Exploring Complexity

In Science and Technology

Nov. 10, 2010

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Logistics

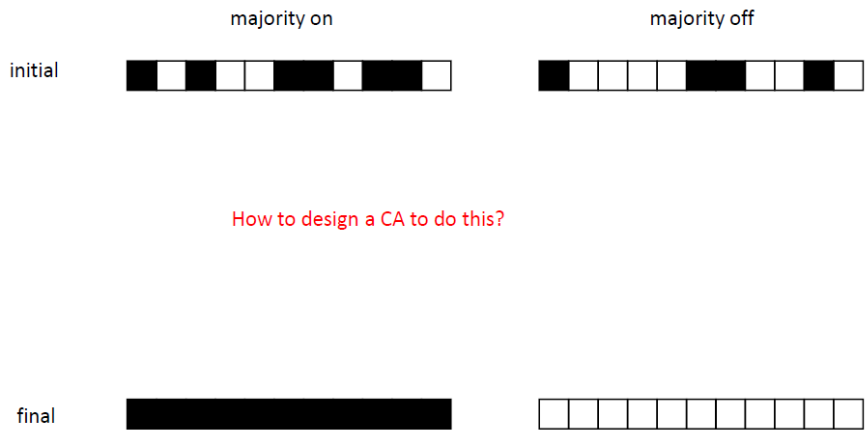
- Due
  - HW6 and Lab5 due Monday Nov. 15
- Hand back and go over
  - HW5 and Lab 4
- Final Paper Handout
  - Acceptable sources
- Questions?

How to define “potential for computation”?

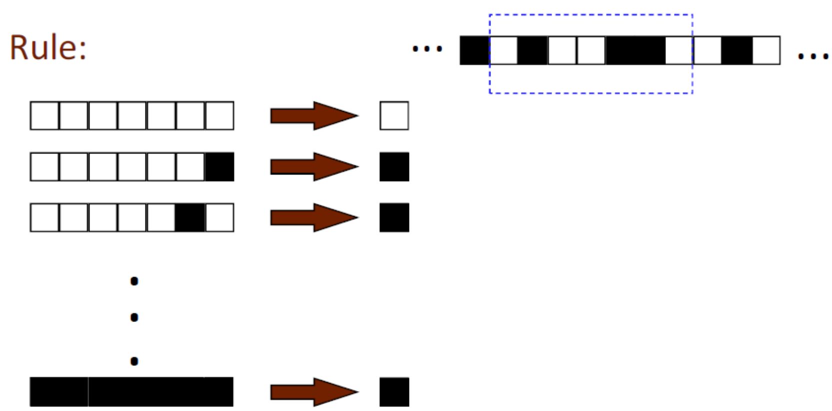
- Adaptation to the Edge of Chaos (N. Packard, 1988)
- Main ideas:
  - Define a task for cellular automata requiring non-trivial computation.
- Use a genetic algorithm to evolve a population of cellular automaton rules, with fitness defined as performance on the task.
- Analyze the distribution of lambda values in the final generation.

A computational task for cellular automata

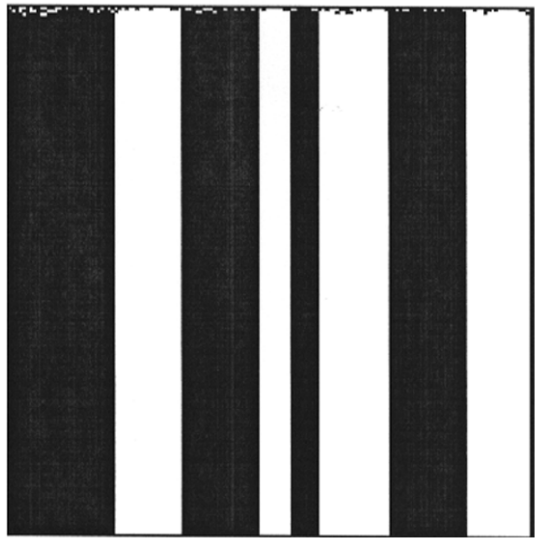
- Design a cellular automata to decide whether or not the initial pattern has a majority of “on”cells.
  - If a majority of cells are initially on, then after some number of iterations, all cells should turn on
  - Otherwise, after some number of iterations, all cells should turn off.



