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Tutorial on Particle Swarm Optimization

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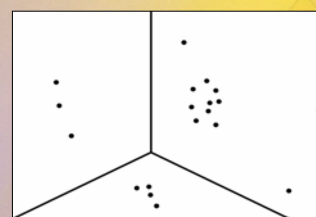
Particle Swarms

Part 1: Sociocognitive Optimization



Artificial Intelligence

Attempted to elicit intelligence from a computing machine by simulating human thought – good idea!

Early AI derived in the Dark Ages of psychology, when study of mind was taboo in science. Based on naïve introspectionism.

Computational Intelligence

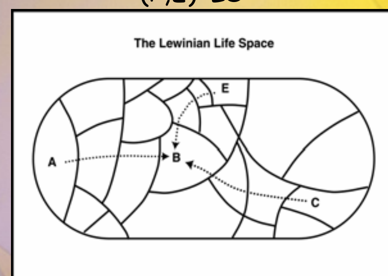
Perhaps we can apply more scientific concepts of mind.

- Self-report gives an unsatisfactory account of “real” cognition
- Sociocognition: thought as a social act
- Self-organization of societies, cultures

Sociocognition

Spanos
Levine, Resnick, and Higgins
Lewin's topological space

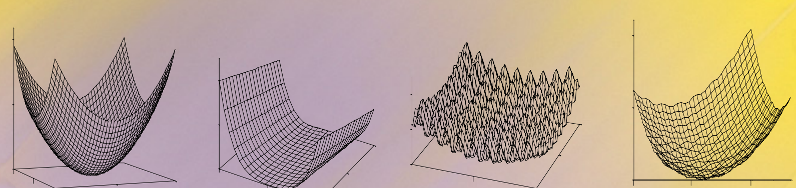
B=f(P,E)
(P,E)=LS



Cognitive Dissonance

Hypothesis 1: There are two major sources of cognition, namely, own experience and communication from others.

Leon Festinger, 1954/1999, *Social Communication and Cognition* (draft)

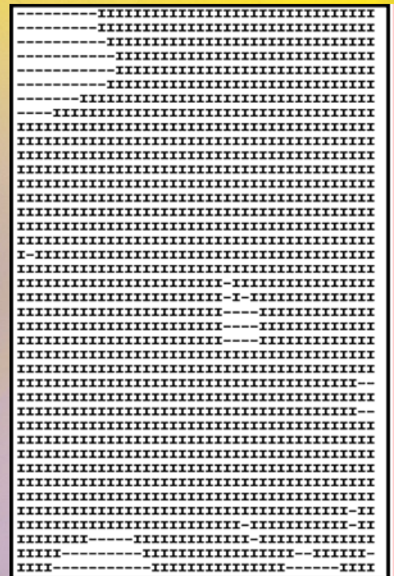


- Types of cognitive relations
- Minimization of dissonance
- Fundamental Attribution Error
- Exploration/exploitation

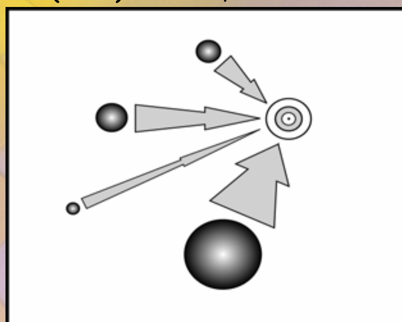
Note: vector=point

Latané's Social Impact Theory

Nowak, Szamrej, and Latané
Psychological Review, 1990



$i=f(SIN)$; $i=sN^t$, $t<1$



Latané (1981)

Complex Adaptive Systems

Complexity (NK landscapes)

