

Co-evolution – with animats in pursuit-evasion

... and in an application to 'sorting networks'

D. Cliff and G. F. Miller

“Co-Evolution of Pursuit and Evasion II: Simulation Methods and Results”. In

P. Maes, M. Mataric, J.-A. Meyer, J. Pollack, and S. W. Wilson (eds) From Animals to Animats 4

MIT Press Bradford Books, pp.506-515, 1996.

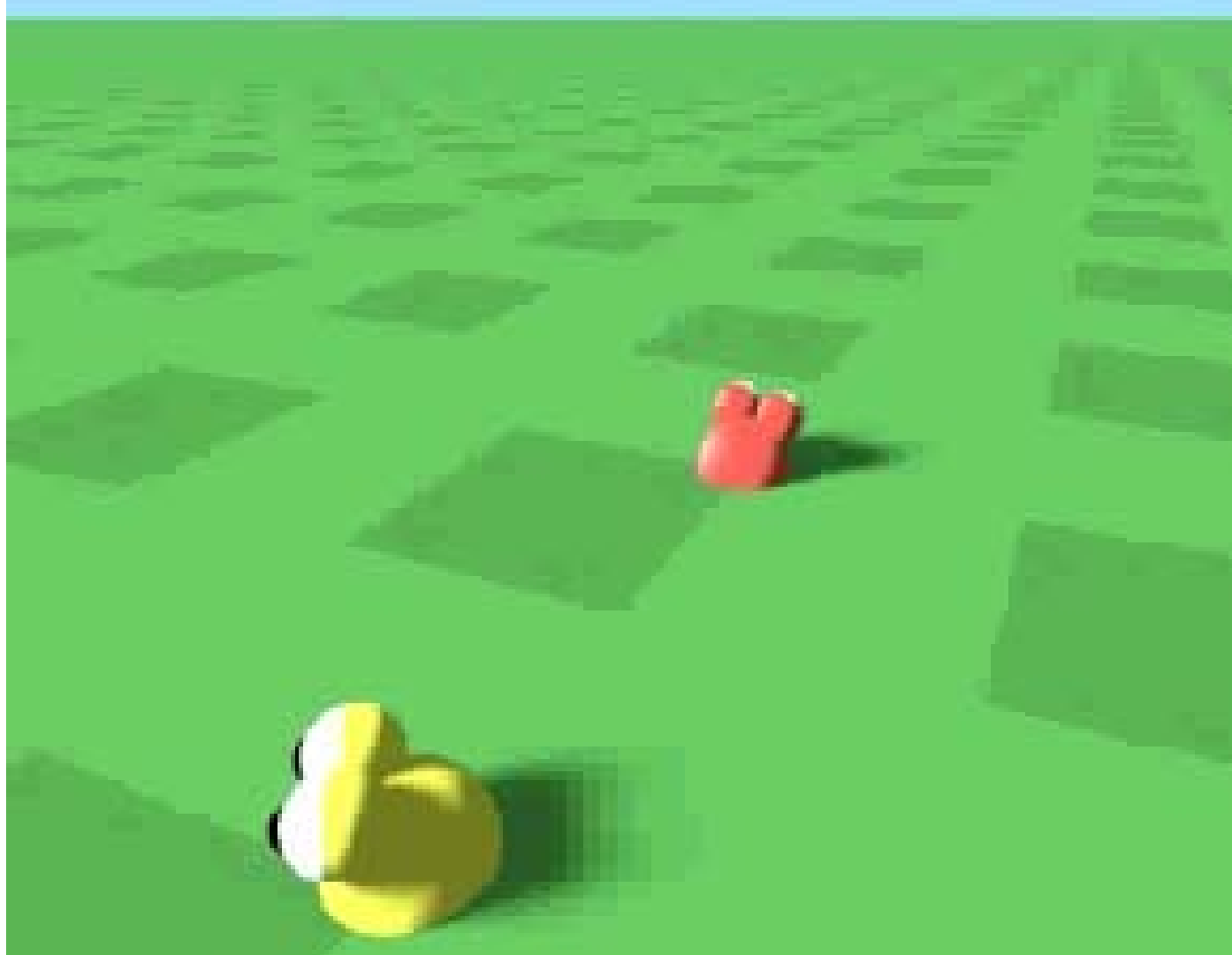
This paper, plus related ones, plus **mpegs** on

<http://www.cogs.susx.ac.uk/users/davec/pe.html>

# Pursuit/Evasion – gen 200

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Two (or more) species evolve in a situation where the selection pressure on one species (eg the Predators or Pursuers) depends (at least in part) on the current fitness of the other species (Prey or Evaders) .. .. and vice versa

Arm's Race, or 'Red Queen effect'

-- you run as fast as you can yet stay in same place  
(... figuratively !)

