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Computational Modeling for Science and Engineering: Agent-Based Models

Eduardo Izquierdo, Ph.D. (he/him)
Assistant Professor, Cognitive Science Program
Neuroscience Program, Complex Systems Program
Luddy School of Informatics, Computing, and Engineering
Indiana University Bloomington

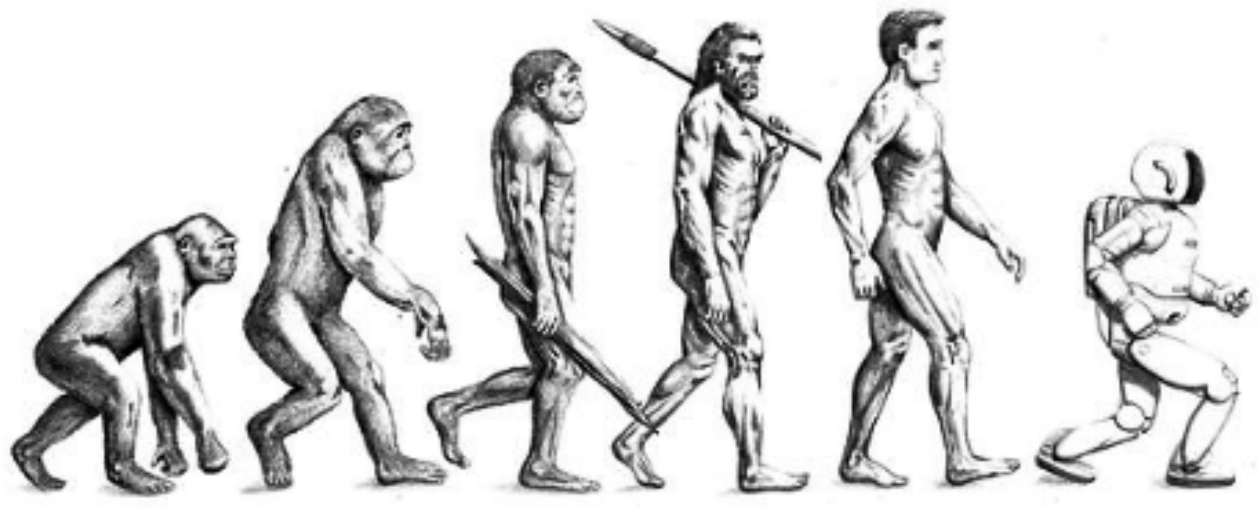
Academic Background

BA in Computer Engineering
Universidad Simon Bolivar
Venezuela

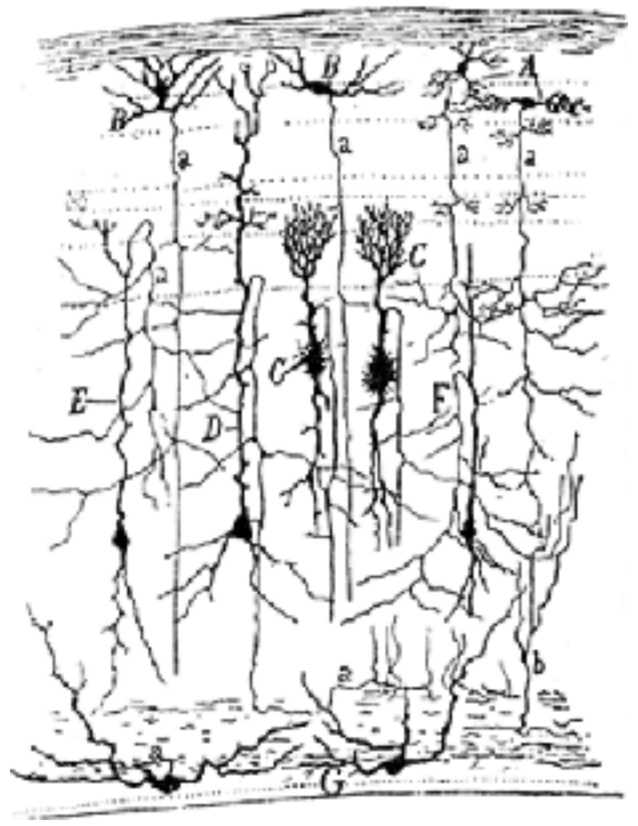
Ph.D. in Computer Science and AI
Sussex University
UK

Postdoc in Neuroscience Institute
Oregon University
US

Faculty in Cognitive Science
Indiana University
US

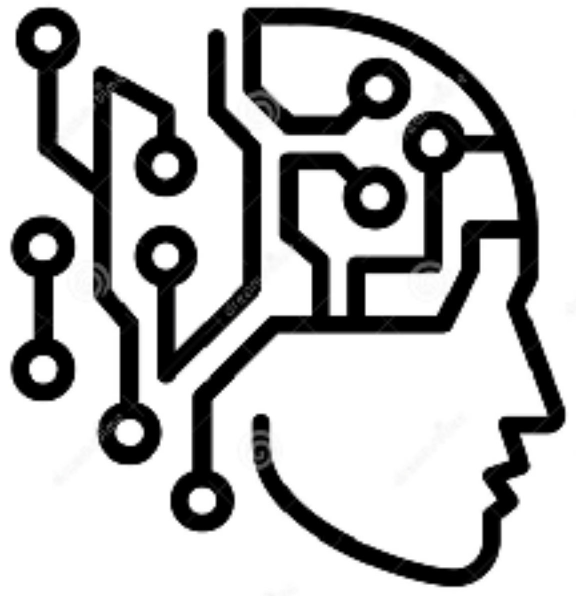


Evolutionary Computation



Computational Neuroscience

Cognitive Science



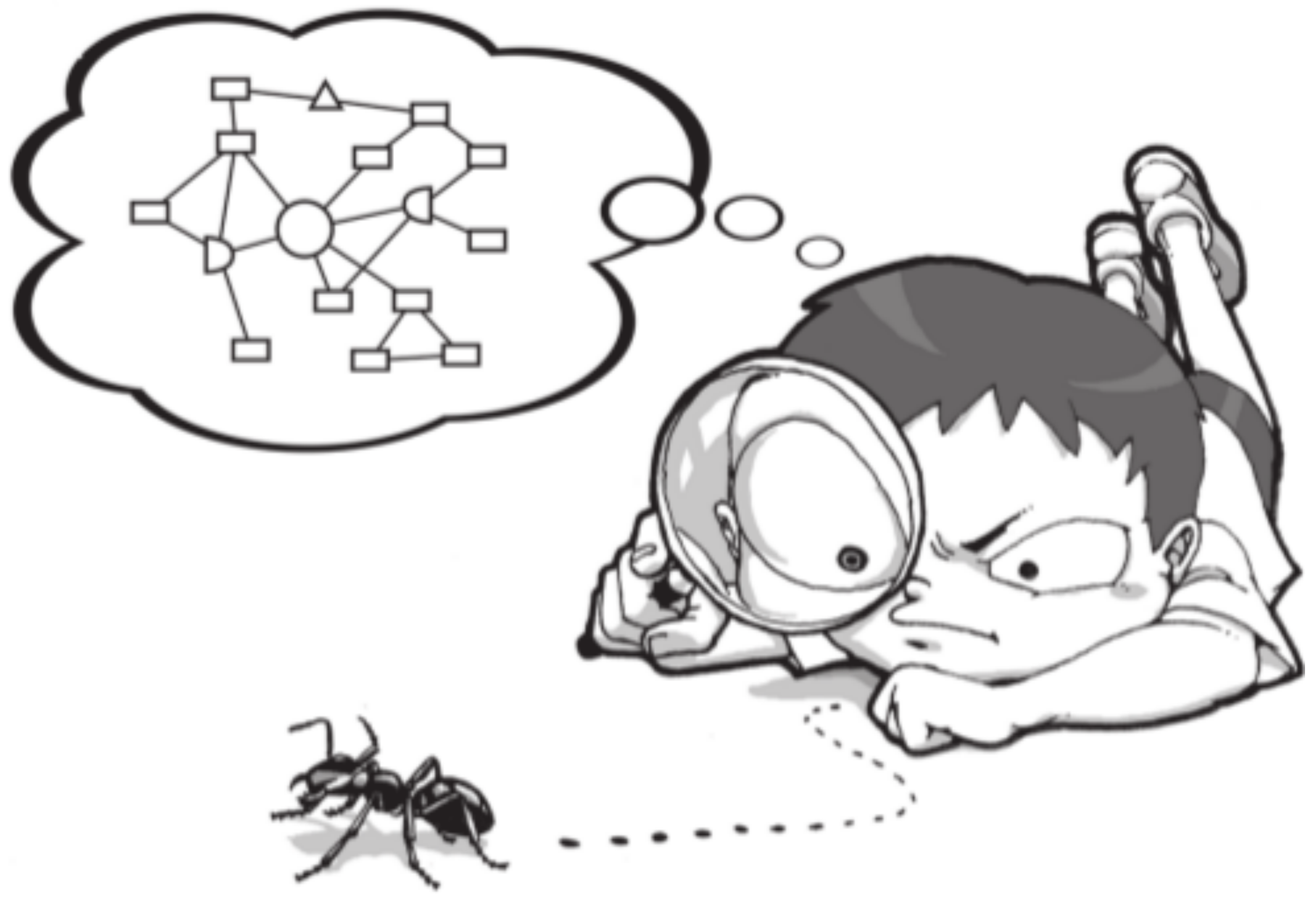
Artificial Intelligence

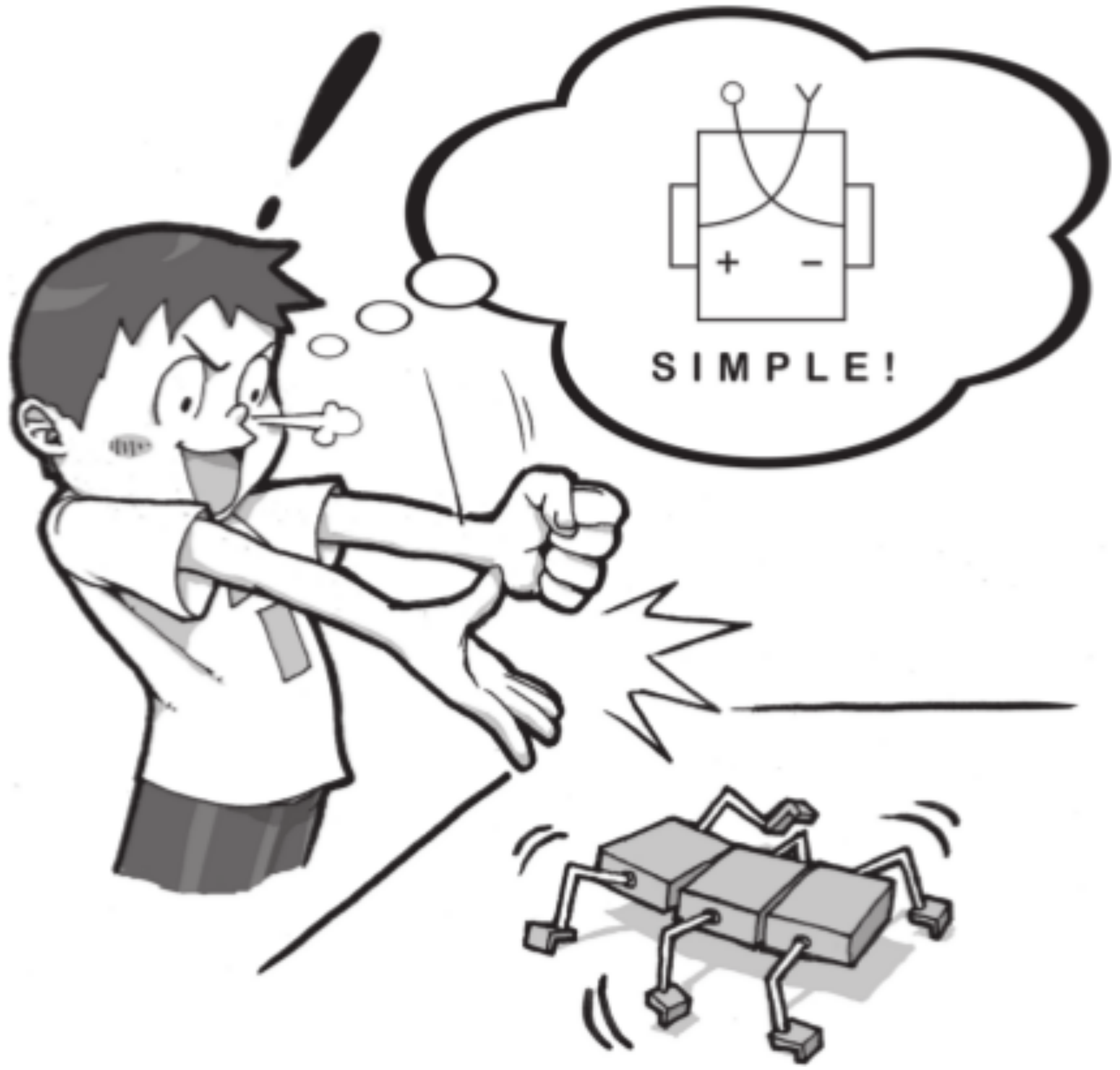
Outline

1. Context for Lecture (a "second" class, hands-on projects)
2. Broad Motivation
3. Teaching Philosophy
4. Understanding Complex Systems
5. Agent-Based Modeling
    1. Fundamentals
    2. Two models in detail with demos
    3. Survey of examples across disciplines
6. Neural Networks and Evolutionary Algorithms
7. Open Discussion

Broad Motivation

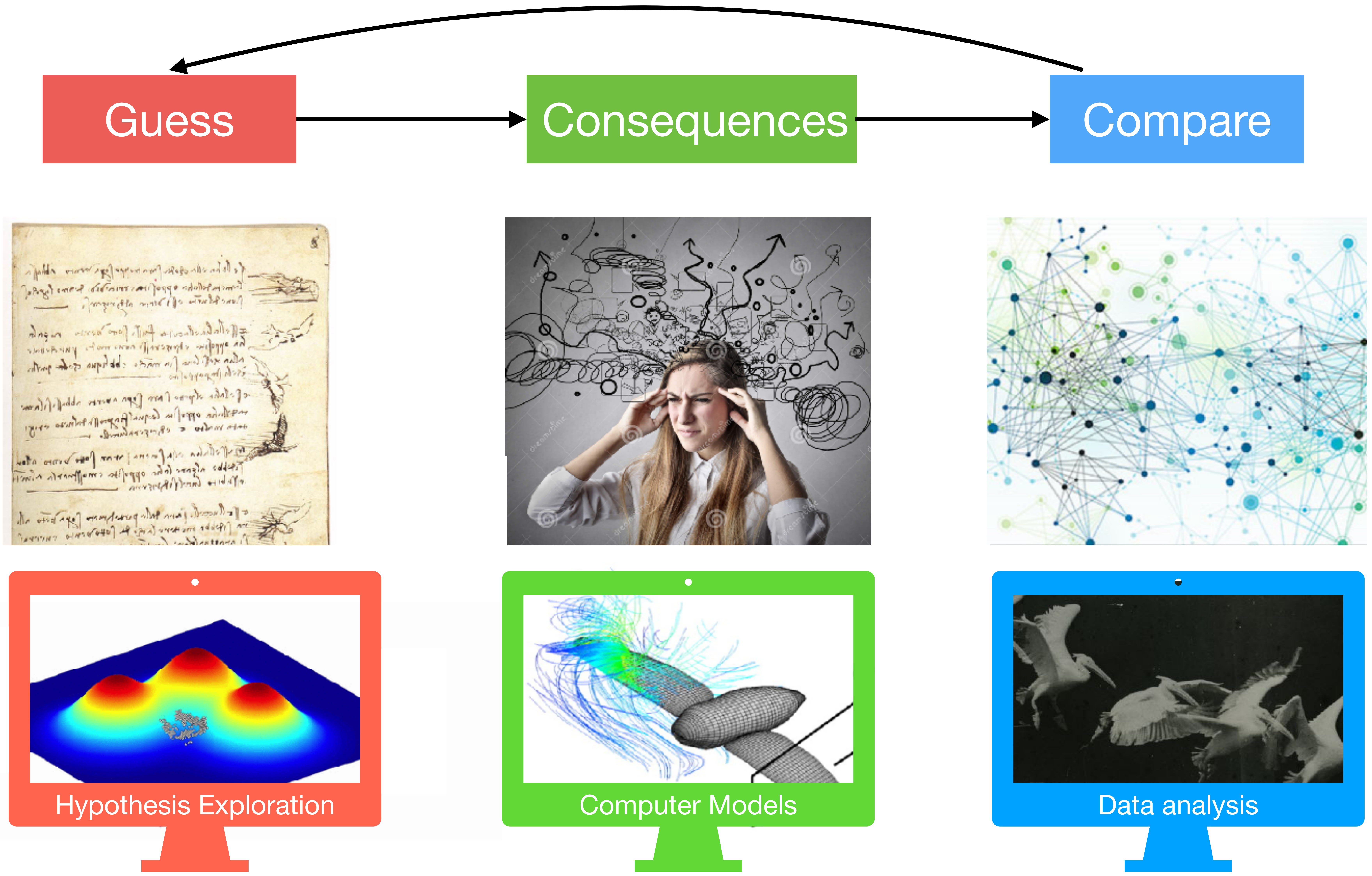
Better understand natural phenomena by
developing computational models that replicate aspects of it.





