Introduction

What is ABM, Classic Models

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Introduction

Modelling and Simulation?

The term modelling refers to the development of a (e.g., physical, mathematical, or logical) representation of a system, entity, phenomenon, or process.

The term simulation refers to the execution (or solution) of the model in time.

The concept of a system

“aggregation or assemblage of objects joined in some regular interaction or interdependence”

The concept of a system

The system has certain distinct objects each of which has some properties of interest:

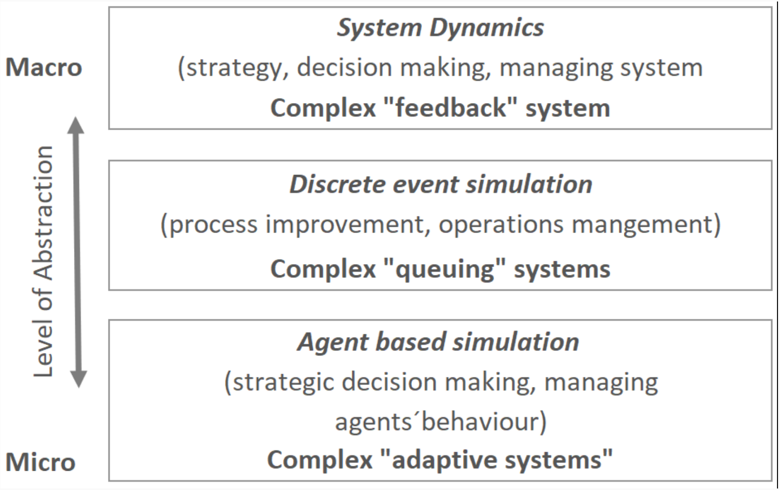
- Object of interest in the system -> Entity (Agents)
- Property of entity -> Attribute (state variables)
- Relationships between entities
- Process that cause change in the system -> Activity(Actions)
- Description of entities, attributes and actions at a point in time -> State of the system
- Progress of a system studied by observing the change in state of a system -> Simulation

System environment

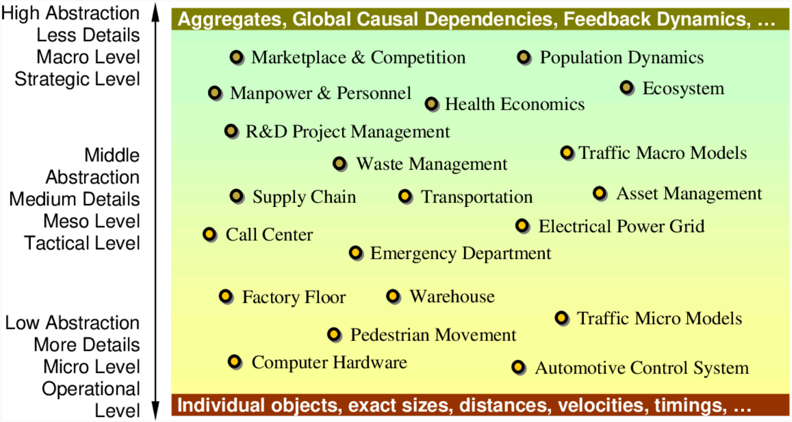
The changes occurring outside the system and that, affecting the system are said to occur in the system environment. E.g. wind force on a structure

- Endogenous – describes activities within a system
- Exogenous – activities in the environment that affect the system
- No exogenous activity - closed system
- Exogenous activity present – open system

The family of simulation modelling



The family of simulation modelling



What is ABM?

The aim of ABM is to look at global consequences of individual or local interactions in a given space. Agents are seen as the generators of emergent behavior in that space.

— [John Holland]

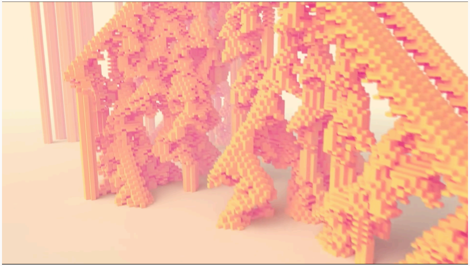
ABMs consist of a space, framework or environment in which interactions take place and a number of agents whose behavior is defined in this space is defined by a basic set of rules and by characteristic parameters.