This provides very much an **implicit** fitness function rather than explicit one.

# This study of coevolution

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Studied in deliberately simplified environment - a 2-D infinite plane with no walls or obstacles, just one pursuer, one evader

Animats (animal/robot) - term often used in SAB

## **Motors:**

These animats have left and right wheels. Variable forces can be applied L and R, simple Newtonian physics

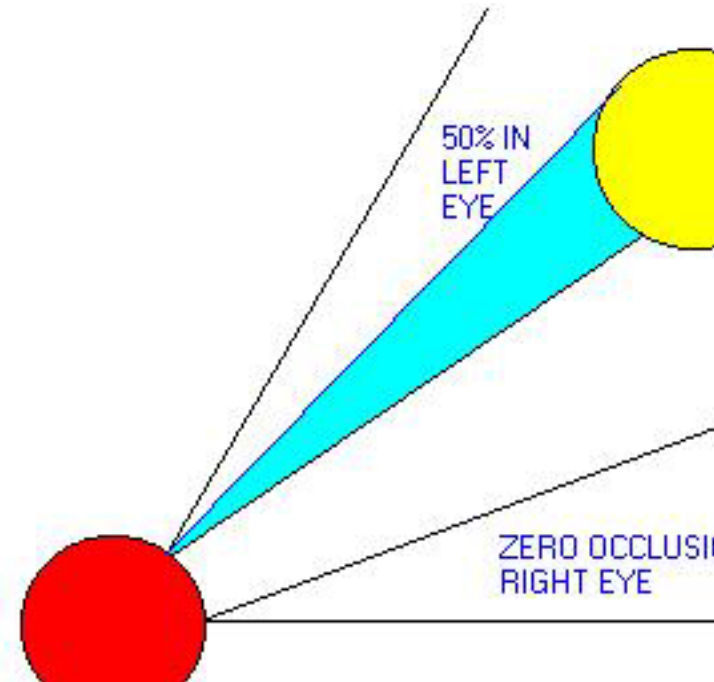
Fuel use (from limited fuel tank) proportional to square of force.  
Friction acts to slow you down.

# Sensors

Each animat has several (typically 2) simulated 'photoreceptors'  
Position (relative to straight-ahead) and angle of acceptance (wide/narrow) is genetically specified -- and hence can co-evolve with the 'brain'

Each sensor returns proportion of  
of its angle-of-view which is **not**  
obscured by any object on horizon

Hence simulation is a very  
simplified version of real physics,  
but still has some significant  
element of physical plausibility



# Neural Network Control System

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The control system is a CTRNN  
(continuous-time recurrent neural network model),  
of precisely the Beer type (see previous lecture).

Fully connected ANN, with (fixed) weights and biases that are  
genetically specified -- ie evolved.

2 neurons connected to 'eyes', 2 to motors.

A Genotype for any one Animat specifies -

- 1) the sensory morphology
- 2) the architecture (weights etc) of the ANN

The Genetic Algorithm evolves 2 completely distinct populations ('species')

Spatially distributed GA -- individuals in the population are spread out over a 'mating' grid, and will only mate, and replace, close neighbours on this grid.



# Evaluation

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## Evaluation:

All in the population of pursuers are tested against the same best-of-last-generation evader.

And vice versa.

Several trials from random starts:

Evader fitness = how long before caught

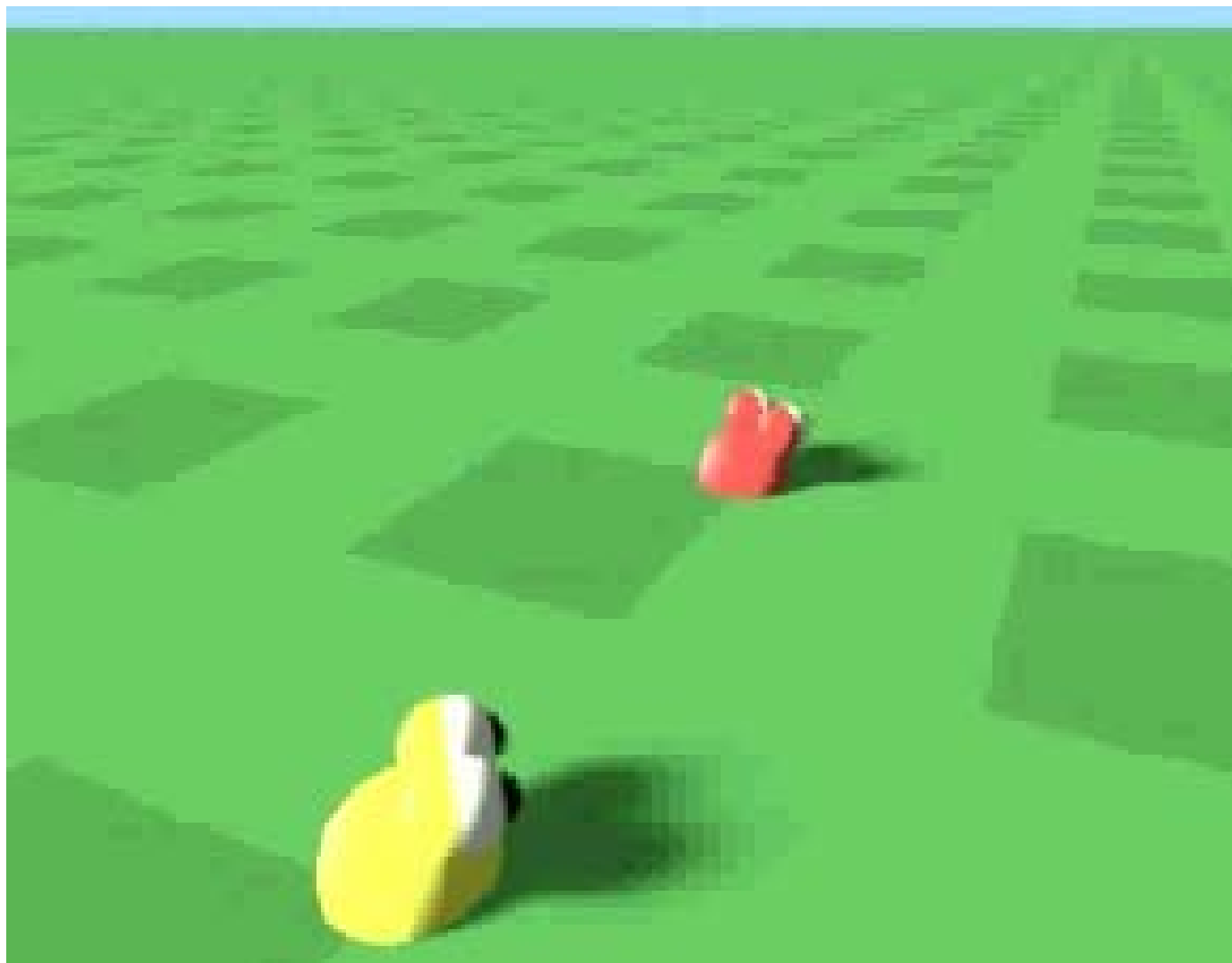
Pursuer fitness = ++ for 'approaching evader'

