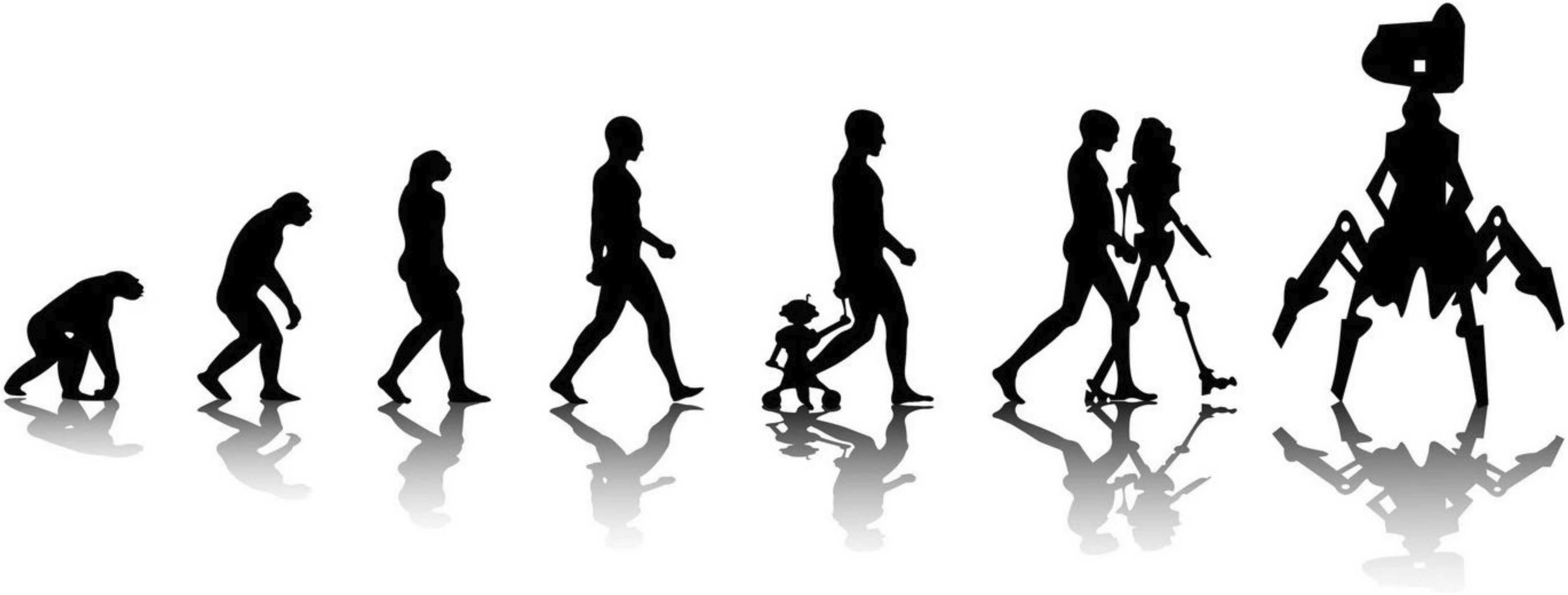

Modern Robotics: Evolutionary Robotics
COSC 4560 / COSC 5560

Professor Cheney
4/30/18

Studying Biology with Evolutionary Computation and Artificial Life

The evolutionary origins of modularity

Jeff Clune[1,2,†], Jean-Baptiste Mouret[3,†] and Hod Lipson[1]

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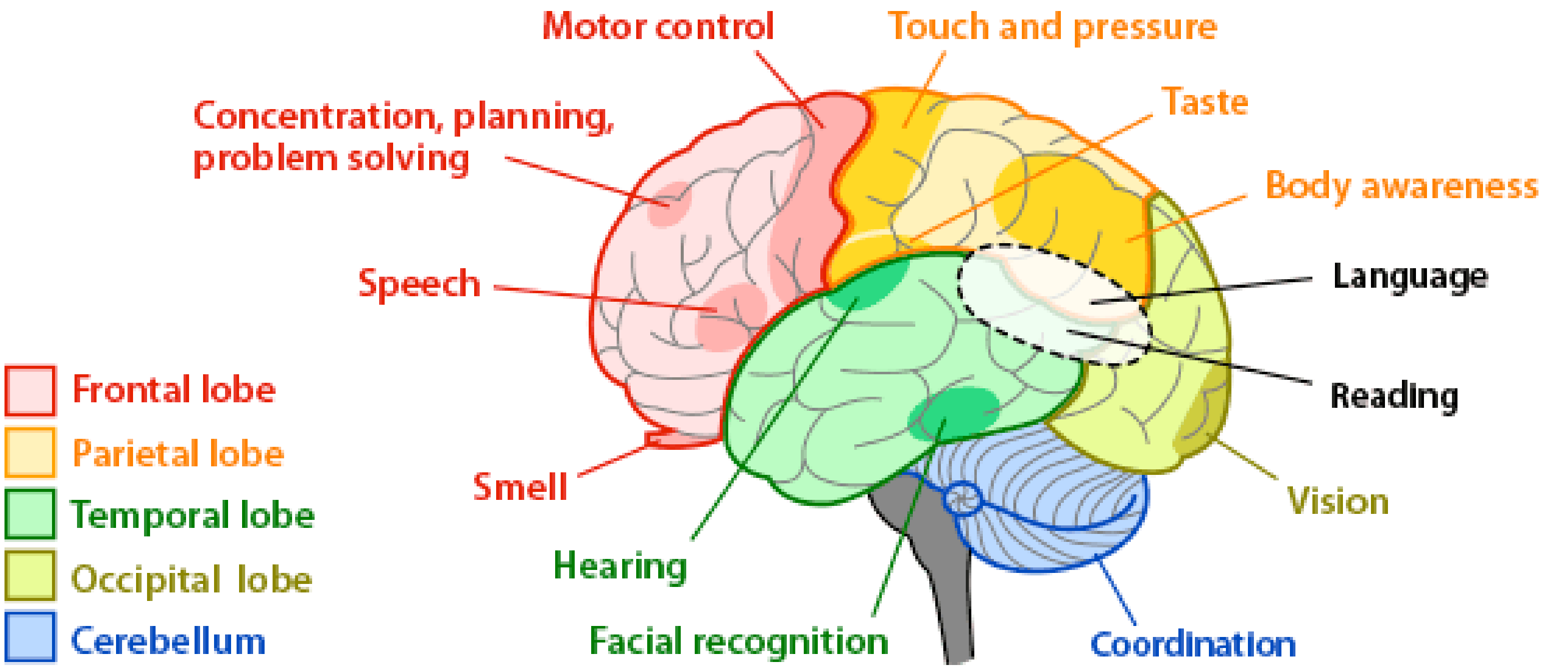
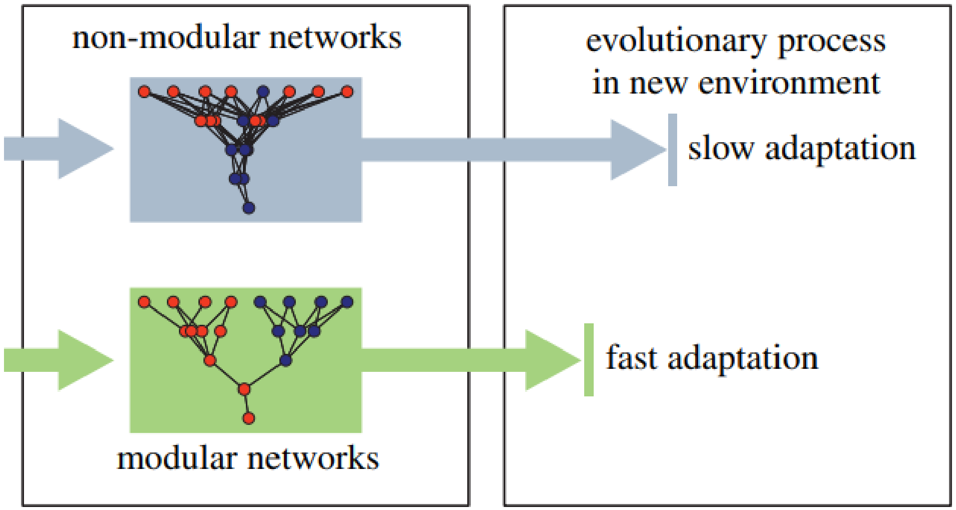
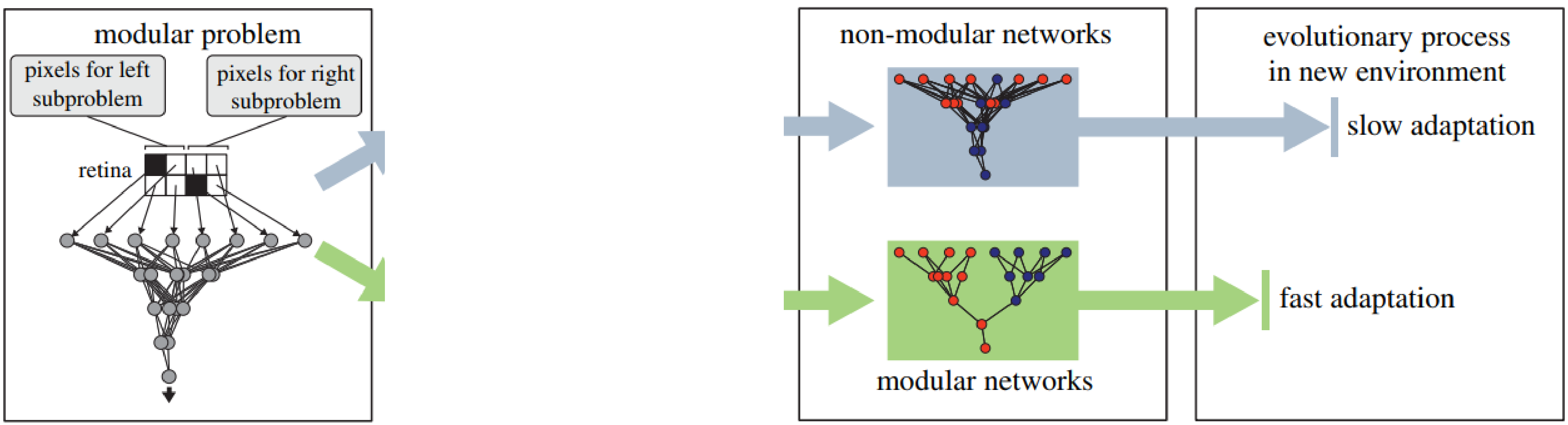
[2]University of Wyoming, Laramie, WY, USA
[3]ISIR, Université Pierre et Marie Curie-Paris 6, CNRS UMR 7222, Paris, France



