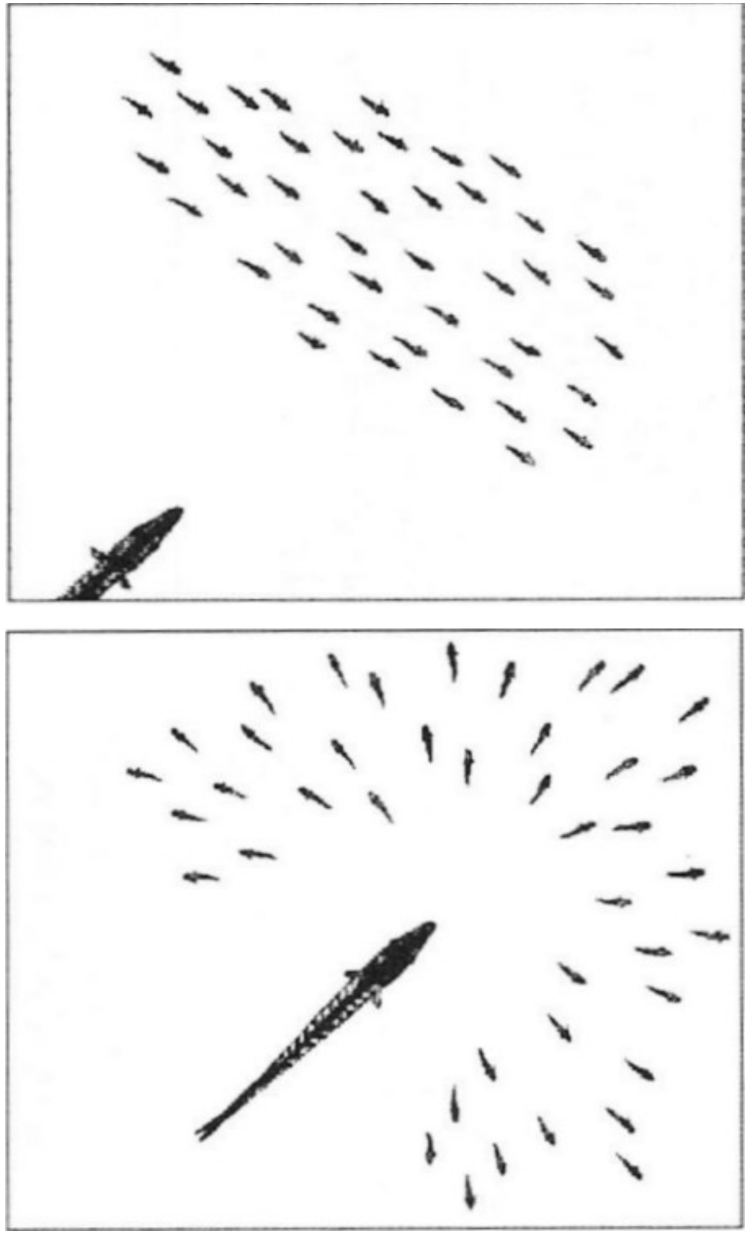
Coordinated Collective Movement

- Groups of animals can behave almost like a single organism
- Can execute swift maneuvers
  - For predation or to avoid predation
- Individuals rarely collide, even in a frenzy of attack or escape
- Shape is characteristic of the species, but flexible
- Why? Adaptive significance
  - Prey avoiding predation
  - More efficient predation by predators
  - Other efficiencies

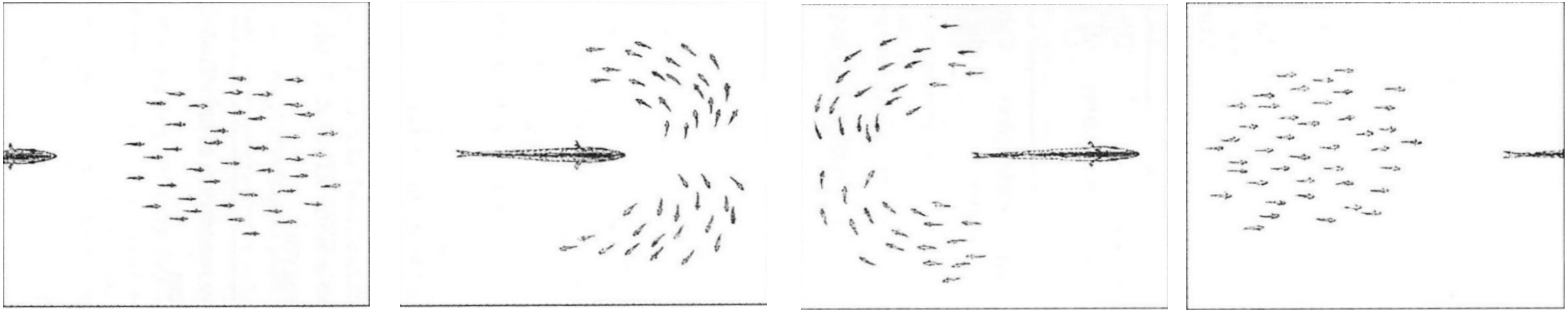
Murmuration

Avoiding Predation

- More compact aggregation
  - Predator risks injury by attacking
- Confusing predator by:
  - United erratic maneuvers (for example, zigzagging)
  - Separation into subgroups (for example, flash expansion and fountain effects)



Avoiding Predation: Fountain Effect



Avoiding Predation

CBS Miami YouTube: https://www.youtube.com/watch?v=DeBd6pmkWuU

Avoiding Predation

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Better Predation

- Coordinated movements to trap prey
  - Parabolic formation of tuna
- More efficient predation
  - Killer whales encircle dolphins
  - Take turns eating

Other Efficiencies

- Fish schooling may increase hydrodynamic efficiency
  - Endurance may be increased up to 6X
  - School acts like "group-level vehicle"
- V-Formation increases efficiency of geese
  - Range 70% greater than that of individual
- Lobsters line up single file by touch
  - Move 40% faster than when isolated
  - Decreased hydrodynamic drag

Characteristic Arrangement of School

- Shape is characteristic of the species
- Fish have preferred distance, elevation, and bearing relative to their neighbors
- Fish avoid coming within a certain minimum distance
  - Closer in larger schools
  - Closer in faster moving schools

What else could be happening besides self-organization?

- “Templates”?
  - There is no evidence that water currents, light, chemicals guide collective movement
- “Leaders”?
  - No evidence for leaders
  - Those in front may drop behind
  - Those on flank may find themselves in front
  - Each adjusts to several neighbors
- “Blueprint” or “recipe”?
  - Implausible for coordination of large schools
    - For example, there are schools with millions of herrings, hundreds of millions of cod

Self-Organization Hypothesis

- Simple attraction and repulsion rules generate schooling behavior
  - Positive feedback: Brings individuals together
  - Negative feedback: But not too close…
- Rules rely on local information only:
  - For example, positions and headings of a few nearby fish
  - No global plan or centralized leader

Mechanisms of Individual Coordination

- Vision
  - Governs attraction and alignment
- Lateral line: sensory organ in fish
  - Sensitive to water movement
  - Provides information on speed and direction of neighbors
  - Governs repulsion and speed matching
- How is this information integrated into behavioral planning?
  - Most sensitive to nearest neighbors

Huth and Wissel (1992) Model

- All fish follow the same rules
- Each uses some sort of weighted average of positions and orientations of nearest neighbors
- Fish respond to neighbors probabilistically
  - Imperfect information gathering
  - Imperfect execution of actions
- No external influences affect fish
  - No water currents, no obstacles, etc.