Illustrations by Shun Iwasawa in Pfeifer (2001)

Expanding the Role of Computers in Science, Engineering, and Technology



Teaching philosophy

Active learning

Intrinsic motivation

Integrating research and teaching

Develop cooperation among students

Diverse backgrounds and talents

Always available to talk

Are there examples of computational models that you know about?

What makes something worthy of creating a computational model of it?

What can we learn from a computational model?

What are the different purposes of Computer Simulations?

Exploratory and Heuristic: Used to communicate knowledge to others, and/or to represent information to ourselves.

Predictions. If we know something about the behavior of the individual components, and the environment, we may be able to predict the emergent pattern of the collective behavior.

Understanding. If we know something about the collective behavior, we can explore the behavior of the individual components necessary to arrive at such pattern.

Changing the system. We may not like the macrobehavior. We may want to change the pattern with minimal changes to either the incentives of the individuals or the environmental conditions.

Agent-Based Models

A computational model for simulating the actions and interactions of agents in order to understand the behavior of a system.

Modeling behaviors at the level of the interacting agents (micromotives).

Studying the resulting properties of the collective (macrobehavior).

In cases where the macrobehavior is not easily predictable, or the micromotives are not well understood — emergence.

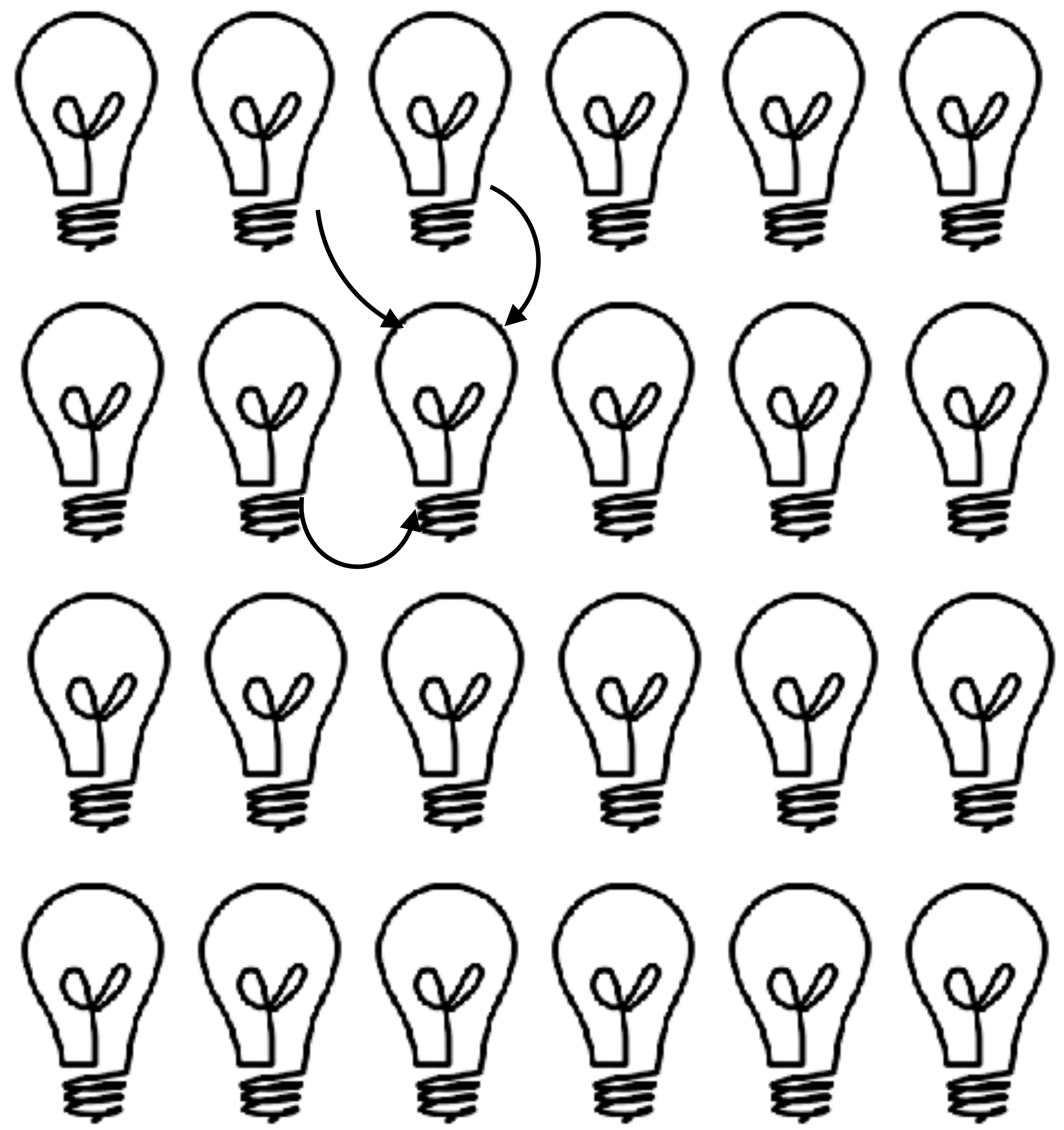
Typically, this involves cases where the individual agents are making decisions based on local (limited) information.

A first simple ABM: Cellular Automata

(1) Regular grid of cells, each in one of a finite number of **states**, such as *on* and *off*.

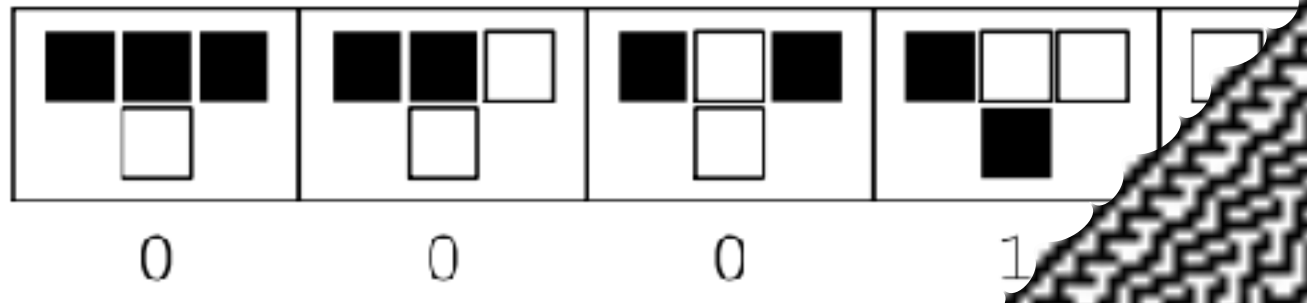
(2) For each cell, a set of cells called its **neighborhood** is defined relative to the specified cell.

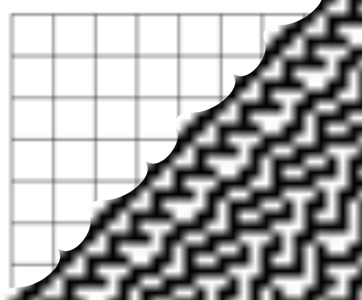
(3) An **update rule** about how the state of each cell changes as a function of its neighborhood.

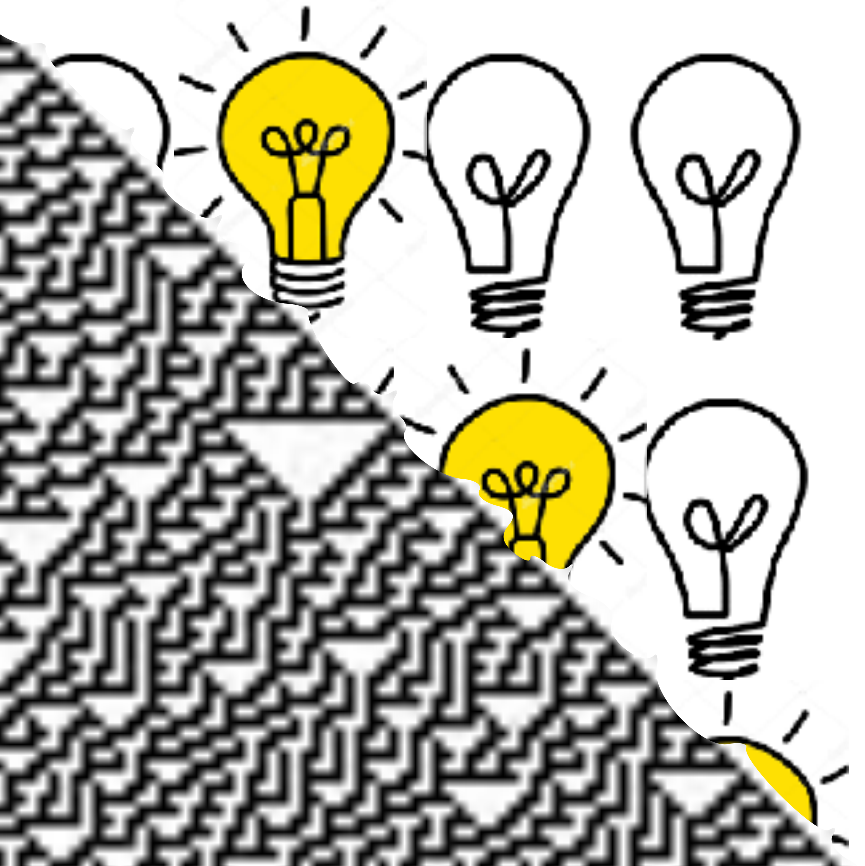


Cellular Automa

A cellular automaton is perha ealized version of a
complex system. We will v mple in some detail.





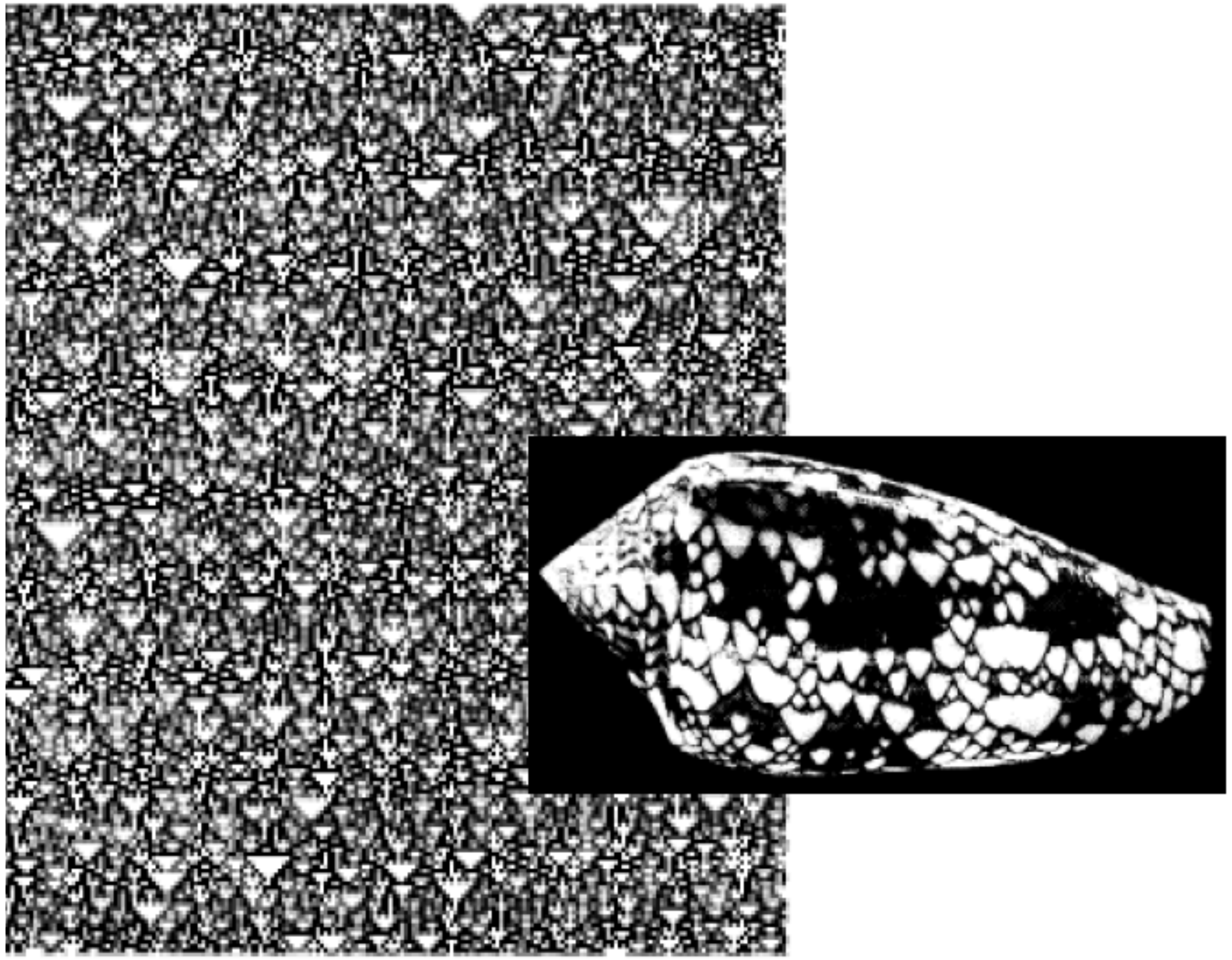


Demo #1:
1D Cellular Automata

Cellular Automata

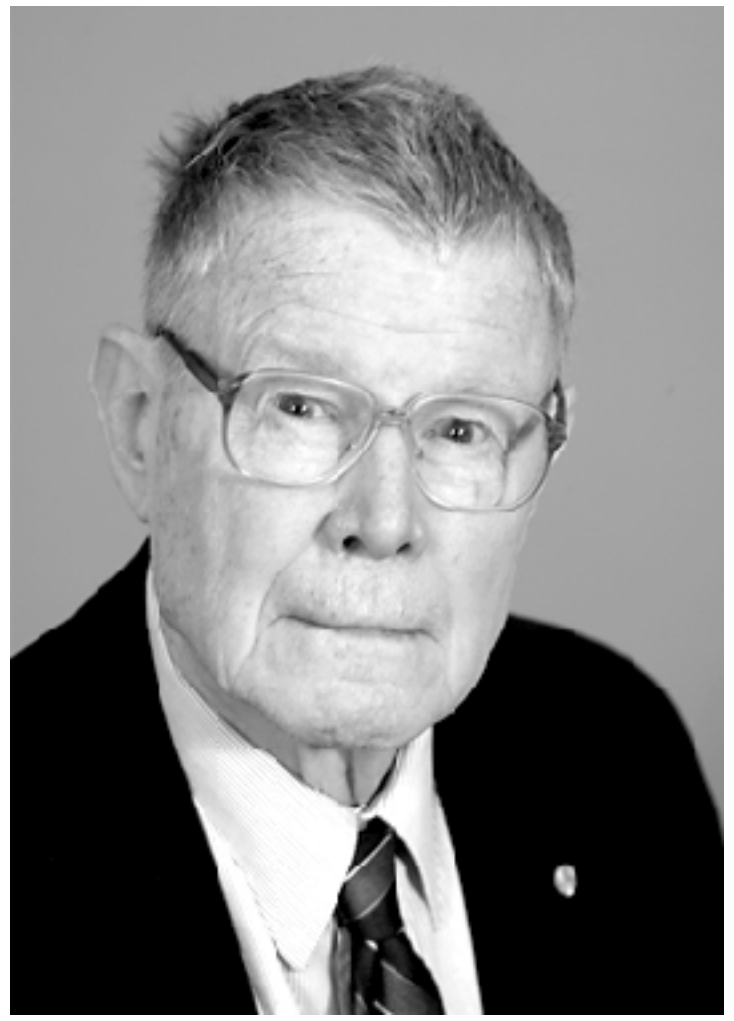
Like complex systems in nature, CAs are composed of large numbers of simple components with no central controller, each of which communicates with only a small fraction of the other components.

Despite their simplicity, CAs can exhibit complex behaviors that are difficult to predict from the cell update rule.



Demo: https://devinacker.github.io/celldemo/

Segregation Model



Thomas Schelling was the co-recipient of the 2005 Nobel Prize in Economics for having enhanced our understanding of conflict and cooperation through game-theory analysis.