Motor control
Touch and pressure
Concentration, planning, problem solving
Taste
Body awareness
Speech
Language
Reading
Smell
Hearing
Vision
Facial recognition
Coordination
Frontal lobe
Parietal lobe
Temporal lobe
Occipital lobe
Cerebellum


non-modular networks
evolutionary process
in new environment
slow adaptation
fast adaptation
modular networks



modular problem
pixels for left subproblem
pixels for right subproblem
retina
non-modular networks
modular networks
evolutionary process in new environment
slow adaptation
fast adaptation

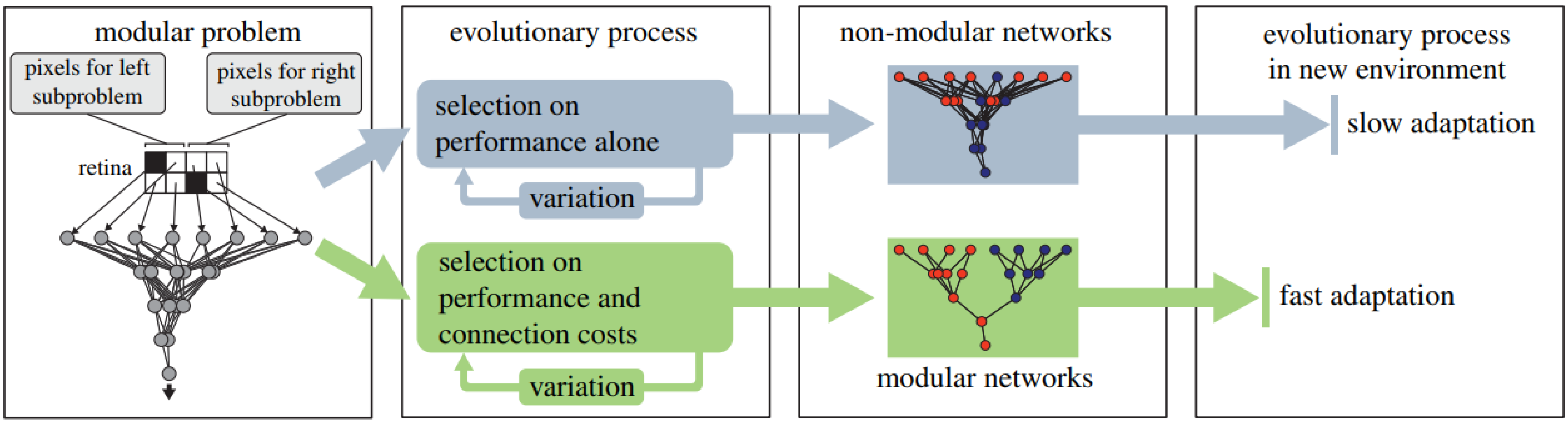
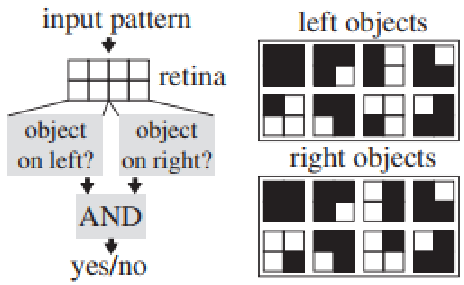