Packard used cellular automata with 6 neighbors for each cell:



A candidate solution that does not work: local majority voting



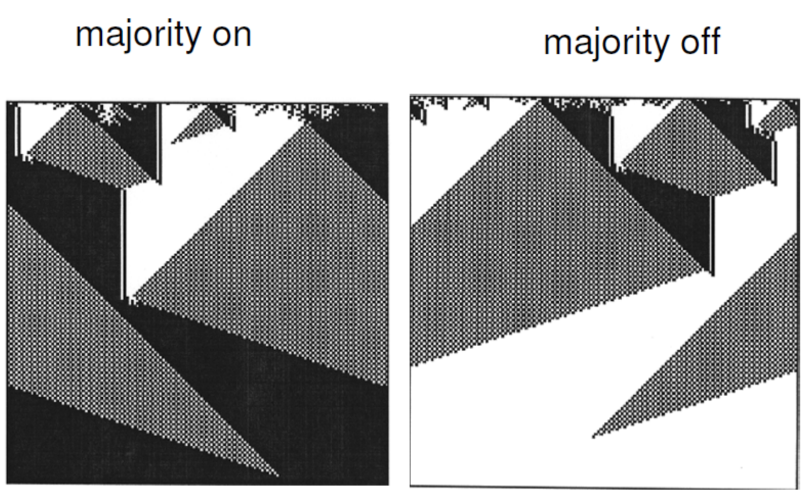
Evolving cellular automata with genetic algorithms

- Create a random population of candidate cellular automata rules
- The “fitness” of each cellular automaton is how well it performs the task. (Analogous to surviving in an environment.)
- The fittest cellular automata get to reproduce themselves, with mutations and crossovers.
- This process continues for many generations.

Stephen Wolfram's last problem

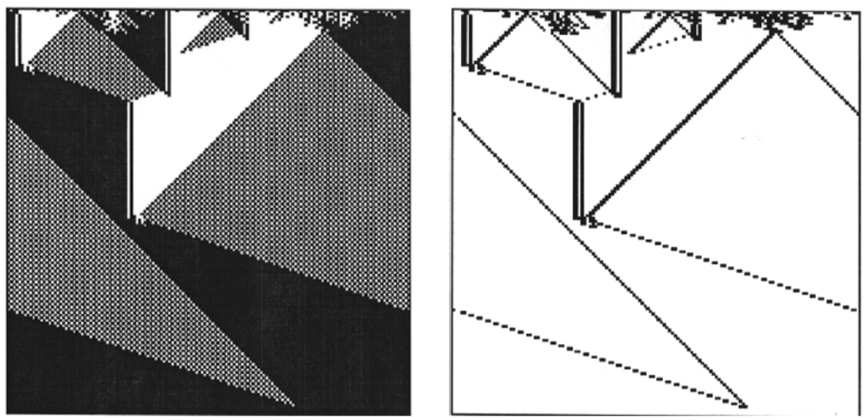
- from ``Twenty problems in the theory of cellular automata'' (Wolfram, 1985):
- 20. What higher-level descriptions of information processing in cellular automata can be given?
- "It seems likely that a radically new approach is needed"

A cellular automaton evolved by the genetic algorithm



How do we describe information processing in complex systems?

- Simple patterns filtered out: “Particles”



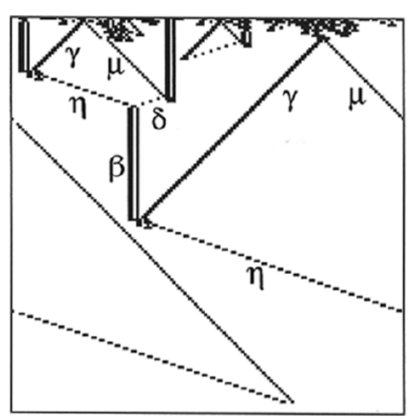
Laws of particle physics

Regular Domains		
$\Lambda^0 = 0^*$	$\Lambda^1 = 1^*$	$\Lambda^2 = (01)^*$

Particles (Velocities)	
$\alpha \sim \Lambda^0\Lambda^1$ (0)	$\beta \sim \Lambda^1 01 \Lambda^0$ (0)
$\gamma \sim \Lambda^0\Lambda^2$ (-1)	$\delta \sim \Lambda^2\Lambda^0$ (-3)
$\eta \sim \Lambda^1\Lambda^2$ (3)	$\mu \sim \Lambda^2\Lambda^1$ (1)