Range of Behavioral Patterns

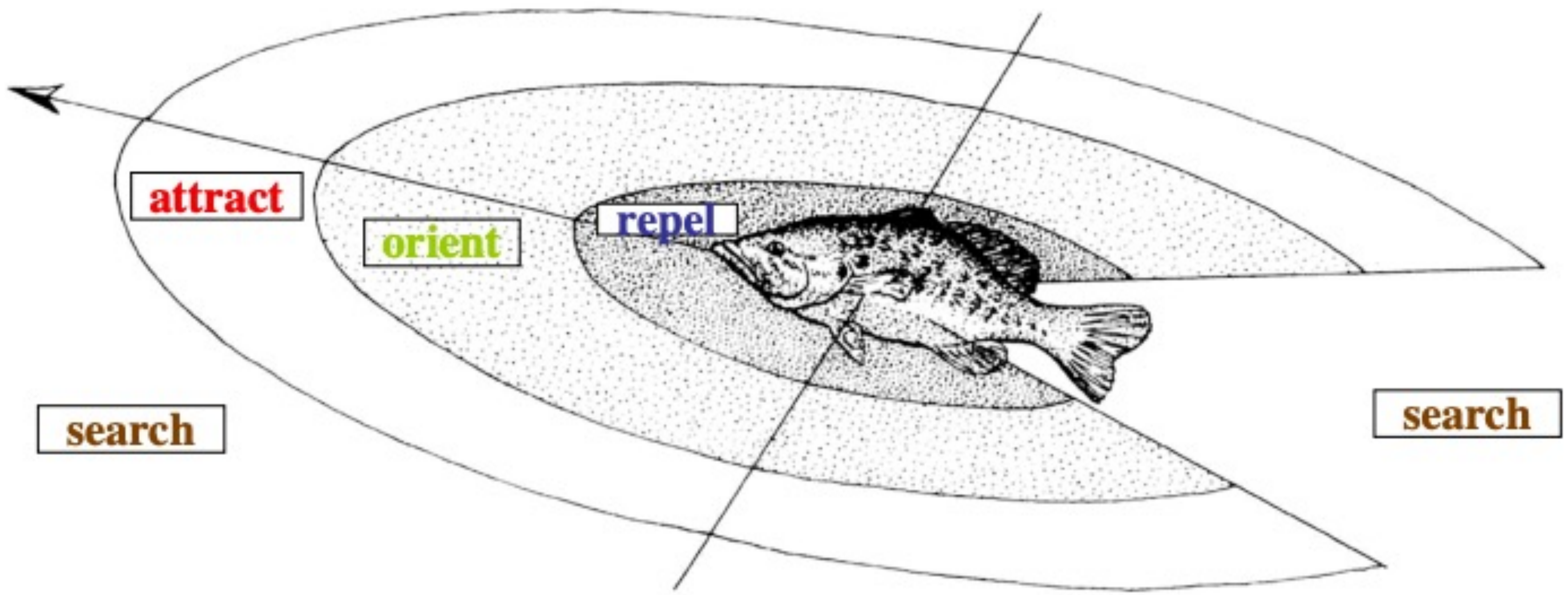


Fig. adapted from Camazine & al., Self-Org. Biol. Sys.

Adapted from Bruce MacLennan's slides on Cellular Automata from his CS420/CS 527 lecture notes

Model of Behavior of Individual

- Determine target direction from each of the three nearest neighbors
  - If it’s in the repel range, then 180 degrees + direction to neighbor
  - If it’s in the orient range, heading of neighbor
  - If it’s in the attract range:
    - Accelerate if it’s ahead, decelerate if behind
    - Return direction to neighbor
  - Else: Return our own current heading
- Determine overall target direction as average of three neighbors inversely weighted by their distances
- Turn a fraction in this direction (determine by flexibility) + some randomness

Limitations

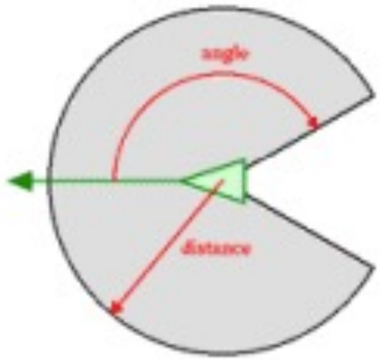
- Model addresses only motion in absence of external influences
- Ignores obstacle avoidance
- Ignores avoidance behaviors such as:
  - flash expansion
  - fountain effect
- Updated version(1997) has addressed some of these issues

Huth-Wissel Schooling Model

Boids

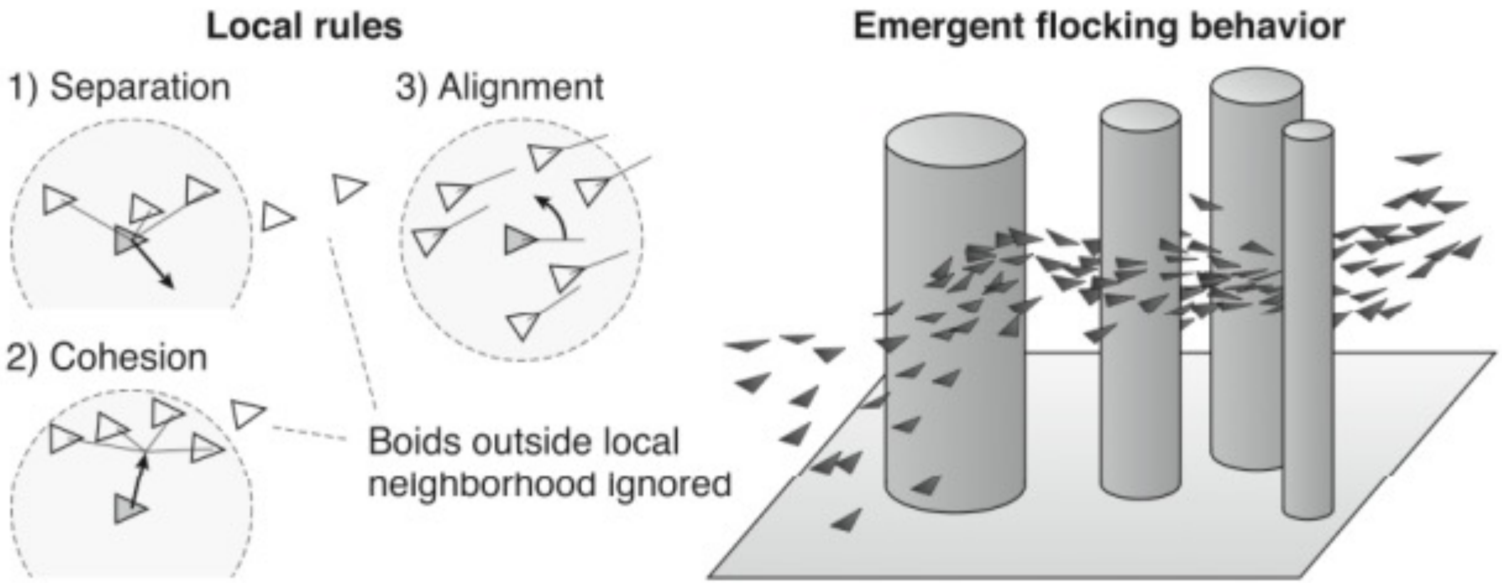
- A model of flocks, herds, and similar cases of coordinated animal motion created by Craig Reynolds in 1986
- Flockmates are those that are within ”vision”
- If nearest flockmate < minimum separation, turn away
- Otherwise:
  - Align with average heading of flockmates
  - Cohere by turning towards average flockmate direction
- All turns limited to a specific maxima
- Note fluid behavior from deterministic rules

Boids



- Sensing: Boid perceives angle and distance of neighboring boids

1. **Separation:** Boid maintains a given distance from other boids
2. **Cohesion:** Boid moves towards center of mass of neighboring boids
3. **Alignment:** Boid aligns its angle along those of the neighboring boids



Boids Example

http://www.netlogoweb.org/launch#http://ccl.northwestern.edu/netlogo/models/models/Sample%20Models/Biology/Flocking.nlogo

Boids Example with Perspective

http://www.netlogoweb.org/launch#http://www.netlogoweb.org/assets/modelslib/Code%20Examples/Perspective%20Demos/Flocking%20(Perspective%20Demo).nlogo

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Question 1

- What is the hypothesis for how swarms/schools operate?
  - A) Leaders
  - B) Blueprint or recipe governed by environment
  - C) Rules based on local information