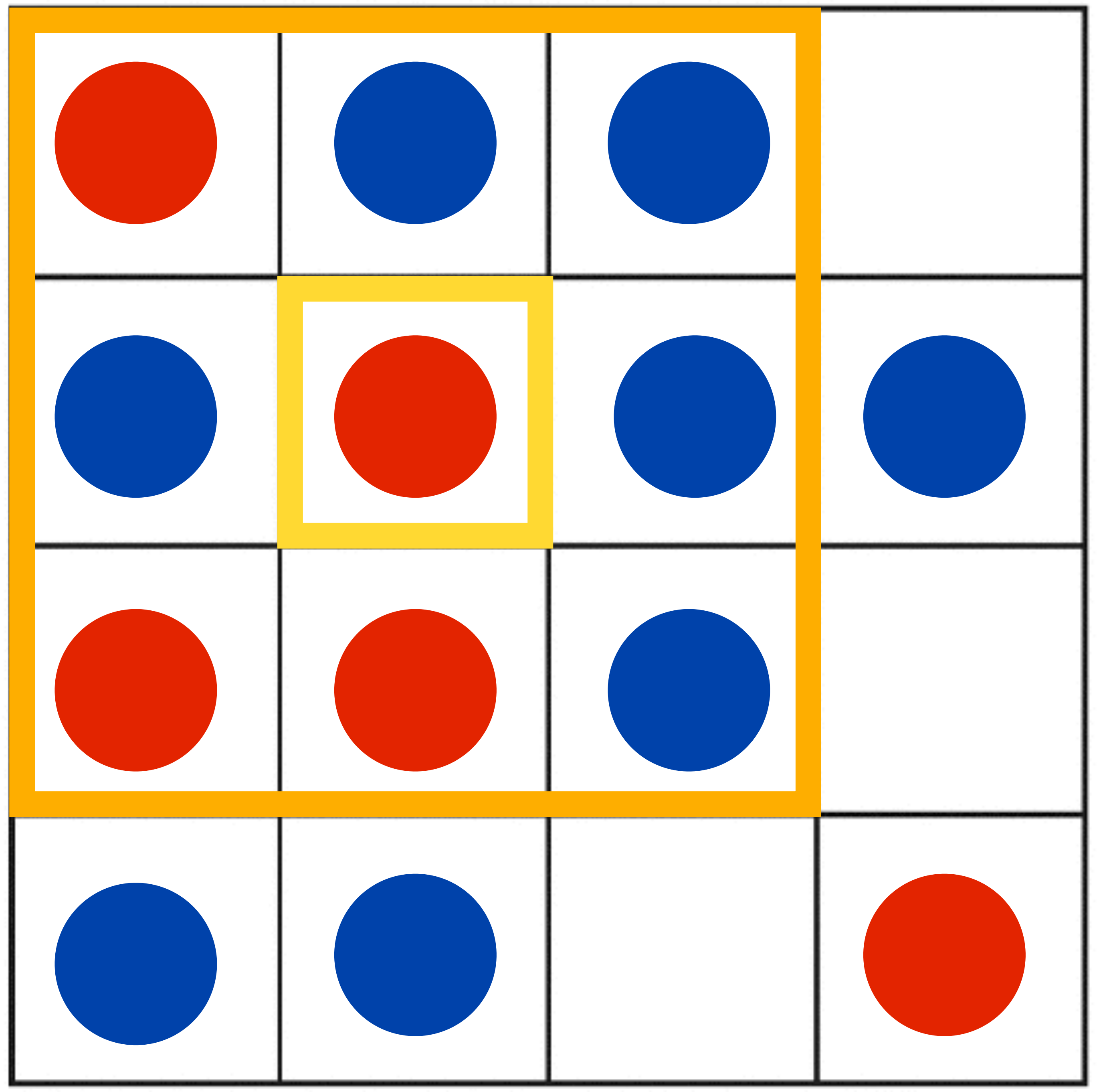
An interesting and important puzzle (1978):

After 1964 housing discrimination was illegal.

Since 1950 racial prejudice has declined.

Yet neighborhoods remained highly segregated through the 60s and 70s.

Three states (red, blue, vacant).



<u>Update rule:</u>

1. Stay if there are X (or more) “kin” as neighbors.

2. Move to random location if less than X.

Is there a number X that seems relatively okay - somewhat tolerant?

Demo #2:
Schelling's Model of Segregation

Insights and open questions

Result

City can "tip" into high segregation even if agents have only mild preferences for living with others of their own type.

Take home message

1. Does not need to be imposed (top-down).

2. Does not reflect individual preferences (bottom-up).

3. Instead, it self-organizes through dynamic interaction.

Variations

Different "tolerance" levels.

Different "vacancy" proportions.

Different proportions of races.

Population growth / decay.

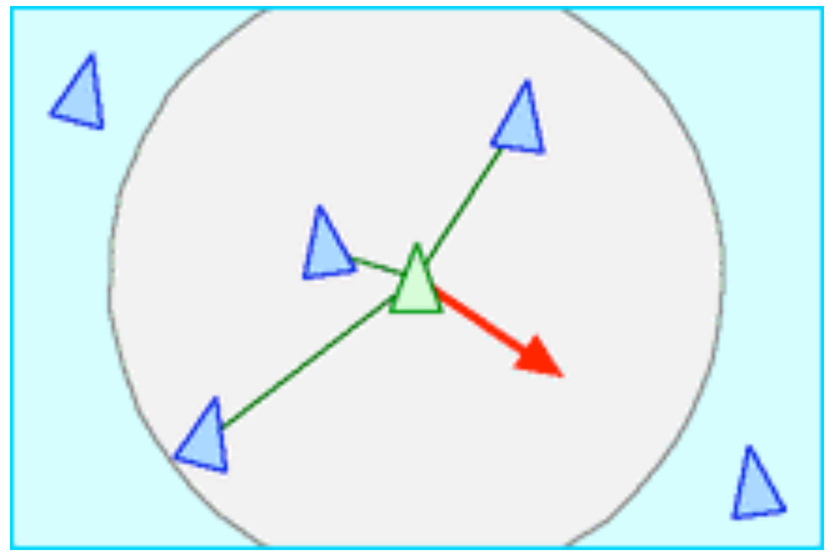
Non-random rule for choosing new home location.

Different "tolerance" levels for each species.

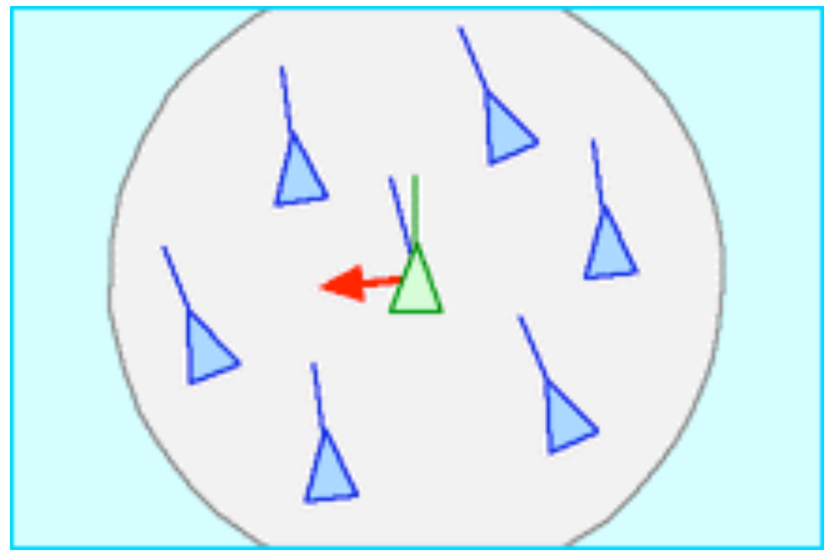
More than two species.

Flocking model

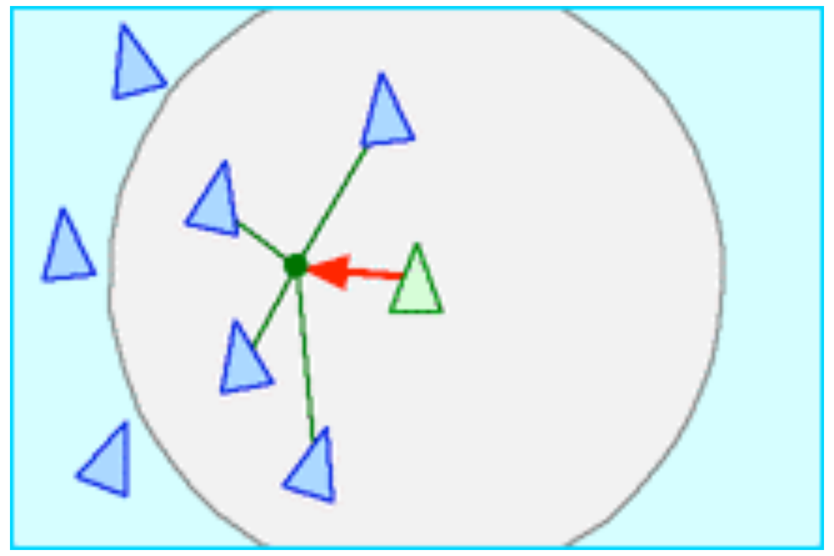
Separation: steer to avoid crowding local flockmates.

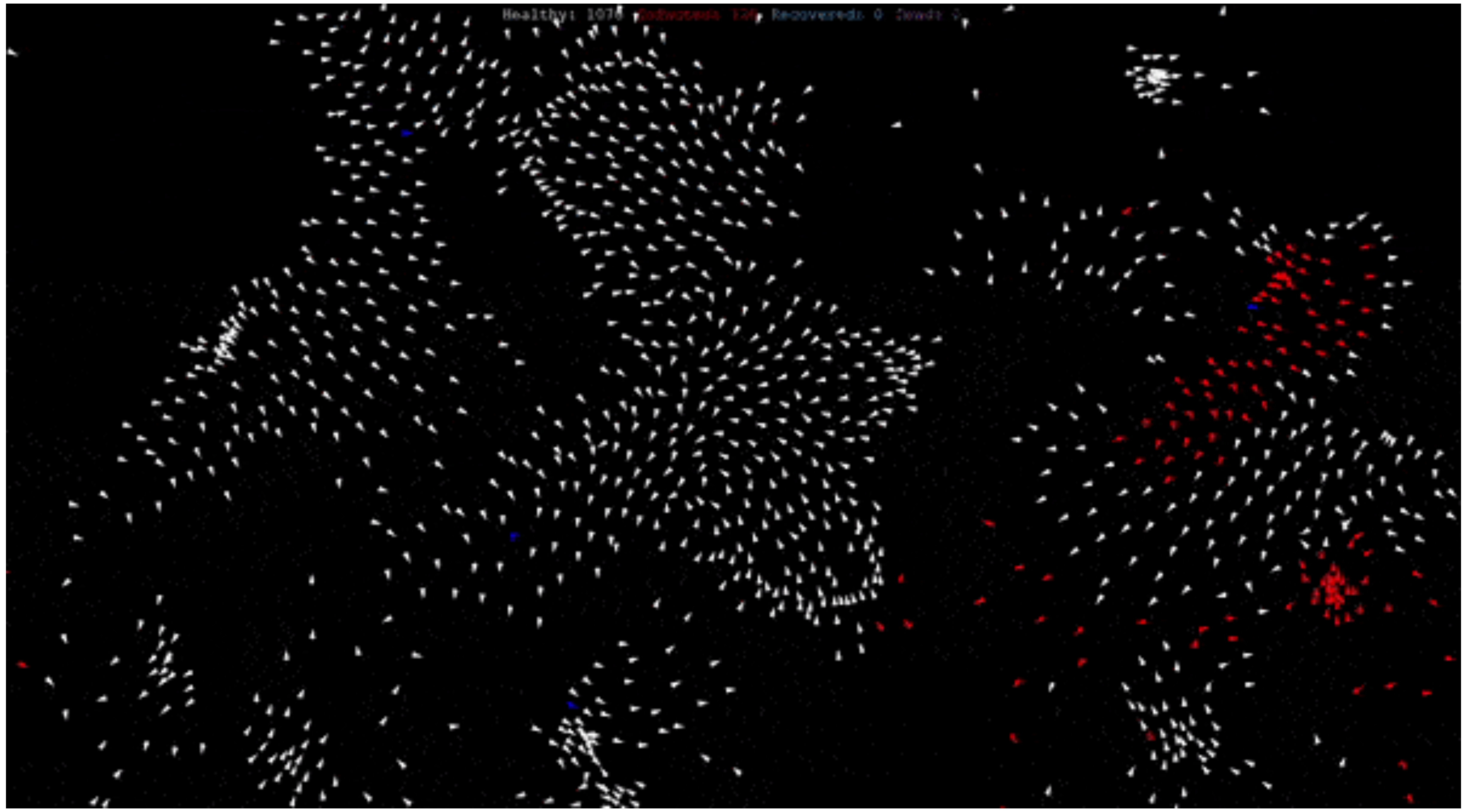


Alignment: steer toward the average heading of local flockmates.



Cohesion: steer to move toward the average position of local flockmates.





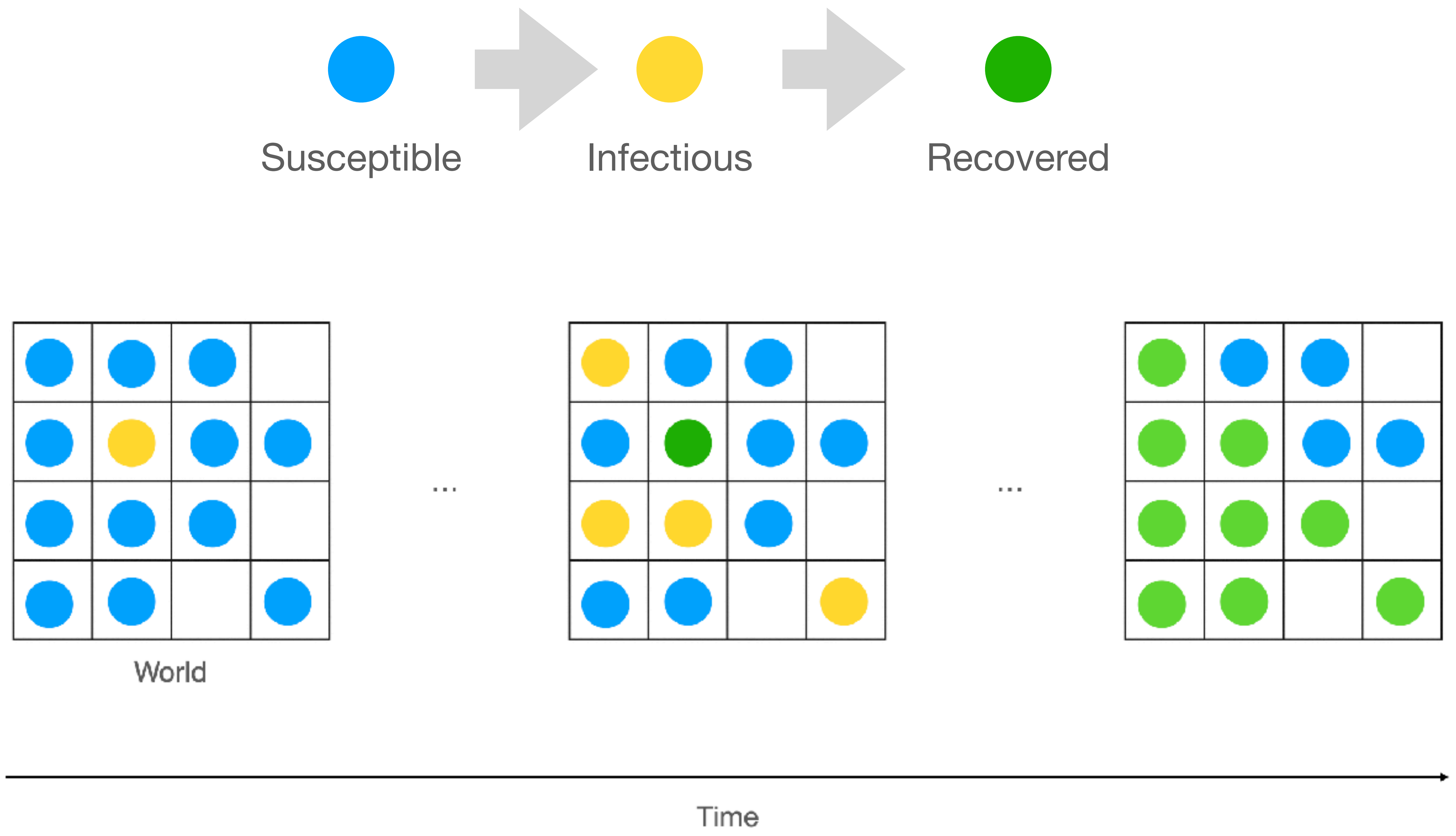
Simulating the spread of a virus

Each individual can be susceptible, infectious, or recovered. People can infect others based on proximity.