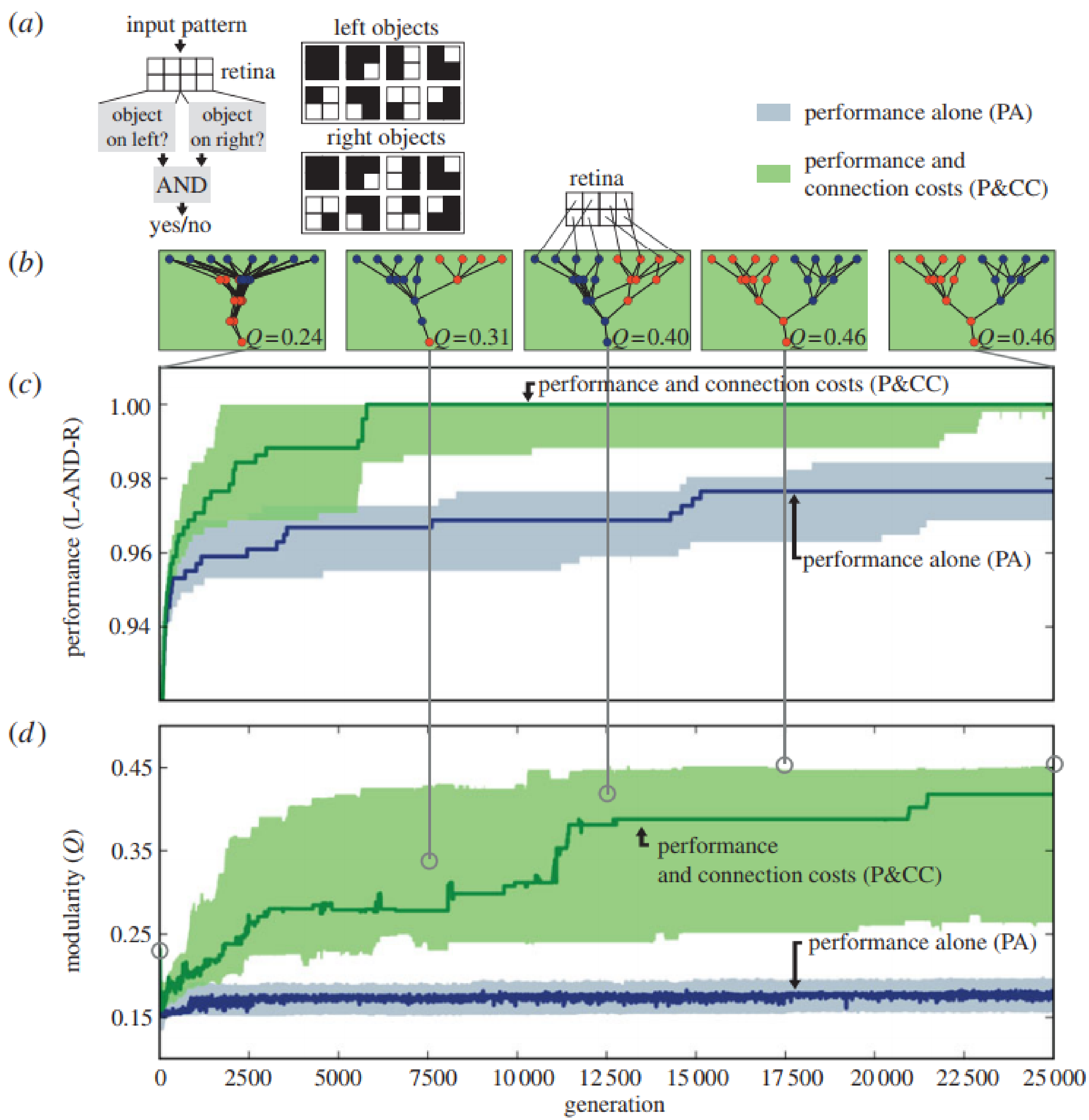
Figure 1. Main hypothesis. Evolving networks with selection for performance alone produces non-modular networks that are slow to adapt to new environments. Adding a selective pressure to minimize connection costs leads to the evolution of modular networks that quickly adapt to new environments.

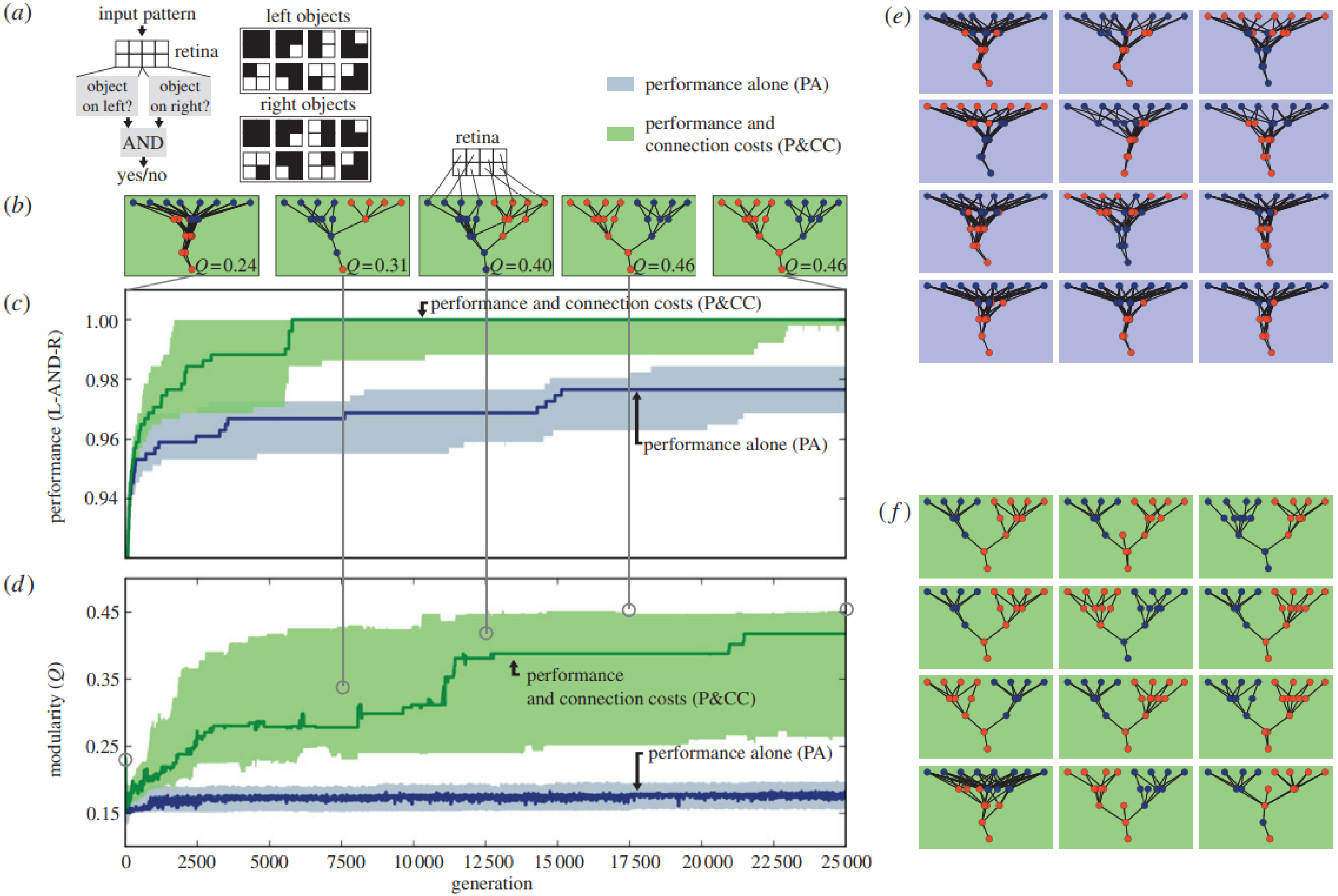
We compare a treatment where the fitness of networks is based on performance alone (PA) to one based on two objectives: maximizing performance and minimizing connection costs (P&CC). A multi-objective evolutionary algorithm is used [28] with one (PA) or two (P&CC) objectives: to reflect that selection is stronger on network performance than connection costs, the P&CC cost objective affects selection probabilistically only 25 per cent of the time, although the results are robust to substantial changes to this value (§4).