Particle Swarm Optimization

Particle Swarm Optimization

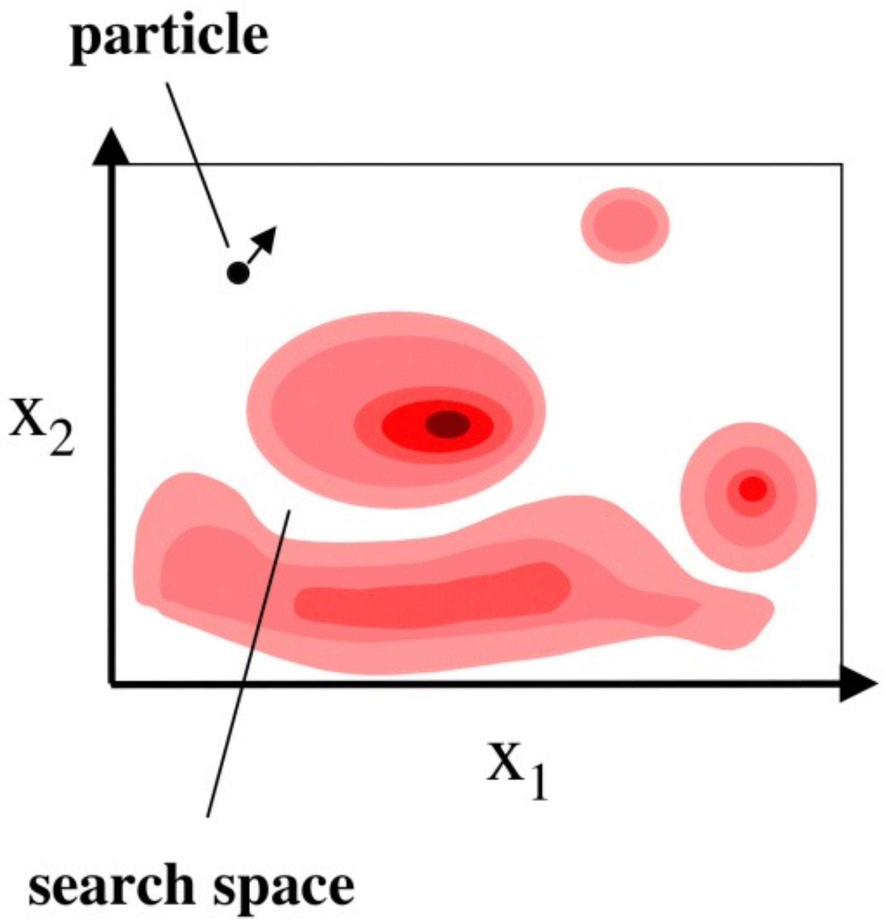
- Particle Swarm Optimization is an optimization algorithm inspired by birds flocking to find the best food area.
- A caricature scenario:
  - The flock wants to find the area with the highest concentration of food (insects).
  - Birds do not know where that area is, but each bird can shout to their neighbors how many insects are at its location.
  - Birds also remember their own location where they found the highest concentration of food so far.
- The flock is most likely to succeed when birds combine three strategies:
  - 1) Brave: keep flying in the same direction
  - 2) Conservative: fly back towards its own best previous position
  - 3) Swarm: move towards its best neighbor

Motivation

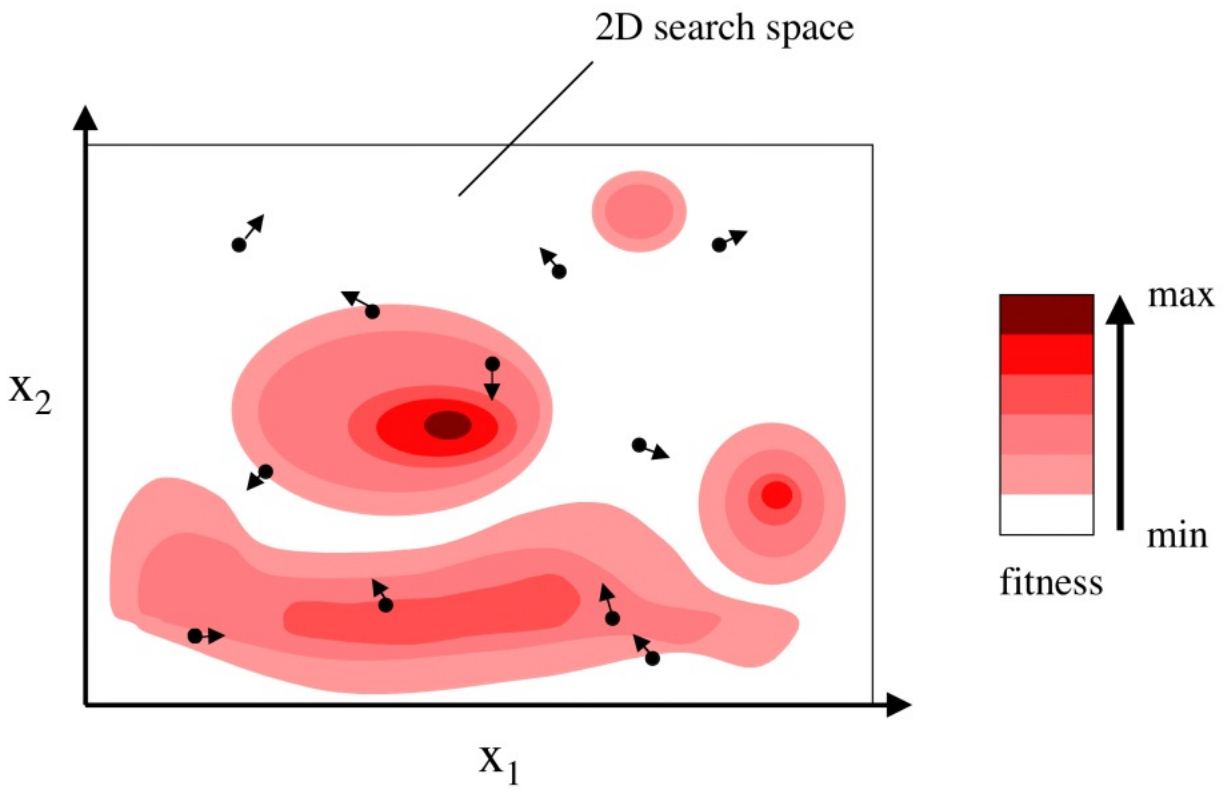
- Originally a model of social information sharing
- Abstract vs. concrete spaces
  - Cannot occupy the same locations in concrete space
  - Can in abstract space (two individuals can have the same idea)
- Global optimum (and perhaps many suboptima)
- Combines:
  - Private knowledge: best solution each has found so far
  - Public knowledge: best solution the entire group has found