Variations:

1. Symptomatic/ asymptomatic, possibility of death, limited hospital capacity, etc.

2. Movement by individuals in the space, hubs like supermarkets, etc.

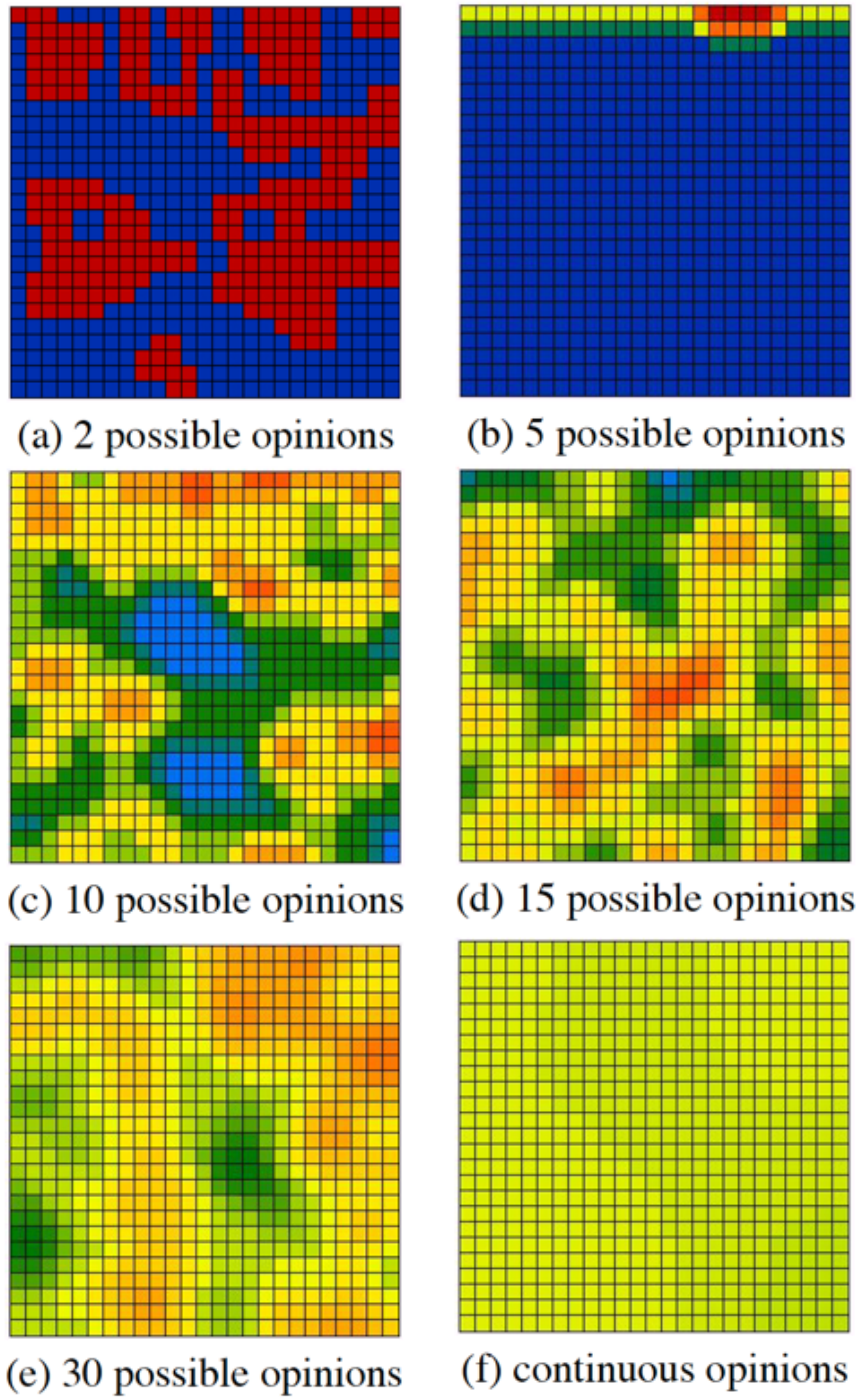


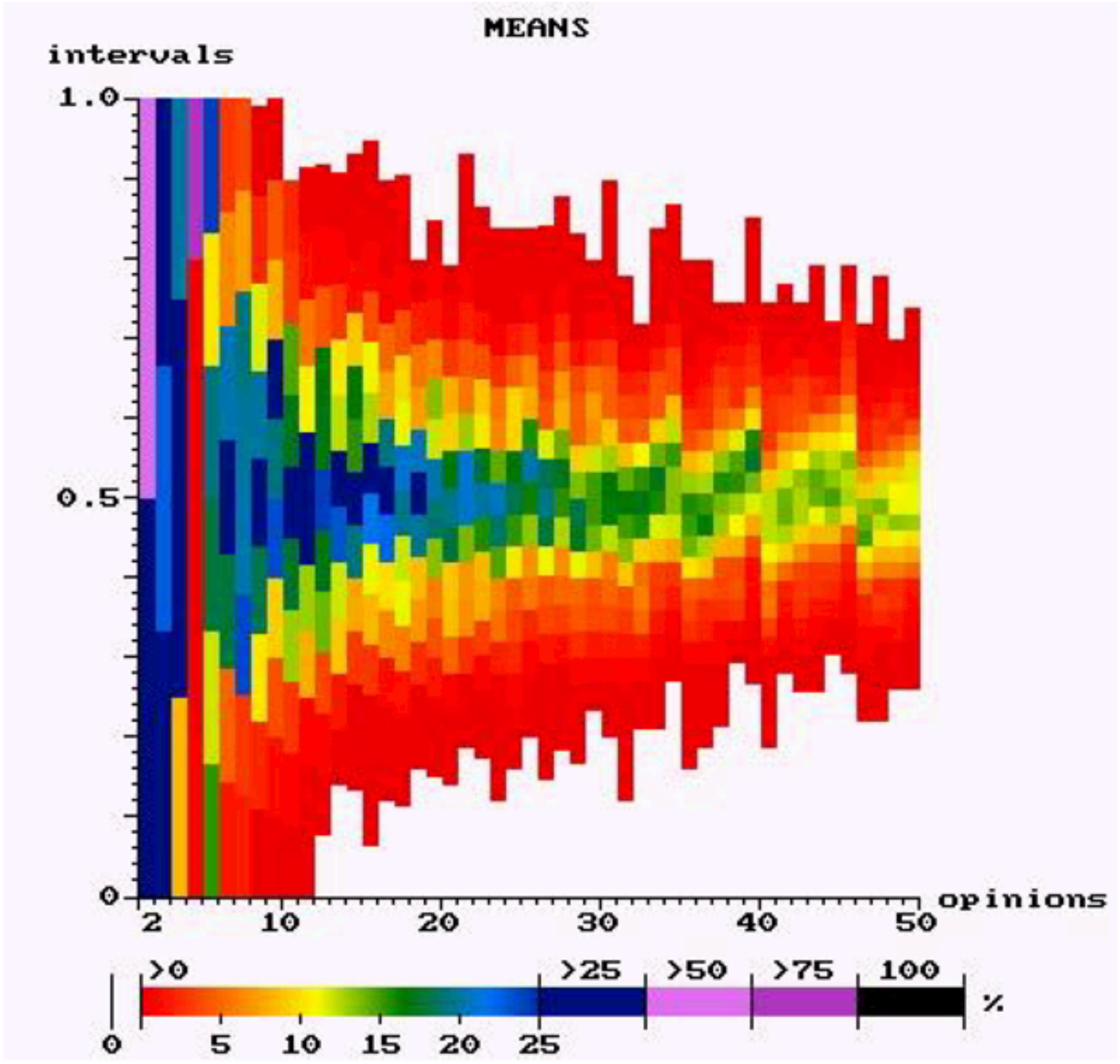
Opinion Dynamics

All cells occupied by individuals with an opinion.

The opinion are the state of the cells taken from interval [0,1] and discretized to *n* states (from 2 to 50).

Individuals update their opinion by averaging over the opinion of their neighbors (same weight, self including).


(a) 2 possible opinions
(b) 5 possible opinions
(c) 10 possible opinions
(d) 15 possible opinions
(e) 30 possible opinions
(f) continuous opinions



Polarization when few discrete options. Continuous opinion ends in ubiquitous middle-ground agreement.

Opinion dynamics on social networks

Each individual can have an opinion.

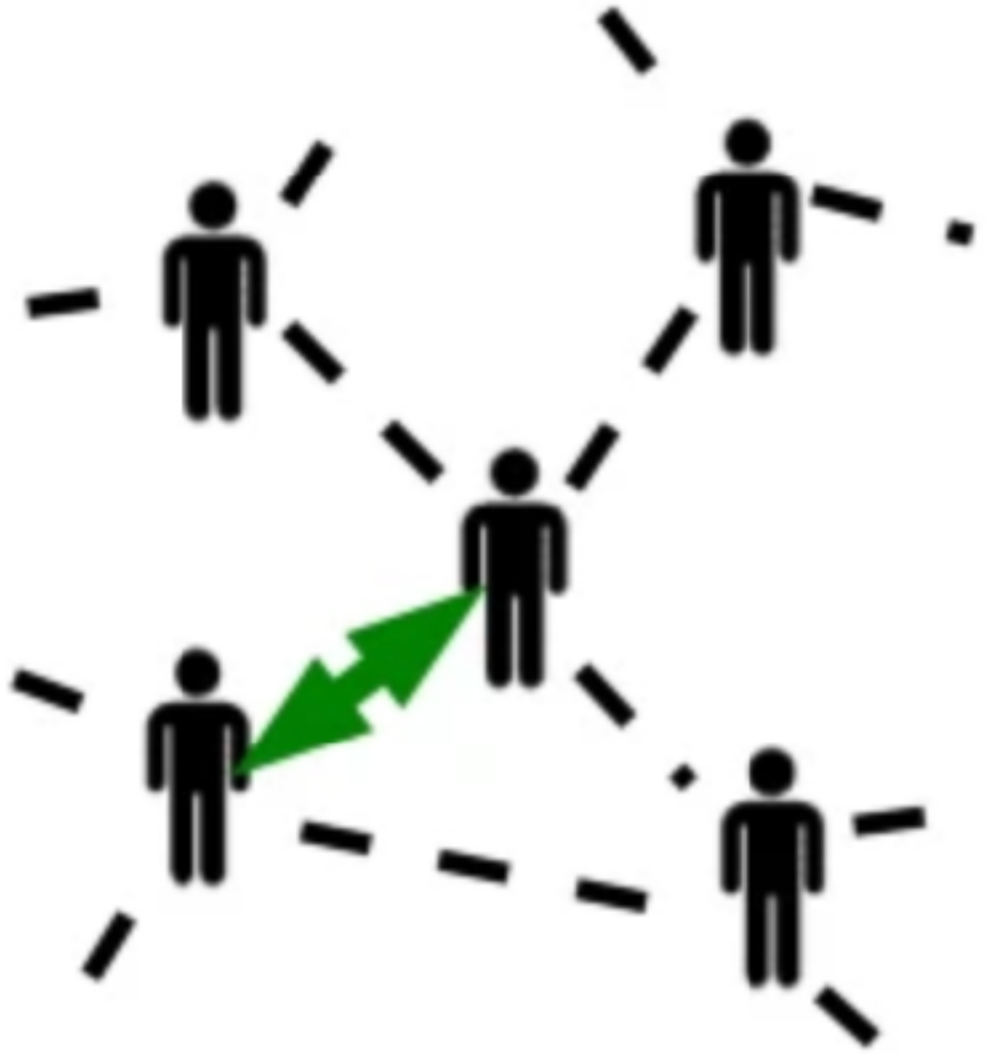
People can change opinions based on other's opinions in their circles.

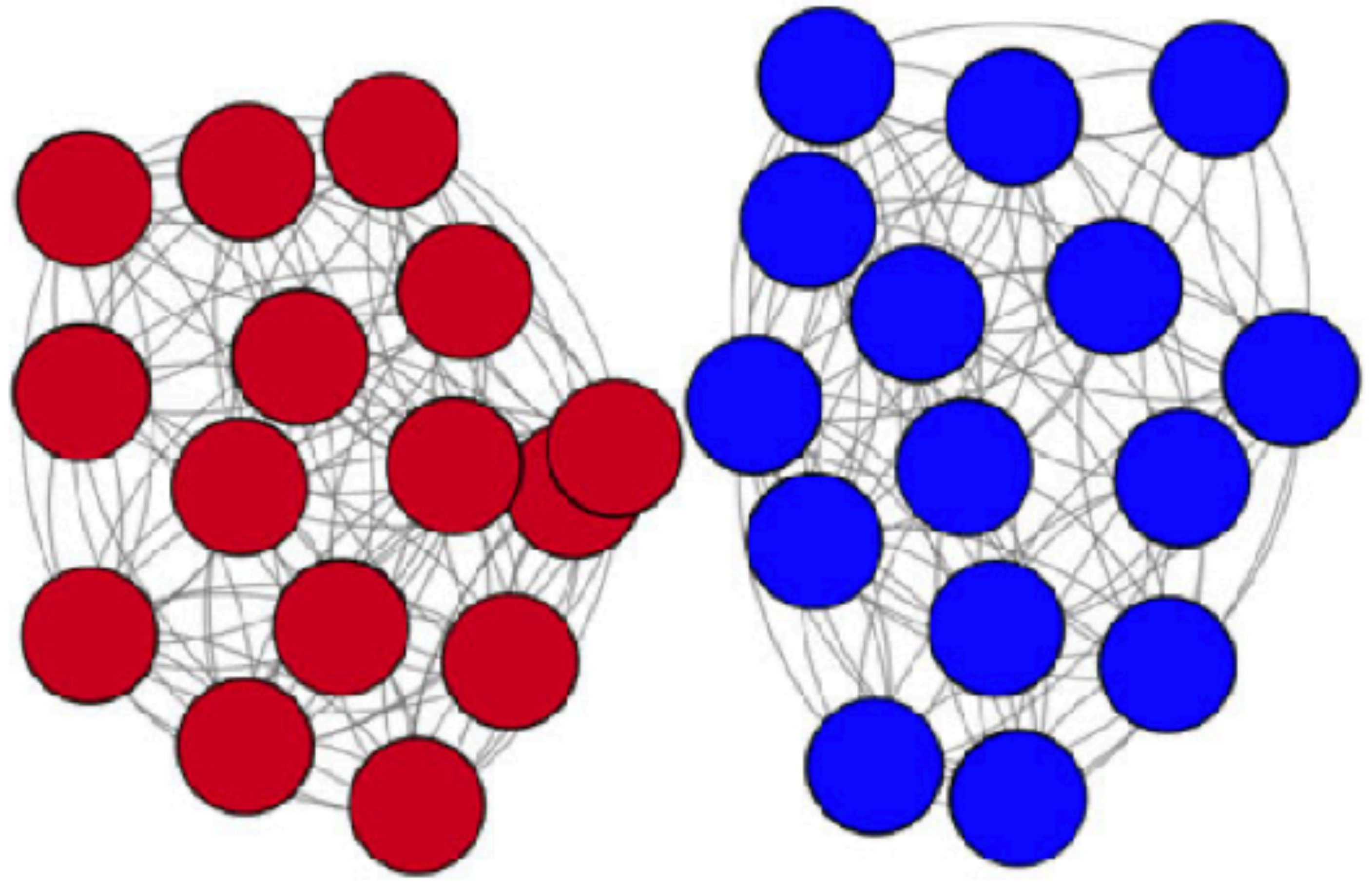
What effect does topology have on opinion dynamics?