+ bonus for hit , sooner the bigger

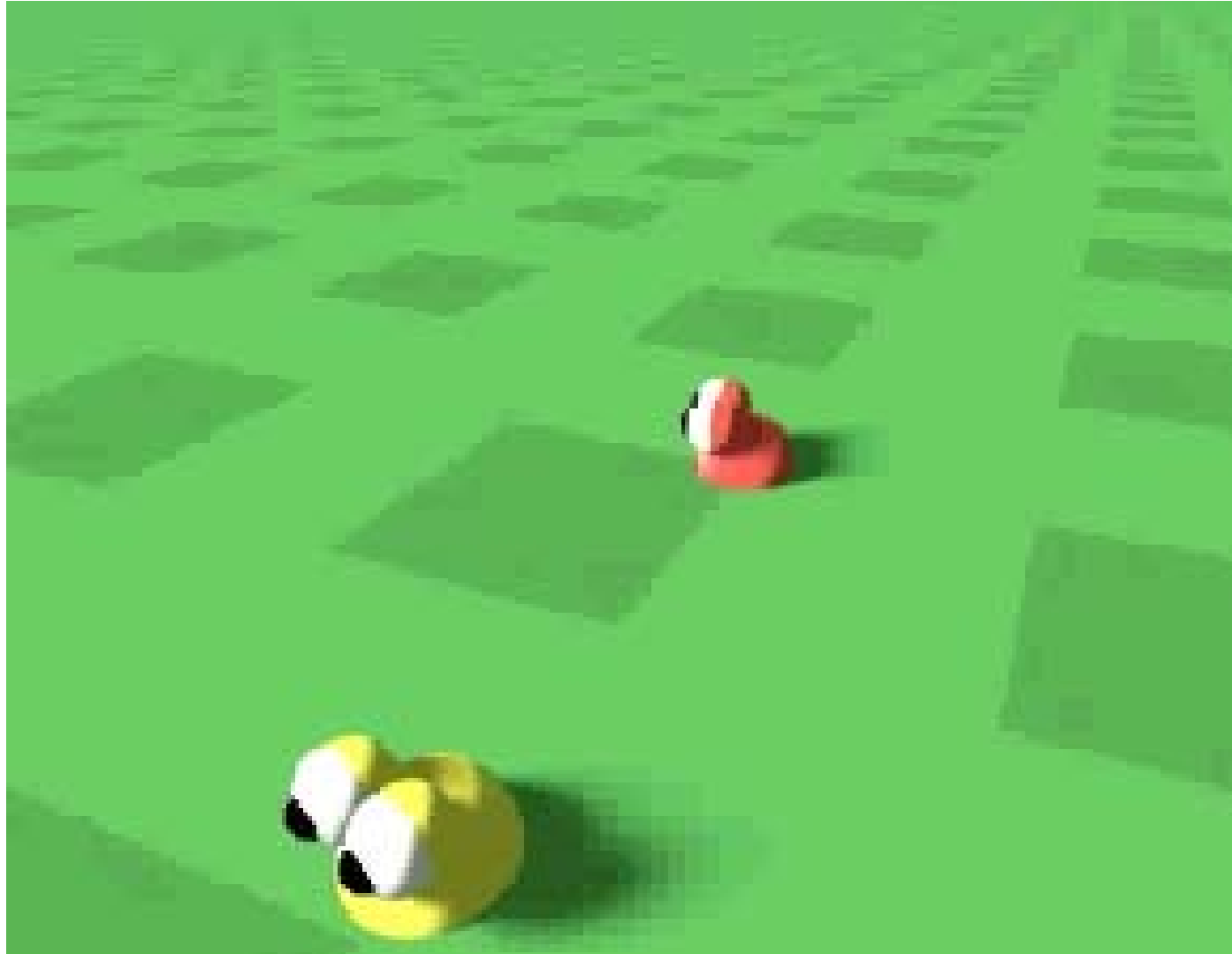
# Random Start – gen 0

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# A Successful run – gen 999



# Potential Circular Trap

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That last picture showed successful pursuers/evaders from generation 999

But at gen 0, there was a pursuer which failed to catch an evader and at gen 999 likewise.

So in what sense has there been any 'advance'?

Possibility of 'no real advance' in coevolution

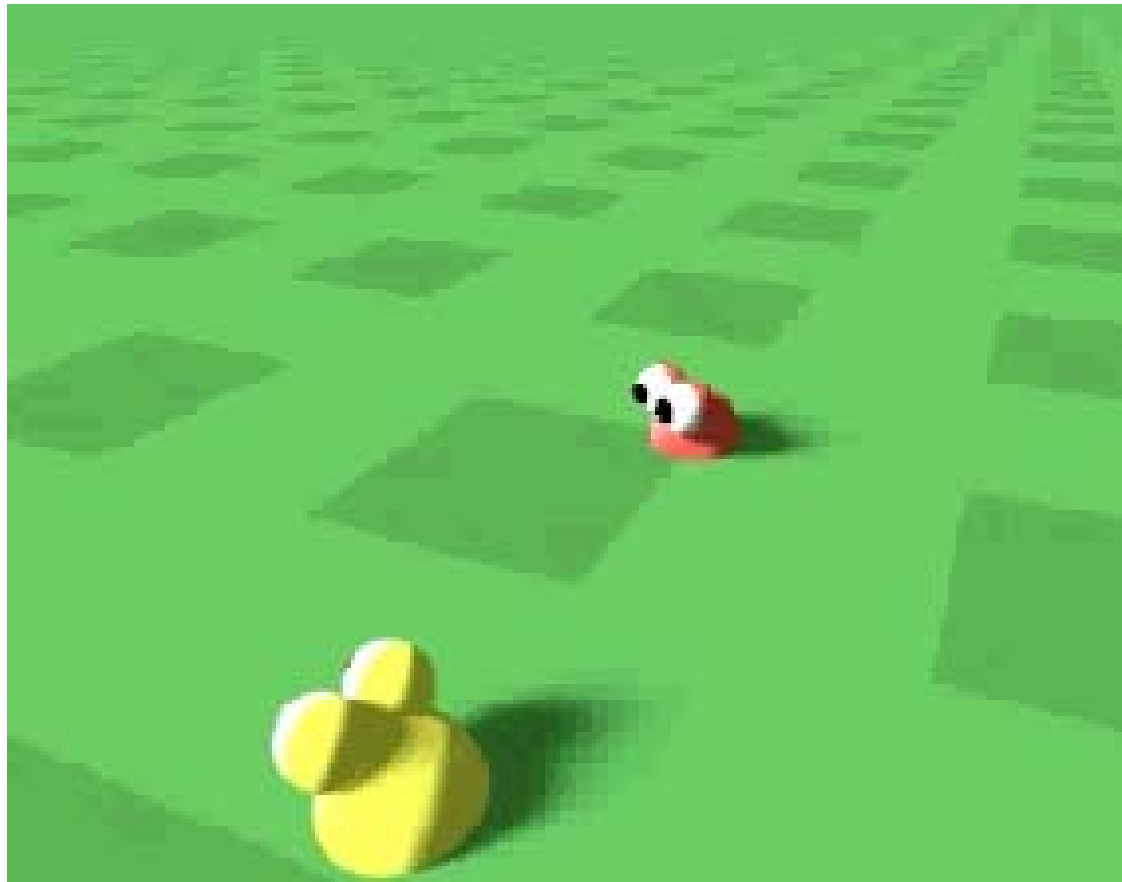
-- cf Stone Scissors Paper game, no strategy can be supreme forever.