From Birds to Particles

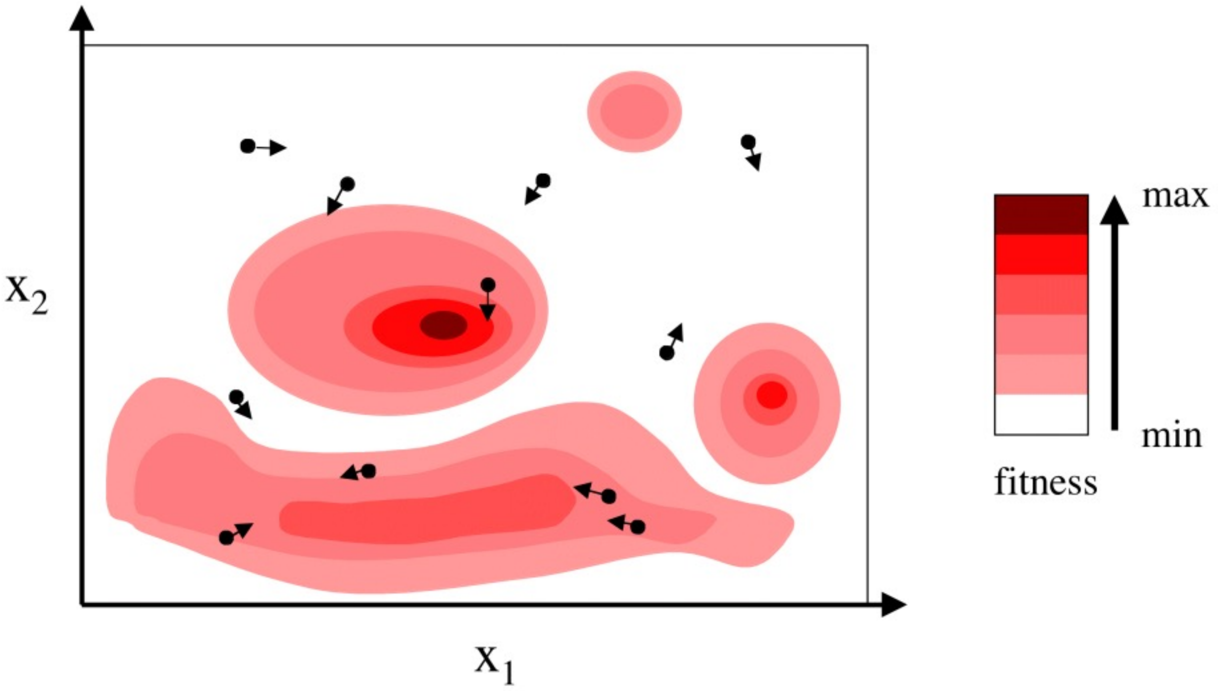
- The food concentration describes the search space of the optimization problem and the birds (particles) are the local solutions for that problem.
- What is a particle?
  - A particle consists of:
    - $\vec{x_i}$ position
    - $\vec{v_i}$ velocity
    - $\vec{p_i}$ best position found so far
    - Velocity and position update rules