(*a*)



input pattern
retina
object on left?
object on right?
AND
yes/no
left objects
right objects


(a)
input pattern
retina
object on left?
object on right?
AND
yes/no
left objects
right objects
performance alone (PA)
performance and connection costs (P&CC)
(b)
retina
Q=0.24
Q=0.31
Q=0.40
Q=0.46
Q=0.46
(c)
performance and connection costs (P&CC)
performance alone (PA)
performance (L-AND-R)
1.00
0.98
0.96
0.94
(d)
modularity (Q)
0.45
0.35
0.25
0.15
performance and connection costs (P&CC)
performance alone (PA)
0
2500
5000
7500
10 000
12 500
15 000
17 500
20 000
22 500
25 000
generation



(a)
input pattern
retina
object on left?
object on right?
AND
yes/no
left objects
right objects
performance alone (PA)
performance and connection costs (P&CC)
(b)
retina
Q=0.24
Q=0.31
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performance and connection costs (P&CC)
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performance and connection costs (P&CC)
performance alone (PA)
0
2500
5000
7500
10 000
12 500
15 000
17 500
20 000
22 500
25 000
generation
(e)
(f)

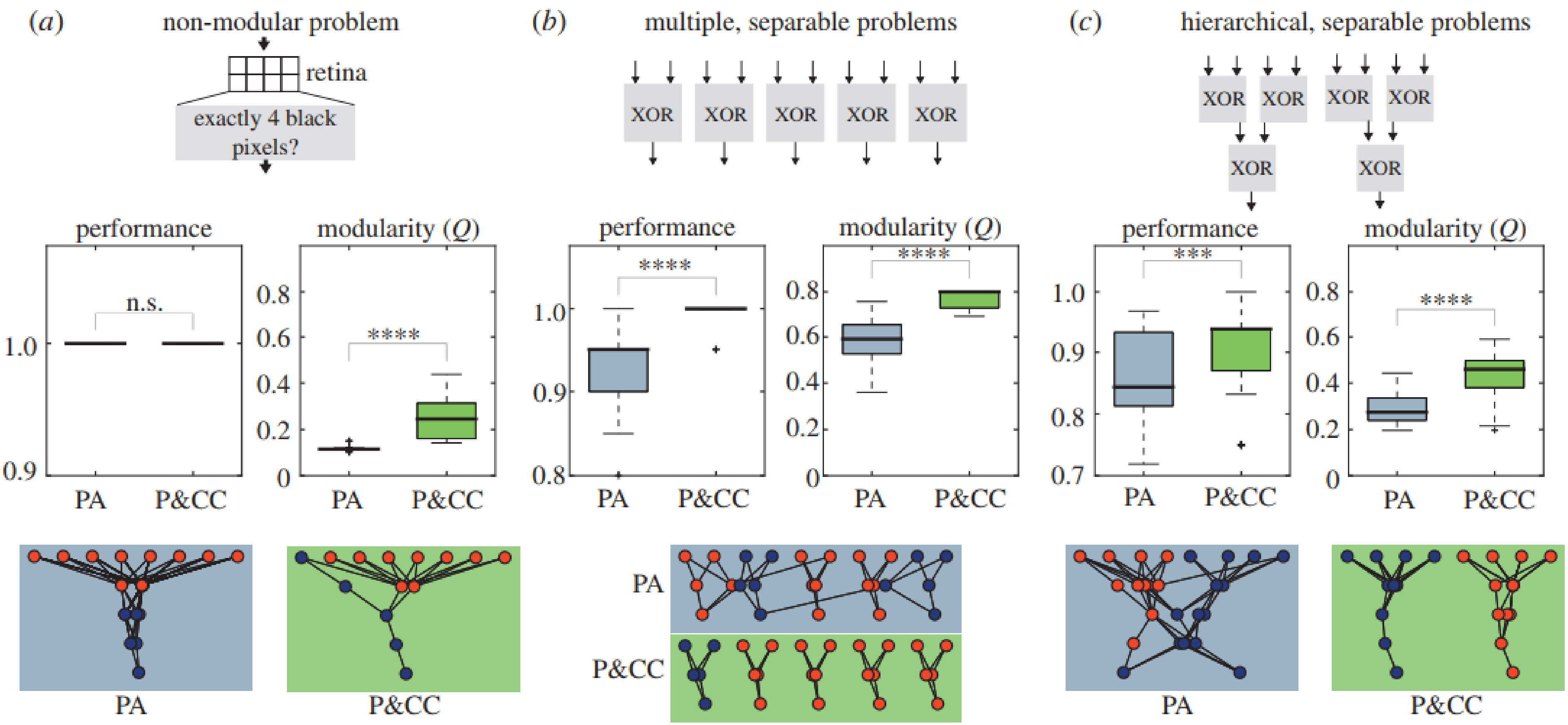

Figure 5. Results from tests with different environmental problems. (*a*) Even on a non-modular problem, modularity is higher with P&CC, though it is lower than for modular problems. (*b*,*c*) P&CC performs better, is more modular, and has better functional decomposition than PA when evolving networks to solve five separate XOR functions and hierarchically nested XOR functions. The examples are the final, highest-performing networks per treatment. Electronic supplementary material figures S2–S4 show networks from all trials. Three and four asterisks indicate p values less than 0.001 and 0.0001, respectively, and *n.s.* indicates no significant difference.

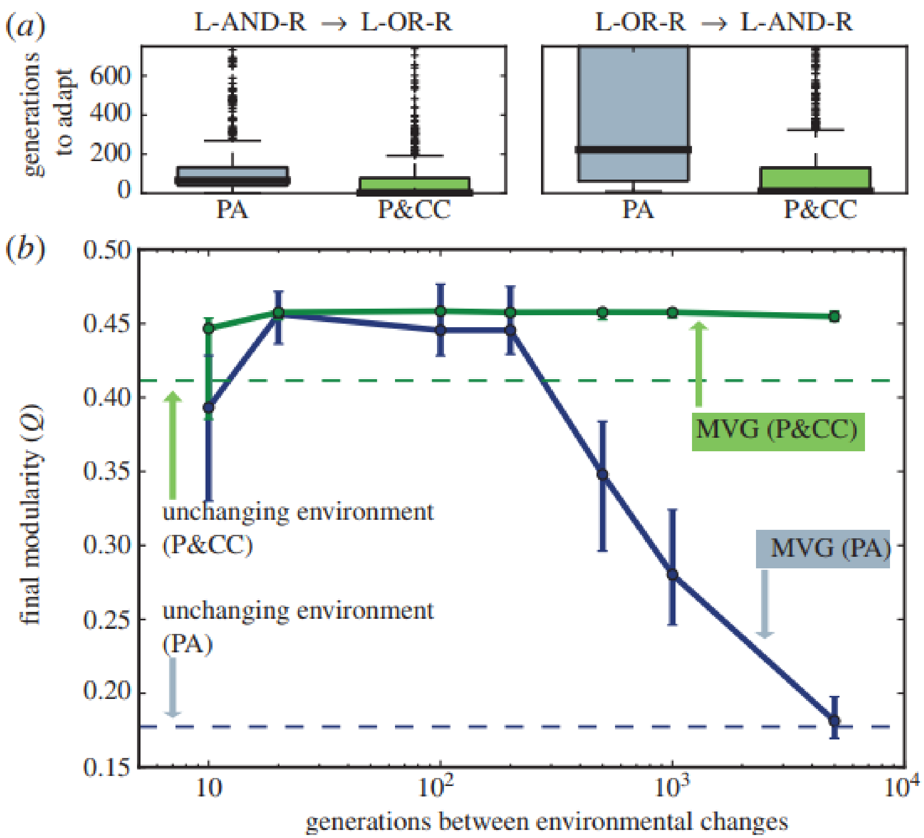

Figure 4. Evolving with connection costs produces networks that are more evolvable. (*a*) P&CC networks adapt faster to new environments than PA networks. Organisms were first evolved in one environment (e.g. L-AND-R) until they reached perfect performance and then transferred to a second environment (e.g. L-OR-R). Thick lines are medians, boxes extend from 25th to 75th data percentiles, thin lines mark 1.5 × IQR (interquartile range), and plus signs represent outliers. Electronic supplementary material figure S6 is a zoomed-out version showing all of the data. (*b*) P&CC networks in an unchanging environment (dotted green line) have similar levels of modularity to the highest levels produced by MVG (solid blue line). Combining MVG with P&CC results in even higher modularity levels (solid green line), showing that the forces combined are stronger than either alone.

