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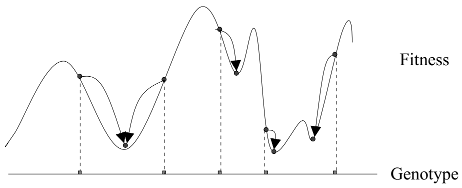
Combining local search with evolutionary search

References: Belew and Mitchell (eds) "Adaptive Individuals in Evolving Populations", 1996; Evolutionary Computation, Vol 4, #3, 1996, special issue on the Baldwin Effect, Belew 1989, Ackley and Littman, 1991.

It is often useful to combine genetic algorithms with local algorithms. These are sometimes called memetic algorithms.

- Evolutionary search moves members of the population near local optima
- Local search takes them the rest of the way.



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Sometimes called "memetic" algorithms.

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Darwinian or Lamarkian

Which strings should go into the next population?

- The strings modified by local search? (Lamarkian)
- The strings unmodified by local search? (Darwinian)

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The case for Lamark

Reference: Hart and Belew, 1996. Looked a simple problem

Objective function:

$$f_\sigma = \frac{\sigma}{4000}\sum_{i=1}^{n} x_i^2 + \left(1 - \prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right)\right).$$

Local search: Conjugate gradient and Solis-Wets.

GA-Local search hybrids: compared the Lamarkian and Darwinian approaches.

Results: Lamarkian approaches were significantly better than the other approaches in most of the trials. Darwinian was better when the local searches were infrequent.

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Interpretation: Initially, the population is distributed across the state space. With a GA alone, it would correlate around one peak. With frequent local searches, the population remains more diverse; Lamarkianism enhances this.

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The case for Darwin

References: Wales and Doye, 1999

Observation: Darwinian combining of evolutionary and local search is equivalent to modification of the objective function.

Interpretation: All strings within a basin of attraction of an optima have the same effective objective function. Thus, the population remains more diverse.

Application: Finding clustering structure of atoms, genetic algorithm/local search hybrids are among the most successful algorithms. Wales and Doye introduce the *basin-hopping* algorithm which implements this objective function modification in simulated annealing.

Results: Are comparable to the genetic algorithm.

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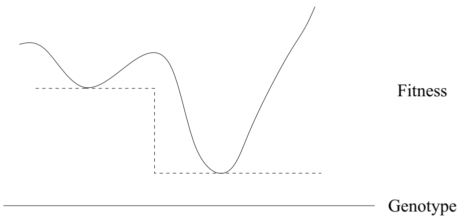

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The Baldwin Effect

J. M. Baldwin, 1896

Interaction of learning and evolution could lead to indirect inheritance of acquired characteristics.

Two steps

1. Plasticity (e.g. learning) can increase fitness of partial mutation (otherwise useless).
2. Genetic assimilation — adaptation becomes genetically encoded and innate.
   - plasticity has costs.

Seemingly Lamarkian, but no transfer of information from soma to germ cell.

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Hinton - Nowlan Model (1987)

Genotype: string of 1's, 0's, ?'s ($L = 20$).

$$101??0?1\cdots$$

Phenotype: Perceptron with 0-1 weights.

Ideal phenotype: Perceptron with all weights equal to 1.

Plasticity: Randomly assign 1 or 0 to each ? weight. 1000 trials.

Fitness:

$$20 - \frac{19}{1000}\text{min}\,[\#\text{ trials to find ideal}, 1000]$$

Learning has a cost.

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Without learning: A needle in a haystack problem; solution is never found.

With learning: Search problem is smoother. Ideal solution found after about 10 generations ($N = 1000$). Proportion of ?'s in genotype decays to zero; proportion of 1's goes to 1.

Conclusions:

- Learning guides evolution.
- With plasticity, evolution can work even where only a perfect solution imparts fitness advantage (J. M. Smith).