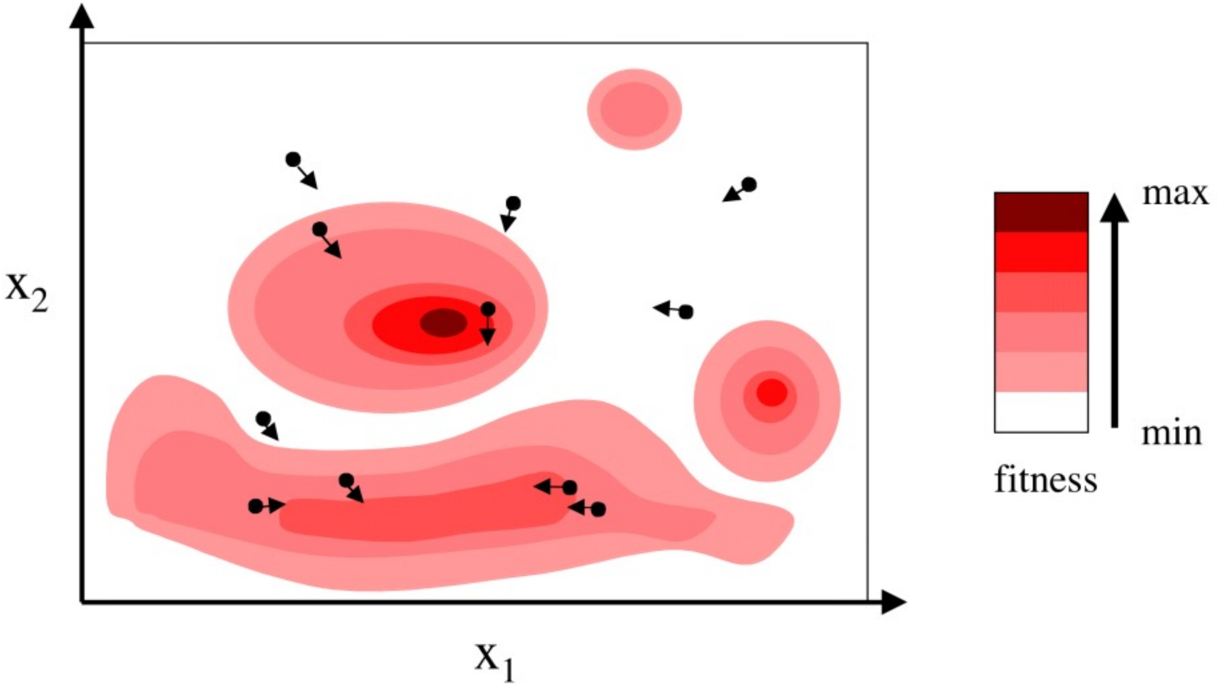
PSO Example



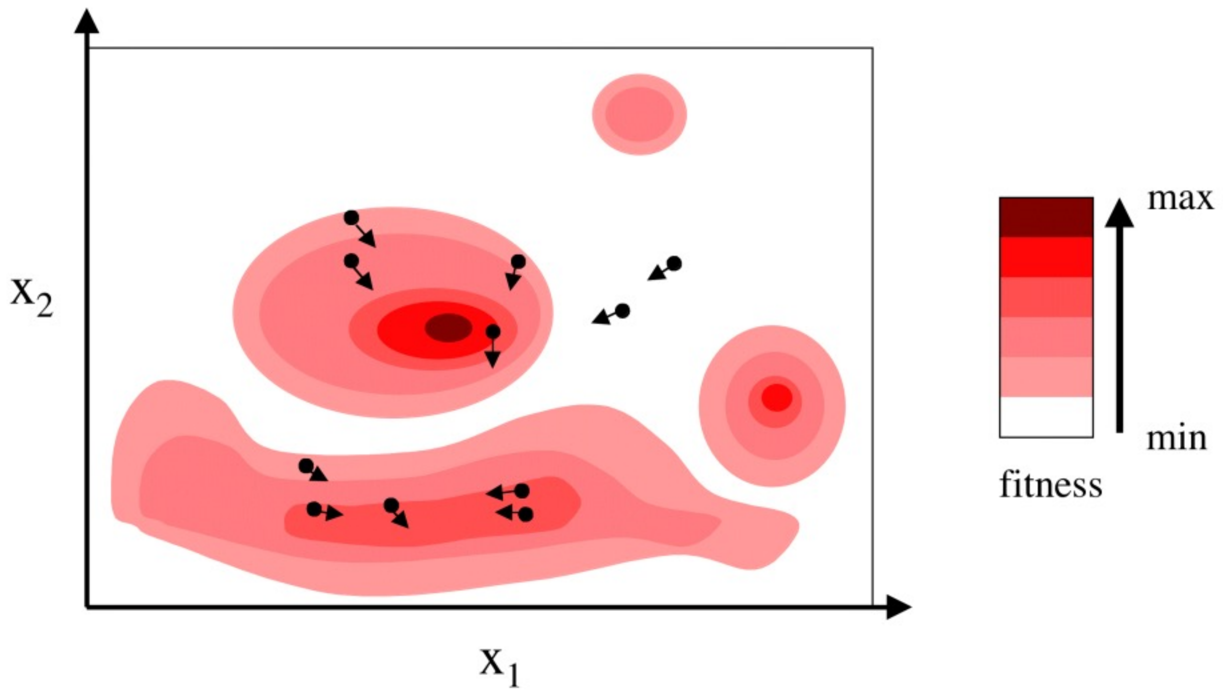
PSO Example



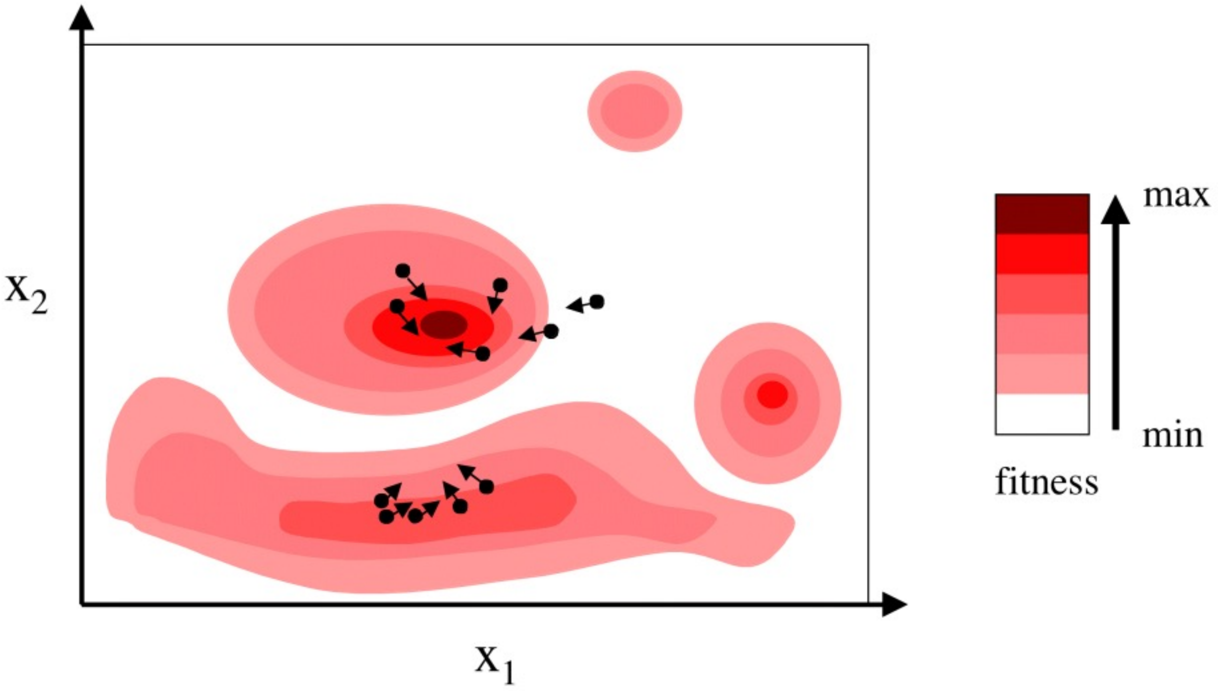
PSO Example



PSO Example



PSO Example



Variables

- $\boldsymbol{x_k}$ = current position of particle *k*
- $\boldsymbol{v_k}$ = current velocity of particle *k*
- $\boldsymbol{p_k}$ = best position found by particle *k*
- $Q(\boldsymbol{x})$ = quality of position $\boldsymbol{x}$
- g = index of best position found so far
  - $g = argmax_k Q(\boldsymbol{p_k})$
- ϕ_1, ϕ_2 = random variables uniformly distributed over [0,2]
- w = inertia < 1

Velocity and Position Updating

- $v'_k = wv_k + \phi_1(p_k - x_k) + \phi_2(p_g - x_k)$
  - wv_k maintains direction (*inertial* part)
  - $\phi_1(p_k - x_k)$ turns toward private best (*cognition* part)
  - $\phi_2(p_g - x_k)$ turns toward public best (*social* part)
  - There's also a random component in each of these!
- $x'_k = x_k + v'_k$
  - Allowing $\phi_1, \phi_2 > 1$ permits overshooting and better exploration (important!)
  - Good balance of exploration and exploitation
  - Limiting $\|v_k\| < \|v_{max}\|$ controls resolution of search

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Question 2

- Particles in particle swarm optimization use only local information
  - A) True
  - B) False

To the Notebook!

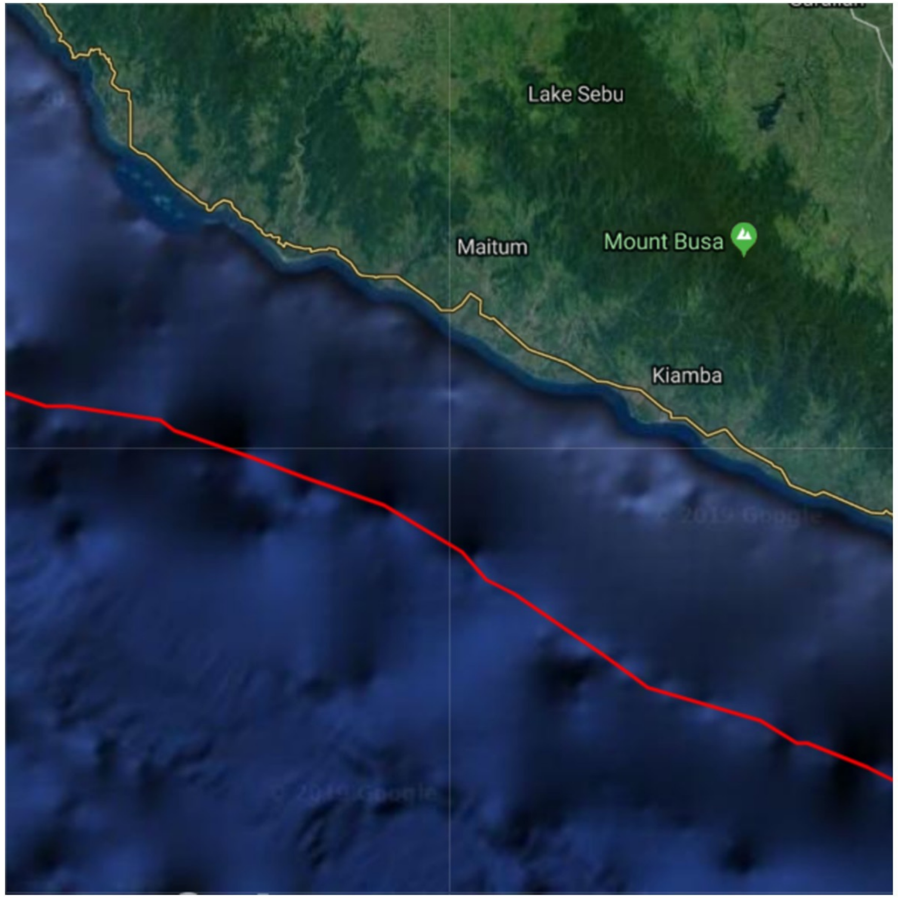
Particle Swarm Optimization

Improvements

- Alternative velocity update equation:
  - $v'_k = \chi[wv_k + \phi_1(p_k - x_k) + \phi_2(p_g - x_k)]$
  - χ = constriction coefficient (controls magnitude of v_k)
- Alternative neighbor relations:
  - Spatial: limited interaction ranges
  - Star: Fully connected (each responds to best of all others)
  - Circle: Connected to K immediate neighbors (slows information flow)
  - Wheel: Connected to one axis particle (moderate information flow)

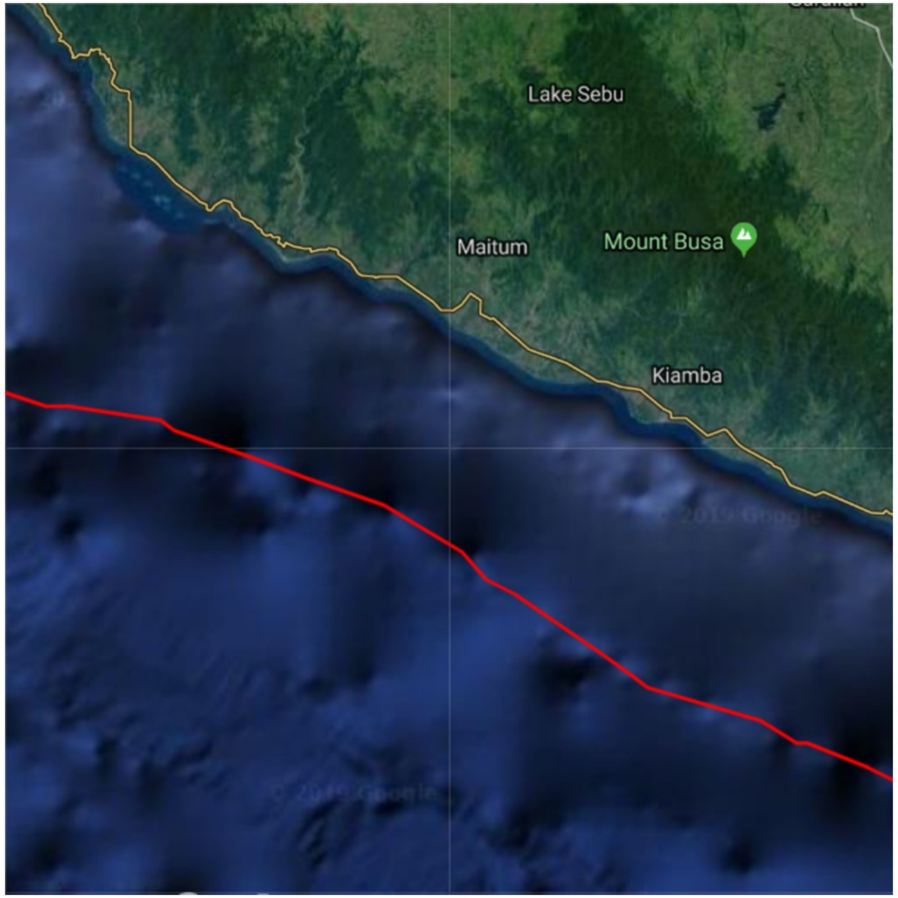
Application of PSO: Optimal placement of tsunami sensors