The evolutionary origin of complex features

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§ Digital Life Laboratory, California Institute of Technology, Pasadena, California 91125, USA

A long-standing challenge to evolutionary theory has been whether it can explain the origin of complex organismal features. We examined this issue using digital organisms—computer programs that self-replicate, mutate, compete and evolve. Populations of digital organisms often evolved the ability to perform complex logic functions requiring the coordinated execution of many genomic instructions. Complex functions evolved by building on simpler functions that had evolved earlier, provided that these were also selectively favoured. However, no particular intermediate stage was essential for evolving complex functions. The first genotypes able to perform complex functions differed from their non-performing parents by only one or two mutations, but differed from the ancestor by many mutations that were also crucial to the new functions. In some cases, mutations that were deleterious when they appeared served as stepping-stones in the evolution of complex features. These findings show how complex functions can originate by random mutation and natural selection.

WHAT IS LIFE?

WHAT IS LIFE?

WHAT IS LIFE?

MRS GREN

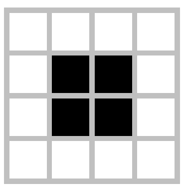
Movement,
Reproduction,
Sensitivity,
Growth,
Respiration,
Excretion
Nutrition

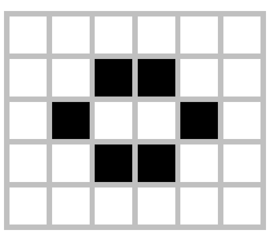
Energy (metabolism)
Homeostasis
Self-sustainability
Information Processing
Cellular Structure
Evolution

Game Of Life
(Conway, 1970)

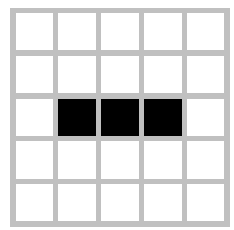
**based on von Neumann's "universal constructor" (1966)*

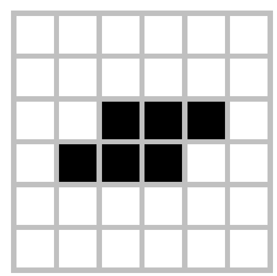
Still Life

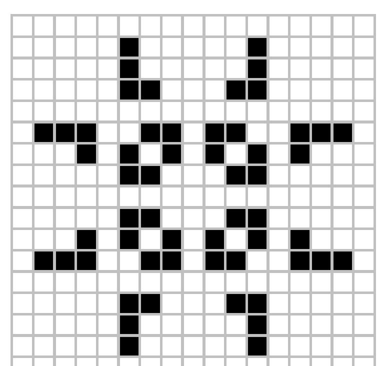




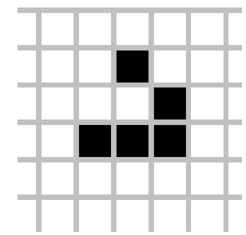
Oscillators

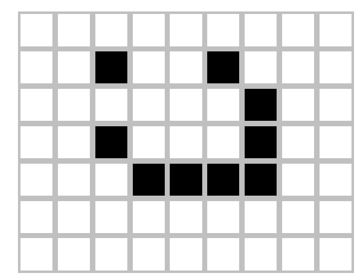






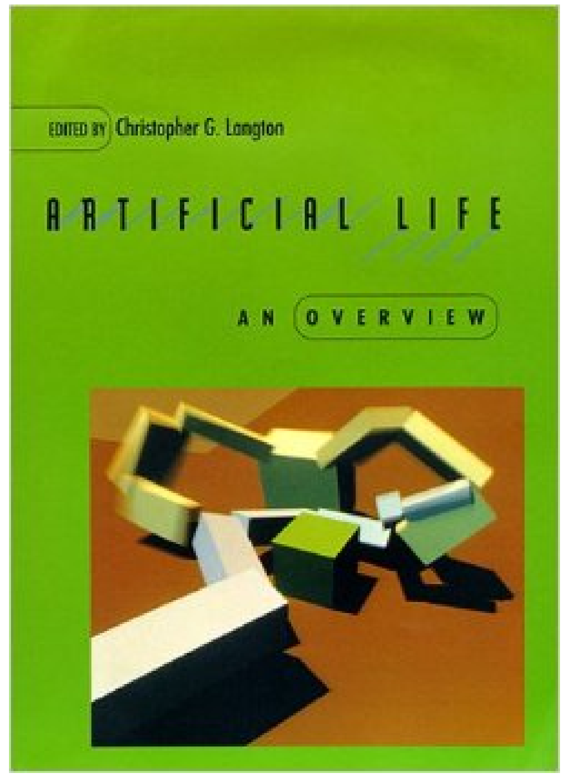
"Spaceships"





Game Of Life
(Conway, 1970)

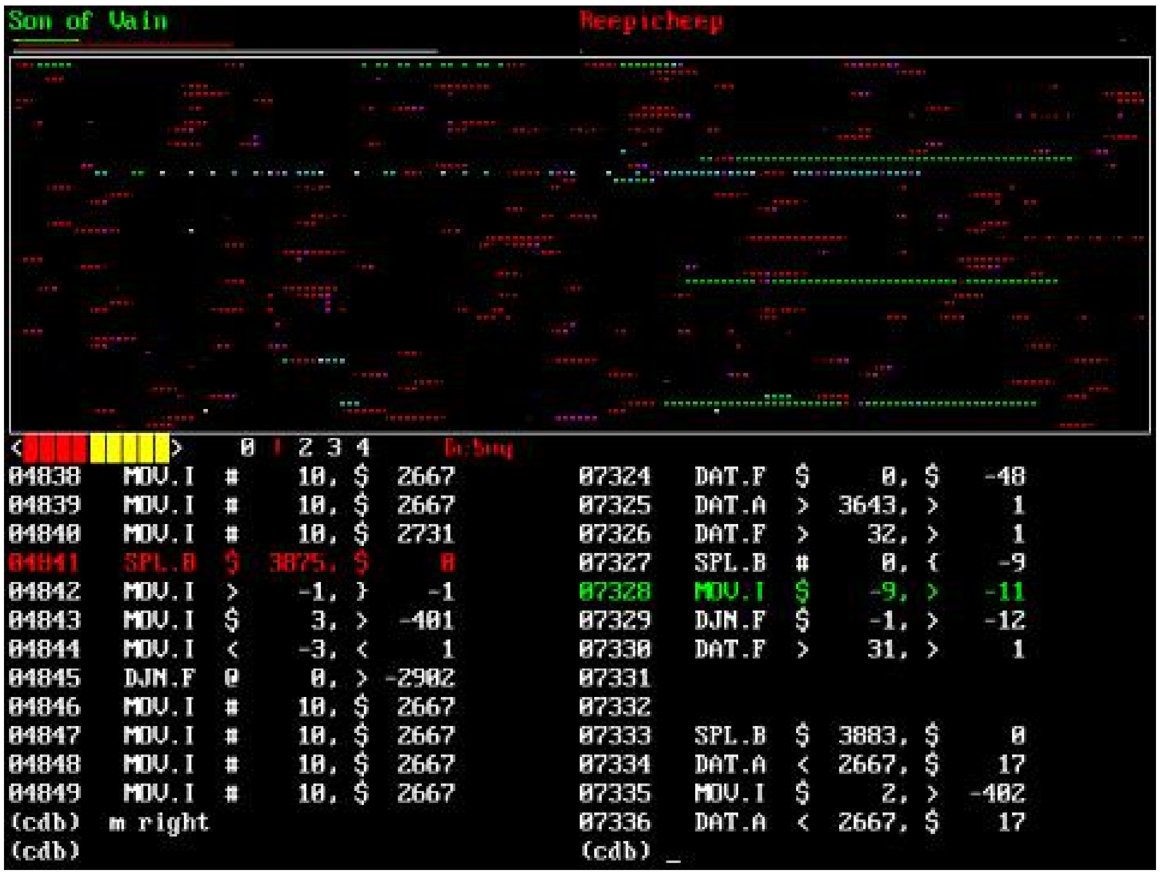
Langton Loop/Ants
(Langton, 1984-86)