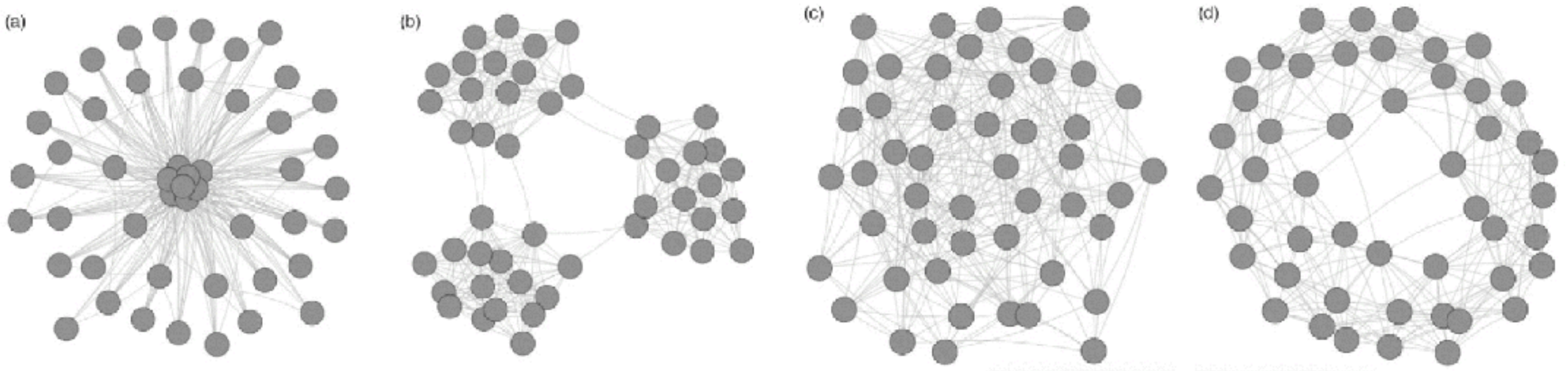
Variations:

1. Different levels of influence and susceptibility.

2. Dynamic connections: changing who you follow based on heuristics.





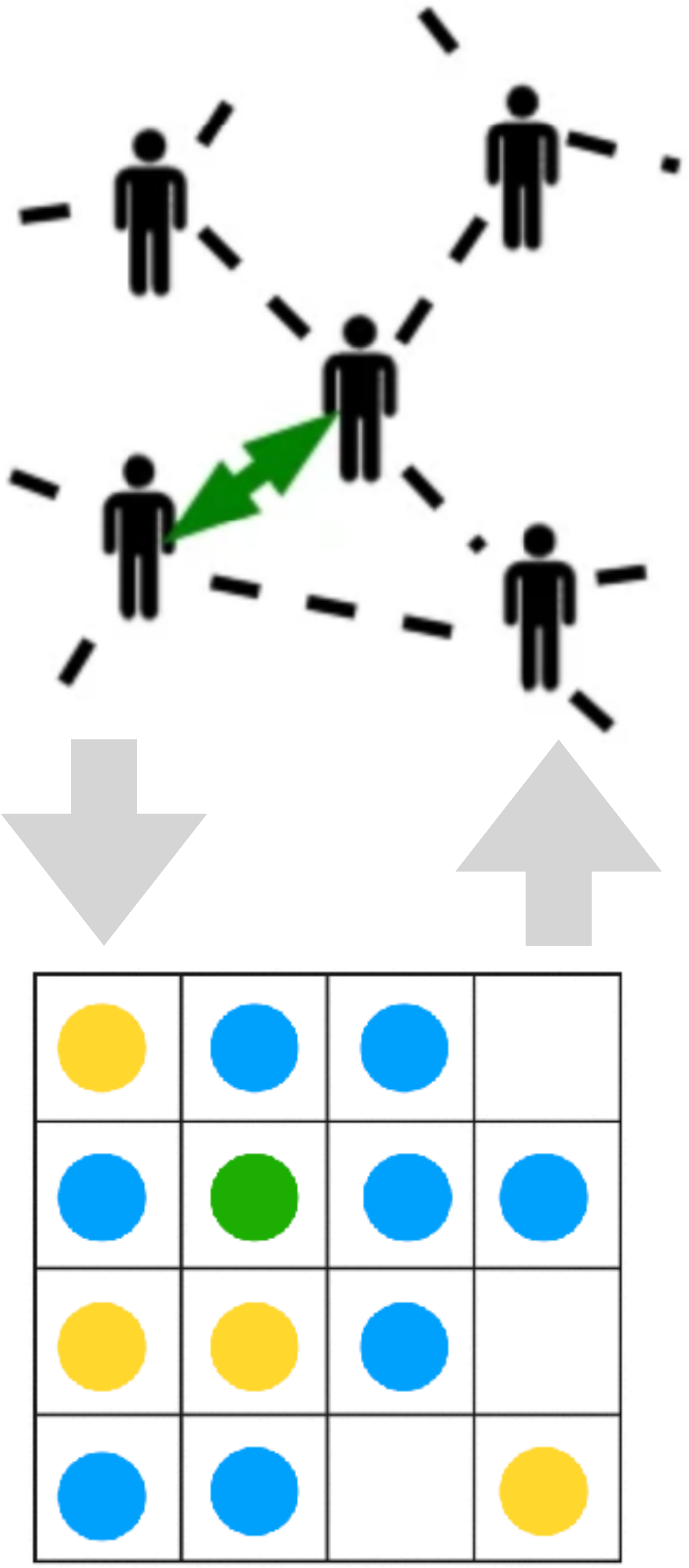


Multi-level models: Spread Virus + Opinion

At one level, there can be a virus that is spreading based on physical proximity.

At a different level, there can be opinions that are being exchanged at the level of social networks.

Both these are the same individuals.



The local area might influence somebody's opinion.

The opinion might have consequences for the spread.

Axelrod’s Dissemination of Culture

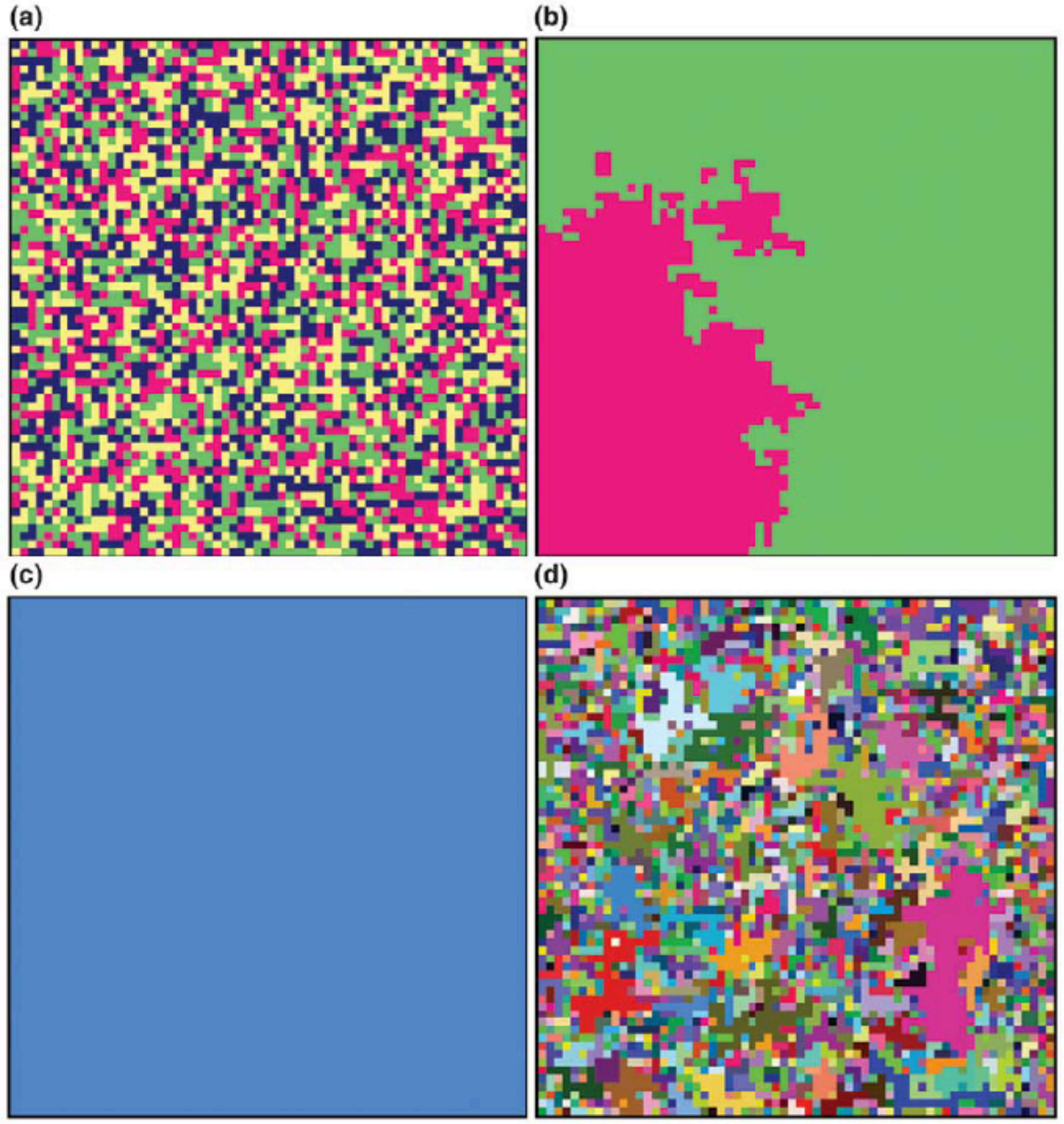
'Culture' idealized to "the set of individual attributes that are subject to social influence.”

Culture is something people learn from each other, and hence something that evolves through social influence.

Two simple assumptions:

People are more likely to interact with others who share many of their cultural attributes, and

These interactions tend to increase the number of cultural attributes they share (thus making them more likely to interact again).



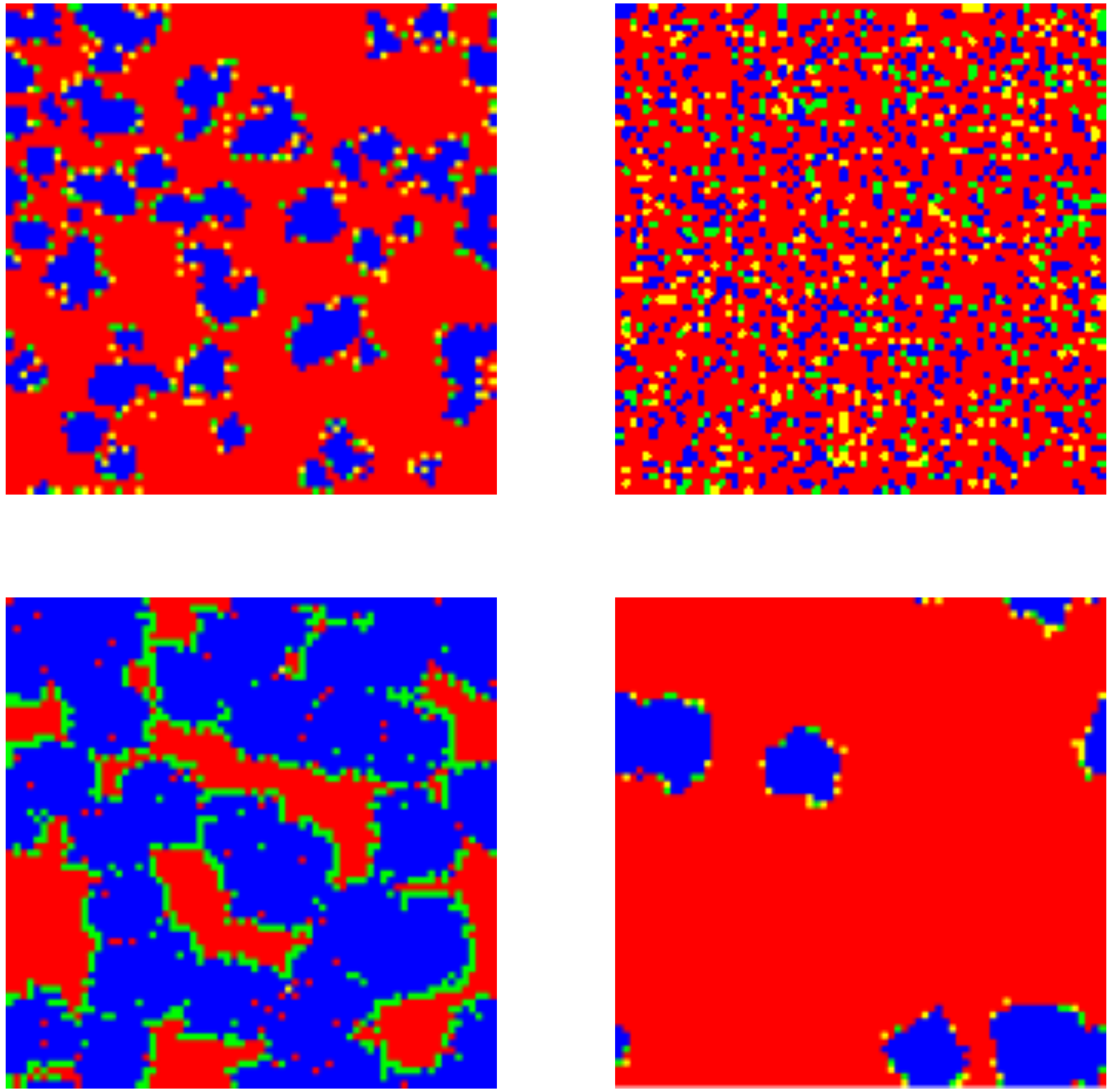
Games in Structured Populations

States: Cooperate or Defect.

Interactions: Each individual plays with the neighbors. The score for the player is the sum of the pay-offs. At the start of the next round, each cell is occupied by the player with the highest score in its neighborhood (self including).

		Row player C	Row player D
Column player	C	R	S
	D	T	P

$$T > R > P > S$$



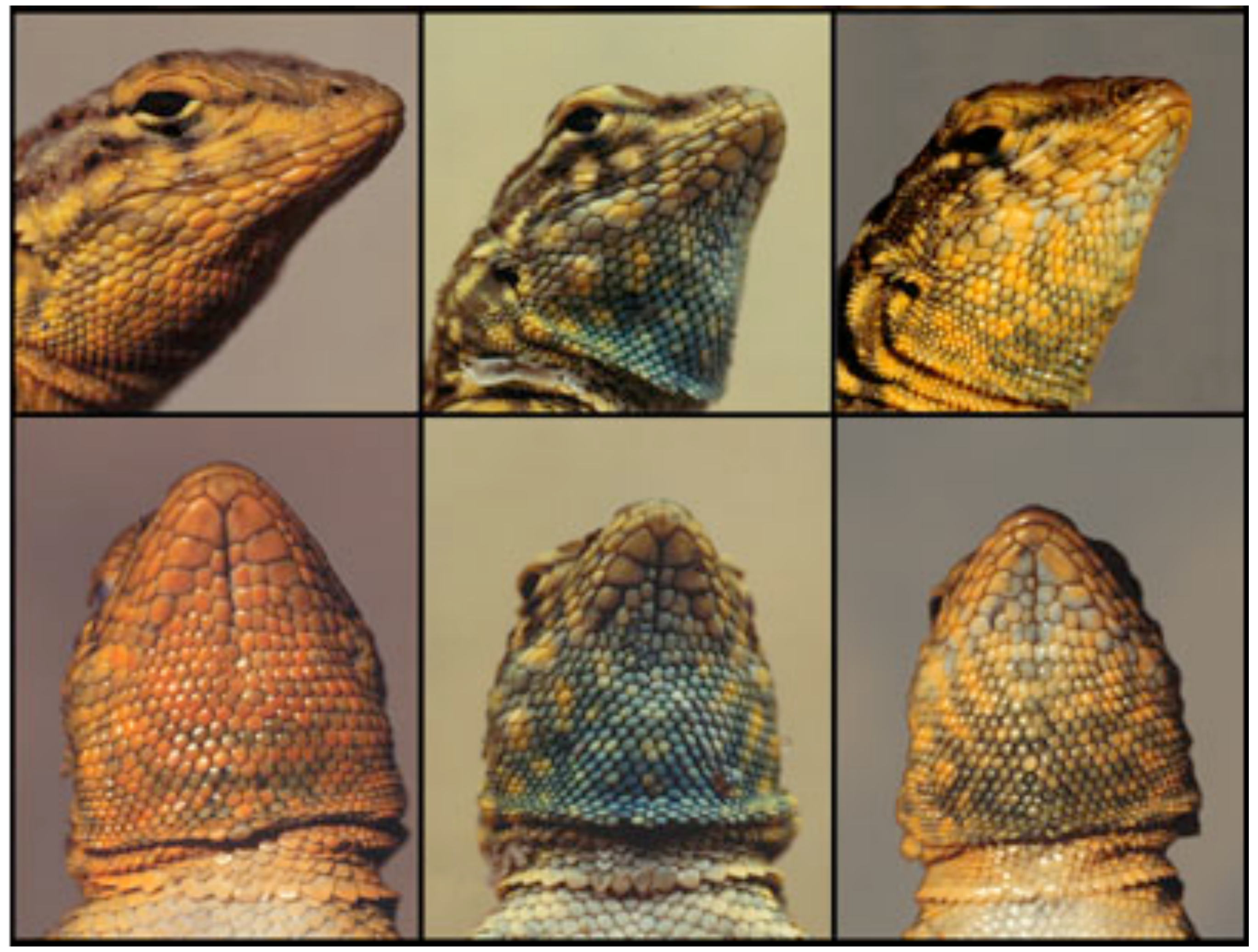
Rock-Paper-Scissors Game

Mating behavior of side-blotched lizards (*Uta stansburiana*).