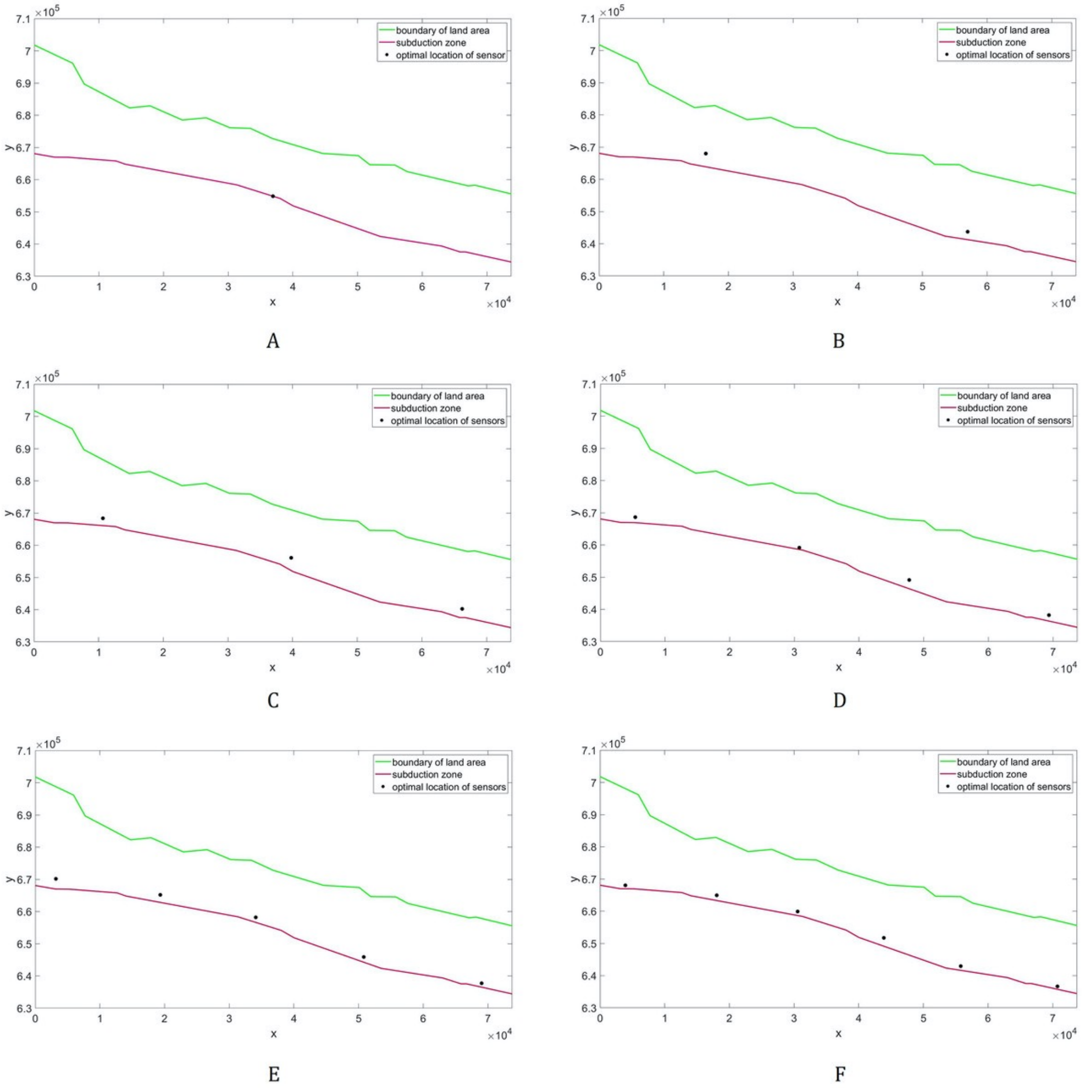
- Rapid detection and early warning systems demonstrate crucial significance in tsunami risk reduction measures.
  - So far, several tsunami observation networks have been deployed in tsunamigenic regions to issue effective local response.
  - However, guidance on where to station these sensors are limited.
- Ferrolino et al. address the problem of determining the placement of tsunami sensors with the least possible tsunami detection time.
  - They use the solutions of the 2D nonlinear shallow water equations to compute the wave travel time.
- They optimized with PSO.
- They used their proposed method to determine the placement of sensors for early tsunami detection in Cotabato Trench, Philippines.



Ferrolino, Angelie, Renier Mendoza, Ikha Magdalena, and Jose Ernie Lope. "Application of particle swarm optimization in optimal placement of tsunami sensors." *PeerJ Computer Science* 6 (2020): e333.

Application of PSO: Optimal placement of tsunami sensors





Ferrolino, Angelie, Renier Mendoza, Ikha Magdalena, and Jose Ernie Lope. "Application of particle swarm optimization in optimal placement of tsunami sensors." *PeerJ Computer Science* 6 (2020): e333.

Application of PSO: Hybrid Wind/Tidal/PV/Battery Energy System

- A new method proposed in this work to optimize the power generated by a hybrid renewable energy system which consists of Wind turbine/Tidal turbine/PV module/Batteries.
- Developed to minimize the cost of energy.
  - The problem is defined as an economic problem, taking into consideration the optimal sizing of the system, high reliability, planning expansion for future development, the state of charge of the battery.
  - The total net present cost (TNPSC) is introduced as the objective function, taking into consideration the minimum fitness values in the particle swarm process.
- This system has been designed to satisfy a stand-alone area in Brittany, France, as an example of load demand.

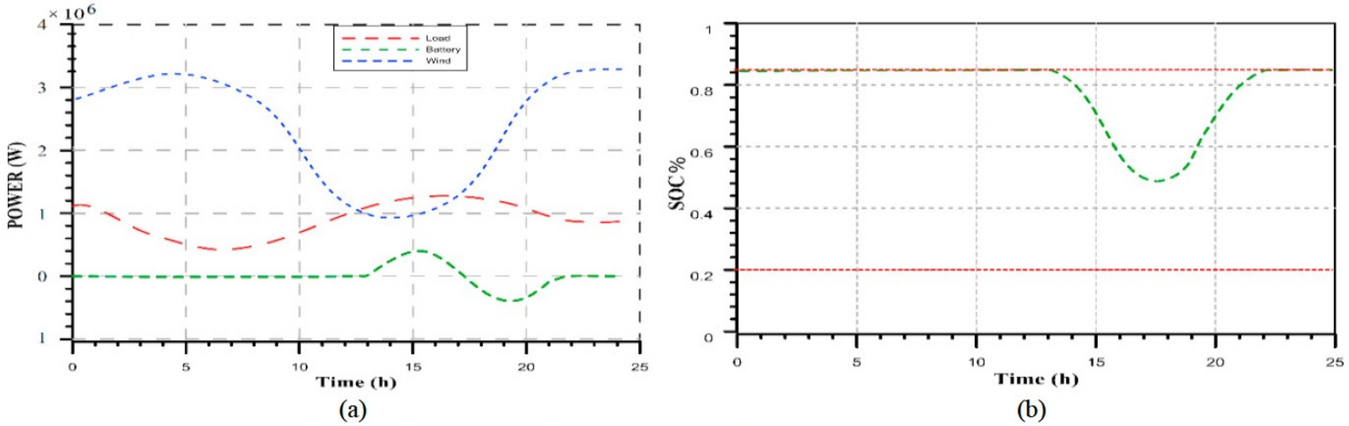


Fig. 2 Optimal results scenario 1 (a) Variation in power generation, load, and battery energy (b) Variation in battery SOC

Mohammed, Omar Hazem, Yassine Amirat, and Mohamed Benbouzid. "Particle swarm optimization of a hybrid wind/tidal/PV/battery energy system. Application to a remote area in Bretagne, France." *Energy Procedia* 162 (2019): 87-96.