— [Craig Reynolds]

What is an ABM?

Agent-based models are not really mathematical models.

They are ***algorithmic*** models that try to describe the world in terms of processes or algorithms.



Lotka-Volterra

Lotka-Volterra describes the evolution of two species, a predator y and prey x:

$$\frac{dx}{dt} = \alpha x - \beta xy$$

$$\frac{dy}{dt} = \delta xy - \gamma y$$

α defines the birth rate of prey, β defines the predation rate, δ defines the growth of predators when eating prey, γ defines the death rate of predator.

Assumes that every prey and predator are equally likely to meet.

Homework: Try to calculate the stability of fixed points

Lotka-Volterra - ABM

It is possible to create a simple 'equivalent' ABM. Let's call the prey sheep and the predators wolves.

What is the environment?

What are the rules for the sheep?

What are the rules for the wolves?

What are the parameters of the model?

Lotka-Volterra - ABM

Environment:
Just create a 2D euclidean space (could be cell based). Should be of sufficient size. Too small impacts interaction probability. Agents will move around in this space - once the agents come close enough they interact.

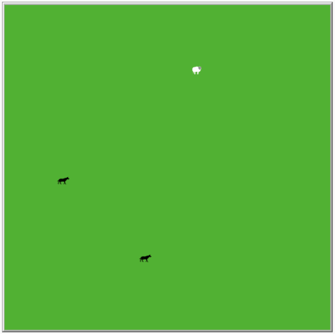
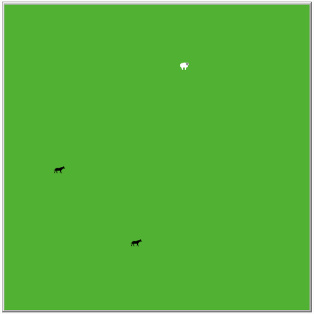


Figure 1: 2D predator-prey model

Sheep:

Need to define two rules - these two rules correspond to the two terms in the equation (birth and predation)

- Predation happens when a sheep meets a wolf. So we need to define how the sheep moves.
- Birth is spontaneous in the simple model - works the same way as the ODE. Note that the birth rate parameter defines the probability of a single sheep producing another.



Think about alternatives here that are very easy to implement in the ABM that would be much harder analytically.

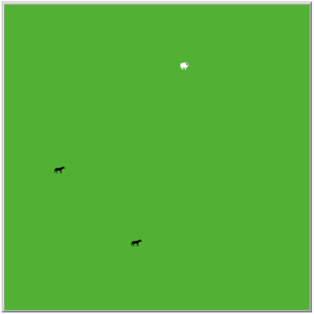
Lotka-Volterra - Wolves

wolves

Again, need to define two rules - these two rules correspond to the two terms in the equation (death and predation/birth)

- Again, predation(birth) happens when a sheep meets a wolf. So we need to define how the wolves move.
- Death works the same way as the ODE. Note that the death rate parameter defines the probability of a single sheep producing another.

Think about how the wolves behave in the ODE? How do they 'move'?



Lotka-Volterra - Issues

Firstly, stability? We have a finite population in the ABM - there is always a probability that we kill the last wolf or sheep. Fix this by making the population and environment very large.

Modifications?

- Add biased movement - sheep avoid wolves, or herd. Wolves chase sheep within a range.
- Require sheep/wolves to meet for birth. Wolves fight?
- Add more species - add grass to support the sheep.

For many of these cases you can achieve with partial differential equations, or more ODEs. Sometimes this can become tricky - with an ABM this is straight forward.

Lotka-Volterra - Try

Try *wolf-sheep v1.nlogo* This is the simplest version of the ABM predator prey

Movement:

```
rt random 50
lt random 50
fd 1
```

Parameters:

Sheep-birth: Probability a single sheep gives birth asexually

wolf-death: Probability that a single wolf dies

Rules: One simple rule - if the sheep and wolf are on the same square, the wolf eats the sheep and reproduces.

Mean field approximation

Coarse Graining

Common approaches to the analysis of agent-based models include extensive Monte Carlo simulation of the model or the derivation of coarse-grained differential equation models to predict the expected or averaged output from the agent-based model (Nardini et al. 2021).