# Possible Variations

Test evader from gen 200 against pursuer from gen 999.

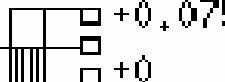
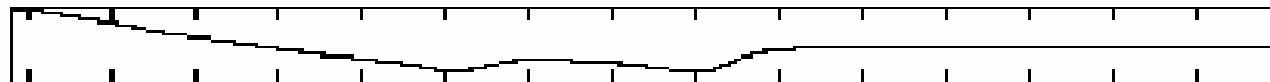
Later work extended this idea, of monitoring current gen against best of previous gens.

- Does this escape from the circular trap?

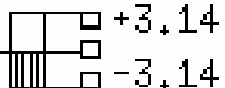
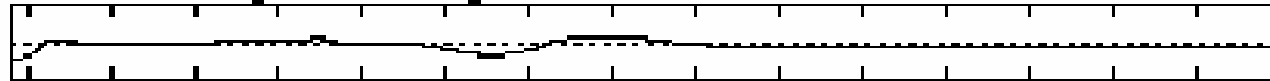


# Analysis of behaviour

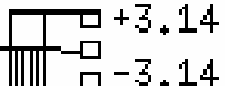
Distance



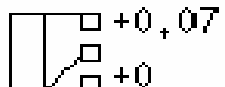
Pursuer\_Target\_Bearing\_off\_front



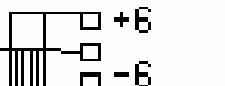
Evader\_Target\_Bearing\_off\_rear



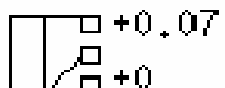
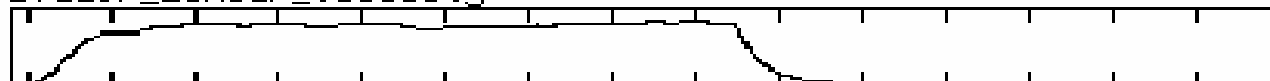
Pursuer\_Linear\_Velocity



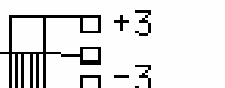
Pursuer\_Angular\_Velocity



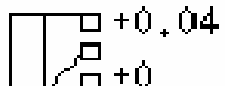
Evader\_Linear\_Velocity



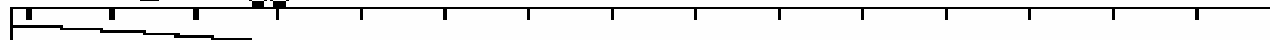
Evader\_Angular\_Velocity



Pursuer\_Energy



Evader\_Energy



Can coevolution be used for engineering purposes?

Here is an example

**"Coevolving Parasites improve Simulated Evolution as an Optimization Procedure".** W. Daniel Hillis. In Artificial Life II, Langton Taylor Farmer Rasmussen (eds) Addison-Wesley (1991) pp 313-322

Danny Hillis -- Connection machines --powerful very distributed p machines.