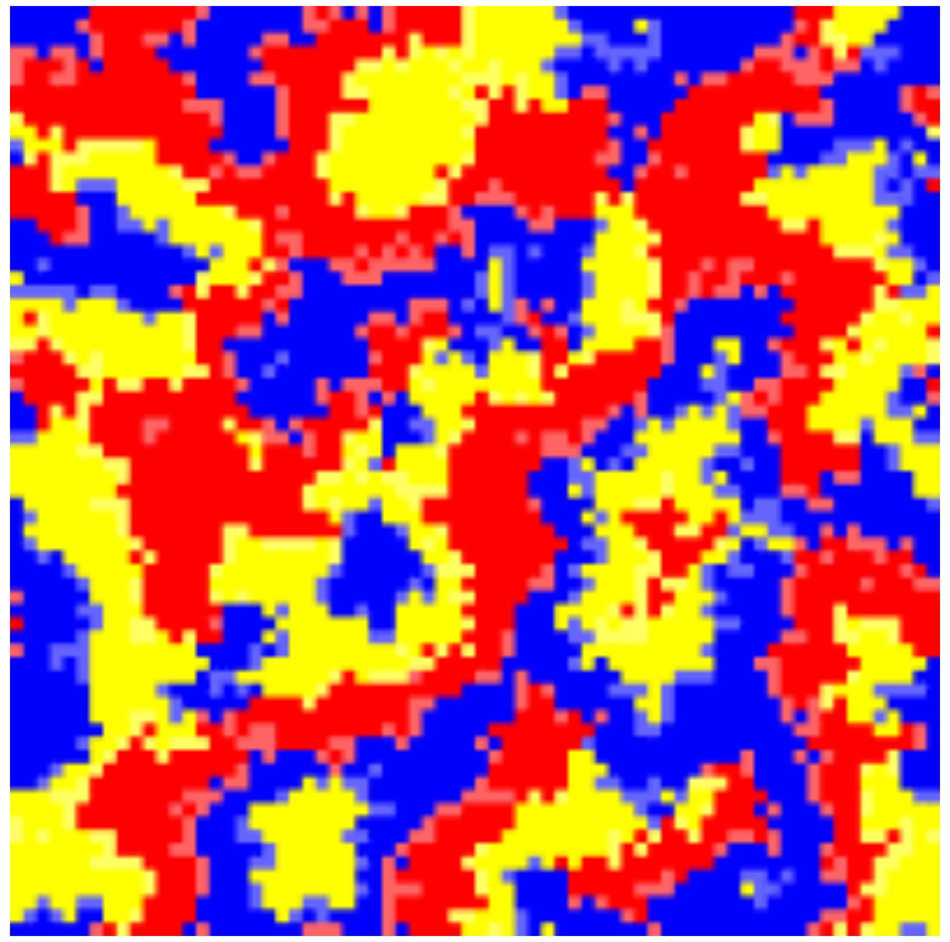
Males display three kinds of strategies: Monogamous males guard their female. Polygamous males defend a territory and keep a female harem. Opportunistic males sire offspring in secretive copulations.

A population dominated by one one strategy is subject to invasion by another.

In the Prisoner Dilemma's game, voluntary participation can be a third strategy that induces cyclic dominance strategies (and allows cooperation to survive).



Zamudio & Sinervo, *PNAS* 2000



Hauert et al., *Science* 2002

Denebourg's Ant Raid Patterns

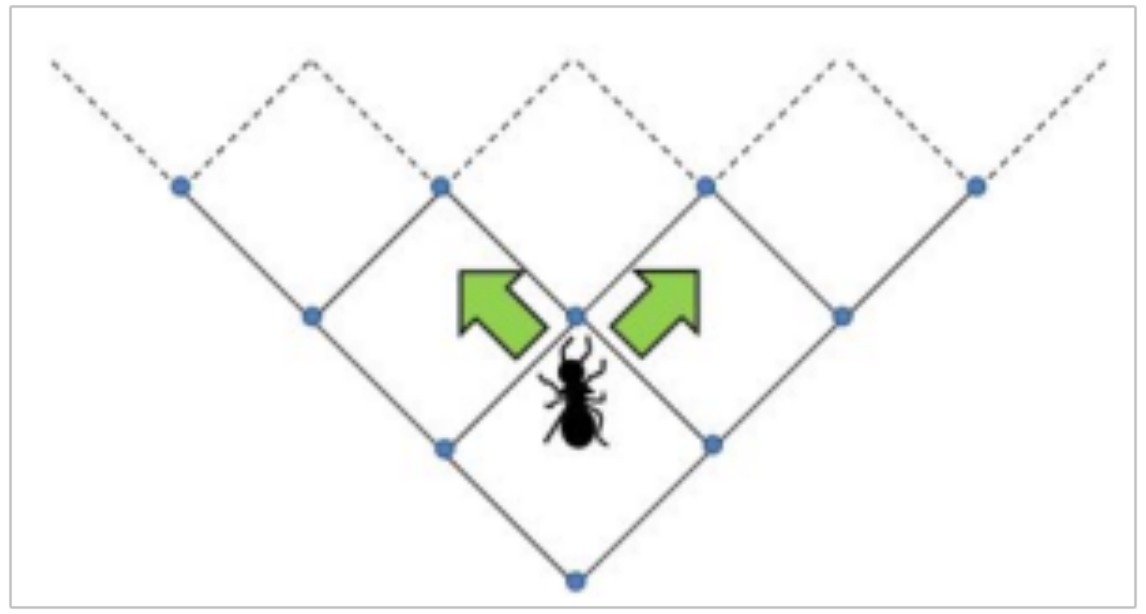
As ants move around they deposit a pheromone, which increases the likelihood that other ants will follow the same path.

Ants that have found food lay more pheromone than ants that haven't.

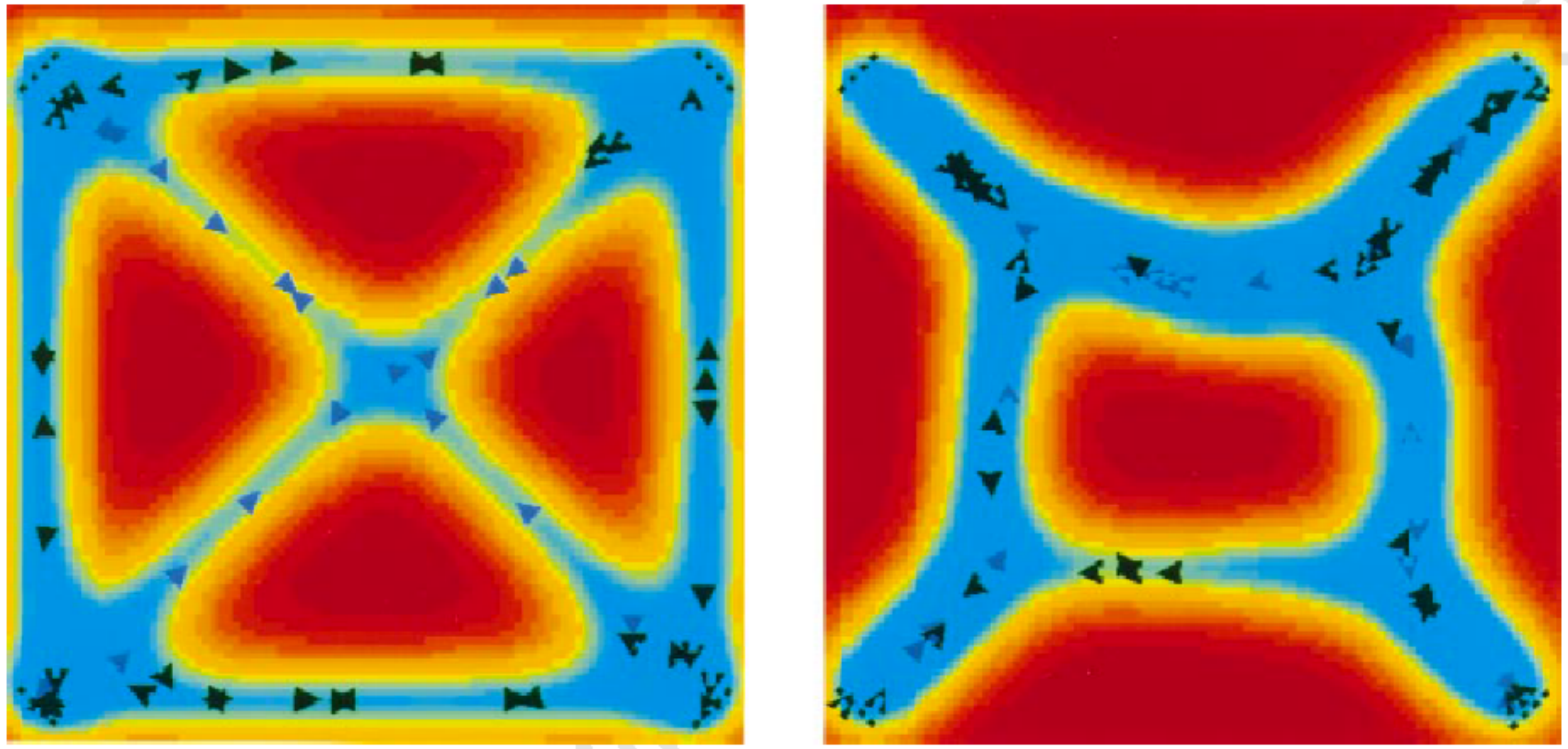
Ants live in a 2D lattice world. All start from a corner (nest).

Once the ant finds food it turns back using the same strategy.

In the starting configuration, each point in the world has a chance of containing food.



Human Trail Systems



Modelling the evolution of human trail systems. *Nature* **388,** 47–50 (1997). https://doi.org/10.1038/40353

Sugarscape

Cells contain different amounts of sugar/wealth.

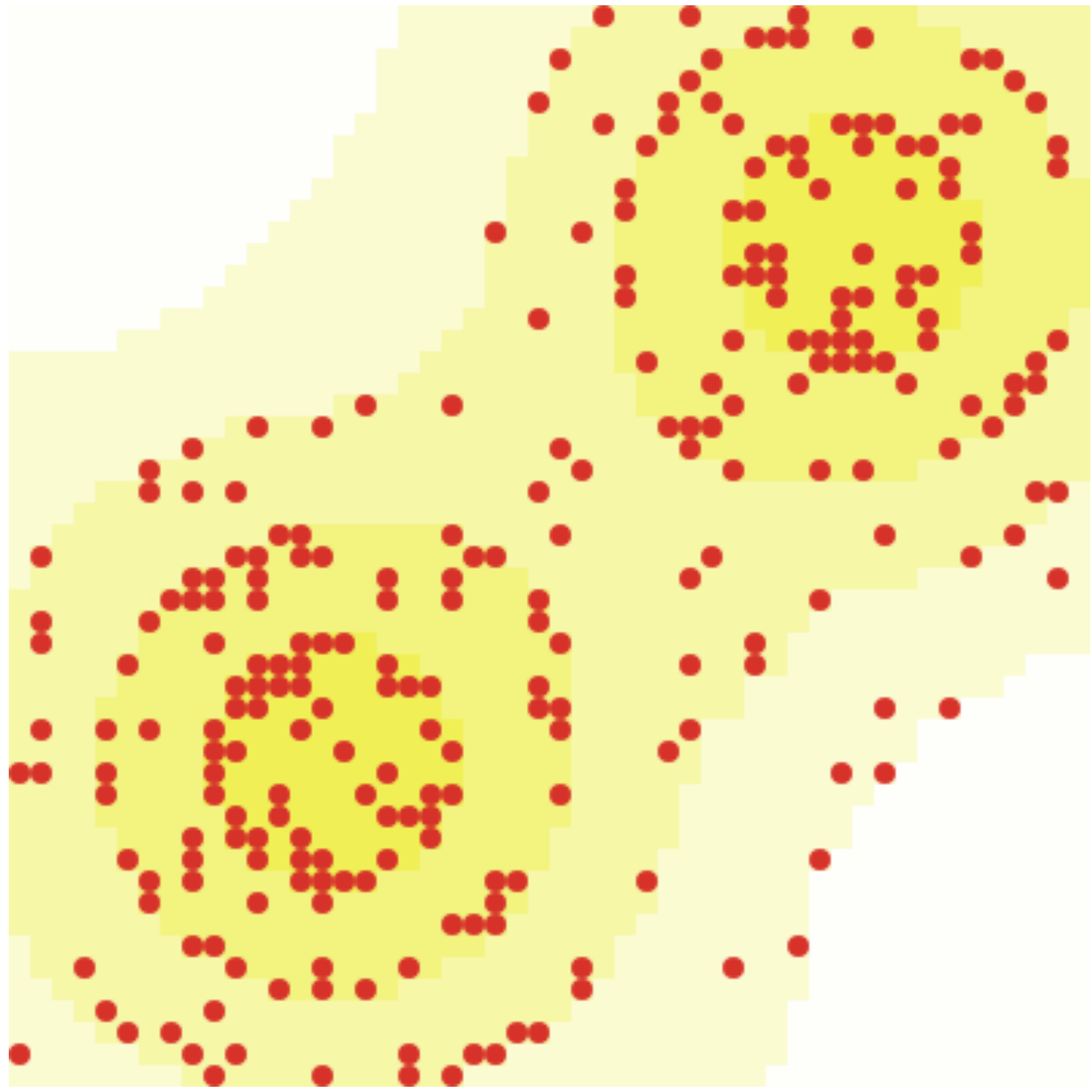
Agents come into the world with a vision range and a metabolism. Their basic rule is: Look at all sites within your vision. Pick the unoccupied site with the most sugar. Go there and eat it.

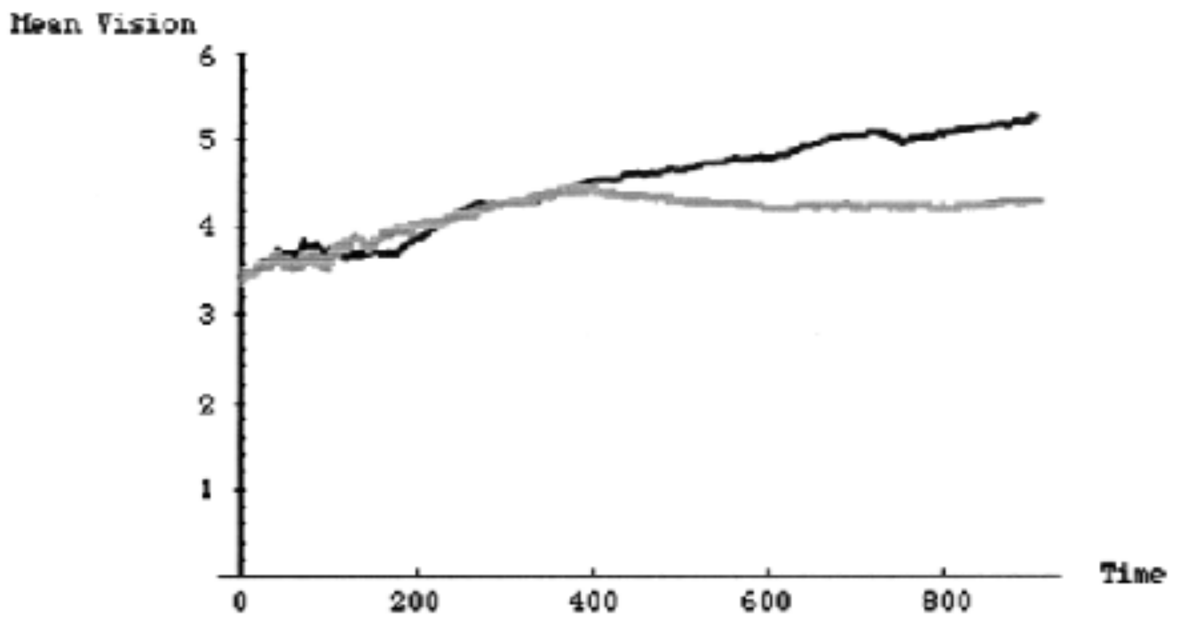
In every step agents look around, find closest cell filled with sugar, move and metabolize.

Their sugar stock is increased by this amount, and then decreased by their metabolic rate.