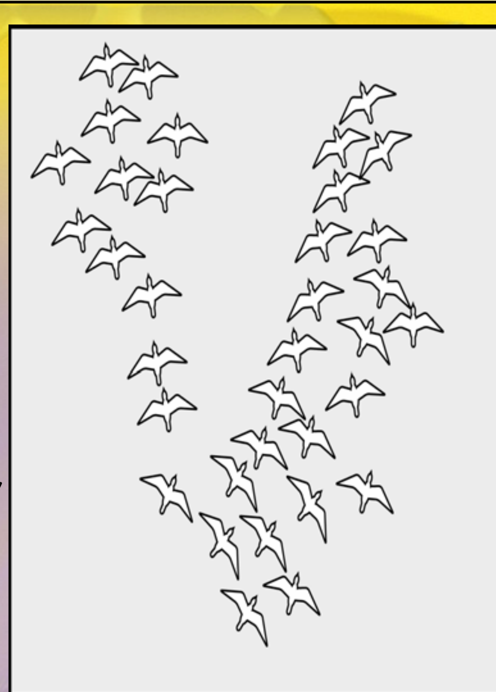
Self-organization
Emergence
(Immergence – downward causation)

Cellular automata
- Fixed point attractors
- Periodic attractors
- Chaotic attractors
- The "edge of chaos"

The Game of Life
Alife

Flocks, Herds, and Schools

- Heppner & Grenander
- Craig Reynolds



- Steer toward the center
- Match neighbors' velocity
- Avoid collisions
- (Seek roost)

Evolutionary Computation

Emulates natural evolution to "breed" solutions to hard problems, write computer programs, build robots, etc.

Population of proposed problem solutions

Variation operators
- Mutation
- Crossover

Selection

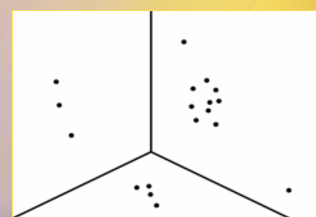
D.T. Campbell: "Blind variation and selective retention"

Particle Swarms

Sociocognitive space

- Certainly high-dimensional (i.e., Burgess & Lund)
- Abstract – attitudes, behaviors, cognition
- Heterogeneous with respect to evaluation (dissonance)
- Multiple individuals

Individual has position="mental state": $\vec{x}_i$
Individual changes: $\vec{v}_i$



Particle Swarms

Individuals learn from their own experience

$$\begin{cases} \vec{v}_i \leftarrow \vec{v}_i + U(0,\varphi) \otimes (\vec{p}_i - \vec{x}_i) \\ \vec{x}_i \leftarrow \vec{x}_i + \vec{v}_i \end{cases}$$

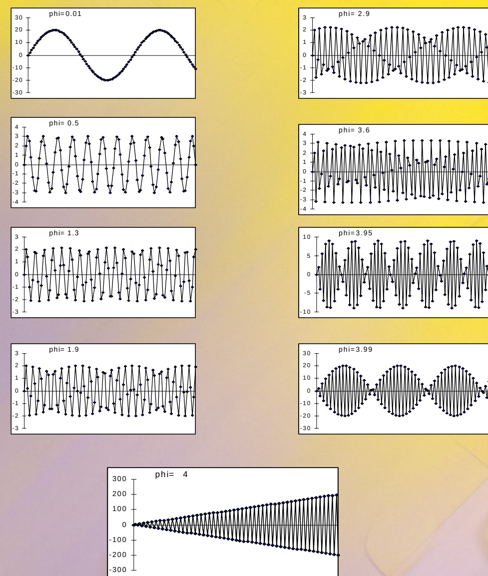
```
for i=1 to popsize
  for j=1 to dimension
     v[i][j]=v[i][j]+rand()*(p[i][j]-x[i][j])
     x[i][j]=x[i][j]+v[i][j]
  next j
next i
```

This formula, iterated over time, causes each individual *i*'s trajectory to oscillate around its previous best point p_i in the sociocognitive space.

It stochastically adjusts *i*'s velocity depending on previous successes, and occasionally updates p_i – the previous best.