This work done in late 1980s, 64,536 processors, populations 50 1000000, 'about 100 to 1000 generations per minute'

Evolving minimal *sorting networks*



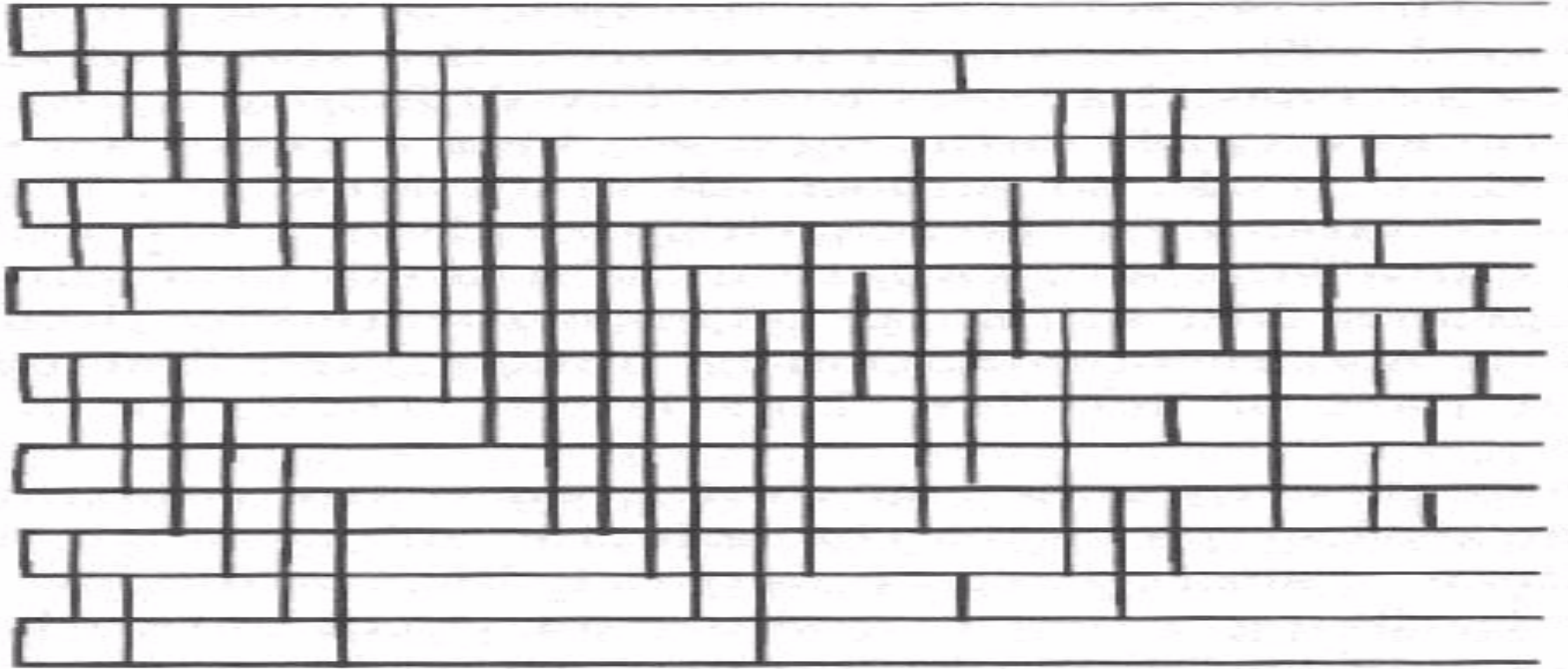
# Sorting Networks

A sorting network is something that can be given **any** scrambled list of  $N$  objects with different values (here  $N=16$ ) --- and it is in effect an algorithm that will systematically sort the list into order by a sequence of **'compare and maybe swap's**.

The sorting network is a series of pairs of numbers,  $[a\ b]$  which can be interpreted as:-

- ✓ Compare the  $a^{\text{th}}$  and  $b^{\text{th}}$  items in your scrambled list.
- ✓ If in wrong order, swap, otherwise leave

# Picturing Sorting Networks



Visual way to represent, 16 rows represent the 16 items to be re-ordered. Starting from left, the vertical bars show rows to be compared/swapped. Numbering rows from 0 to 15, above swaps are:  
[0 1] [2 3] ... [14 15] [0 2] [4 6] [8 10] .....

# Minimal Sorting Networks

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The previous diagram has a total of 60 swaps and was (in 1991) the shortest-known, discovered by MW Green

It is a **perfect** sorter, in that if you present it with **any** scrambled list after going through all the 60 swaps from left to right then the list comes out perfectly ordered.

[ note: for swaps shown as bars in same vertical column, it will not matter which is done first]

The problem is to find the shortest network, ideally better than this one which still sorts anything.

# How to check if it works

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Do you have to check if it sorts all possible combinations of numbers in the list – **NO!**

It can be shown that if a network correctly sorts any scrambled list of 0s and 1s (so that it finishes up with all the 1s at the top, all the 0s at the bottom), then the network will also sort any list of real-valued items.

So can test a 16-network exhaustively with only  $2^{16}$  tests (about 32,768) – instead of 16 factorial (about  $2 \times 10^{13}$ ).