A birth, death and migration (BDM) agent-based model

$$A_\alpha + 0_\beta \xrightarrow{P_p/4} A_\alpha + A_\beta,\ \beta \in \mathcal{B}(\alpha) \tag{1}$$

$$A_\alpha \xrightarrow{P_d} 0_\alpha \tag{2}$$

$$A_\alpha + 0_\beta \xrightarrow{P_m/4} 0_\alpha + A_\beta,\ \beta \in \mathcal{B}(\alpha). \tag{3}$$

A birth, death and migration (BDM) agent-based model

$$
\begin{aligned}
C_\alpha(t) &= \mathbb{P}\left[A_\alpha(t), A_\beta(t)\right] \\
&\quad + \mathbb{P}\left[A_\alpha(t), A_0(t)\right]; \\
1 - C_\alpha(t) &= \mathbb{P}\left[0_\alpha(t), A_\beta(t)\right] \\
&\quad + \mathbb{P}\left[0_\alpha(t), A_{0\beta}(t)\right]; \\
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&\quad + \mathbb{P}\left[0_\alpha(t), 0_\beta(t)\right];
\end{aligned} \tag{4}
$$

A birth, death and migration (BDM) agent-based model

$$F(t; \alpha, \beta) = \frac{\mathbb{P}\left[A_\alpha(t), A_\beta(t)\right]}{C_\alpha(t) \cdot C_\beta(t)}. \tag{5}$$

$$\begin{aligned}
\mathbb{P}\left[A_\alpha(t), A_\beta(t)\right] &= C_\alpha(t) \cdot C_\beta(t) \cdot F(t; \alpha, \beta); \\
\mathbb{P}\left[A_\alpha(t), 0_\beta(t)\right] &= C_\alpha(t) \cdot \left(1 - C_\beta(t) F(t; \alpha, \beta)\right); \\
\mathbb{P}\left[0_\alpha(t), A_\beta(t)\right] &= C_\beta(t) \cdot \left(1 - C_\alpha(t) F(t; \alpha, \beta)\right); \\
\mathbb{P}\left[0_\alpha(t), 0_\beta(t)\right] &= 1 - C_\alpha(t) - C_\beta(t) + C_\alpha(t) \cdot C_\beta(t) \cdot F(t; \alpha, \beta).
\end{aligned} \tag{6}$$

A birth, death and migration (BDM) agent-based model

$$\frac{d\,C_\alpha(t)}{d\,t} = K_{\text{birth}} + K_{\text{death}} + K_{\text{migration}}. \tag{7}$$

$$K_{\text{birth}} = \frac{P_p}{4} \sum_{\beta \in \mathcal{B}(\alpha)} \mathbb{P}[0_\alpha(t), A_\beta(t)], \tag{8}$$

$$K_{\text{death}} = -P_d \cdot C_\alpha(t), \tag{9}$$

$$K_{\text{migration}} = \frac{P_m}{4} \sum_{\beta \in \mathcal{B}(\alpha)} \left(\mathbb{P}\left[0_\alpha(t), A_\beta(t)\right] - \mathbb{P}\left[A_\alpha(t), 0_\beta(t)\right]\right) \tag{10}$$

A birth, death and migration (BDM) agent-based model

$$\frac{dC}{dt} = \frac{P_p}{4} \sum_{\beta \in \mathcal{B}(\alpha)} (\mathbb{P}[0_\alpha(t), A_\beta(t)] + \frac{P_m}{4} \sum_{\beta \in \mathcal{B}(\alpha)} (\mathbb{P}[0_\alpha(t), A_\beta(t)] - \mathbb{P}[A_\alpha(t), 0_\beta(t)])$$

- $\mathrm{P}_d \cdot C_\alpha(t)$
(11)

$$\frac{dC_\alpha(t)}{dt} = \frac{P_m}{4} \sum_{\beta \in \mathcal{B}(\alpha)} (C_\beta(t) - C_\alpha(t)) + \frac{P_p}{4} \sum_{\beta \in \mathcal{B}(\alpha)} C_\beta(t)(1 - C_\alpha(t) \cdot F(t; \alpha, \beta)) - P_d \cdot C_\alpha(t)$$