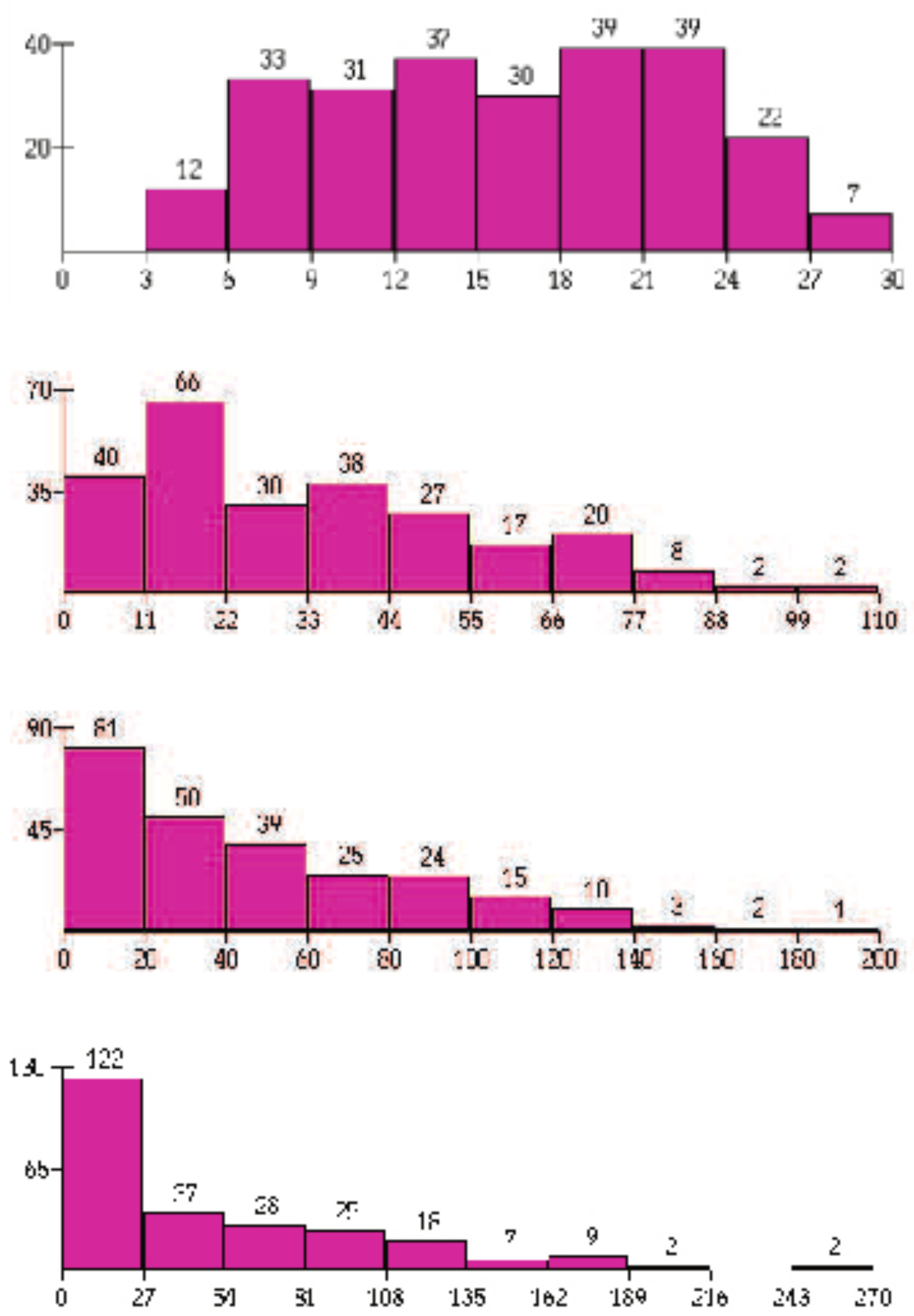
If the result is negative, they die; otherwise they go again.

This rule, with reproduction and inheritance, proves sufficient to generate power law wealth distributions characteristic of human societies.

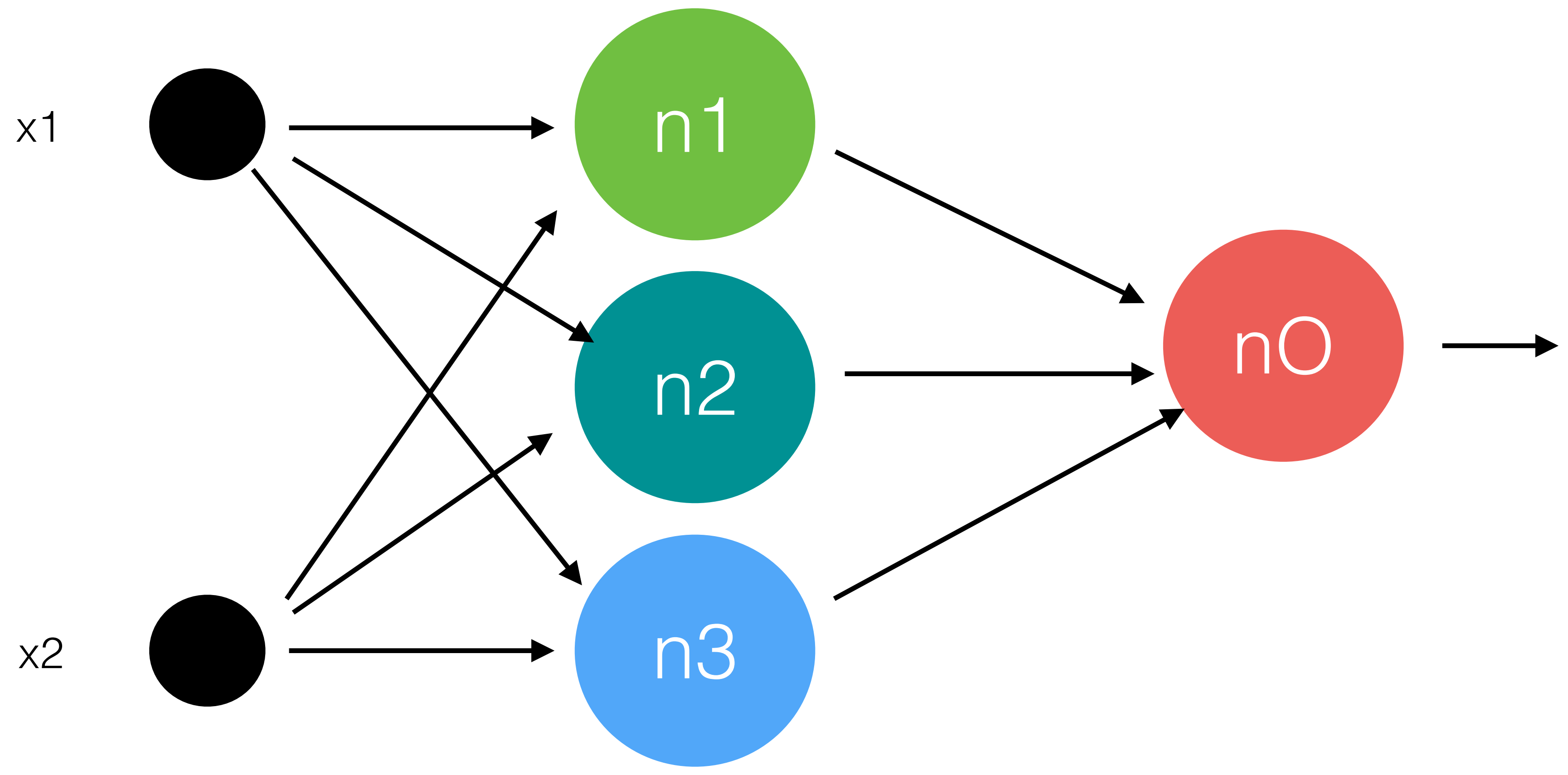




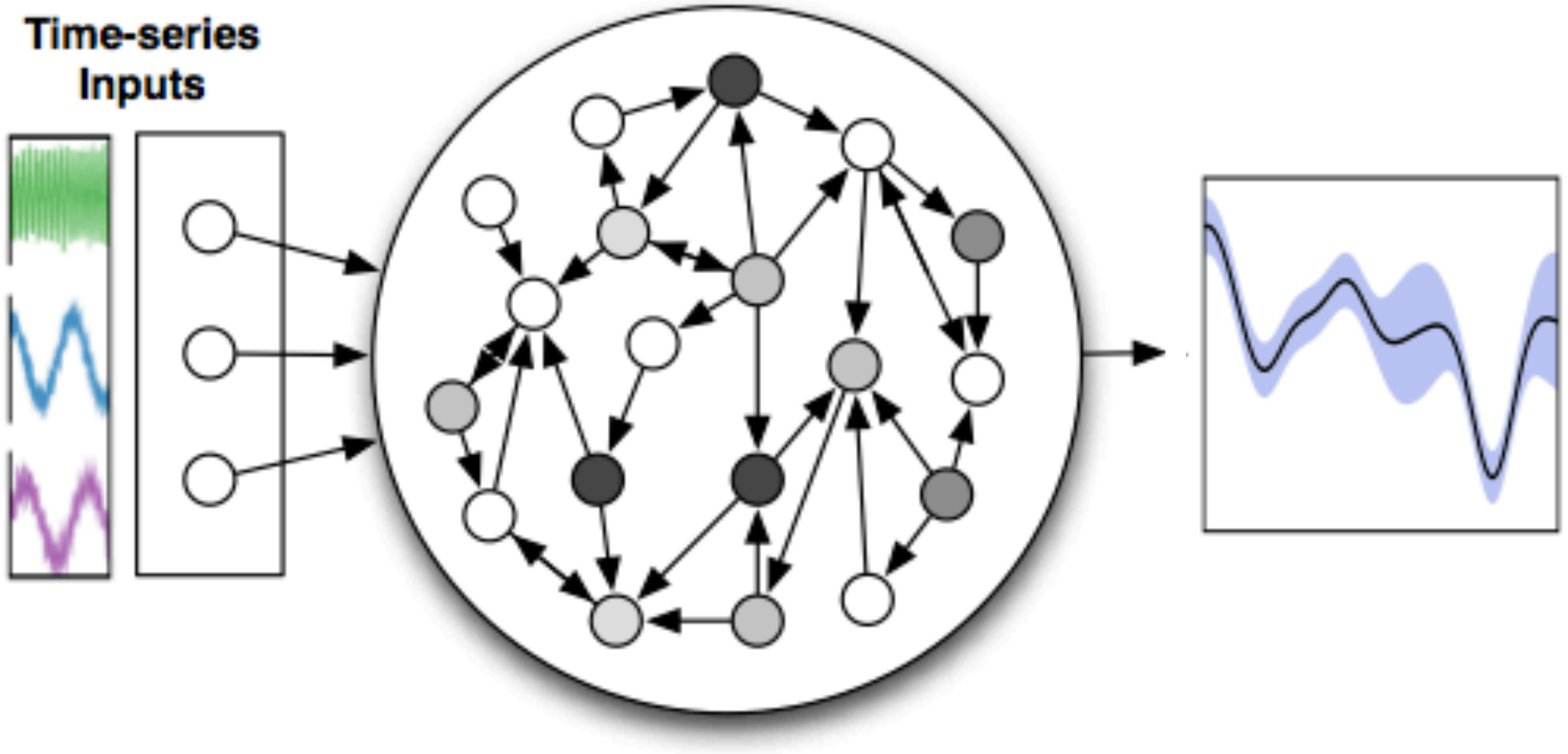
Effect of inheritance on selection
Source: Epstein and Axtell (1996, p. 68)

