Portions of this slideshow: Philippe Pasquier

Image credit: Jon McCormack, *Eden* (2000-10)

Carlos Castellanos | School of Interactive Games & Media | Rochester Institute of Technology

Current Topics in Interactive Development - IGME 480

RIT

Outline of Today's Lecture

- Artificial Life & Creative Ecosystems

Artificial Life & Creative Ecosystems

Flocks, Boids and Swarms

- Complex Systems
  - systems with many interacting components
  - simple individual behavior leads to complex emergent collective behavior without a central controller
  - “bottom-up”, distributed behaviors
  - self-organization

Artificial Life & Creative Ecosystems

Flocks, Boids and Swarms

- Boids and Flocking
    - moving reactive agents that simulate flocking
    - Craig Reynolds, in the 1980s, developed Boids as model of flocking

Artificial Life & Creative Ecosystems

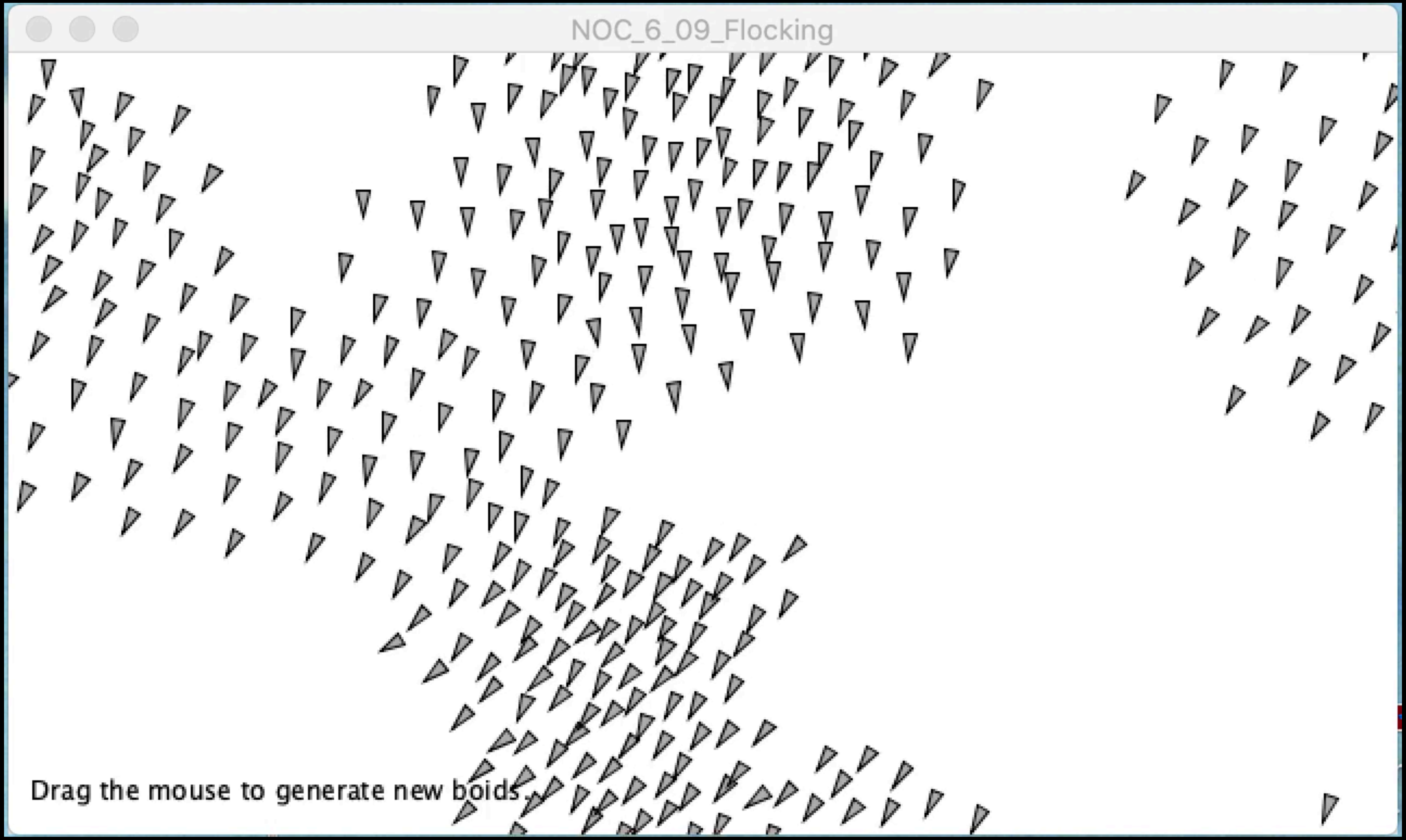
Flocks, Boids and Swarms

- A Boid agent implements 3 simple behavioral rules:
  - Avoidance: move away from a flock that is too close
  - Imitate: fly in the average direction and speed of the flock by averaging the velocity and direction fo the other bids in the neighborhood
  - Center: Minimize exposure to the flock exterior by drifting towards the perceived center of the flock

Artificial Life & Creative Ecosystems

Flocks, Boids and Swarms

- Unlike subsumption architecture, where one rule is chosen at a time, a boid combines its three behaviors into a single action
  - Current velocity of a void is calculated using:
    - $V_{new} = uV_{old} + (1-u)w_aV_{avoid} + w_iV_{imitate} + w_cV_{center}$
    - $V_{new\ and}\ V_{old}$ are the new and old movement velocity vectors
    - w_a, w_i and w_c are weighting factors
    - Priority of avoidance $w_a > w_i$ and $w_a > w_c$
    - u acts as a momentum factor
    - The new position:
      - $P_{new} = P_{old} + tV_{new}$
      - t is the step size (or increment factor)


NOC_6_09_Flocking
Drag the mouse to generate new boids.

Artificial Life & Creative Ecosystems

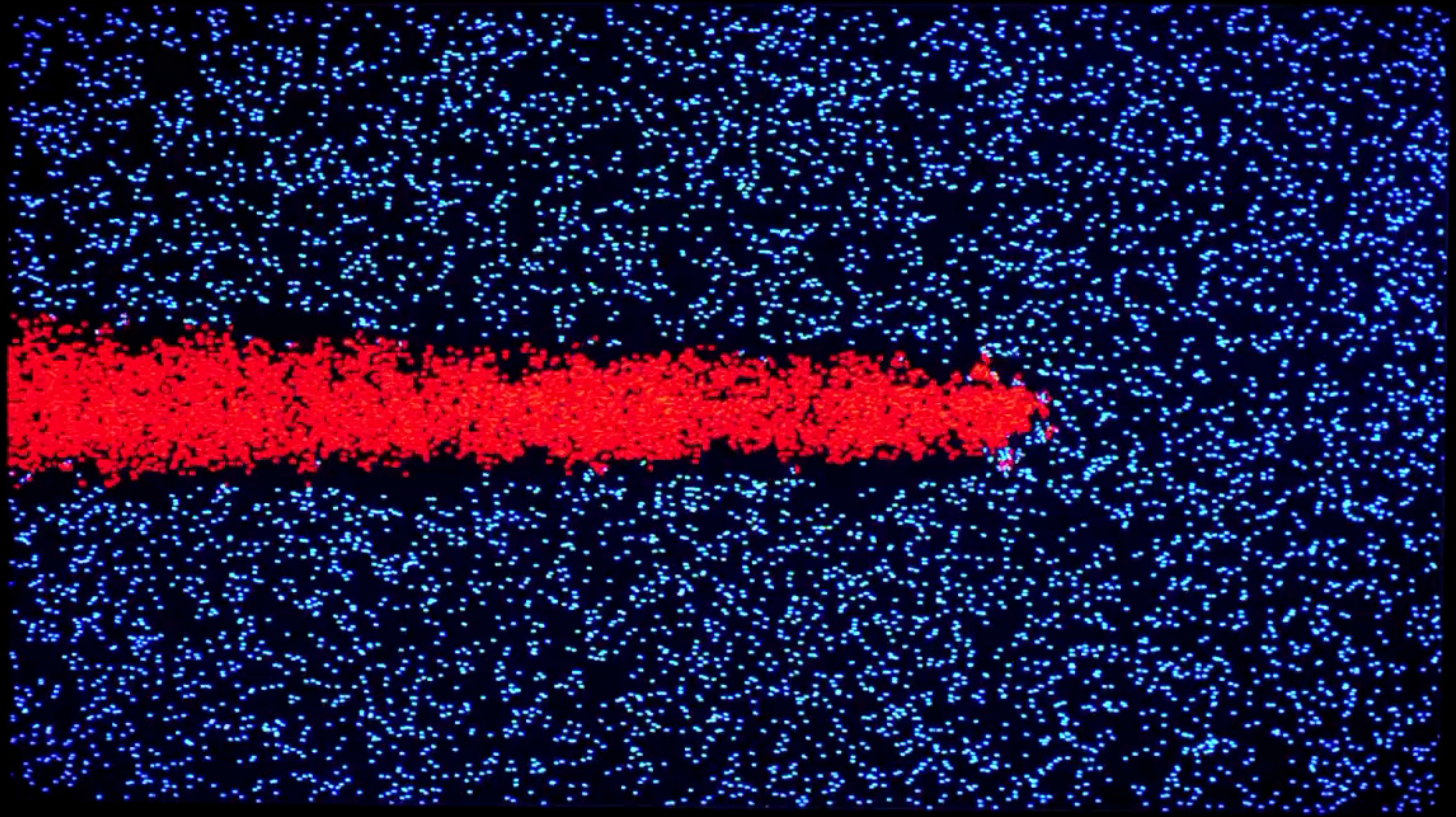
Flocks, Boids and Swarms

- Swarm Art
    - Swarm painting
    - Ant painting
    - interactive installations
    - hardware/robotics
    - aesthetic visualizations
    - animation
    - film
    - music
    - etc

Penousal Machado, Tiago Martins, Hugo Amaro, Luís Pereira

MULTIPLE RENDERING STYLES ARE POSSIBLE

Penousal Machado, Tiago Martins, Hugo Amaro, Luís Pereira



War (2015), Antoine Schmitt

Swarm Wall (2012), Correl Lab (CS research Lab), Colorado University
Nicholas Farrow, Ken Sugawara, Michael Theodore

Artificial Life & Creative Ecosystems

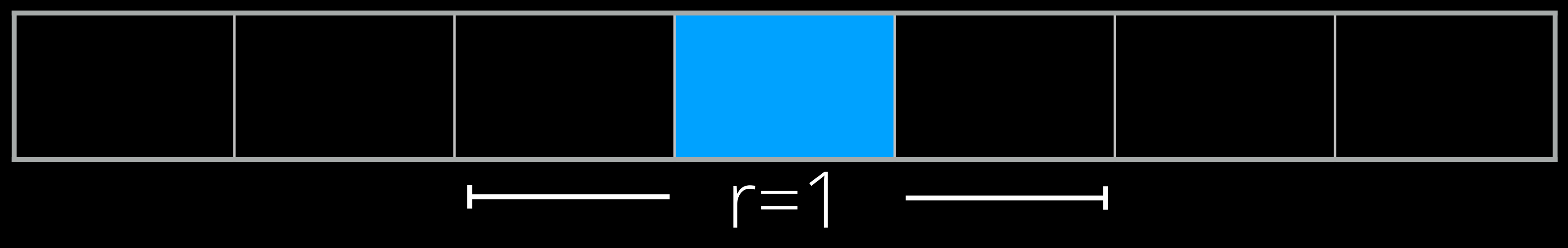
Cellular Automata

- Cellular Automata (CAs) are discrete models of computation consisting of:
  - an n-dimensional grid of cells that can be in a finite number of states
  - a transition rule that indicates for a given cell what state it should be in at the next time step (or iteration or generation) given: (a) its current state and (b) the state of the cells in its neighborhood
  - these cells then evolve through a number of discrete time steps according to these rules
- CAs were developed in the 1950s by Konrad Zuse, Stanislav Ulam and Jon Von Neumann

Artificial Life & Creative Ecosystems

Cellular Automata

- 1-dimensional CA
  - The neighborhood of a cell consists of the cell and its adjacent cells (to the left and right); usually described by its radius *r* (e.g. r=1)



  - Example: rule 30 (Wolfram Classification Scheme)