(12)

A birth, death and migration (BDM) agent-based model

$$\frac{d}{dt}C(t) = P_p \cdot C(t) \cdot (1 - C(t) \cdot F(t;1)) - P_d \cdot C(t) \tag{13}$$

$$\frac{d}{dt}C(t) = P_p \cdot C(t) \cdot (1 - C(t)) - P_d \cdot C(t) \tag{14}$$

A birth, death and migration (BDM) agent-based model

$$\frac{d}{dt}C(t) = r \cdot C(t)(1 - \frac{C(t)}{K}) \tag{15}$$

$$C(t) = \frac{K \cdot C(0) \cdot e^{rt}}{K + C(0) \cdot (e^{rt} - 1)} \tag{16}$$

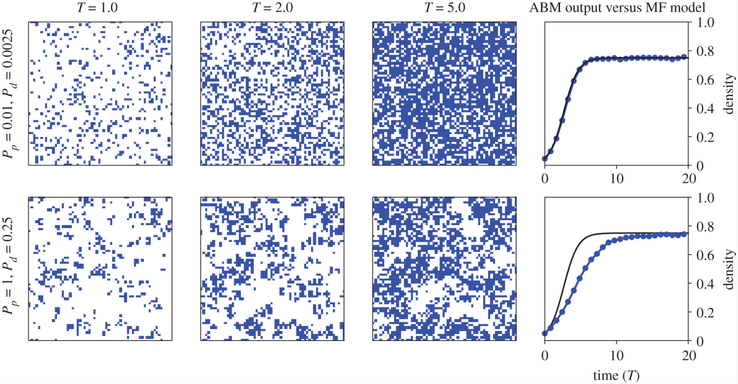


Figure 2: ABM simulation snap shots for the BDM ABM

An epidemic (SIR) agent-based model

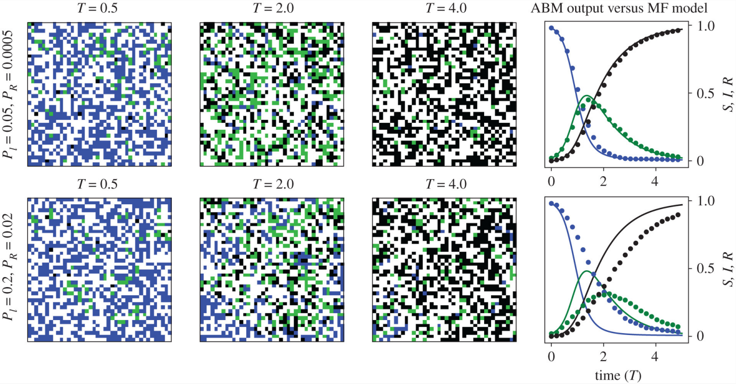


Figure 3: ABM simulation snap shots for the SIR ABM

Please read (Nardini et al. 2021) section 2.2

When ABM?

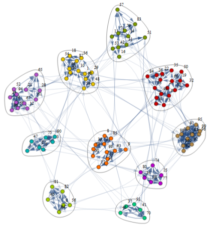
Which approach to use when?

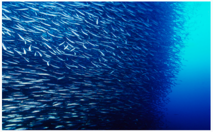
- No ‘clear-cut’ answer exists. It depends on your objective and expected ‘resolution’.
- Agent based models are often harder to develop, verify, validate and document, need more computational power to simulate and their results are more difficult to interpret.
- Why bother? Remember: sometimes our objective is to (describe the behavior, variability and the interactions among organisms, not merely the quantity of whole populations).

Choose Wisely! Always motivate Why ABM?

When or Why ABM? (Bonabeau 2002)

- When the ***interactions*** between the agents are complex, nonlinear, discontinuous, or discrete (for example, when the behavior of an agent can be altered dramatically, even discontinuously, by other agents).
- When ***space*** is crucial and the agents' positions are not fixed. Example: fire escape, theme park, supermarket, traffic.
- When the population is ***heterogeneous***, when each individual is (potentially) different.
- When the ***topology*** of the interactions is heterogeneous and complex. Example: when interactions are homogeneous and globally mixing, there is no need for agent-based simulation, but social networks are rarely homogeneous, they are characterized by clusters, leading to deviations from the average behavior.
- When the agents exhibit ***complex behavior***, including learning and adaptation. Example: NASDAQ. No single definitive definition...