Interactions	
decay	$\alpha \to \gamma + \mu$
react	$\beta + \gamma \to \eta$, $\mu + \beta \to \delta$, $\eta + \delta \to \beta$
annihilate	$\eta + \mu \to \emptyset_1$, $\gamma + \delta \to \emptyset_0$

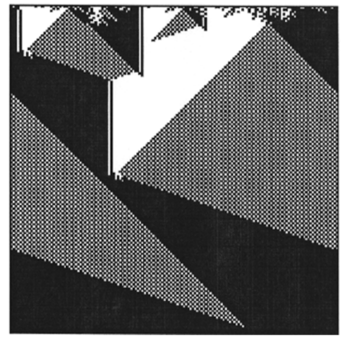
Particles

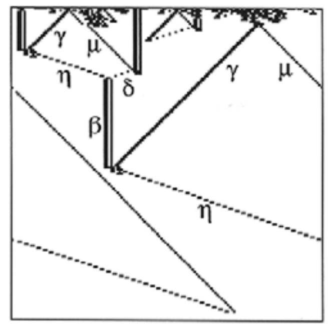


Reasoning with Particles

… the α and β particles encode different types of information about the initial configuration. The α particle decays into γ and μ. The γ particle carries the information that it borders a white region; similarly, the μ particle carries the information that it borders a black region. When γ collides with β before μ does, the information contained in β and γ is combined to deduce that the large initial white region was smaller than the large initial black region it bordered. This new information is encoded in a newly created particle η, whose job is to catch up with and annihilated the μ (and itself).

Complexity: A Guided Tour, p. 166-7

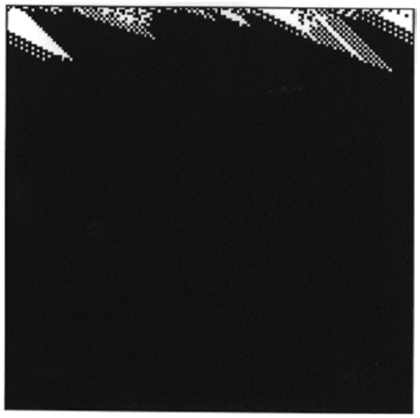




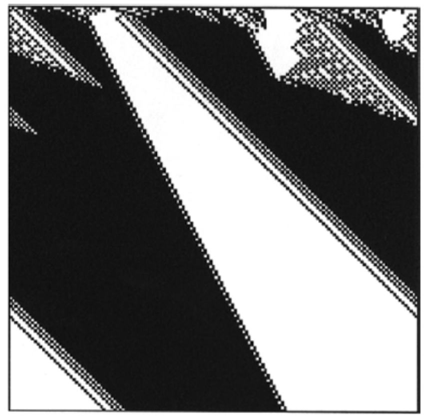
Level of particles can explain:

- Why one CA is fitter than another
- What mistakes are made
- How the GA produced the observed series of innovations
- Particles give an “information processing” description of the collective behavior
  - “Algorithmic” level