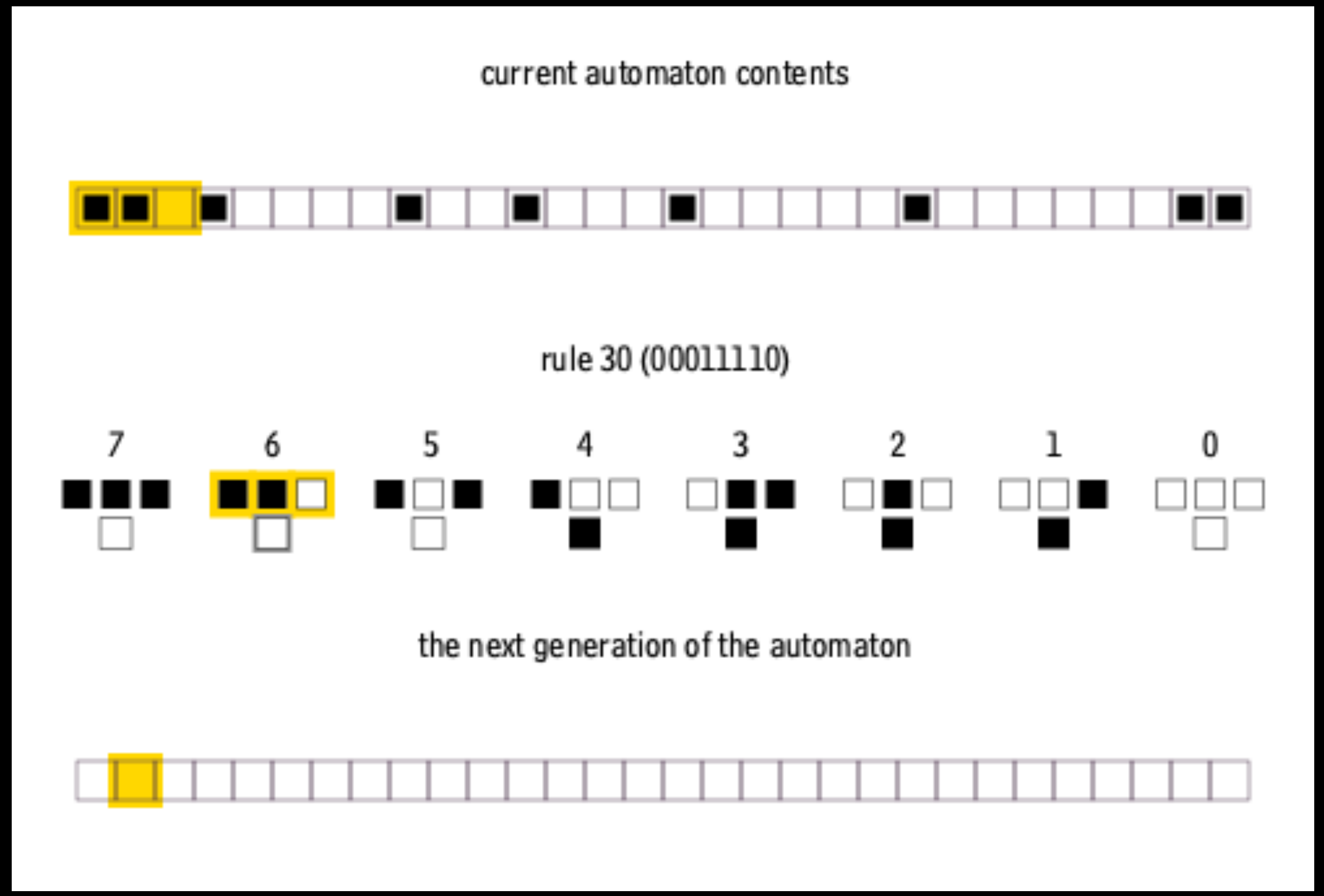
Neighborhood	111	110	101	100	011	010	001	000
Resulting State	0	0	0	1	1	1	1	0

Artificial Life & Creative Ecosystems

Cellular Automata

- Example: rule 30 (Wolfram Classification Scheme)

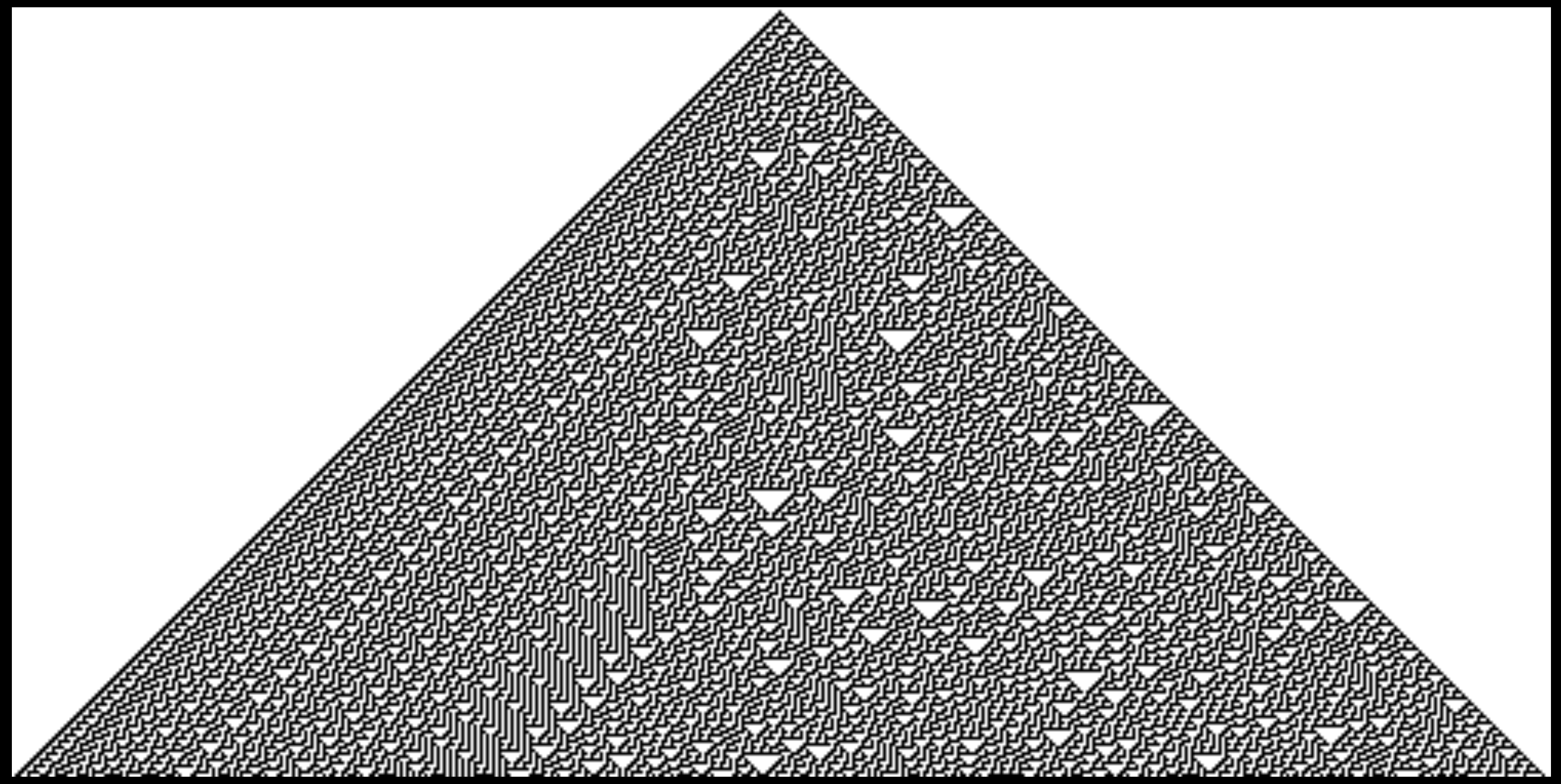
Neighborhood	111	110	101	100	011	010	001	000
Resulting state	0	0	0	1	1	1	1	0