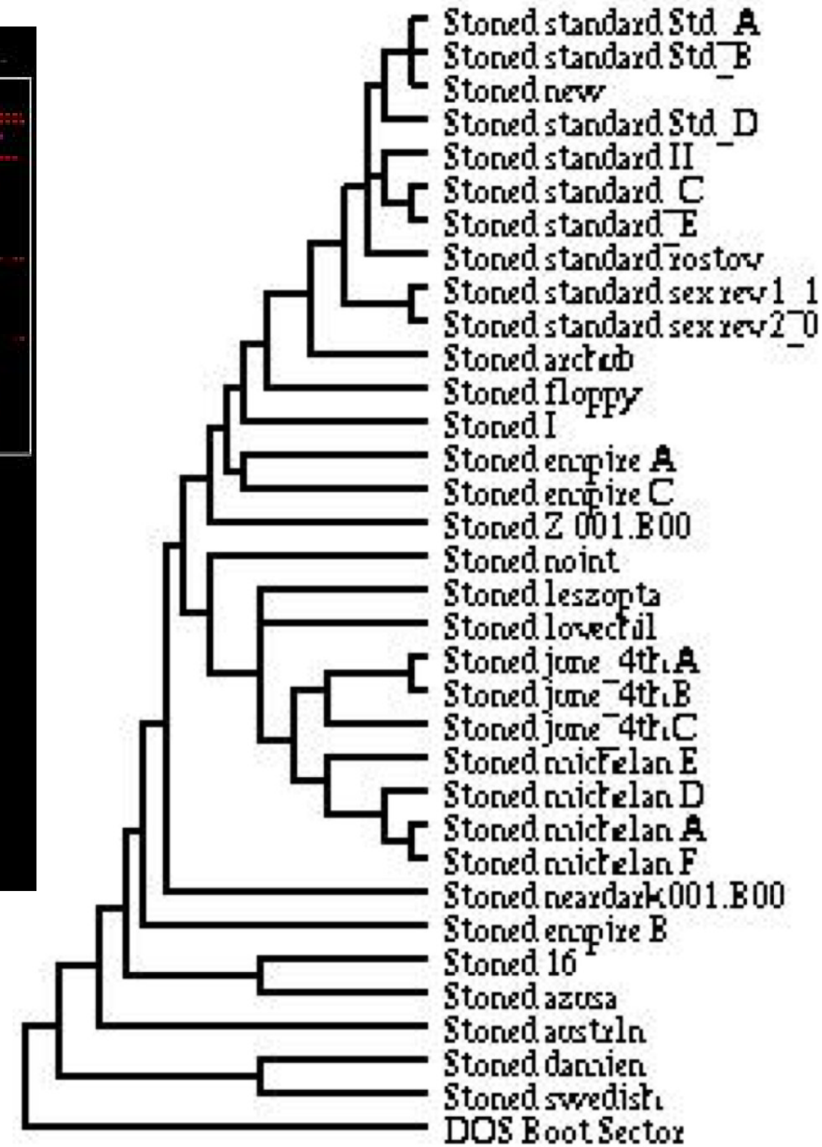


He coined the term “Artificial Life” in the late 1980s when he organized the first "Workshop on the Synthesis and Simulation of Living Systems" (Artificial Life I) at the Lost Alamos National Lab in 1987.

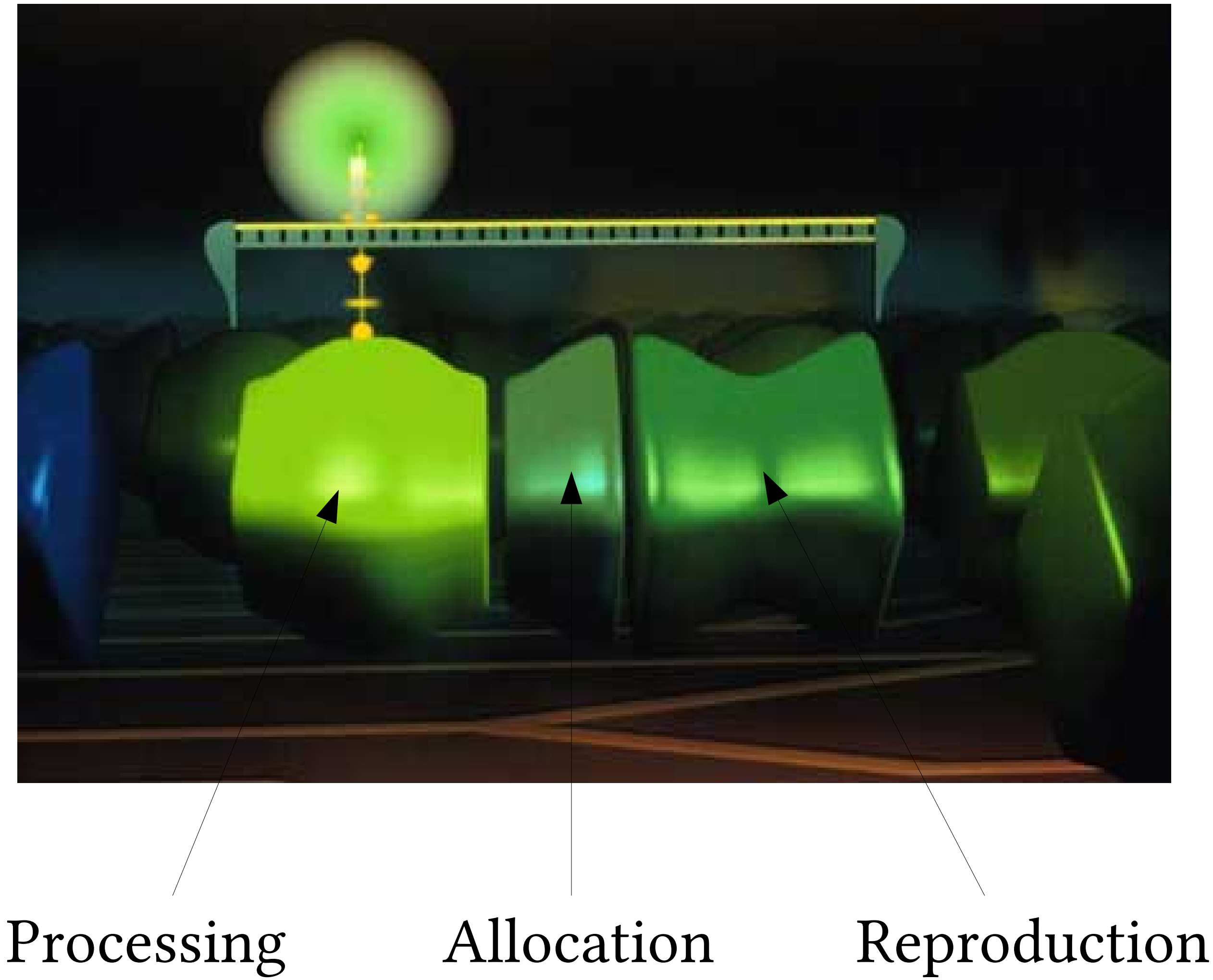

Langton's Ant Colonies
Interactions between multiple ants

Computer (Virus): Core Wars
(Dewdney, 1984)





Computer (Virus) Evolution: **Tierra** (Ray, 1990)