Oscillating trajectories (nonstochastic)

$$\begin{cases} \vec{v}_i \leftarrow \vec{v}_i + (\vec{p}_i - \vec{x}_i) \\ \vec{x}_i \leftarrow \vec{x}_i + \vec{v}_i \end{cases}$$



Particle Swarms

Sociocognitive space can contain many individuals
They influence one another

$$\begin{cases} \vec{v}_i \leftarrow \vec{v}_i + U(0, \frac{\varphi_1}{2}) \otimes (\vec{p}_i - \vec{x}_i) + U(0, \frac{\varphi_2}{2})) \otimes (\vec{p}_g - \vec{x}_i) \\ \vec{x}_i \leftarrow \vec{x}_i + \vec{v}_i \end{cases}$$

(g is neighborhood best)

Evaluate your present position
Compare it to your previous best and neighborhood best
Imitate self and others

The "Drunkard's Walk"

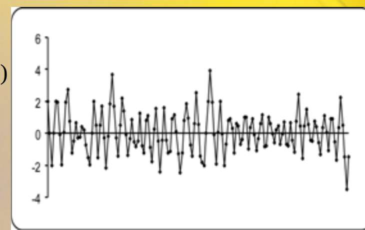
The particle will explode out of control if it is not limited in some way. Three methods have been widely used:

Vmax

$$v_{id} = v_{id} + U(0,\frac{\varphi_1}{2}) \otimes (p_{id} - x_{id}) + U(0,\frac{\varphi_1}{2}) \otimes (p_{gd} - x_{id})$$

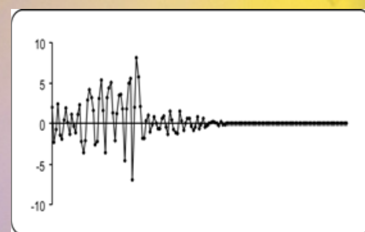
$$if\ v_{id} > V\max\ then\ v_{id} = V\max;$$

$$else\ if\ v_{id} < -V\max\ then\ v_{id} = -V\max$$



Inertia weight

$$v_{id} = \alpha\, v_{id} + U(0,C_1) \otimes (p_{id} - x_{id}) + U(0,C_2) \otimes (p_{gd} - x_{id})$$



Constriction coefficient

$$v_{id} = \chi(v_{id} + U(0,\frac{\varphi_1}{2}) \otimes (p_{id} - x_{id}) + U(0,\frac{\varphi_2}{2}) \otimes (p_{gd} - x_{id}))$$

(note that these last two are equivalent)

Binary Particle Swarms

$$\begin{cases} \vec{v}_i \leftarrow \vec{v}_i + U(0,\frac{\varphi_1}{2}) \otimes (\vec{p}_i - \vec{x}_i) + U(0,\frac{\varphi_1}{2}) \otimes (\vec{p}_g - \vec{x}_i) \\ if\ \vec{U}(0,1) < s(\vec{v}_i)\ then\ \vec{x}_i = 1 \\ else\ \vec{x}_i = 0 \end{cases}$$

(Usu. Vmax, too)

where $s(v) = \dfrac{1}{1+\exp(-v)}$

logistic function
keeps it in (0..1)

Kennedy and Eberhart (1997)
Kennedy and Spears (1998)

Being looked at closely, expanded

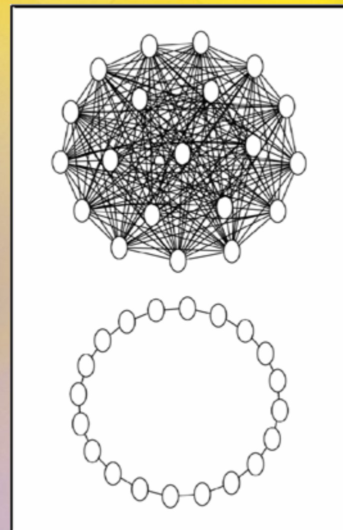
Topology

Traditional ones: gbest, lbest

Topology determines how solutions
spread through the population.