Artificial Life & Creative Ecosystems

Cellular Automata

- Example: rule #30 (Wolfram Classification Scheme)
  - after many generations



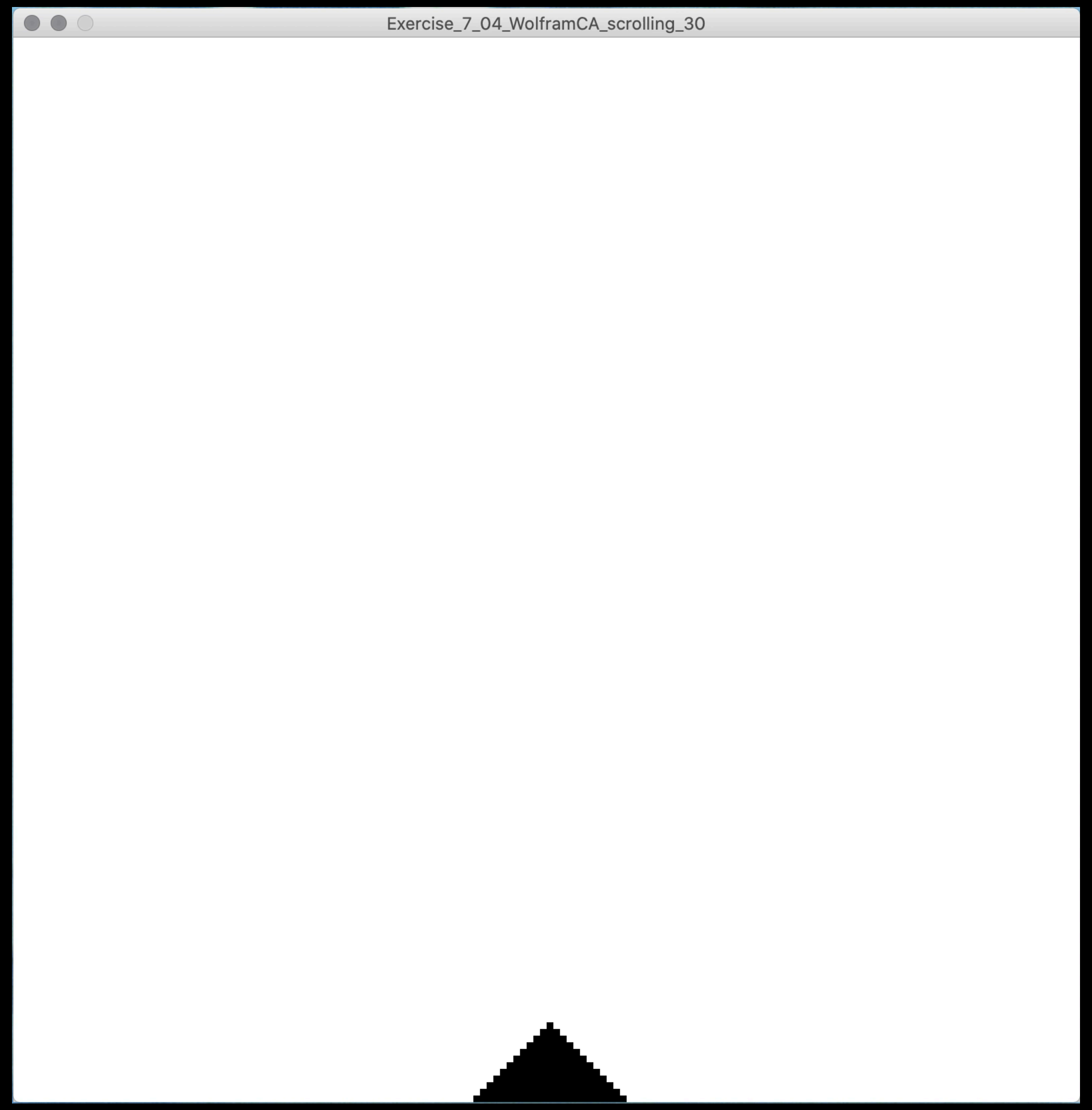
Artificial Life & Creative Ecosystems

Cellular Automata

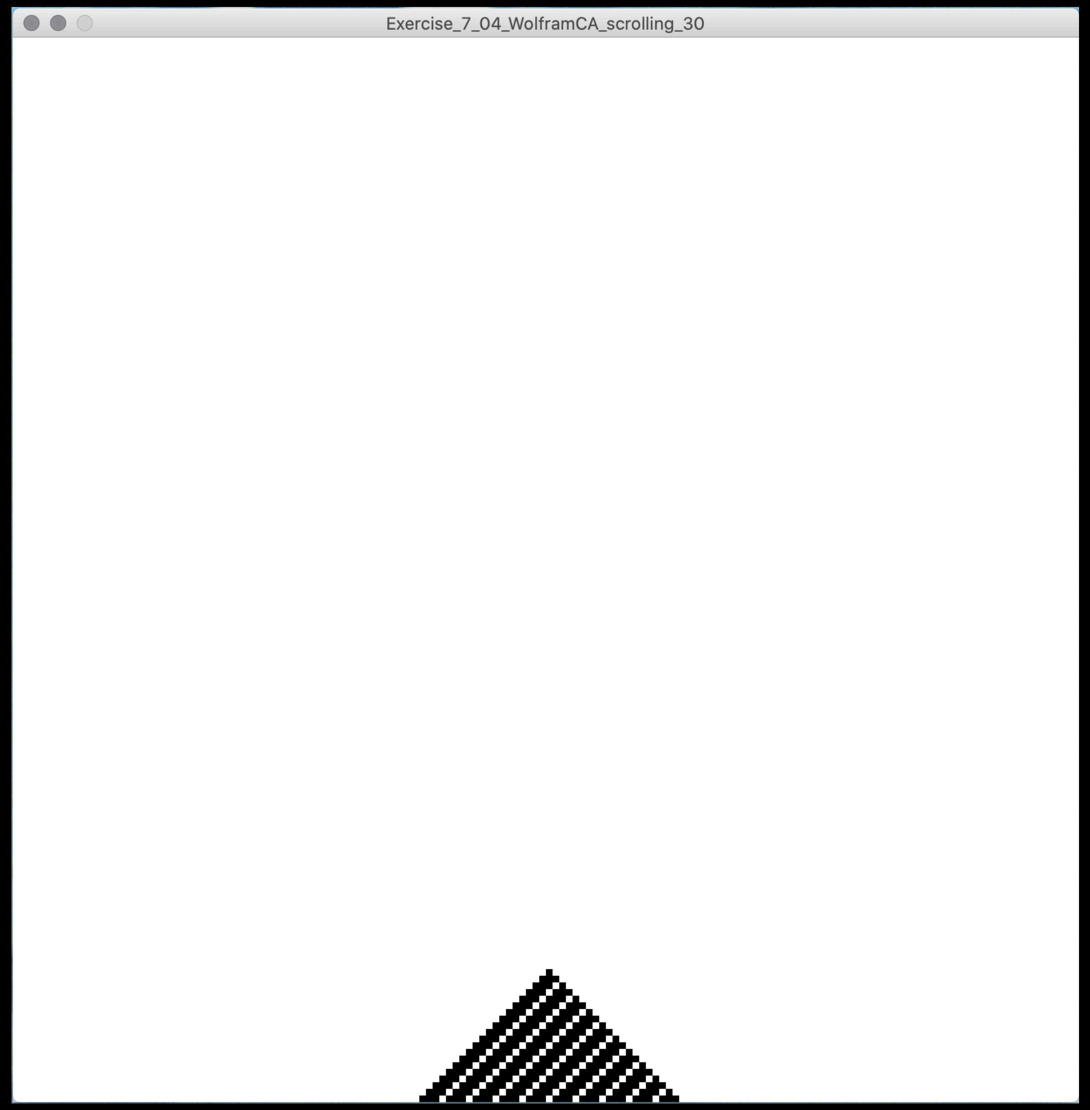
- Stephen Wolfram classifies 1D CAs into four classes:
  - Class1: the CA shows simple uniform behavior to homogeneous, constant final state
  - Class 2: the CA leads to a set of separated simple stable or repetitive structures
  - Class 3: the CA demonstrates a chaotic pattern (e.g. rule 30)
  - Class 4: the CA produces a complex pattern, with complex localized structures, sometimes long-lived and may also demonstrate self-similarity

Artificial Life & Creative Ecosystems

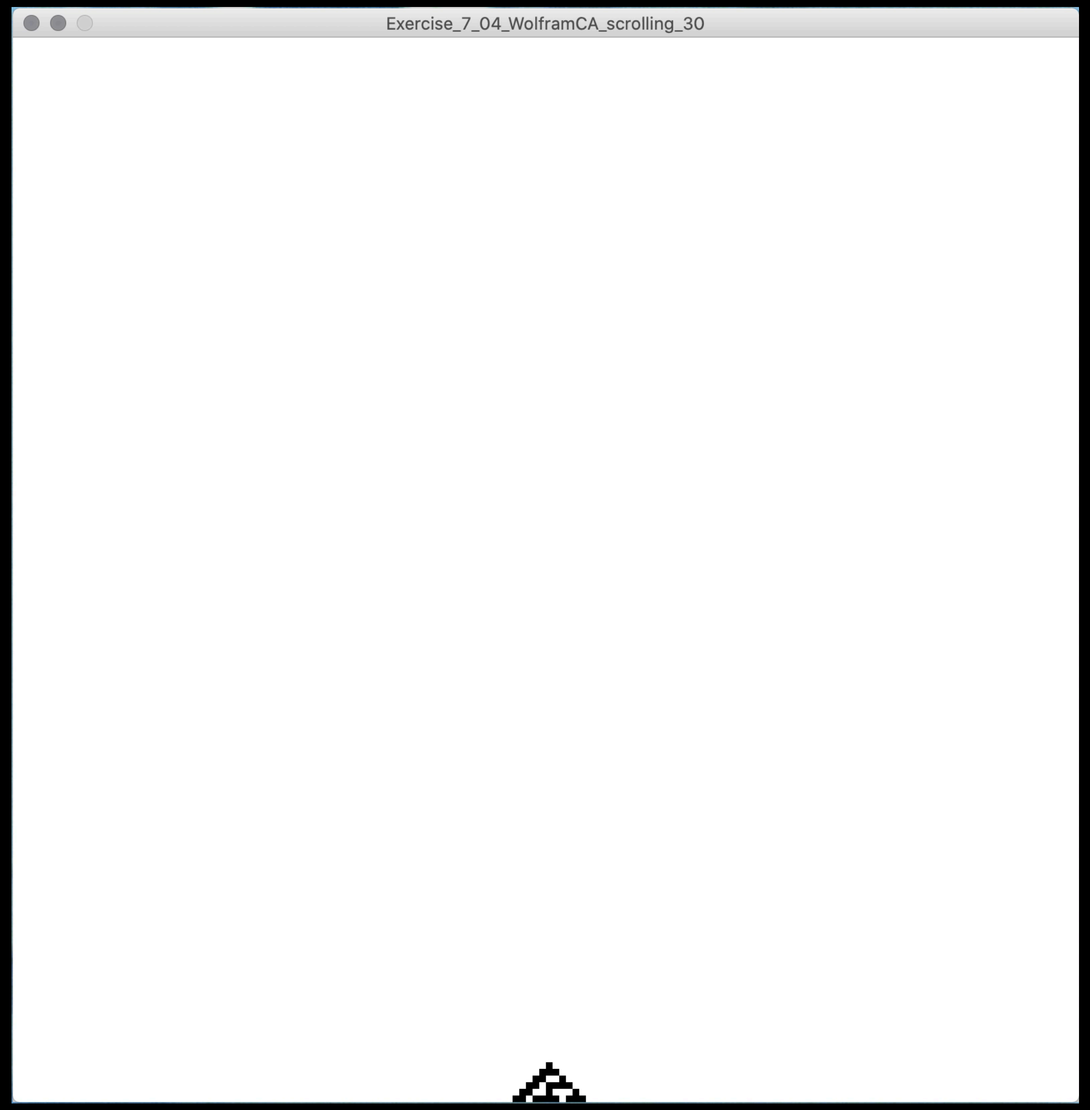
Cellular Automata



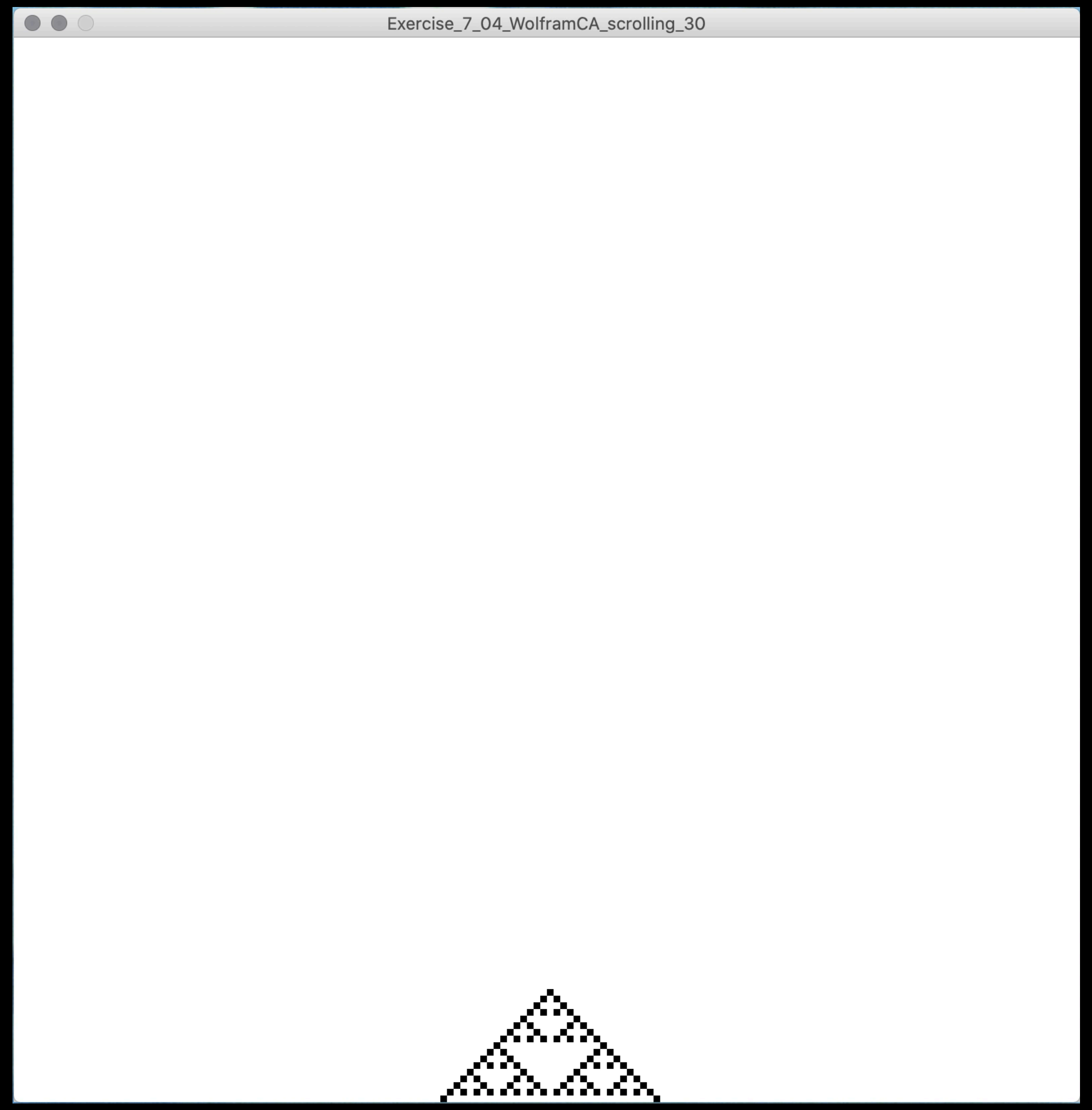
Rule 222 (Class 1)



Rule 190 (Class 2)



Rule 30 (Class 3)



Rule 90 (Class 4)