But this is still a lot of tests -- can one save time? – **YES!**

# Genetic Representation

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We need a genetic encoding, so that strings of characters represent possible sorting networks.

But we are not sure how long any sorting network will be before w  
– after all, we are looking for the shortest.

Hillis chose a sort-of-diploid encoding

haploid = 1 string

diploid = 2 strings

# Diploid encoding

A codon pair looks like this

or this:

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.... 0011 0101 ...	.... 0011 0101 ...
.... 0011 1000 ...	.... 0011 0101 ...

Where top and bottom are different, on left, this means  
test/swap [3 5] (binary 0011 and 0101), followed by  
test/swap [3 8] --- total 2 test/swaps

Where top and bottom are same, as on right, it is just  
test/swap [3 5] --- only one test/swap

# Diploid encoding (cta)

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A full genotype is 60 such codon-pairs,

--- hence encoding between 60 and 120 test/swaps.

cf: homozygous / heterozygous (a bit different !)

# Scoring

The population is initialised with everyone having the same first 3 exchanges (that are known to be sensible), and thereafter randomised.

Then each network is tested on 'how well it sorts -- the percentage of input test scrambled lists which it sorts correctly

Rather than testing on all  $2^{16}$  test cases, it could be tested on a random sample.

OR (see later) the test cases could be chosen cleverly – coevolution

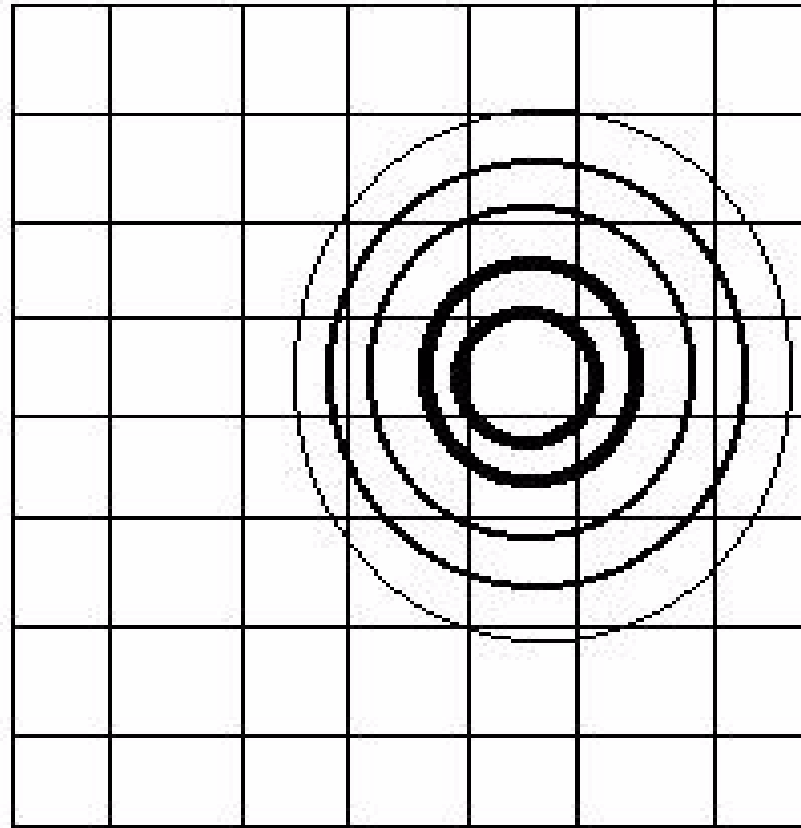


# Spatially Distributed GA

## Tournaments:

pick pairs of contestants in  
local neighbourhood

(Gaussian spread,  
nearer is more likely)



# Reproduction

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**Tournament:** from pair of contestants, compare scores, winner over-writes loser (ie then has 2 copies).

**Mating:** then select mates locally, with same principles

**Recombination** to produce offspring  
(Hillis actually had 15 crossover points '1 per chromosome')

**Mutation:** one bit-flip per 1000 sites.

# Results – Without coevolution

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Typical run like this -- without coevolution -- for up to 5000 generations, with a popn of 64536.