Gbest: immediate
Lbest: slowed

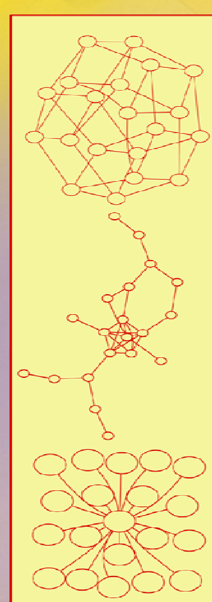
Affects the rate of convergence, parallelism of the search

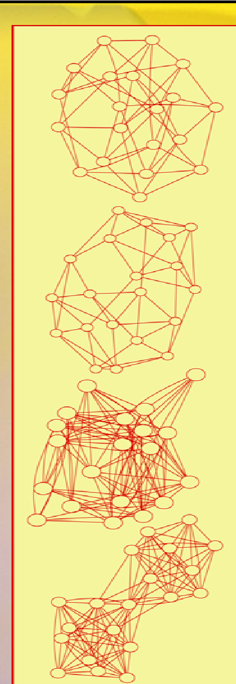


Innovative topologies

Lots of variables to work with:

- Mean degree
- Clustering
- Heterogeneity





FIPS

"Fully Informed Particle Swarm" (Rui Mendes)

Should become the new standard

Distributes total φ across *n* terms

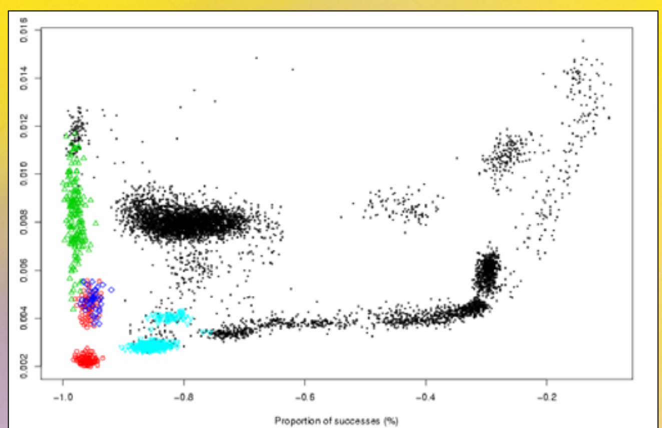
$$\vec{v}_i \leftarrow \chi\left(\vec{v}_i + \sum_{n=1}^{N_i} \frac{U(0,\varphi)\otimes(\vec{p}_{nbr(n)} - \vec{x}_i)}{N_i}\right)$$

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

Best neighbor is not selected
Individual not included in neighborhood
Dependent on topology

FIPS Results

Two performance metrics



Red: Topologies with average degree in the interval (4, 4.25).

Green: Topologies with average degree in the interval (3, 3.25) and clustering coefficient in the interval (0.1, 0.6).

Blue: Topologies with average degree in the interval (3, 3.25) and clustering coefficient in the interval (0.7, 0.9).

Light Blue; Topologies with average degree in the interval (5, 6) and clustering coefficient in the interval (0.025, 0.4).

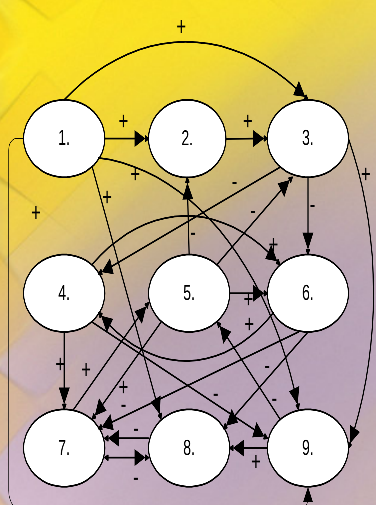
Black: All other topologies.