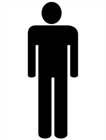


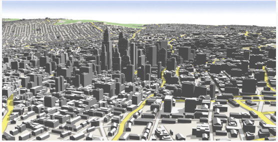
Steps to Building an ABM

General procedure for ABM

General procedure for ABM

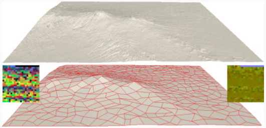
1. Identify what your agents are - May include multiple types





General procedure for ABM

1. Identify what your agents are - May include multiple types
2. Define your environment (how the agents interact)
   - Define your state transformation (how you environment responds/updates)



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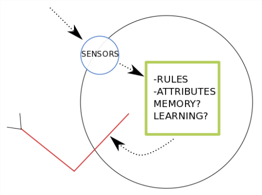
   - Define the action set and rules/behaviour of your agents



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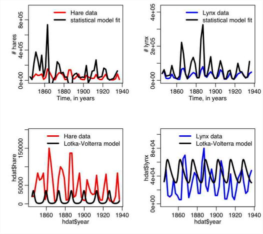
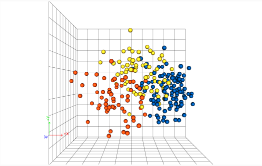
4. Test your model
   - Sensitivity Analysis (remove unused parameters)
   - Validation* against real data (revise rules)





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What is in an ABM?

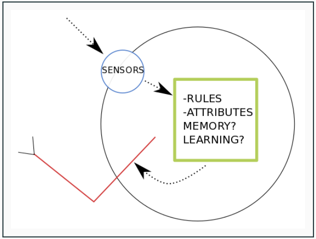
Much of the modelling effort lies in designing the ***rules/behaviours***

ABMs are discrete time usually time-stepped (can be 'event-driven')

All agents are executed once per timestep in a random order.

Executed means they operate a sense-decide-act cycle:

1. ***Sense*** their (local) environment
2. ***Decide*** on an action to take based on input and state/memory
3. ***Act*** in their environment e.g., move, change state, etc.



The unreasonable effective simplicity of ABM

Often you will see ABM applied to every type of system there is.

In some cases ABM might not be the best choice - remember that the model should be designed in the most simple way possible (Occam's razor) while describing the correct dynamics to answer the scientific question you're asking.

However, Agent-based models have seen most success in fields where it's more difficult to derive models from first principles (i.e., physical rules etc.).

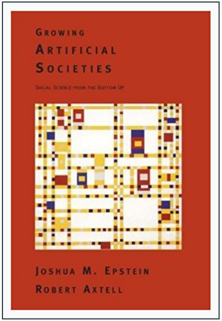
So ABM is useful in social science, understanding human systems (finance, cities, etc.)

Classic Models

Classic Models

Sugarscape (Joshua M Epstein and Axtell 1996)

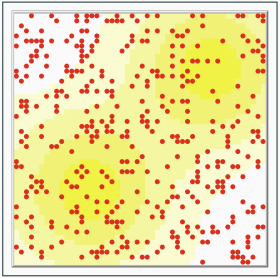
"Growing Artificial Societies" (Joshua M Epstein and Axtell 1996) is a reference book for scientists interested in agent-based modelling and computer simulation. It represents one of the most paradigmatic and fascinating examples of the so-called generative approach to social science (Joshua M Epstein 2006). In their book, Epstein & Axtell present a computational model where a heterogeneous population of autonomous agents compete for renewable resources that are unequally distributed over a 2-dimensional environment.



Sugarscape

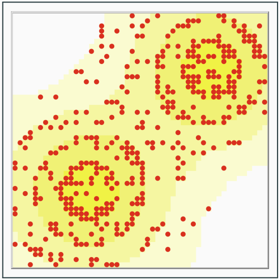
In the book the model evolves into different versions - we'll take a look at one.