How the genetic algorithm evolved cellular automata

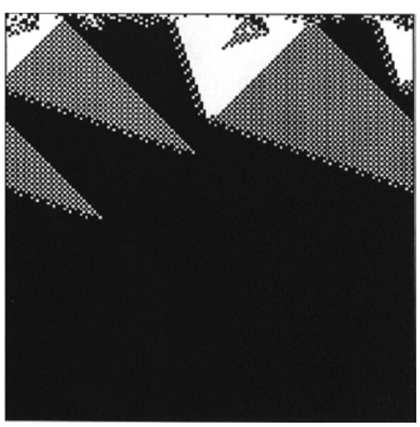


generation 8

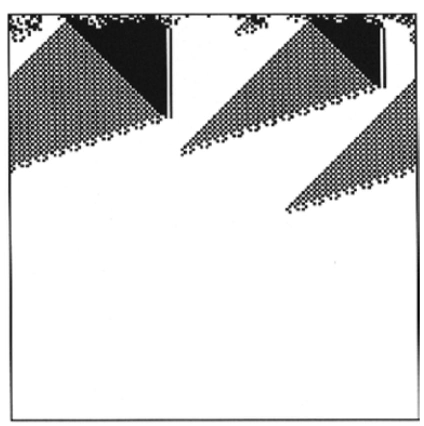


generation 13

How the genetic algorithm evolved cellular automata

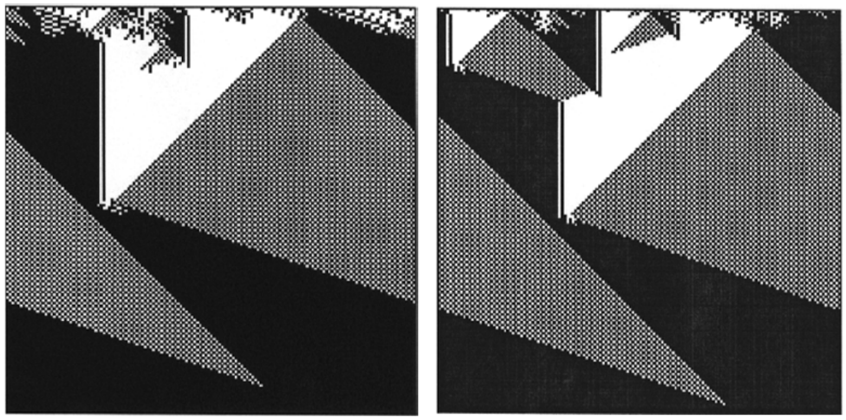


generation 17



generation 18

How the genetic algorithm evolved cellular automata



generation 33 generation 64

Information Processing in Living Systems

- What plays the role of “information” in these systems?
- How is it communicated and processed
- How does this information acquire *meaning*?

Information Processing In:

- Traditional Computers
- Cellular Automata
- The Immune System
  - http://www.youtube.com/watch?v=HUSDvSknIgI
- Ant Colonies
  - NetLogo example
- Biological Metabolism

Information Processing in Living Systems

- What plays the role of "information" in these systems?
  - Statistics and dynamics of patterns over the system's components
- How is it communicated and processed
  - Communication via Sampling
  - Random Components of Behavior
  - Fine-grained Exploration
  - Interplay of Unfocused and Focused Processes
- How does this information acquire *meaning*?

Coevolutionary Learning

- **Problem for learning algorithms:**
  - How to select training examples appropriate to different stages of learning?
- **One solution:**
  - Co-evolve training examples, using inspiration from host-parasite coevolution in nature.

Host-parasite coevolution in nature

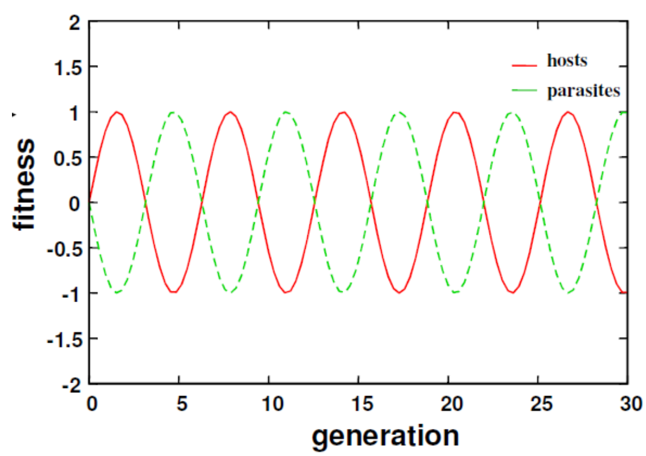
- Feedback
  - Hosts evolve defenses against parasites
  - Parasites find ways to overcome defenses
  - Hosts evolve new defenses
  - Continual “biological arms race”
- Darwin recognized the importance of coevolution in driving evolution
- Coevolution was later hypothesized to be major factor in evolution of sexual reproduction

Coevolutionary Learning

- Candidate solutions and training examples coevolve.
  - Fitness of candidate solution (host): how well it performs on training examples.
  - Fitness of training example (parasite): how well it defeats candidate solutions.

Practical problems observed in coevolutionary learning

- Cycling



Spatial Coevolution

- Works better than non-spatial methods
  - Maintains diversity over long period of time
  - Creates extended "arms race" between hosts and parasite populations
  - Spatial Examples:
    - http://biology.clc.uc.edu/Courses/bio303/coevolution.htm
    - http://necsi.org/projects/evolution/co-evolution/pred-prey/co-evolution_predator.html