Evolutionary Computation and Particle Swarms

Culture as evolution (anthropology)
Adaptation / learning
Memetics
Evolutionary epistemology

Change vs. selection
Fitness and dissonance
Cooperation vs. competition

"Cultures"

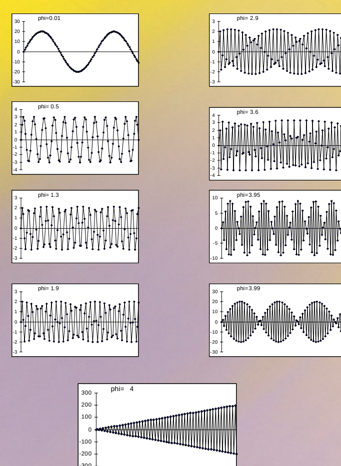


Kosko's "South African" FCM

1 1 1 1 0 0 0 1 1
1 1 1 1 0 0 0 1 1
1 1 1 1 0 0 0 1 1
1 0 0 1 1 1 1 0 0
1 0 0 1 1 1 1 0 0
1 0 0 1 1 1 1 0 0
1 0 0 1 1 1 1 0 0
1 1 1 1 0 0 0 1 1
1 1 1 1 0 0 0 1 1
1 1 1 1 0 0 0 1 1

The Future of Particle Swarms

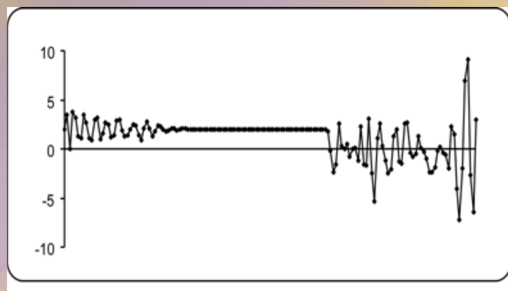
Trajectory Analysis



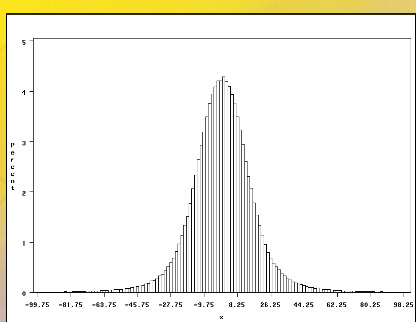
Includes constriction, inertia, convergence, etc.

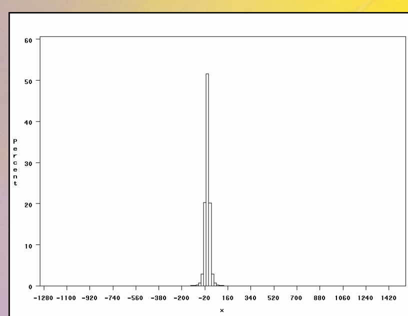
Interaction Analysis

Individual trajectories very weak.
Optimization is a function of interparticle interactions.
The swarm as a whole, and as an aggregation of subpopulations
Effect on trajectory when new “bests” are found
“Immergence” and the effect of culture.



Probability Distribution Analysis





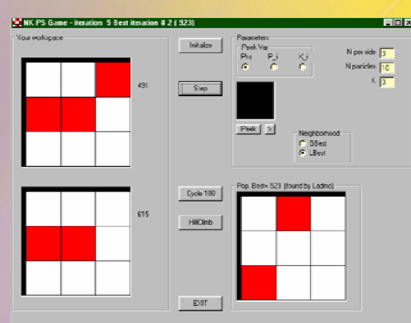
Theory: PS’s place among the EAs
Practice: New versions

Parameters, Conditions, & Tweaks

Initialization methods
Population size
Population diameter
Absolute vs. signed velocities
Population topology
Births, deaths, migration
Limiting domain (XMAX, VMAX)
Multiobjective optimization
“Subvector” techniques
Comparison over problem spaces
Hybrids

Particle Swarms As a General Problem-Solving Methodology

Out of the computer...
Replace eval() with human
Replace particles with humans
Networked computers (with or without users)
Scientific research strategy
Management & innovation



Sociocognition

Particle swarms as social-psychological theory
Not just “what,” but “why”
Social behavior → improved knowledge → adaptation
PS as a “simulation”