PSO vs. Artificial Evolution

- As in artificial evolution, PSO works with a population and some random factor to update solutions
- Contrary to artificial evolution, there is no generation change, no genome, and no competition among the individuals
  - Cooperation instead!
- A major issue in PSO is to transform the parameters of the problem to be solved so that it can be encoded and searched by particles

Lab 4: Particle Swarm Optimization

Lab 4 Summary

- ***Due March 31***
- In this lab, you will be investigating the effect of the parameters of particle swarm optimization on the performance of the algorithm for two classic optimization problems: the Rosenbrock function and the Booth function.
- The particle swarm optimization code we implemented has been expanded and provided to you to use for the lab, though you will need to update it to switch between Rosenbrock and Booth.

Lab Code

Experimental Setup

- The parameters that we will be varying and studying the effect of are:
  - Number of particles (default = 40)
  - Inertia (default = 0.5)
  - Cognition parameter (default = 1)
  - Social parameter (default = 1)
- Unlike the evolutionary algorithms lab, you will fix all but one of the parameters to their defaults and varying each one in isolation at a time to evaluate the effect on performance.

Experimental Setup

- These are the values you should examine for each parameter value (again, keeping all other parameters fixed to their default when you're varying them):
  - Number of particles: 10 to 100, in increments of 10
  - Inertia: 0.1 to 1, in increments of 10
  - Cognition parameter: 0.1 to 4 in increments of 0.1
  - Social parameter: 0.1 to 4 in increments of 0.1
- Because random initialization impacts performance, you should run at least 20 tests for each parameter combination.

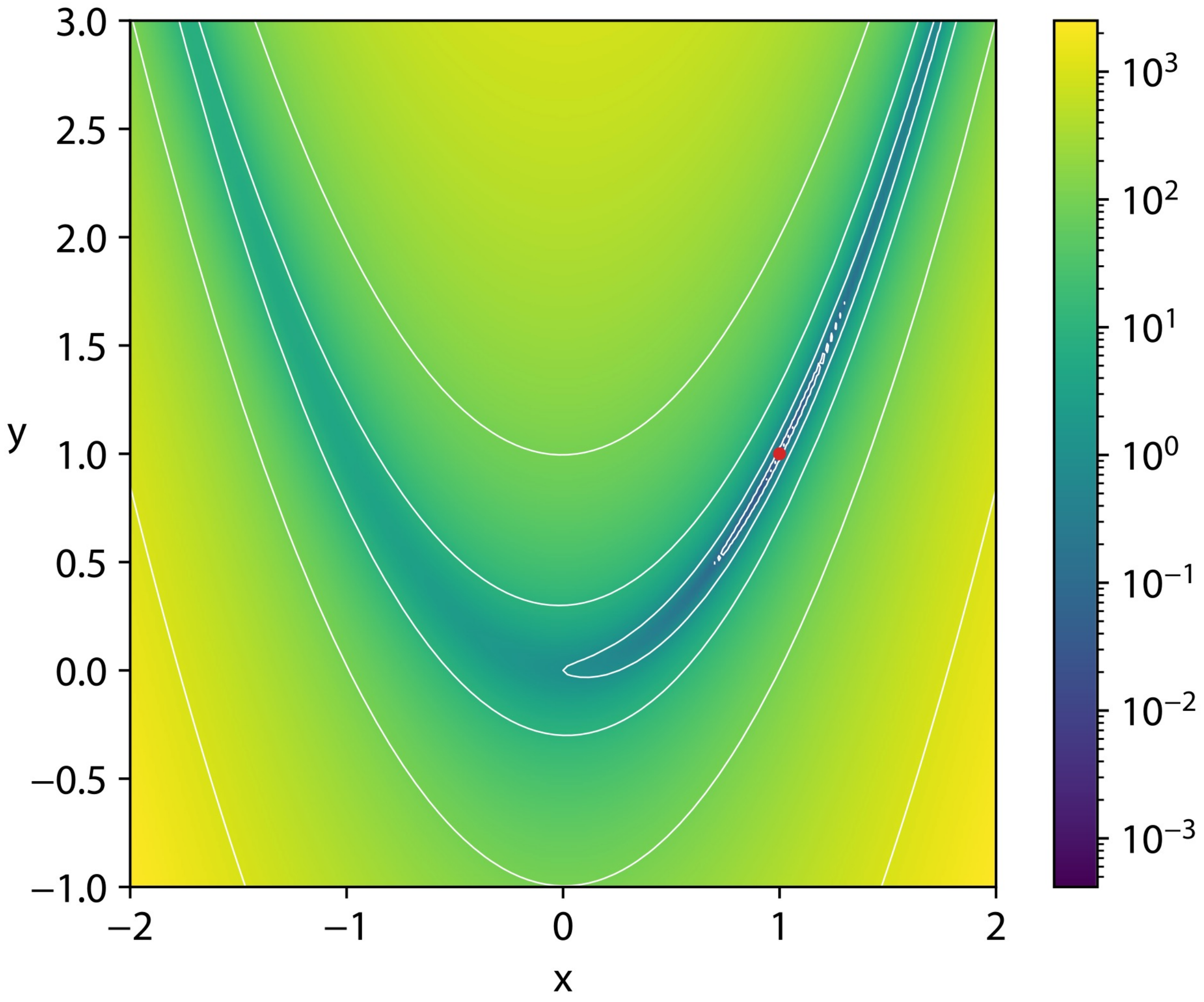
Notes on Convergence

- The provided code prints the arguments used in evaluation, the number of epochs to convergence (which is capped at 1000), the solution that it converged to, and the fitness value of that solution.
- Note that it's possible that the algorithm will NOT converge to the actual solution in some cases.
- The correct solution for both problems is a fitness value of 0.
- If the values are sufficiently different (i.e., the fitness value is greater than 1e-10), then the algorithm has NOT converged to the actual solution.

