Particle Swarm Optimization vs. Genetic Algorithms

A Really Information-Sparse Paper

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Particle Swarm Optimization (PSO)

$$v_{id} = w * v_{id} + c_1 * rand() * (p_{id} - x_{id}) + c_2 * Rand() * (p_{gd} - x_{id})$$
(1)

$$x_{id} = x_{id} + v_{id} \tag{2}$$

w: inertial weight

v_{id}: velocity of particle i in the dth dimension

 c_1, c_2 : multipliers

x_{id}: current position of particle i in the dth dimension

p_{id}: best previous position of particle i in the dth dimension

p_{gd}: best global position of particle i in the dth dimension

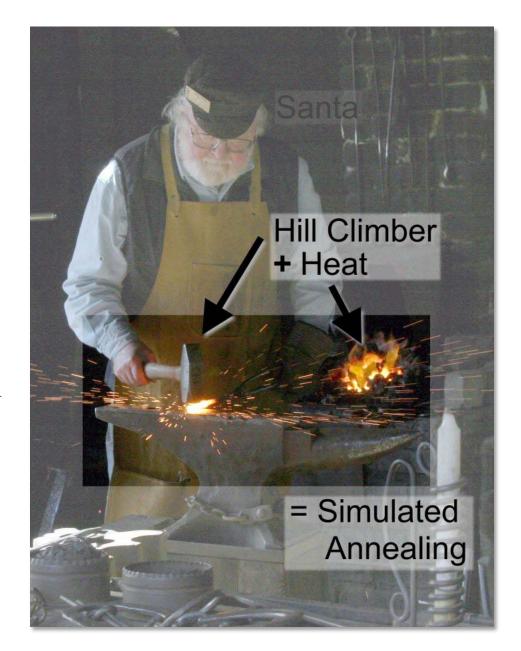


PSO Modifications

- Inertial weight, w, multiplied by the velocities of each particle
 - This allows for control over the long-range vs. fine detail discoveries
 - More inertia implies that the history of previous velocity decisions plays more of a role, creating longer ranged particles seeking nonlocal optima
 - Less inertia suggests shorter range, used for fine grain and local optimization

PSO

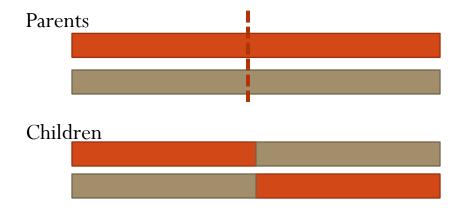
- It is possible to use *w* to model simulated annealing
 - By decreasing the value of w over a run, the system will start out looking very globally and slowly shift to looking locally



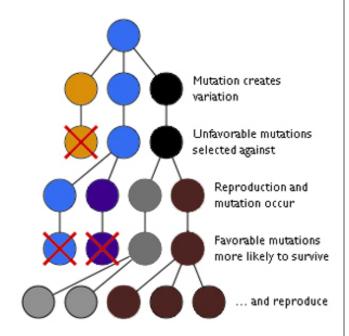
Genetic Algorithms (GA)

- Driven by
 - **Mutation** generation to generation changes
 - **Selection** selection of the *best* specimens
 - Crossover the rules by which chromosomes transfer from parents to offspring

Crossover:

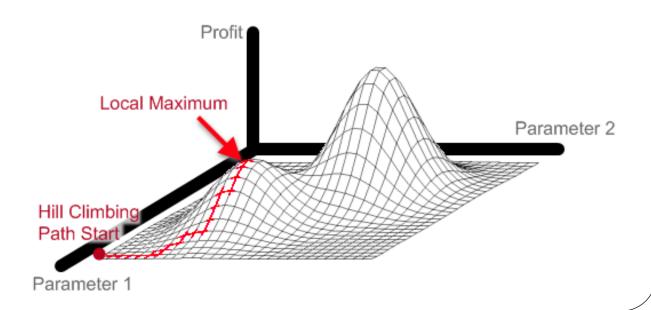


Mutation & Selection:



PSO and GA

- Both approaches struggle with local optima
- Approaches have been developed to overcome this
 - (PSO) High inertial weighting
 - (GA) High mutation rate



Eberhart and Shi

- "The crossover concept is also apparent in the behavior of particles that appear approximately midway between swarms of particles that are clustering around local best positions, or, occasionally, between successive global best positions"
- Most of the content in this paper is common sense or a trivial implication thereof

Qurdstrongs?