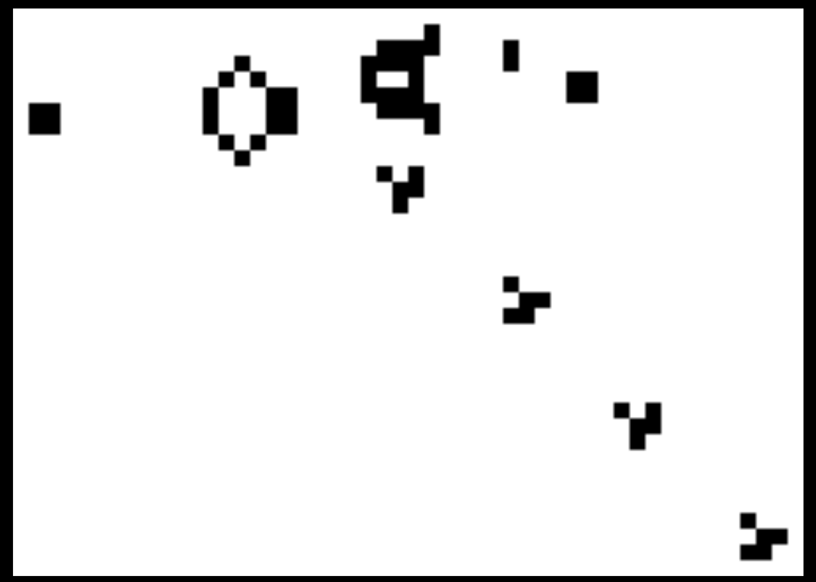
Artificial Life & Creative Ecosystems

Cellular Automata

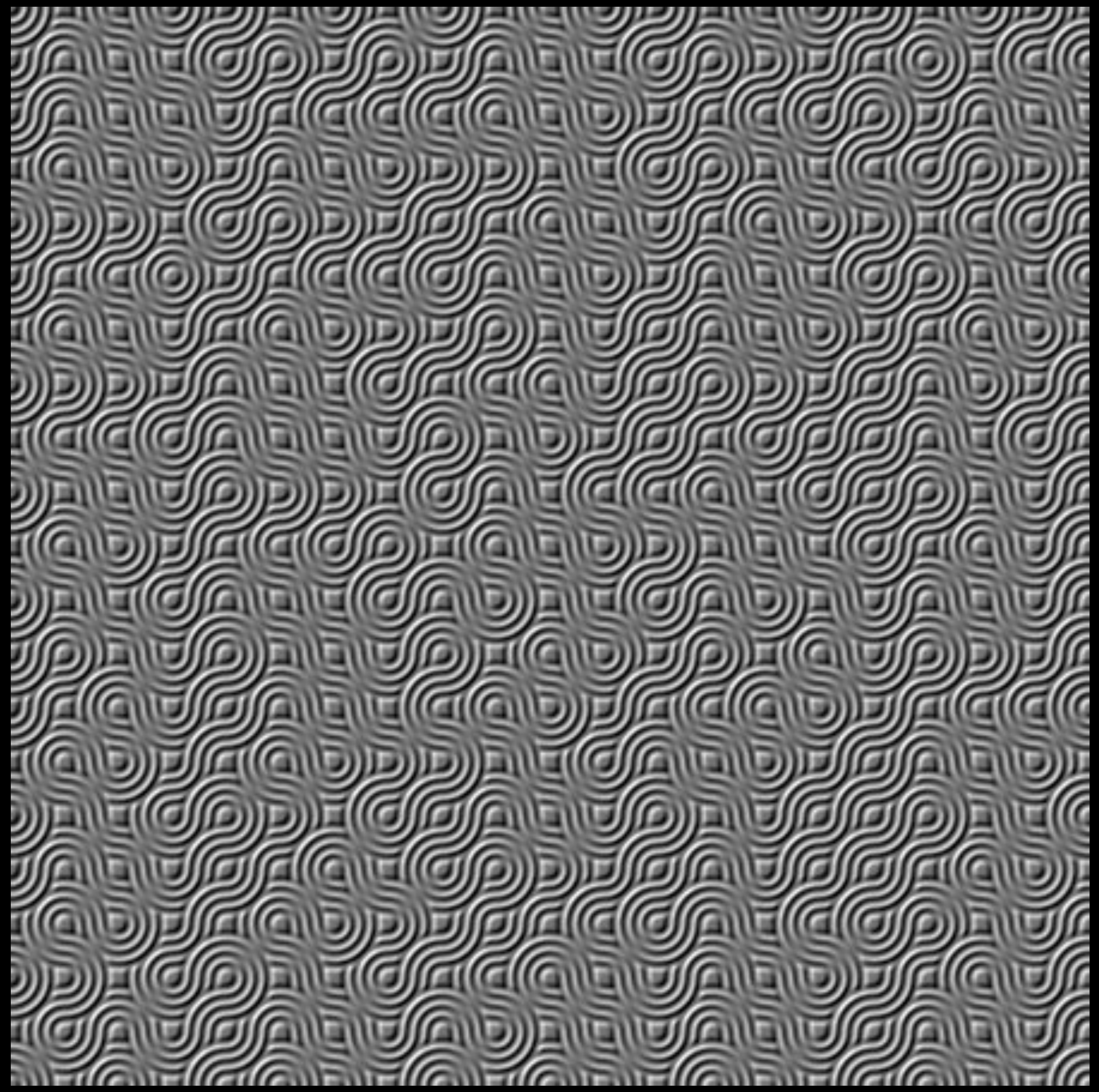
Rule 30

Artificial Life & Creative Ecosystems

Cellular Automata

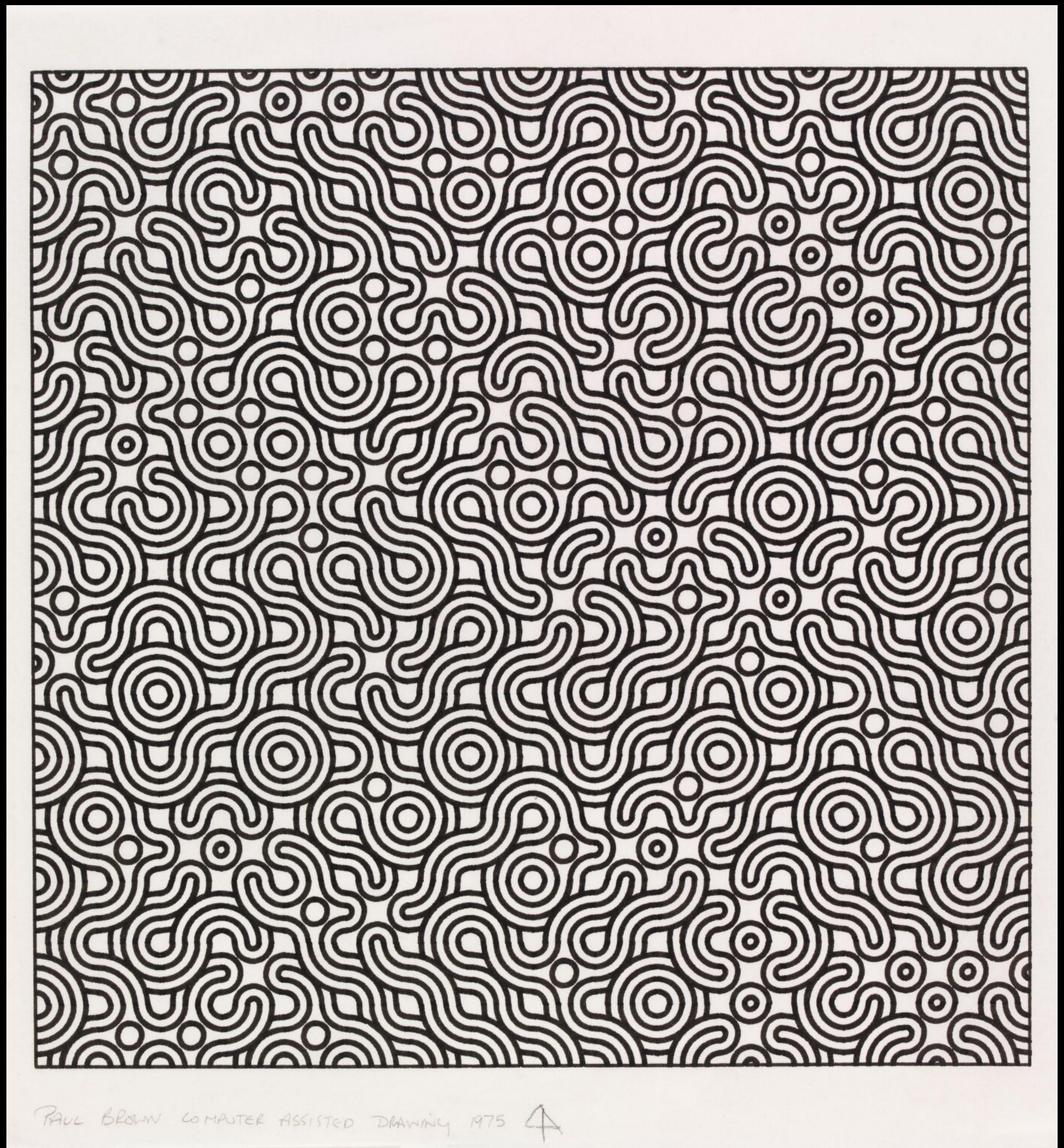


Conways Game of Life (2D CA)



The Deluge (after Leonardo) (1995)
(Giclée print)

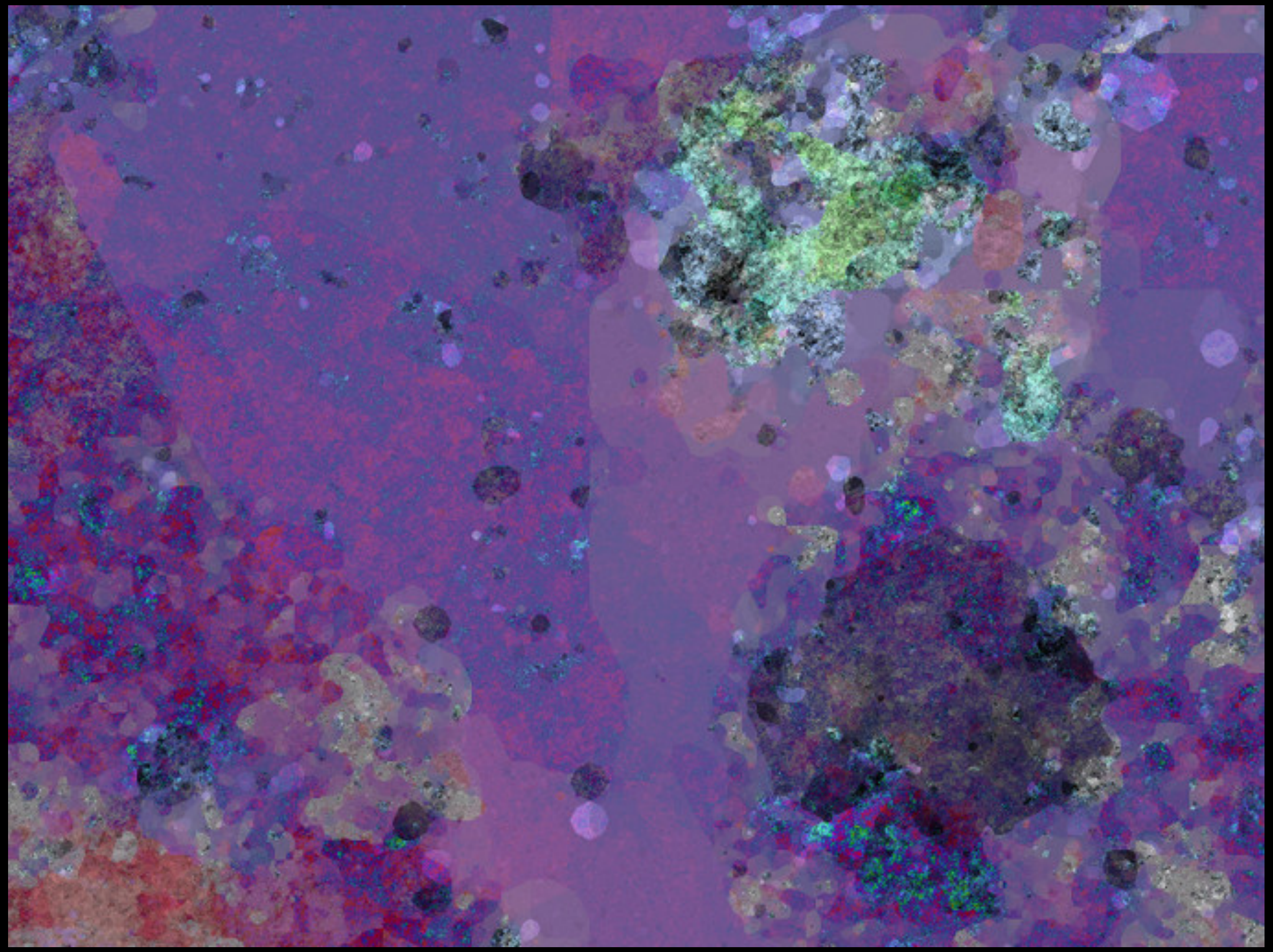
Mud Flats (1996)
(stainless steel detailing and hydraulics)