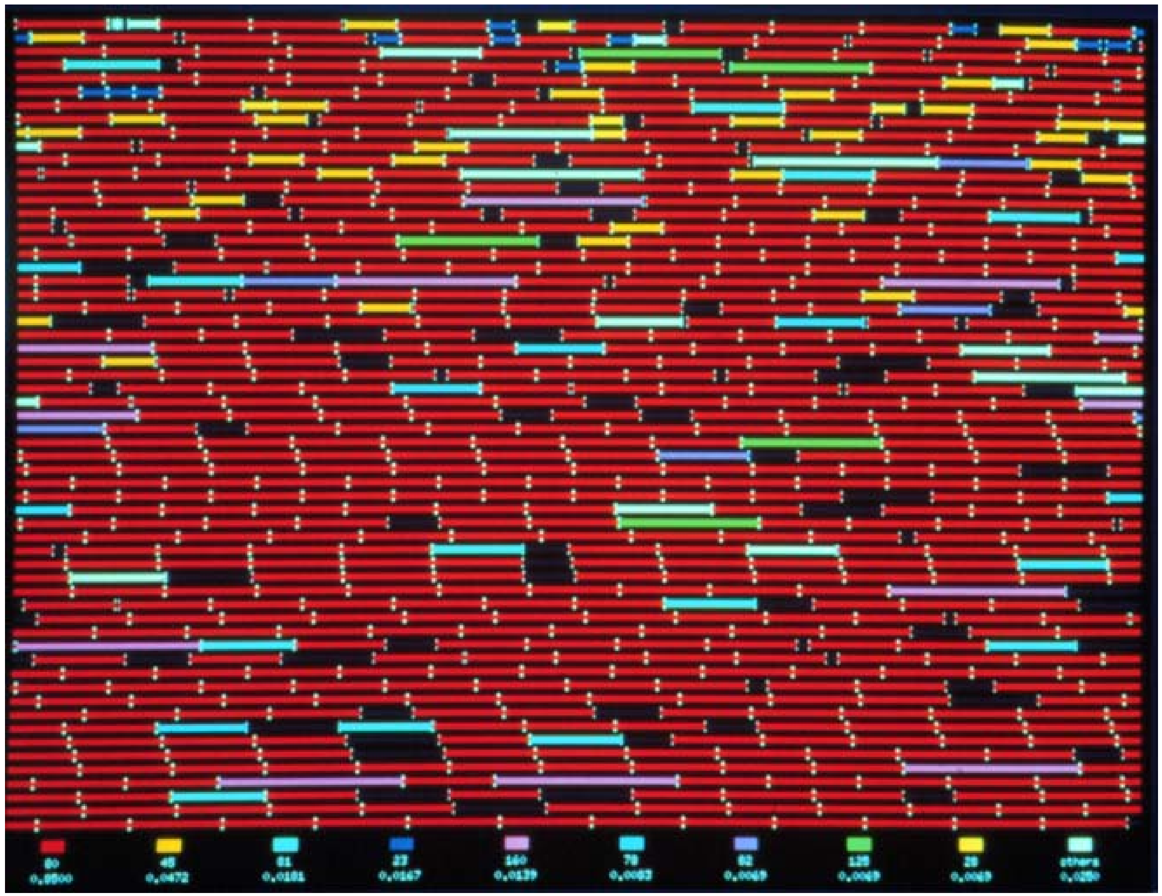


Computer (Virus) Evolution: Tierra (Ray, 1990)

COPY LOOP OF 80AAA

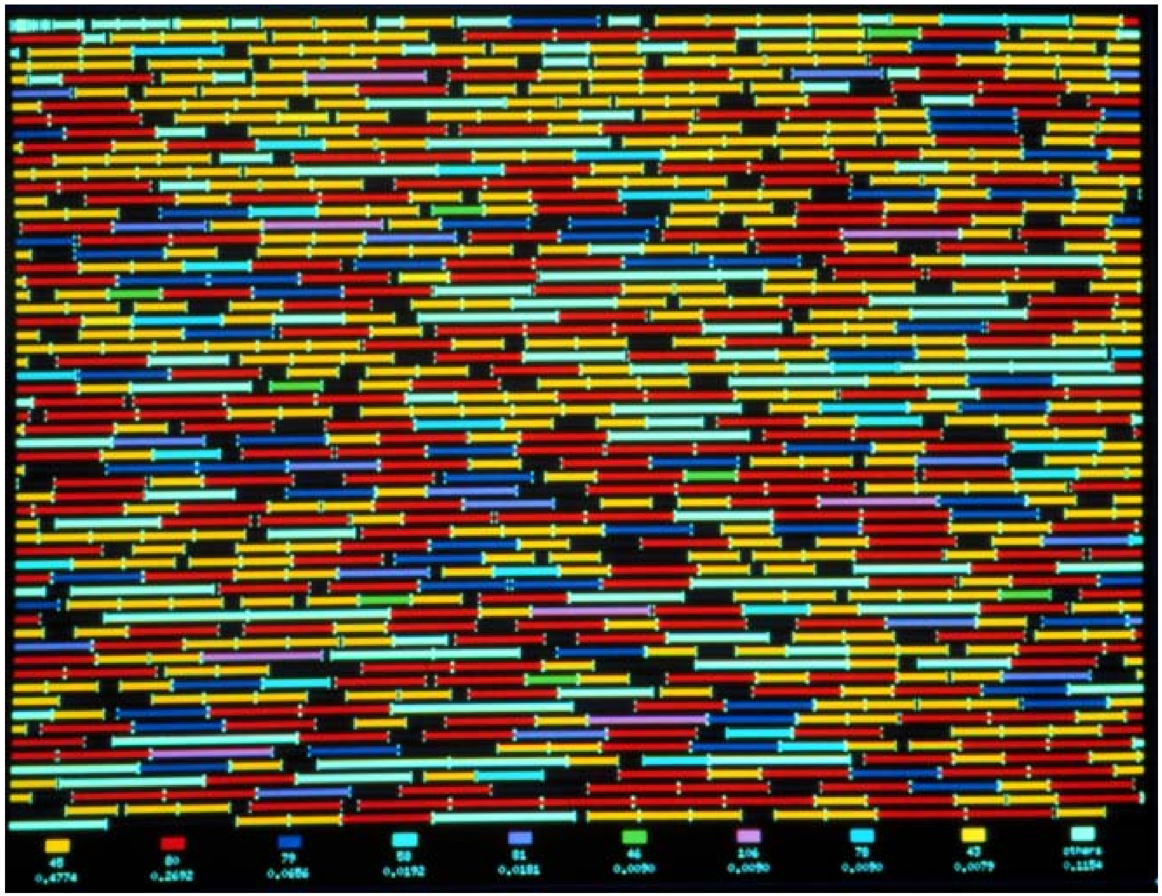
```
nop_1    ; 01  47 copy loop template
nop_0    ; 00  48 copy loop template
nop_1    ; 01  49 copy loop template
nop_0    ; 00  50 copy loop template
mov_iab  ; 1a  51 move contents of [bx] to [ax] (copy instruction)
dec_c    ; 0a  52 decrement cx
if_cz    ; 05  53 if cx = 0 perform next instruction, otherwise skip it
jmp      ; 14  54 jump to template below (copy procedure exit)
nop_0    ; 00  55 copy procedure exit compliment
nop_1    ; 01  56 copy procedure exit compliment
nop_0    ; 00  57 copy procedure exit compliment
nop_0    ; 00  58 copy procedure exit compliment
inc_a    ; 08  59 increment ax (point to next instruction of daughter)
inc_b    ; 09  60 increment bx (point to next instruction of mother)
jmp      ; 14  61 jump to template below (copy loop)
nop_0    ; 00  62 copy loop compliment
nop_1    ; 01  63 copy loop compliment
nop_0    ; 00  64 copy loop compliment
nop_1    ; 01  65 copy loop compliment (10 instructions executed per loop)
```