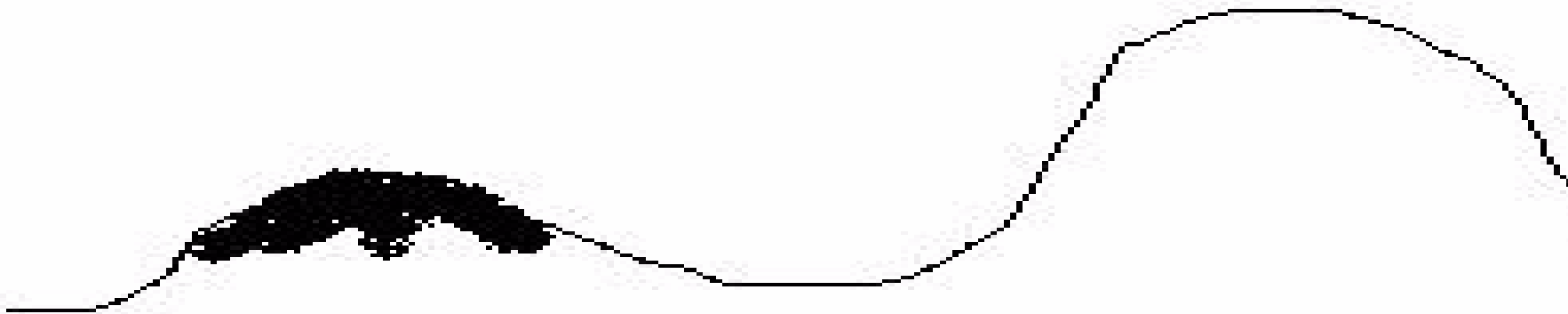
Best scores = sorting networks of 65 exchanges  
-- target was 60.

How can one improve this through coevolution ?

# Inefficiencies - 1

Two main sources of inefficiency in the GA without coevolution:

(1) Local optima -- once the population had found a 3/4 decent solution, it is quite probable that all the neighbouring solutions (genetically similar) will be less fit -- so the population would have to cross a valley to reach 'better ground'.



# Inefficiencies - 2

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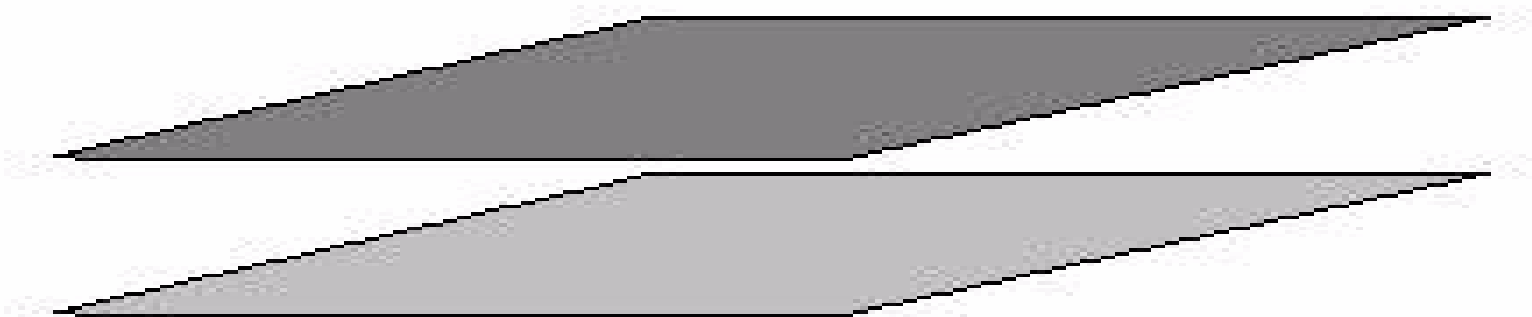
(2) Inefficiency in testing -- once popn was  $\frac{3}{4}$  decent, they all pass most of the test cases, so little differences in scores.

**The answer:** co-evolve a separate population of parasite test-cases which themselves have a fitness function designed to make them as hard as possible for the sorting networks.

This solves both inefficiencies (1) and (2).

Parasite coevolution can generate genetic diversity  
(cf. W Hamilton)

# 2 populations – sorters and parasites



The population of sorting networks is already spatially distributed on a grid. Have a population of parasites likewise distributed on a similar grid overlaid.

Each parasite is a genetically specified group of 10 to 20 test cases rather than all the  $2^{16}$  possible ones.

# Scoring each population

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Each sorting network is tested against the parasite that is on corresponding grid square. The score of the sorting network is 'what proportion of tests does it pass'

The score of the parasite is 'how many tests does it fail the sorter'

Networks get selected, mated, and reproduce on their grid, parasites completely separately on theirs.

Results improved to a minimum size of 61  
(has it been beaten since?)

# Benefits of Coevolution

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Prevents getting stuck in local optima -- as soon as this happens parasites evolve to zap them.

Population is in a constant state of flux.

Second advantage: testing is more efficient -- need only test on a few difficult test cases, which themselves change appropriately according to circumstances.

Hence computationally more efficient.