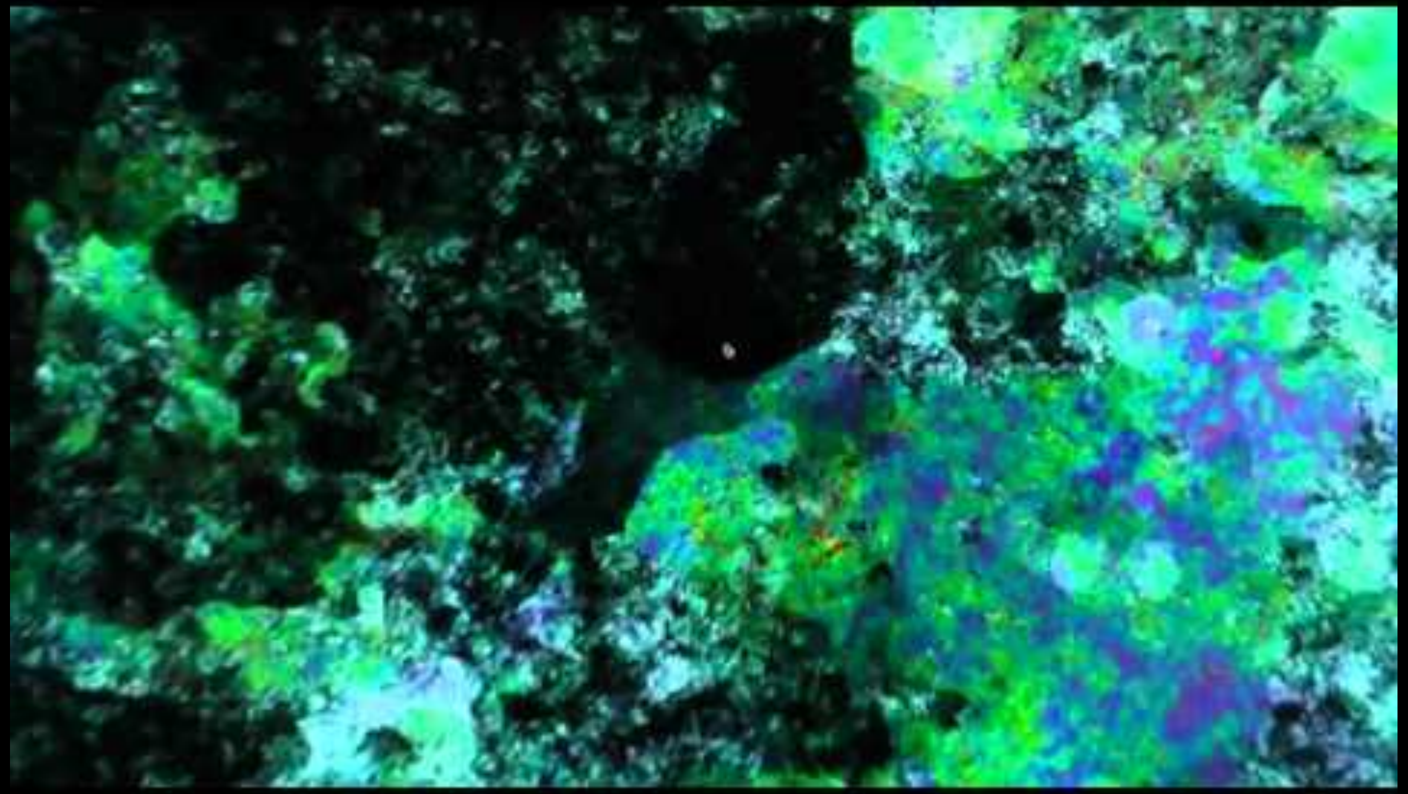


Untitled Computer Assisted Drawing (1975)
(plotter drawing on paper)

Paul Brown

- started working with CAs in the 1970s
- used CAs instead of chance to organize the tiles he was using in his aleatoric visual art





Ima Traveller - Erwin Driessens and Maria Verstappen (1996)

- interactive software for exploring an “infinite universe”
- space develops in real-time in the direction you are moving into (so it never ends)
- pixels divide or merge with others

Noise Square - Mo H. Zareei (2014)

Artificial Life & Creative Ecosystems

Cellular Automata

- Closing thoughts on CAs:
  - Overall the variety of mappings in CAs is impressive
  - Deterministic and discrete, so easy to understand and simple to create but often converge to repetitive patterns (workaround: randomly add noise/randomness)
  - Can be seen as simple reactive agents in a multi-agent system

?

“What will limit us is not the possible evolution of technology, but the evolution of human purposes.”

Stephen Wolfram

What is Life?

Artificial Life & Creative Ecosystems

Introduction to Artificial Life

- What is life?
  - There is currently no consensus regarding the definition of life
  - So we are left with listing properties of systems that we consider “alive”:
    - A state of functional activity and continual change before death, characterized by:
      - autonomous action
      - ability to adapt to an environment in order to survive
      - ability to grow and reproduce
      - ability to maintain a stable internal environment (homeostasis)
      - use of energy to carry out above processes
  - One alternative definition: autopoiesis (Maturana and Varela)
    - “self-production”, a system that produces itself
    - living systems are self-contained, self-referencing and self-realizing autonomous entities that arise out of certain circular and reflexive processes
    - a cybernetic/systems-based definition

Artificial Life & Creative Ecosystems

Introduction to Artificial Life

- Biology is the study of life on earth based on carbon chain chemistry
- However, this does not restrict us from studying other potential kinds of life
- Is “natural” life, a special kind of life?
- Artificial life is the study of life “as it could be” (not just as it is); of non-organic systems beyond the creations of nature that posses the essential properties of life as we understand it and whose environment is artificially created in some alternative media (which is often a digital computer)

“Artificial Life [AL] is the study of man-made [sic] systems that exhibit behaviors characteristic of natural living systems. It complements the traditional biological sciences concerned with the analysis of living organisms by attempting to synthesize life-like behaviors within computers and other artificial media. By extending the empirical foundation upon which biology is based beyond the carbon-chain life that has evolved on Earth, Artificial Life can contribute to theoretical biology by locating life-as-we-know-it within the larger picture of life-as-it-could-be.” (Langton, 1989)

Christopher Langton

Artificial Life & Creative Ecosystems

Biological Agents

- Bio-art is an artistic practice that adapts biotechnology and biological methods and materials to explore life and the implications of biological research
    - blurs boundaries between art and science with an emphasis on philosophical, societal, and environmental issues.
    - critically engages with applications and implications of the life sciences and opens up discussions around implications of biotechnology and manipulation of nature

Microvenus - Joe Davis (1988)

- encoded a symbol for life and femininity into an *E. coli* bacterium
- graphic image converted to DNA base pairs (Davis 1996)
- first non-biological message encoded in DNA
- used to communicate with extraterrestrials

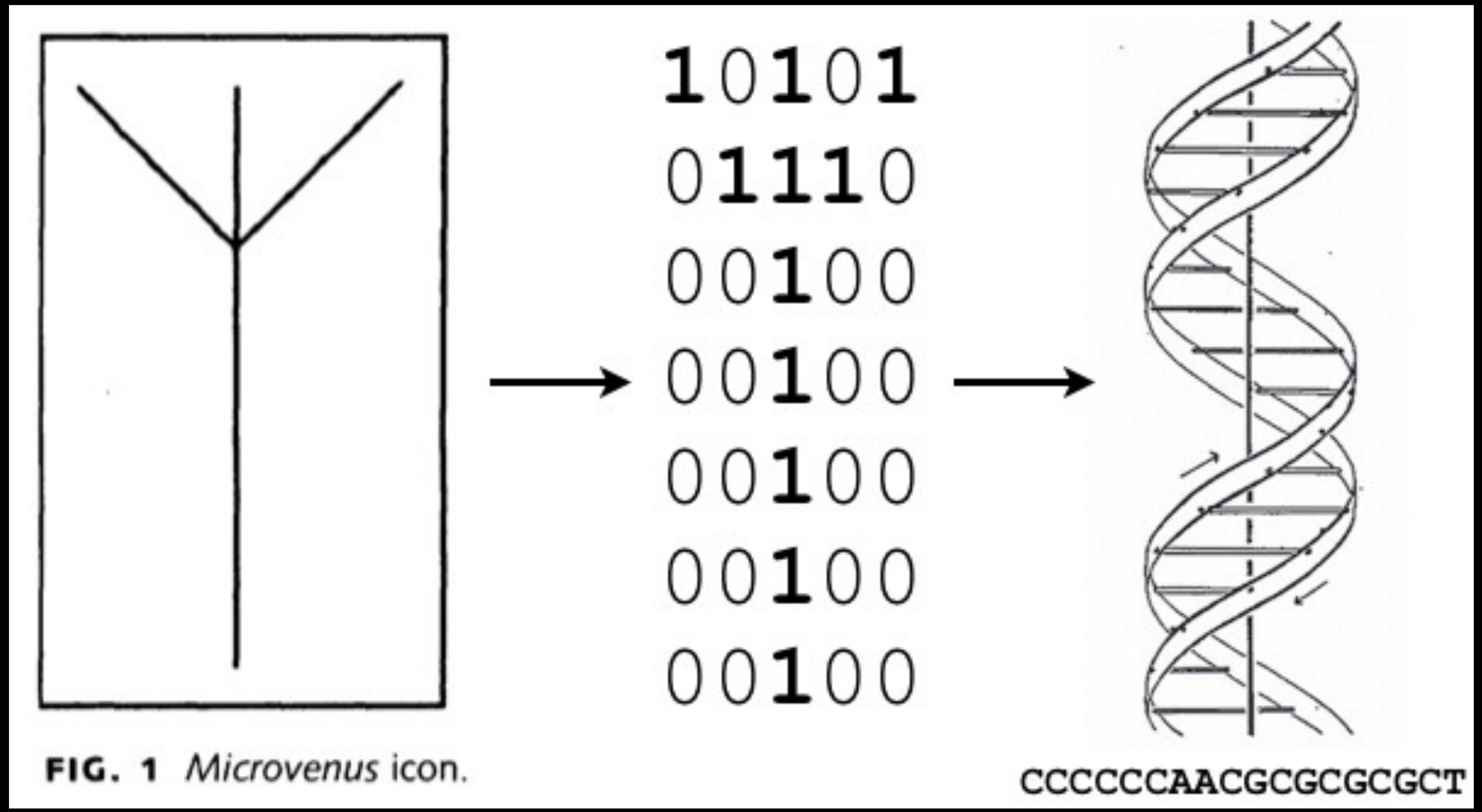


FIG. 1 *Microvenus* icon.

GFP Bunny - Eduardo Kac (2000-06)

- A rabbit, named Alba, whose genome was altered to include the green fluorescent protein (GFP) so that it would fluoresce under UV light
- Transgenic art
- raised all sort of discussions about the use genetic engineering

Artificial Life & Creative Ecosystems

Genetic Algorithms

- Genetic algorithms (GAs) are search-based optimization techniques based upon processes and principles that mimic biological evolution (e.g. genetics and natural selection):
    - Starting with a population of candidate solutions (or individuals or hypotheses), GAs generate successor individuals by repeatedly recombining and mutating parts of the best currently known individuals
    - The popularity of GAs is motivated by:
        - Evolution is known to be a successful and robust method for adaptation within biological systems
        - GAs can search for candidates in which the impact of parts on the overall candidate fitness may be difficult to model.
        - The basic idea is very simple (and yet quite convincing and powerful)
    - GAs are part of a family of related approaches known as evolutionary computing (which includes, genetic programming, evolution strategies, learning classifier systems and more)

Artificial Life & Creative Ecosystems

Genetic Algorithms

- GAs move the design problem from:
  - Knowing how to design the solution to a problem to
  - Knowing how to evaluate potential solutions
- GAs are adaptive heuristic search algorithms (educated guessing or self-discovery)
- Note that here, biological evolution is used as a guide rather than a constraint and in practice many deviations from “real” evolution are used (e.g. Lamarkian evolution)
- GAs were developed by John Holland and his colleagues at University of Michigan in the 1970s