- 50×50 grid that wraps around forming a torus
- Cells have a sugar capacity c, fixed for a single cell, but differs between cells
- The spatial distribution of sugar capacities depicts a sugar topography consisting of two peaks (with sugar capacity $c = 4$)



Sugarscape

- At each tick, each patches sugar grows back either *immediately* or *constantly* (by a value of 1)
- Agents placed randomly.
- Agents have a fixed straight line vision range
- They move to the cell with the most sugar and collect all sugar there. If current location is highest it stays where it is.
- Agents have a metabolism and consume sugar they have collected, they die if they have no sugar to consume - dead agents are replaced by new agents in a new location.



Sugarscape

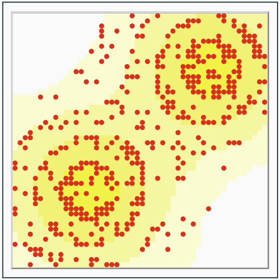
Model has a number of parameters for agents:

vision : how many cells they can see

metabolism : How much sugar they need to survive per step.

maximum age : Number of ticks an agent can survive at maximum.

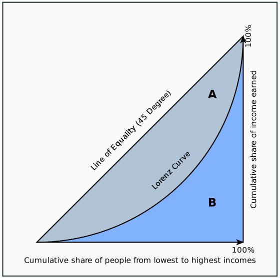
The value for each individual agent is generated from a uniform random distribution based on these parameters.



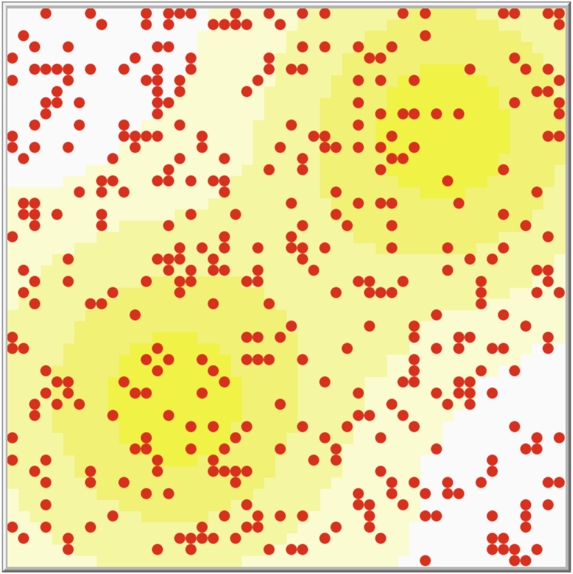
Version 3 - Wealth distribution gets interesting
When a new agent is created their initial sugar level is now generated randomly (from a uniform distribution) with a minimum and maximum parameter. We can then measure how these values impact the distribution of wealth in the population.

They measure the *Gini-coefficient* and the *Lorenz curve*.

$$G = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N}|x_i - x_j|}{2\sum_{i=1}^{N}\sum_{j=1}^{N}x_j}$$



Sugarscape



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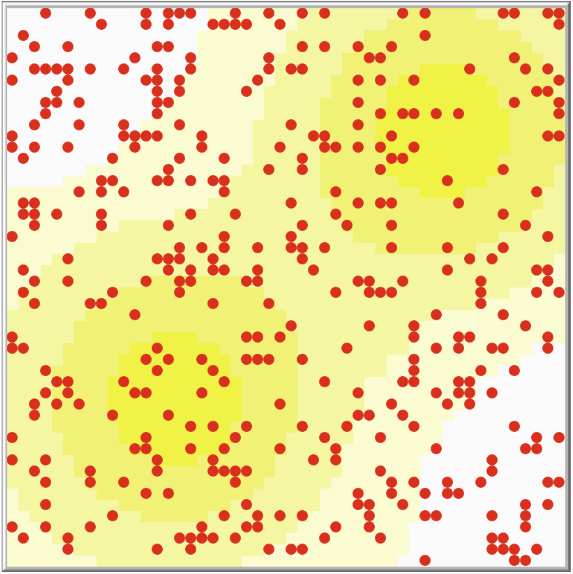

