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Part III
Co-evolutionary learning

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June 18, 1999

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Co-evolutionary learning

Co-evolution: 2 or more populations

- simultaneously evolving
- whose fitnesses are interdependent

Ubiquitous in nature, obviously.

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Evolution of sorting networks

Hillis (1990, 1992) used an evolutionary algorithm to search for minimal sorting networks.

Task: Find a network which will sort any list of 16 elements in the fewest number of comparisons

Best Known Networks

1962	Bose and Nelson	65
1964	Batcher, Knuth	63
1969	Shapiro	62
1969	Green	60

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Hillis's Evolutionary Algorithm

Evolves a list of comparisons

$$(11,5),(7,9),(14,4),\ldots$$

(no attempt to parallelise)

Uses a "diploid" representation

$$\begin{array}{lcccc}
\text{chrom A:} & (11,5), & (7,9), & (14,4), & \ldots \\
\text{chrom B:} & (11,5), & (2,7), & (3,12), & \ldots \\
 & \downarrow & \downarrow & \downarrow & \\
 & (11,5) & (7,9),(2,7) & (14,4),(3,12), & \ldots
\end{array}$$

Fitness: Percentage of test cases correctly sorted.

- no advantage for short lists, except through stability to mutation

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Other features: Performed on a connection machine, on grid using mutation, crossover, and selection.

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Hillis's claim

"Co-evolving parasites improve simulated evolution as an optimisation procedure"

Parasites — set of 10–20 test cases

- parasites evolve via similar GA
- Fitness of a parasite — the number of sorting networks which fail to sort it

Result: A "Biological Arms Race" which leads to the claim above.

Shortest network: Without parasites: 65; with parasites: 61.

This claim has been widely repeated and increasingly applied.

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Problems with Hillis's co-evolution

Red Queen Effect: Mitchell et. al. (unpublished) and Paredis (1997) observed this in evolving cellular automata.

- Co-evolution makes the outcome much worse
- two populations oscillate between two very poor solutions
- Use of fitness-sharing can correct this (Juille and Pollack, 1998).

The sorting problem: It has been argued that this was a very easy task as set up by Hillis (Tufts and Juille 1994, Baum et. al. 1995.) Hillis hard-wired the 32 compares to be those used in most other good networks (the Butterfly). The remaining states reduce to a small number of equivalence classes.

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Co-evolutionary learning with multiple species

A more general case of co-evolution is that of a population in which the fitness is relative to and dependent on the other individuals in the population. Examples include:

Economic modelling: Agents which act as economic entities and buy or sell stock (Palmer et. al. 1991); or evolve bidding strategies (Miller 1993).

Agents which evolve strategies: Evolution of strategies in the prisoner's dilemma game (Axelrod, 1987, Lindgren 1992), learning of strategies by competition (Rosen, 1995), Robo-soccer.

Modelling ecosystems: Artificial life models including ECHO (Holland, Jones, Forrest, 1994) and Tierra (Ray, 1992)

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Conclusions

- Hillis's idea of data-learner co-evolution is not yet known to be useful. Perhaps a co-operative heuristic or some other method should be used.
- Multi-species co-evolution is widely used in modelling populations, economies, societies, etc. Can this be used for learning complex multi-agent systems?