Artificial Life & Creative Ecosystems

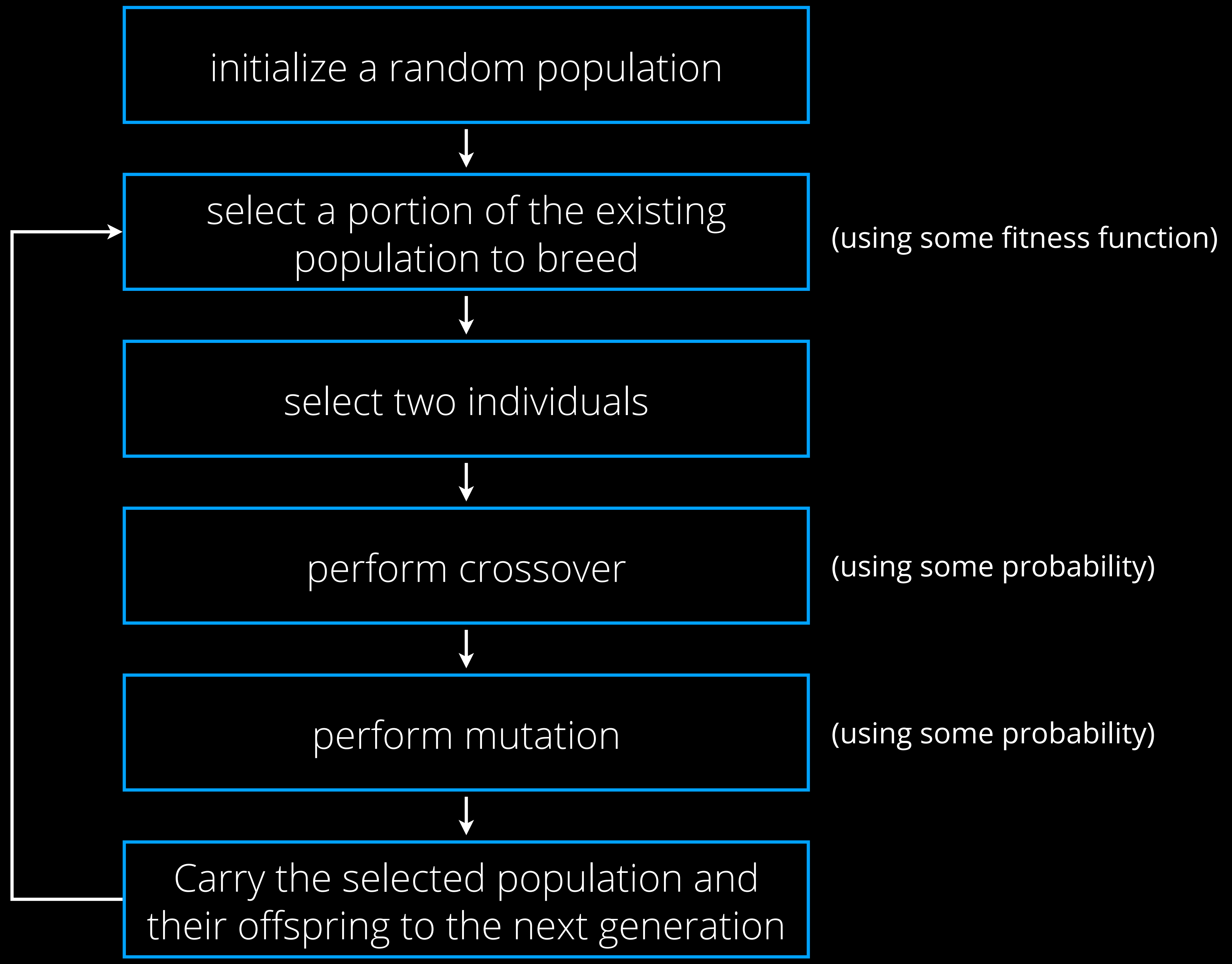
Genetic Algorithms

- Elements of a GA:
  - Representation of candidate solutions, i.e. genes/genotype/chromosome
  - A well-defined fitness function that evaluates candidate solutions (assigns a score); a type of objective function
  - A selection function: partitions a portion of the existing population that is deemed fittest
  - Genetic operators:
    - crossover: recombination of two parent chromosomes
    - mutation: a random change in part of a chromosome

Artificial Life & Creative Ecosystems

Genetic Algorithms

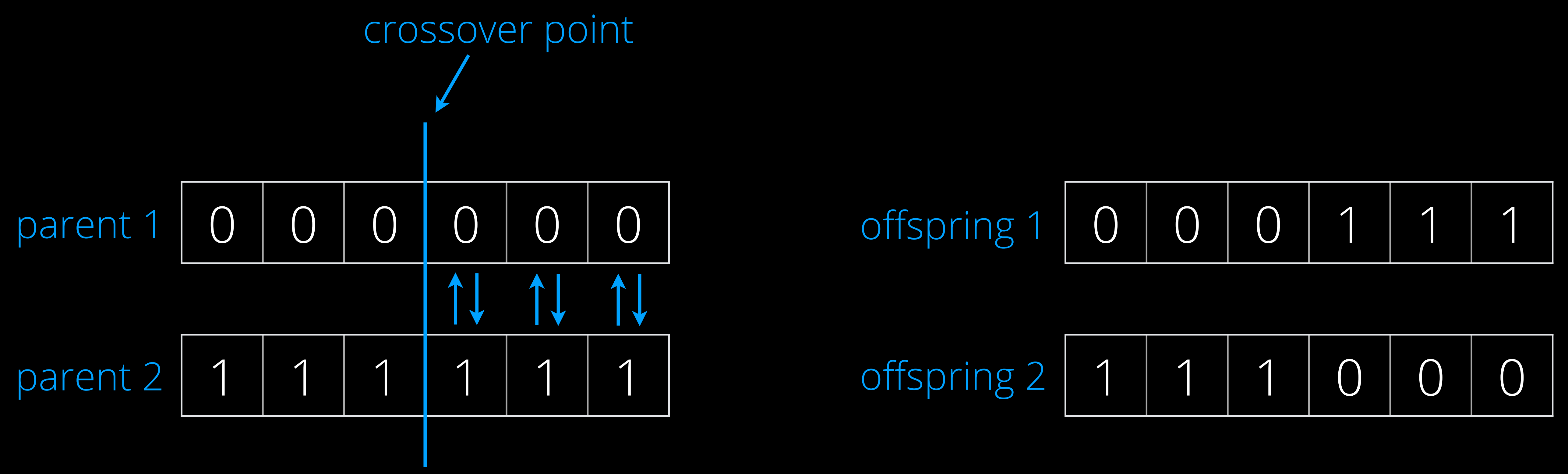
- The basic GA loop:
  - sometimes only offspring are carried to the next generation (replace parents immediately)
  - The ending criteria can be:
    - some fitness threshold reached
    - fixed number of generations
    - no more improvement (in terms of fitness)
    - time, patience, memory or funding



Artificial Life & Creative Ecosystems

Genetic Algorithms

- Crossover



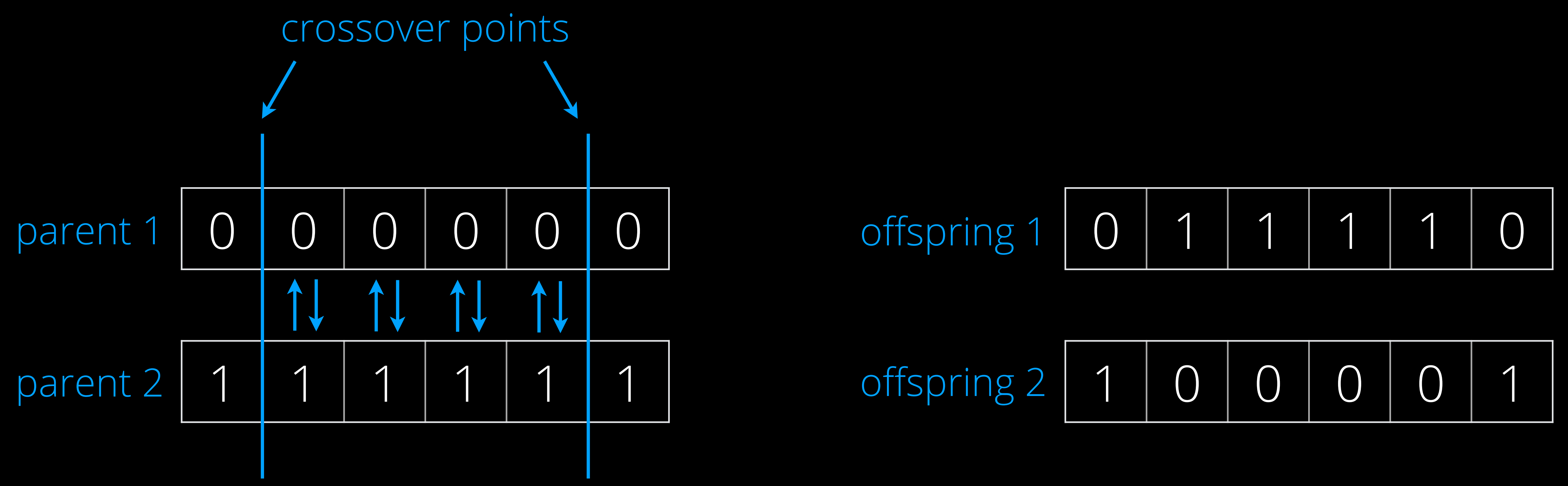
Single-point crossover

- crossover point is usually randomly selected
- typically everything to the right of crossover point is exchanged

Artificial Life & Creative Ecosystems

Genetic Algorithms

- Crossover



Multi-point crossover

- in 2-point crossover (shown here), everything between the two crossover points is exchanged
- can be generalized to *n*-point crossover; picking *n* crossover points; chromosome is broken into more than two segments of contiguous genes and the offspring are created by taking alternative segments from the parent

Artificial Life & Creative Ecosystems

Genetic Algorithms

- Crossover

Uniform crossover

- chromosome is not divided into segments
- each gene is treated separately
- essentially flip a coin for each pair of corresponding genes to decide whether or not they will be swapped.

Artificial Life & Creative Ecosystems

Genetic Algorithms

- Mutation

1	0	0	1	0	1	→	1	0	0	0	0	1

bit-flip mutation

1	2	3	4	5	6	→	1	5	3	4	2	6

swap mutation

5	2	4	4	8	9	→	5	2	4	4	5	9

uniform mutation

(only for integers and floats)

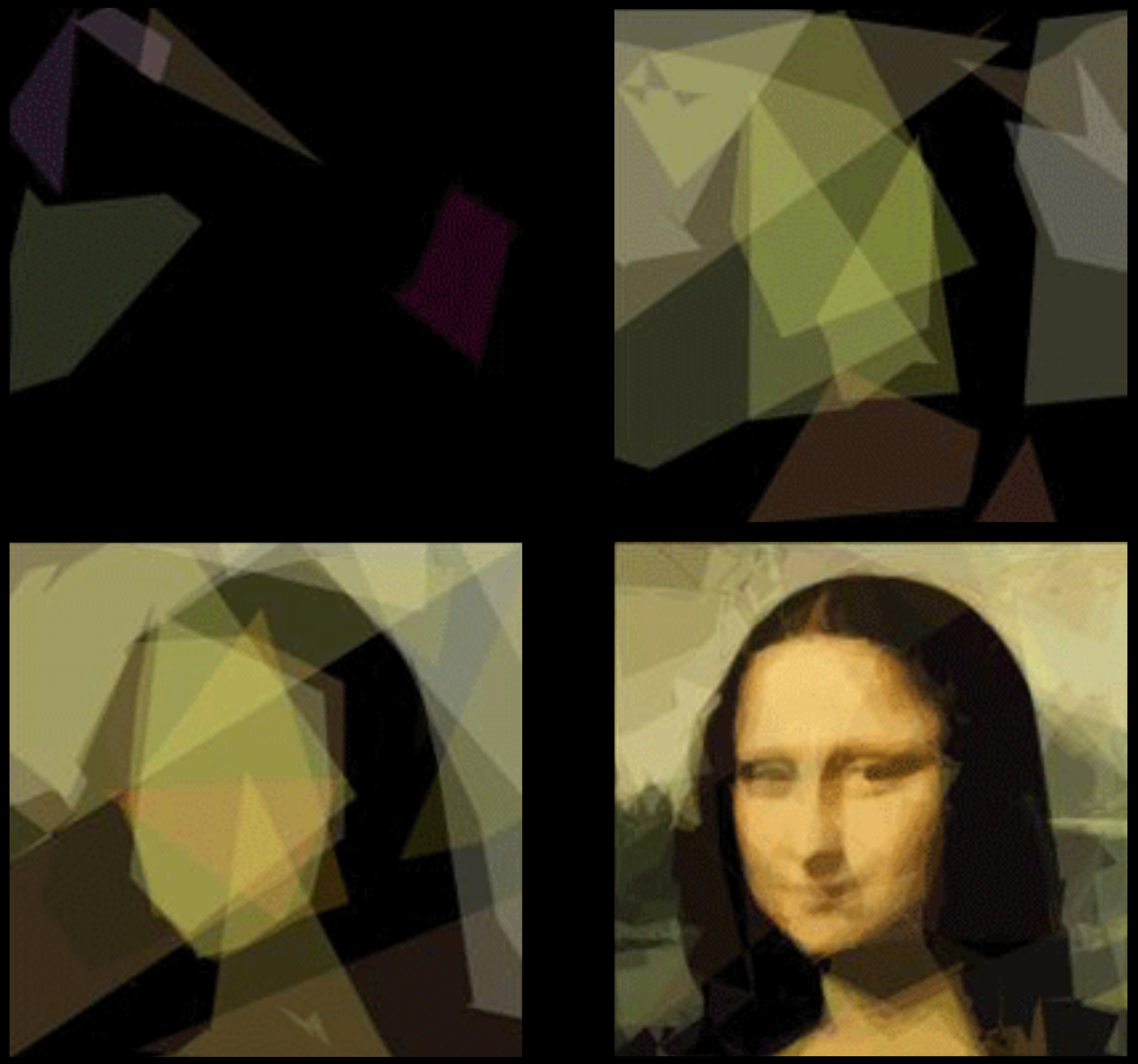
change the value of a gene randomly within its lower and upper bound (e.g. 0-9)

- non-uniform (adding a small amount drawn randomly from a Gaussian distribution) (integers and floats only)
- gaussian (adds a unit Gaussian distributed random value to the chosen gene) (integers and floats only)
- shuffle (randomly shuffle a subset of the chromosome)
- boundary (randomly replaces a gene with either lower or upper bound value (integers and floats only)
- and more...