Rosenbrock Function

$$f(x, y) = (1 - x)^2 + 100(y - x^2)^2$$

Solution is f(1,1) = 0



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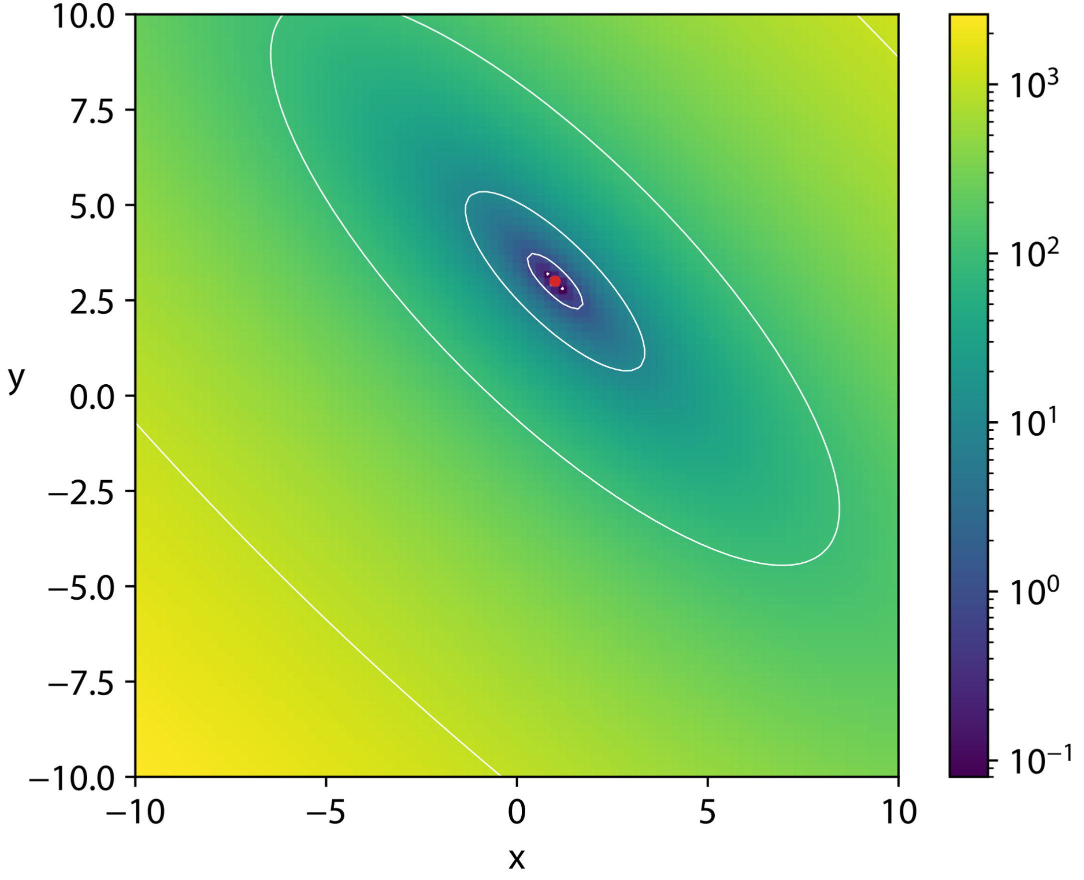
Booth Function

$$f(x, y) = (x + 2y - 7)^2 + (2x + y - 5)^2$$

Solution is f(1,3) = 0



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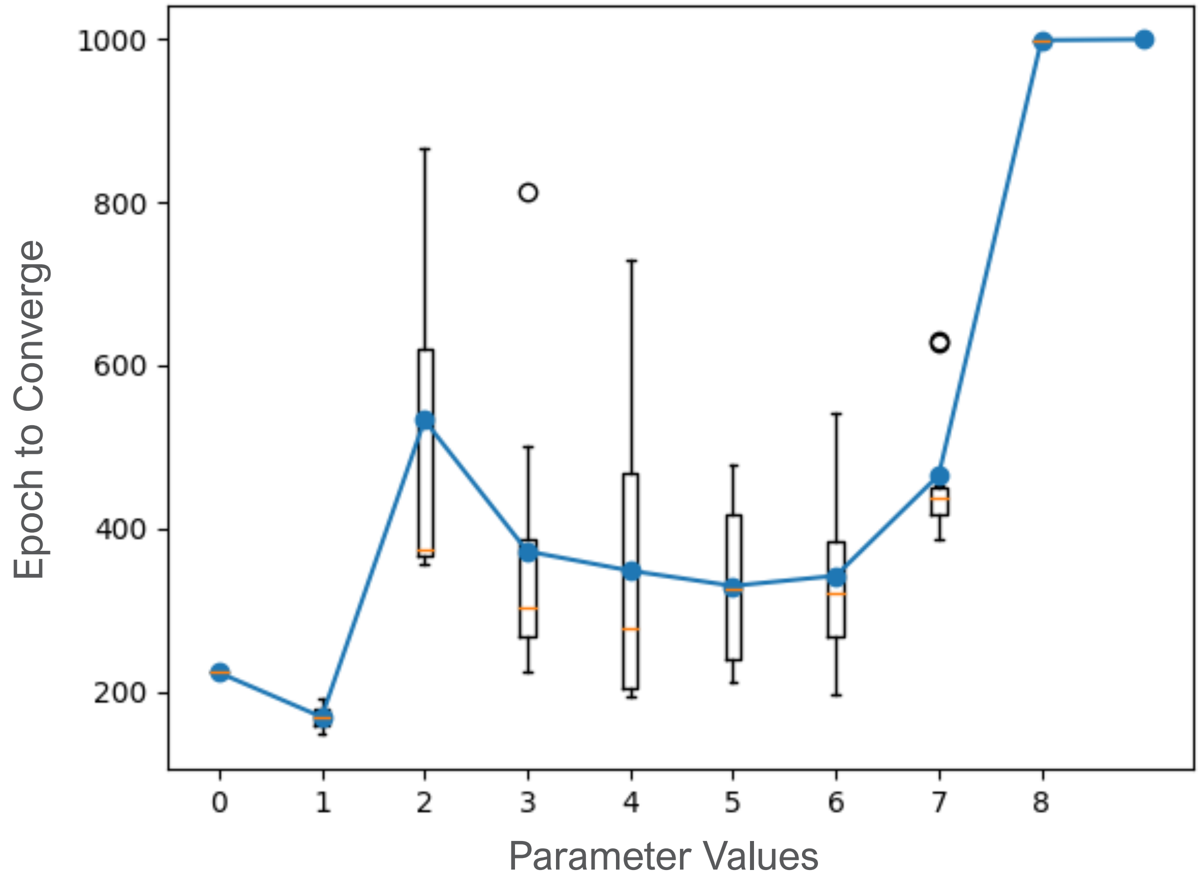
CS 527 Credit

- In addition to the previously mentioned, you will evaluate how the cognition and social parameters varying ***together*** affect performance.
- You will evaluate all combinations of the cognition and social parameters (0.1 to 4 in increments of 0.1).

Graphs

- You will create a plot for each of the four parameters and each problem (eight total) where the x-axis is the parameter value and the y-axis is the number of epochs to convergence.
- You ***should not*** include the tests that did not converge to the correct solution in these plots.
- You should show a boxplot for each of the values.
- Additionally, you should plot a point for the mean convergence epochs for each parameter value and connect those with a line plot (see lecture notes for an example).

Example Graph



Graphs

- You will also create a plot for each parameter (up to eight, up to four for each problem) depicting the number of runs that did not converge to the correct solution.
- If every run converged for all parameter values, note that in your report and omit the figure.
- You may use a line plot, bar chart, or any other plot type of your choosing to depict these results.

CS 527 Graphs

- You will create up to four heatmaps indicating how the performance of the social and cognition parameters interact.
- The first set of two heatmaps will show the mean number of epochs to convergence for each combination of values (omitting those that did not converge to the correct solution) for each problem.
- If any of the runs did not converge for each problem, you will create a second heatmap showing the number of runs that did not converge to the correct value for each combination.

Discussion Questions

- How big of an impact can parameter selection have on performance?
- Do there appear to be optimal values for each parameter? Are the “best” performing values (i.e., those that converge the fastest) the same for each problem?
- Why do some values perform better than others?
- **CS 527**: How do the social and cognition parameters interact with each other? Should one be set higher than the other? Should they be changed proportionally?

CS 420 Grading

- **64 points total:** 16 points for each set of plots created for each parameter value (up to eight total plots for each parameter value).
- **36 points total:** 12 points for each discussion question.
- **Total: 100 points**
- For CS 420, if you complete the social/cognition parameter analysis, that will be an additional 15 points.

CS 527 Grading

- **40 points total:** 10 points for each set of plots created for each parameter value (up to eight total plots for each parameter value) for the CS 420 portion of the project.
- **20 points total:** 10 points for each heatmap set.
- **40 points total:** 10 points for each discussion question.
- **Total: 100 points**

Pop Quiz!

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Question 3

- The primary difference between evolutionary approaches and particle swarm is:
  - A) Population vs. individual
  - B) Random vs. no random
  - C) Competition vs. cooperation

Announcements

- Next time: More inspiration from nature!
  - Insect swarms and collectives inspiring a variety of optimization approaches!
- Reminders:
  - My office hours will be virtual only today
  - We’ll be back in person again on Thursday
  - Final project topics are due on March 31