Computer (Virus) Evolution: Tierra (Ray, 1990)



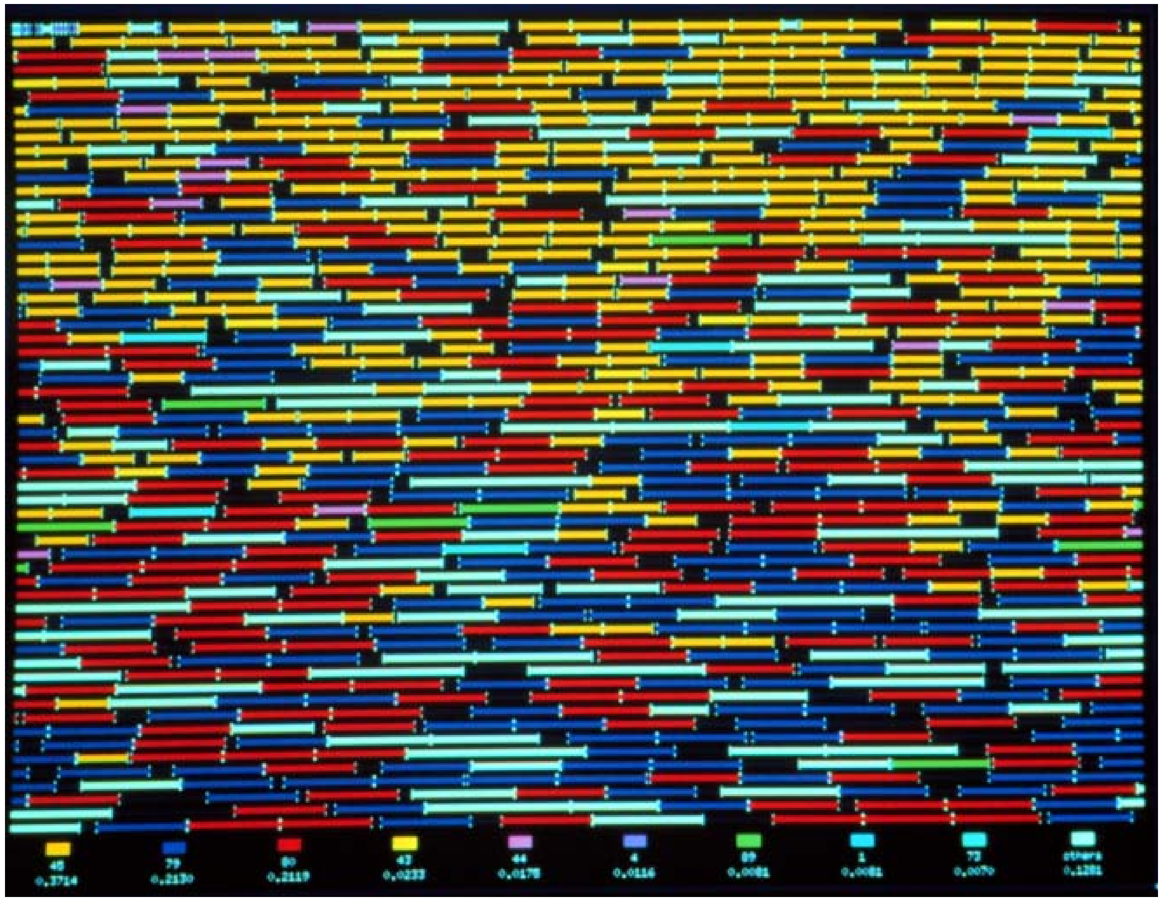
“Hosts, red, are very common.
Parasites, yellow, have appeared but are still rare.”

Computer (Virus) Evolution: Tierra (Ray, 1990)



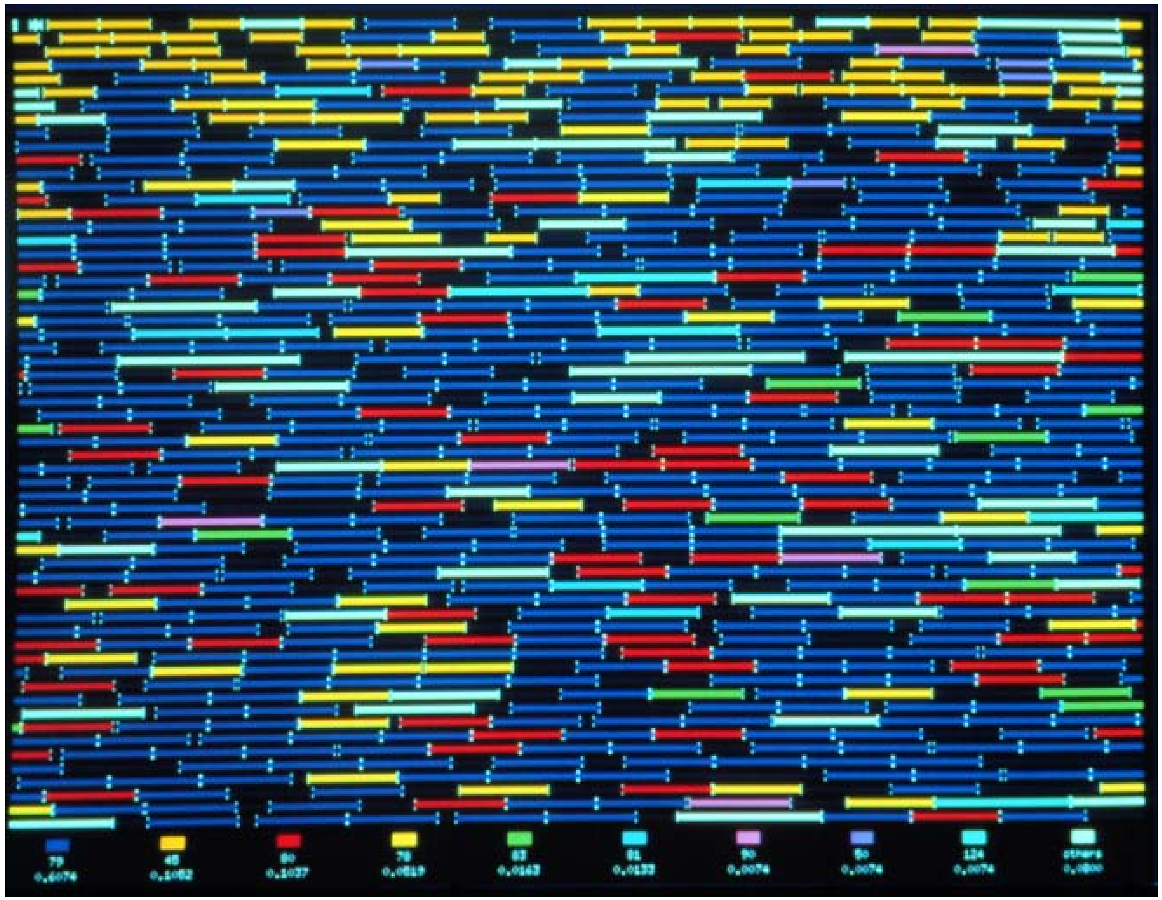
“Hosts, are now rare because parasites have become very common. Immune hosts, blue, have appeared but are rare.”

Computer (Virus) Evolution: Tierra (Ray, 1990)



“Immune hosts are increasing in frequency, separating the parasites into the top of memory.”

Computer (Virus) Evolution: Tierra (Ray, 1990)



"Immune hosts now dominate memory,
while parasites and susceptible hosts decline in frequency.
The parasites will soon be driven to extinction."