Artificial Life & Creative Ecosystems

Genetic Algorithms

- Fitness Function:
    - A type of objective function
    - Example: calculate the error for a GA that renders polygons to recreate some target image (e.g. painting of the Mona Lisa)
        - do a pixel-by-pixel comparison against the target image. The fitness score is the total error.
        - lower score means a closer match (and thus better fitness score).



Artificial Life & Creative Ecosystems

Genetic Algorithms

- Selection Strategies:
  - Truncation: simply retains the fittest x% of the population (simplest and arguably least useful; not used much in practice)
  - Roulette Wheel (also called Fitness-Proportionate): each member of the population is allocated a section of an imaginary roulette wheel.
    - sections are different sizes, proportional to the individual's fitness, (i.e. fittest candidate has the biggest slice of the wheel)
    - wheel is then spun and the individual associated with the winning section is selected.
  - Tournament: two candidates are chosen at random and the fittest is kept with probability *p*
  - Rank: sort the population by fitness, then select a candidate via a probability depending on their rank (as opposed to their fitness value)
  - Elitism: copy a small proportion of the fittest candidates, unchanged, into the next generation

Artificial Life & Creative Ecosystems
Genetic Algorithms

- Pros & Cons of GAs
  - Pros:
    - Avoid local optima (because of their parallelism)
    - Fast
    - Easy to understand and implement
  - Cons:
    - Difficult to determine the “best” solution since solutions are only compared to each other
    - Fitness bottlenecks (for interactive GAs, often used in creative tasks)
    - Fitness evaluation for complex, high-dimensional problems can be slow

?

“Genetic engineers don't make new genes, they rearrange existing ones.”

Thomas E. Lovejoy

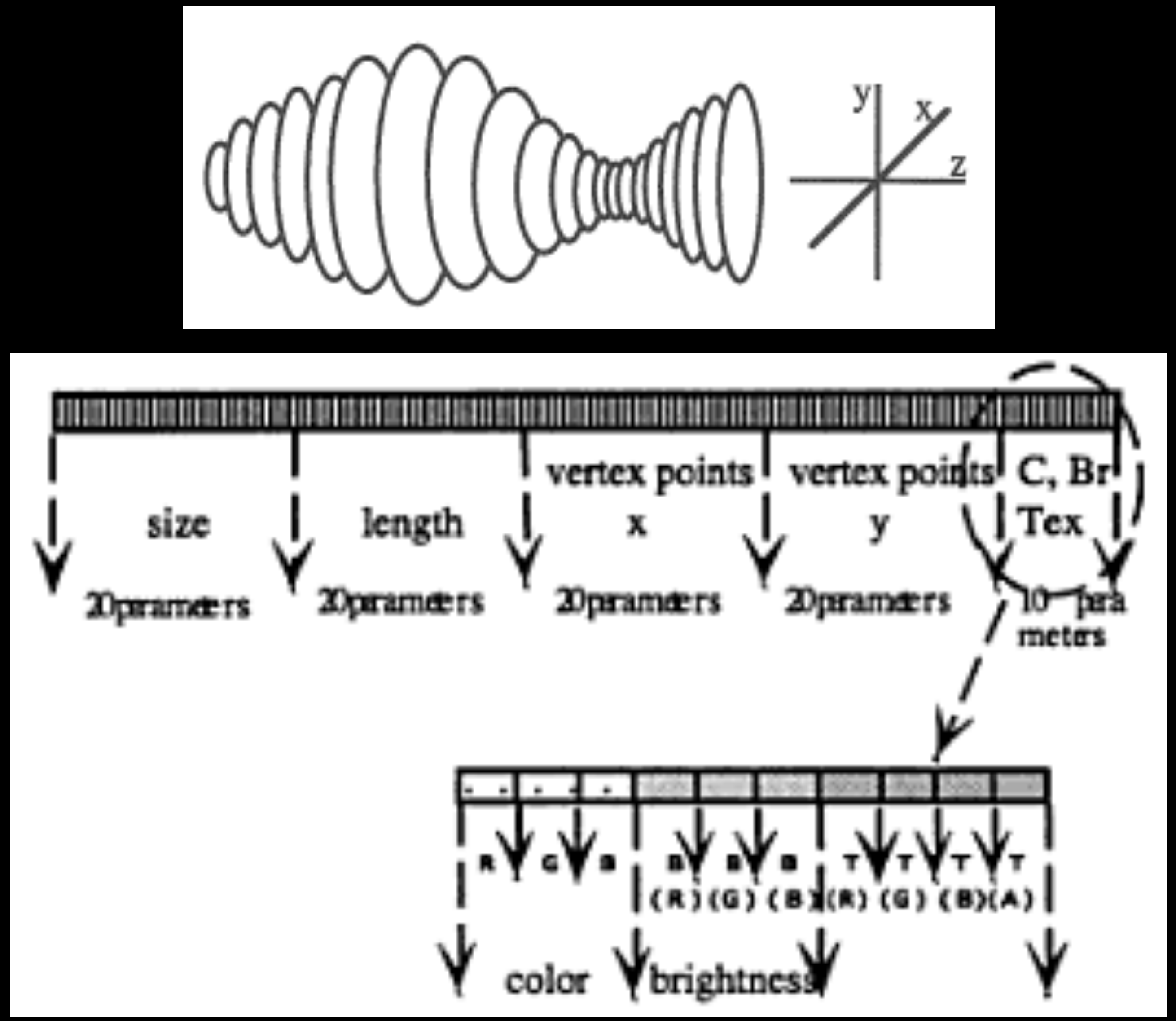
Artificial Life & Creative Ecosystems

Creative Ecosystems

- In nature, ecosystems are abiotic environments in which groups of organisms live
- Inter-organism interactions can take many forms: reproduction, communication, predation, competition, mutualism, parasitism, commensalism
- Two ways of modeling ecosystems:
    - Analytical: uses equations to represent interactions and evolution of various elements of the system
    - Multi-agent simulations: each type of agent and the environment are modeled and a simulation of the system is implemented. A virtual ecosystem.

A-volve - Christa Sommerer and Laurent Mignonneau (1994-95)

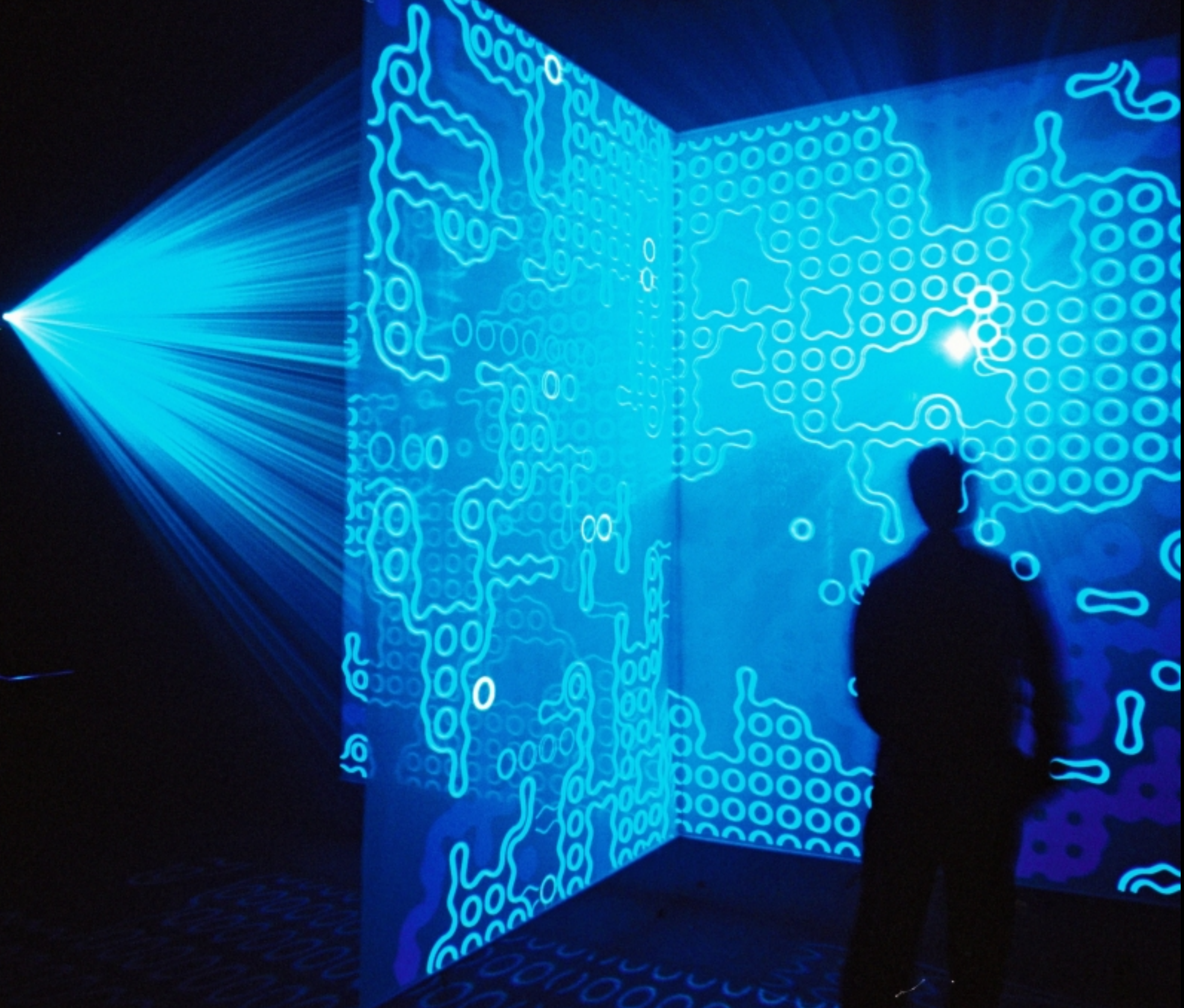
- 3-dimensional creatures projected onto a pool of real water
- creatures will seek, avoid or otherwise interact with participants' fingers when they are placed in the pool
- participants can create new creatures by drawing on a pressure-sensitive tablet



Sommerer et al, 1997

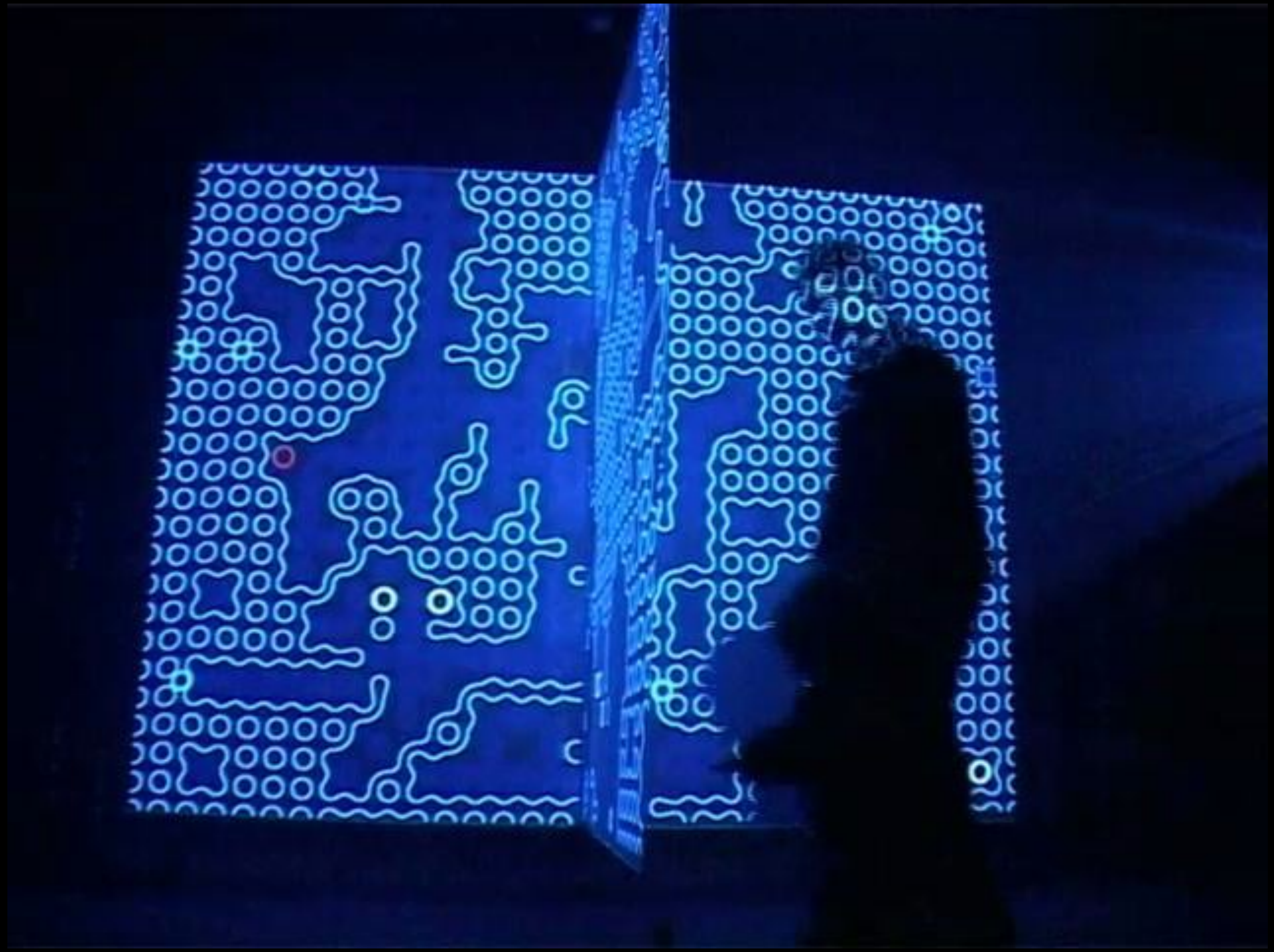
A-volve - Christa Sommerer and Laurent Mignonneau (1994-95)