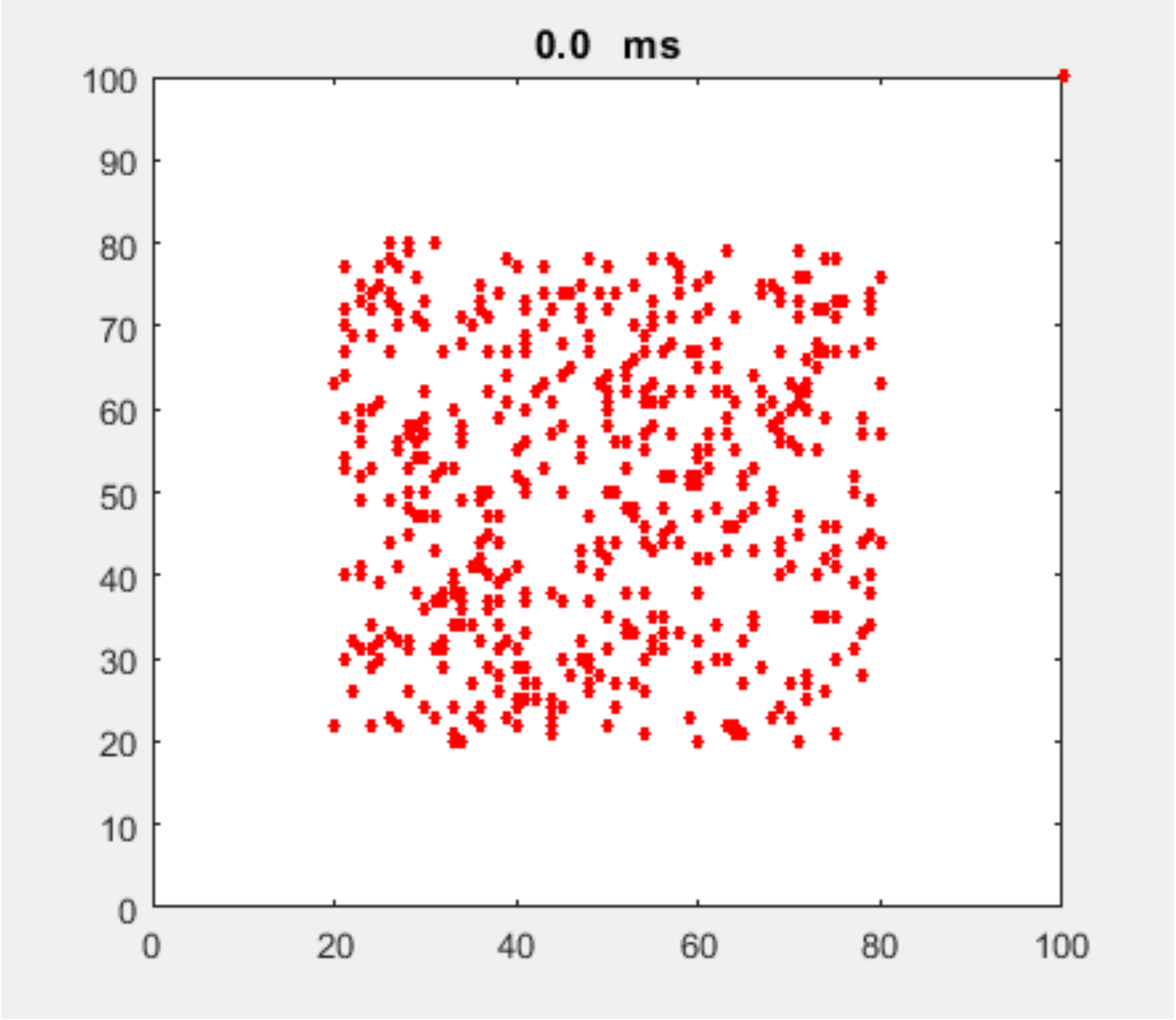


Articial Neural Networks

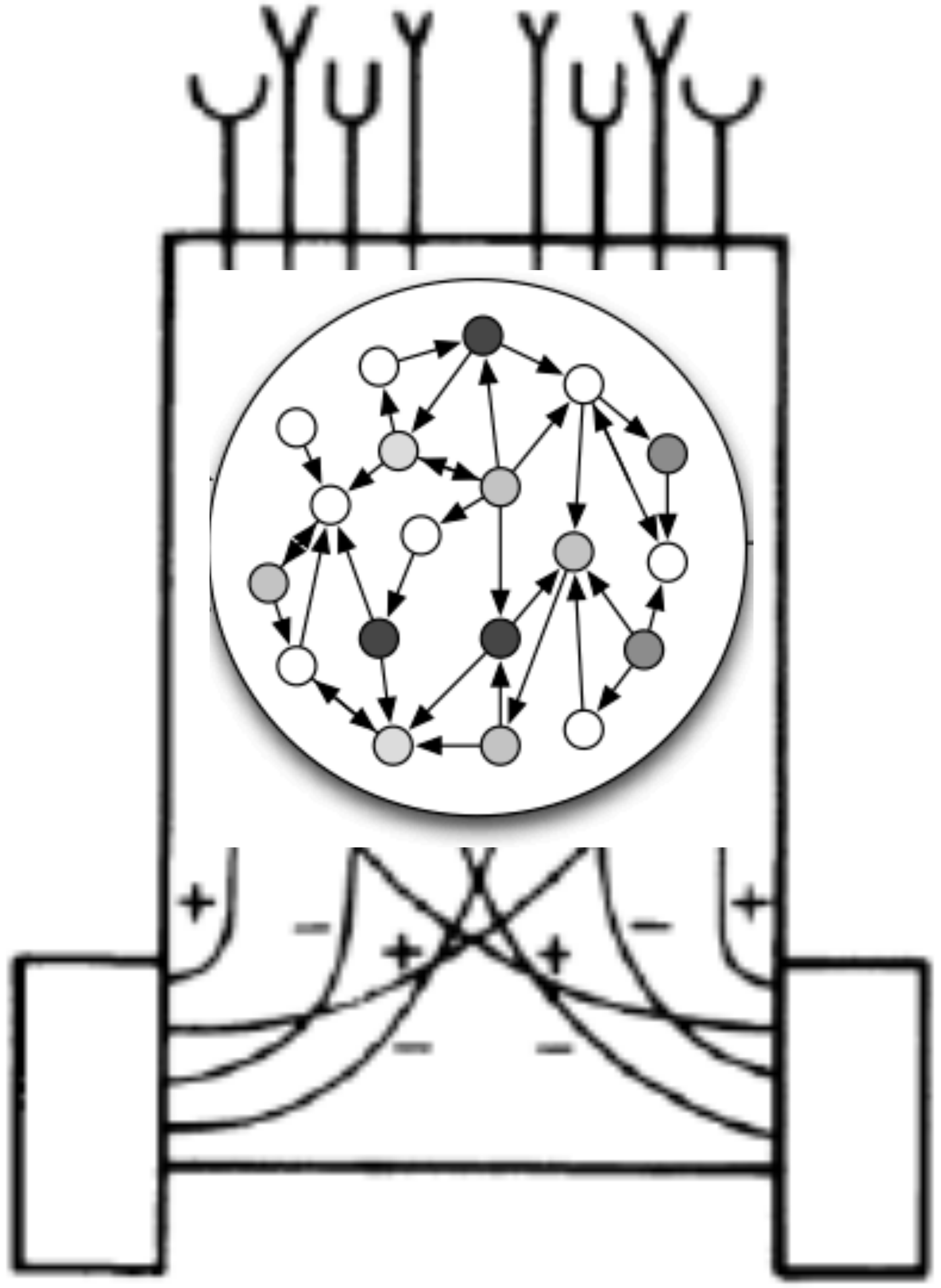


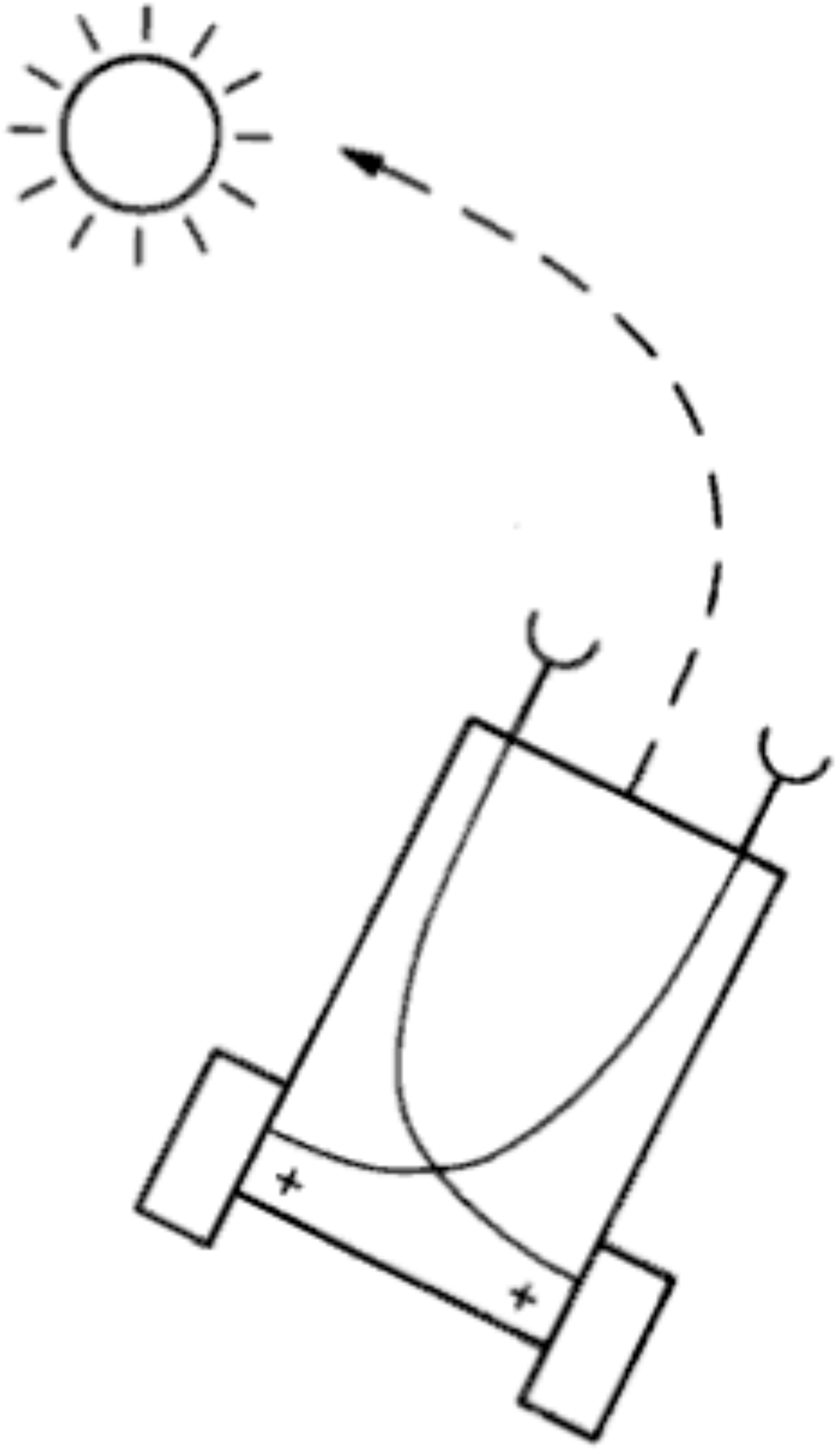
x1	x2	target
0	0	1
0	1	0
1	0	0
1	1	1

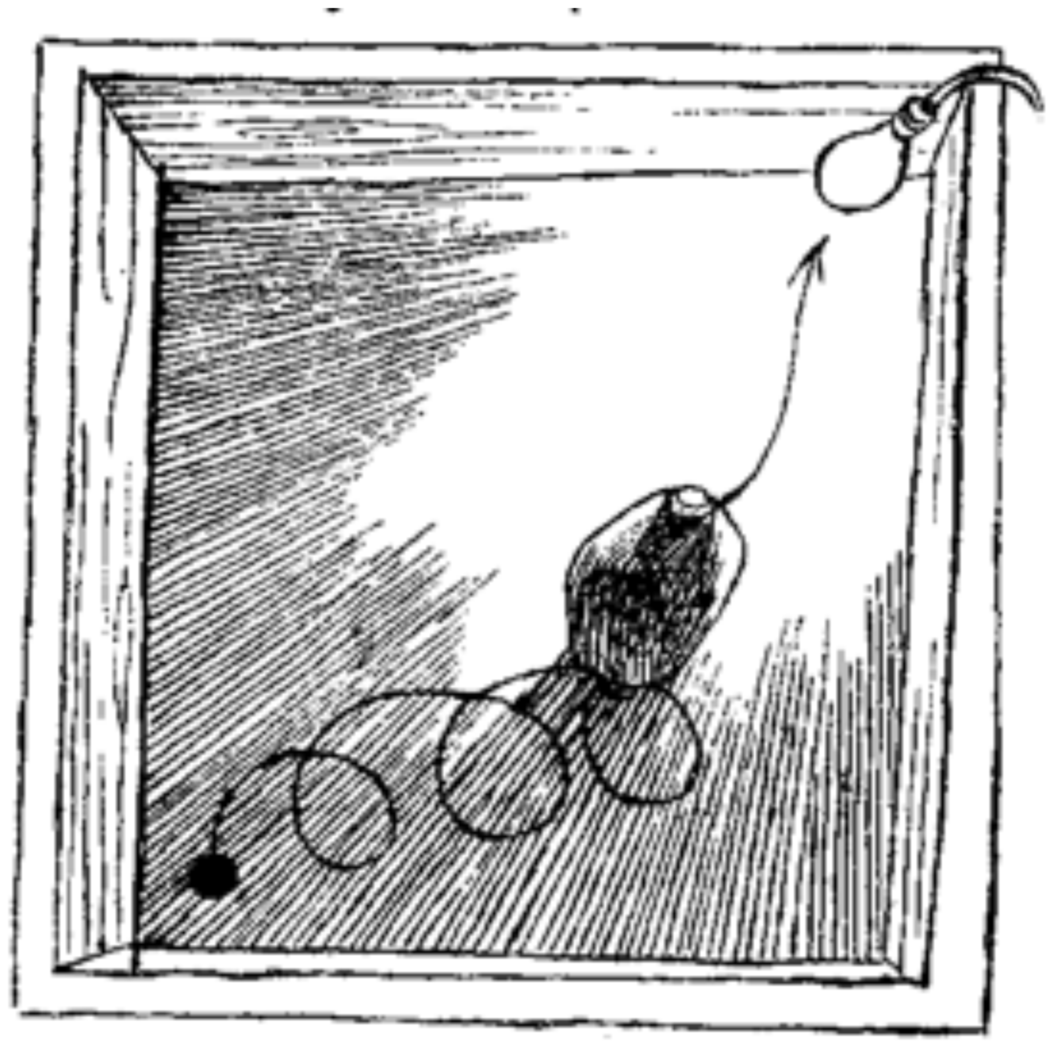




Braitenberg's vehicles





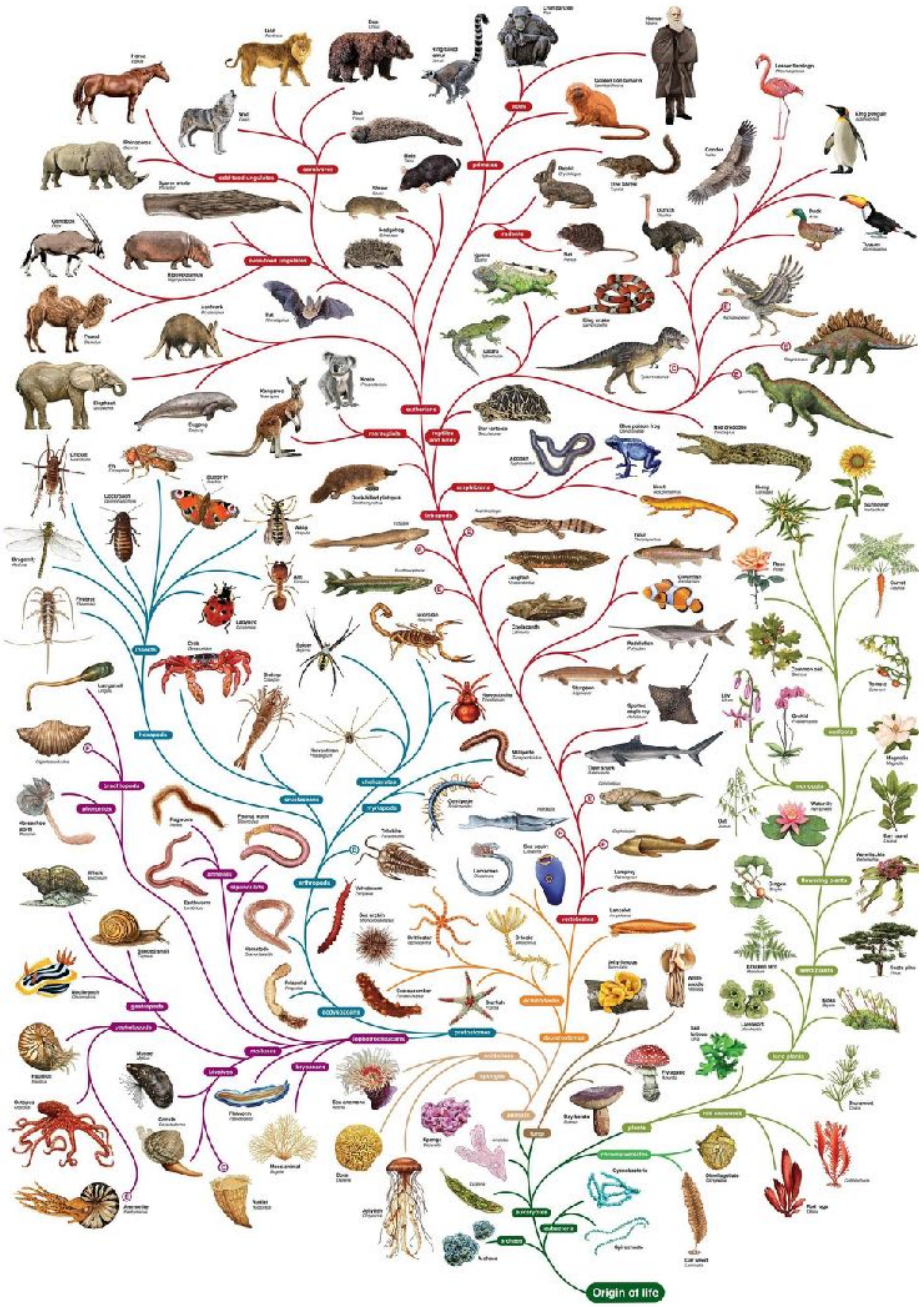


Requirements for Evolution

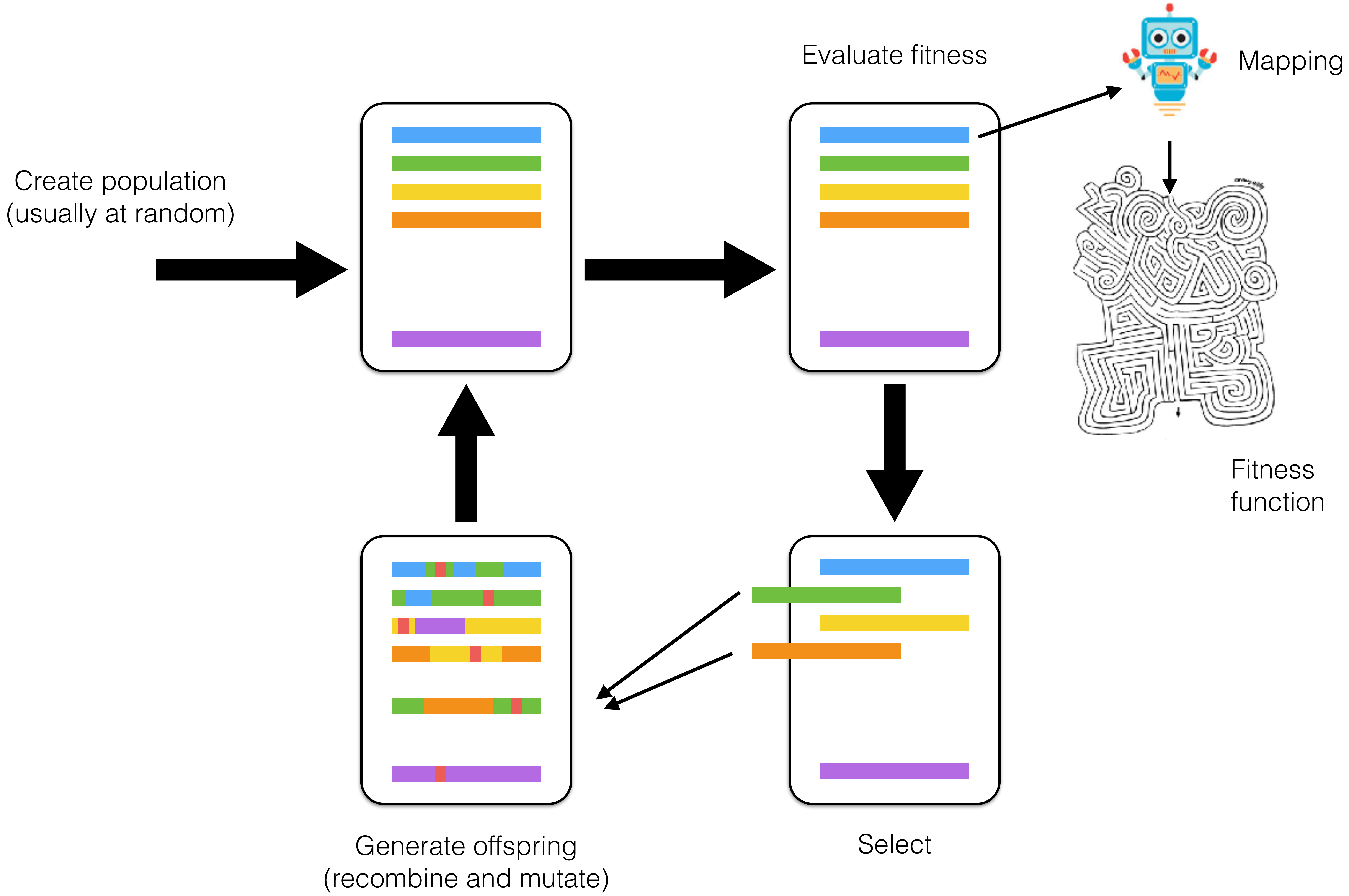
Heredity — there's a form of replication/reproduction and offspring are (roughly) identical to their parents.

Variability — except not exactly the same, some significant variation introduced through mutations.

Selection — the 'fitter' ones are likely to have more offspring.



Artificial Evolution



Summary

Broad Motivation: Better understand natural phenomena by developing computational models that replicate aspects of it.

Specifically relevant for understanding complex systems, those composed of many interacting components.

Agent-Based Modeling, technique for simulating the behavior of cells, individuals, or agents interacting locally and studying the resulting global pattern of collective behavior.

Discussed examples across a wide range of disciplines, two in some detail with demos.