- GAs used for properties such as size & color of the creatures
- Creatures mate and repduce
- predator-prey behavior



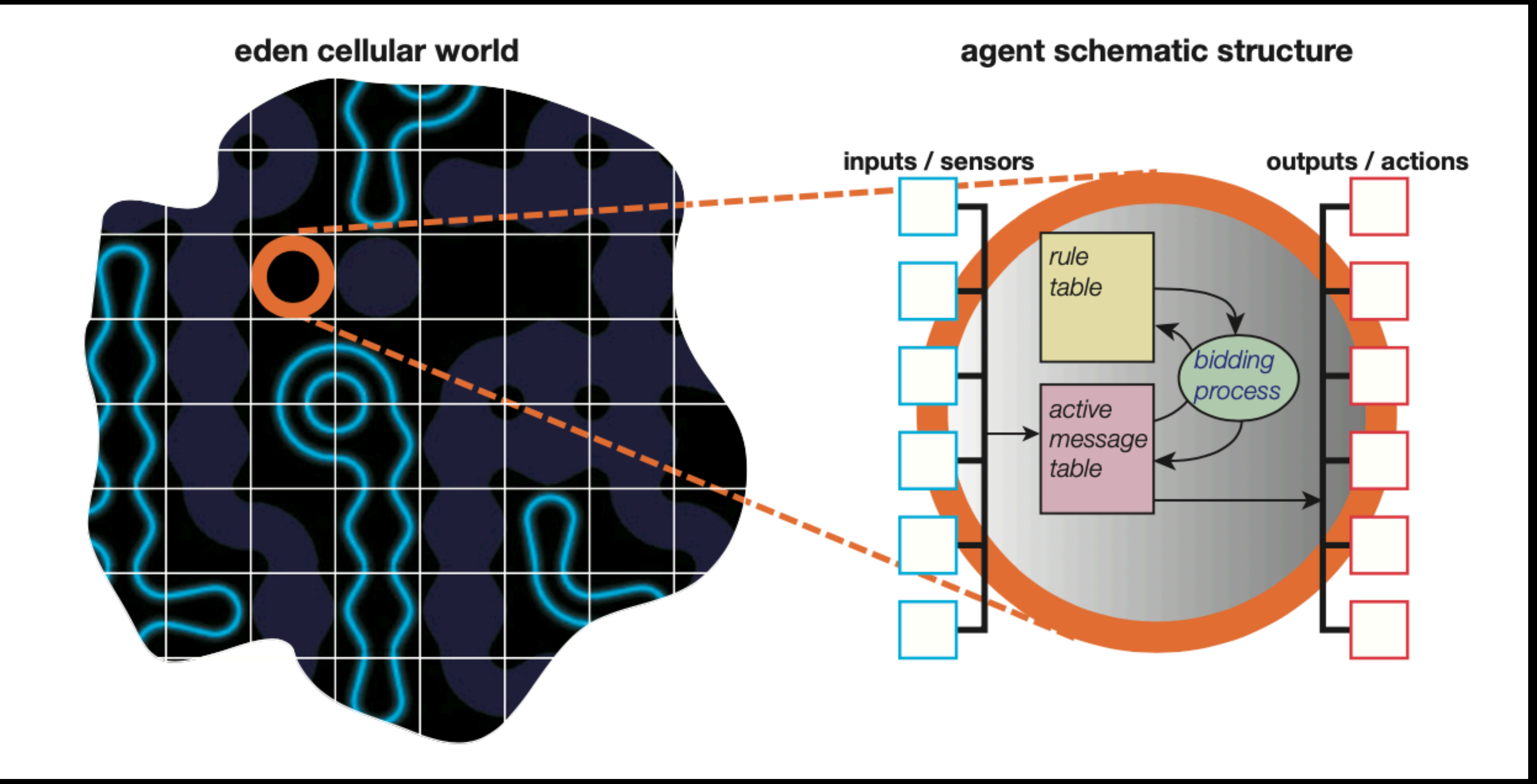
Eden - Jon McCormack (2000-10)

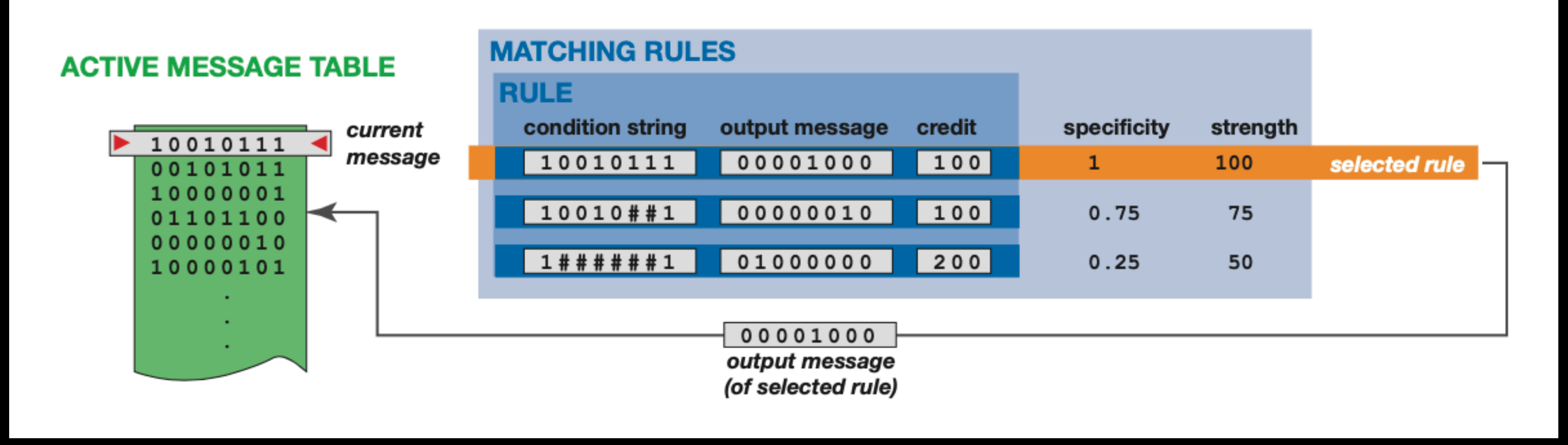
- evolutionary sonic ecosystem
- a society of sonic creatures evolve to fit their landscape
- creatures move about their environment, making and listening to sounds, foraging for food, encountering predators and possibly mating

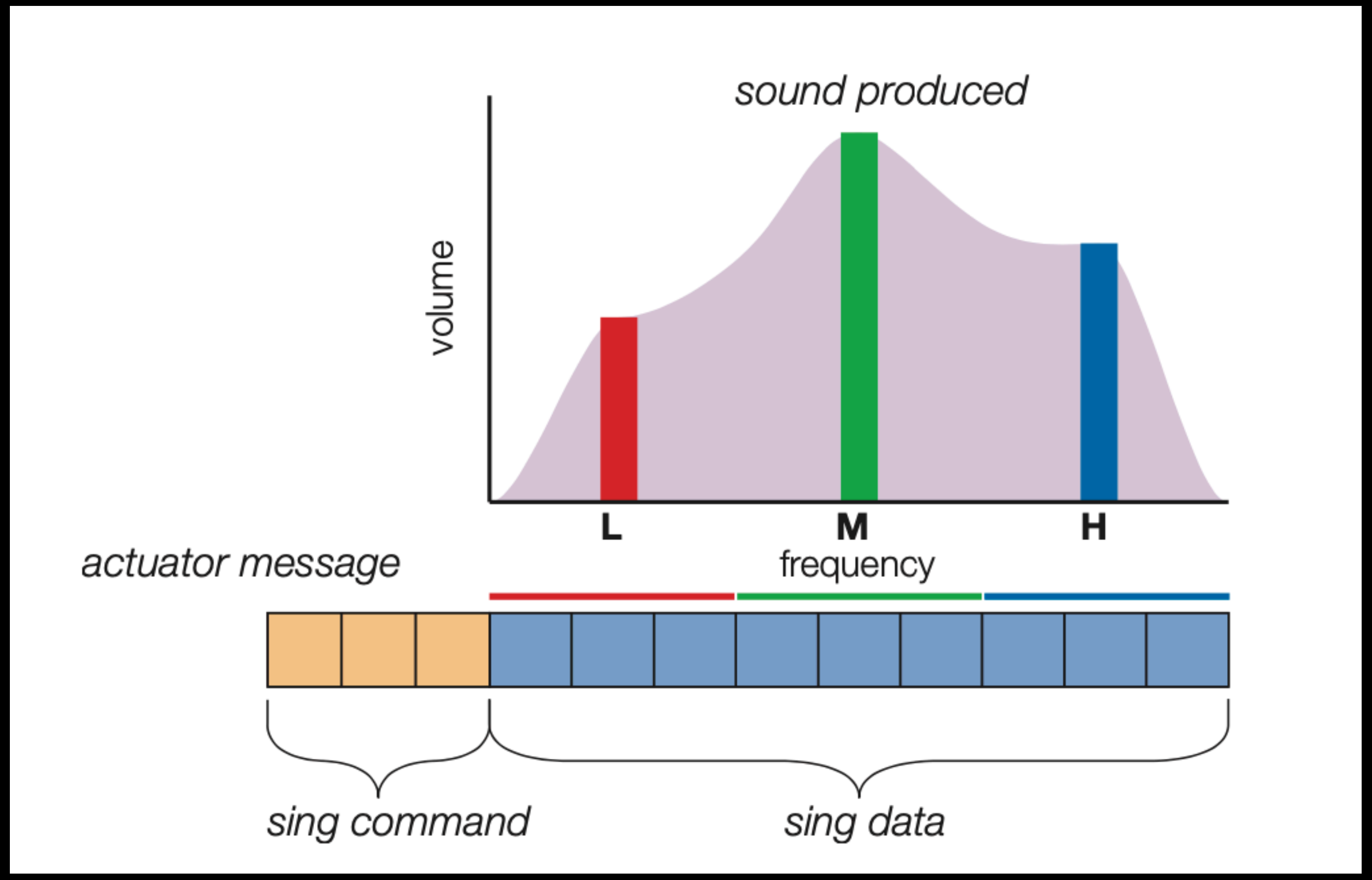


Eden - Jon McCormack (2000-10)

- non-zoomorphic creatures
- primary aesthetic is on sound
- sonic agents hear sounds, locate their source and “sing” to each other
- visual patterns based upon Islamic tiling
- uses Learning Classifier System (Holland 1995, 1975)







(McCormack 2009)

Eden - Jon McCormack (2000-10)

- LCS are basically a combination of GAs and reinforcement learning
- Each agent maintains a database of *rules* called a *rule-table*
- Creatures sense their environment and take action by selecting one of these rules
- These rules are evolved and their “usefulness” is determined by how their faired in the environment
- credit assignment system assigns each rule a credit value, representing the rule’s “usefulness” to the agent
- over time rules that are helpful to the creature’s survival gain credit
- The basic units of genetic exchange through mating are the creature’s rule-tables (evolve new rules and improve existing ones)

The Flock (1993-94)

Ken Rinaldo & Marc Grossman

IVOR DIOSI

MOLDING THE SIGNIFIER (2011-12)


bioagents (molds)
sensors
digital microscope
microscape data
sim tissue (VR-retina)
virtual human
mimetic emoting
disruption

?

“If we are going to teach creation science as an alternative to evolution, then we should also teach the stork theory as an alternative to biological reproduction.”

Judith Hayes