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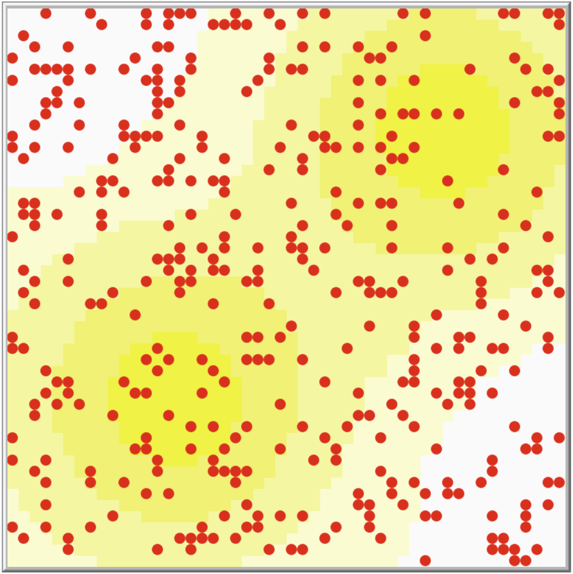


Many more versions exist in the book gradually adding more and more processes and analysis.

- Social Networks
- Migration
- Sex, Culture, Conflict
- Trade
- Disease Transmission

The book is an excellent text for how to build artificial societies inside a computer. Or, how to use agent-based models to study social phenomena.

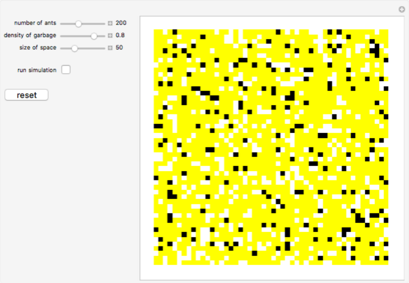
These models are not really predictive - but present stylised facts and help illuminate core dynamics that drive social phenomena.

Garbage collection by ants

"Turtles, Termites and Traffic Jams". Tiny pieces of garbage scattered in a 2-D space, where many ants are wandering **randomly**. When an ant comes to a place where there is some garbage, it behaves according to the following very simple rules:

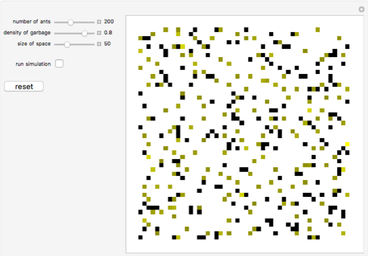
- If the ant is holding a piece of garbage, it drops the piece.
- If the ant isn't holding any garbage, it picks up a piece of garbage.

What would result from these rules?



Garbage collection by ants

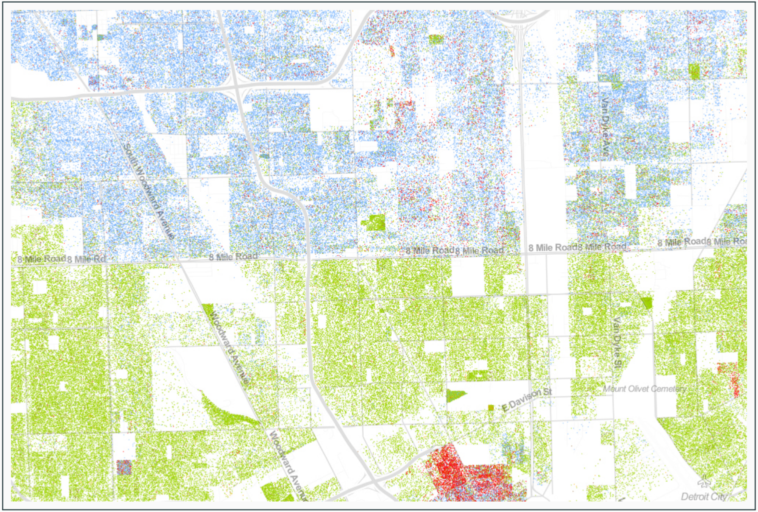
If you implement the model right, you will see that these very simple behavioral rules let the ants spontaneously collect and pile up garbage and clear up the space in the long run. This model tells us how such emergent behavior of the collective is sometimes counter to our natural intuition.



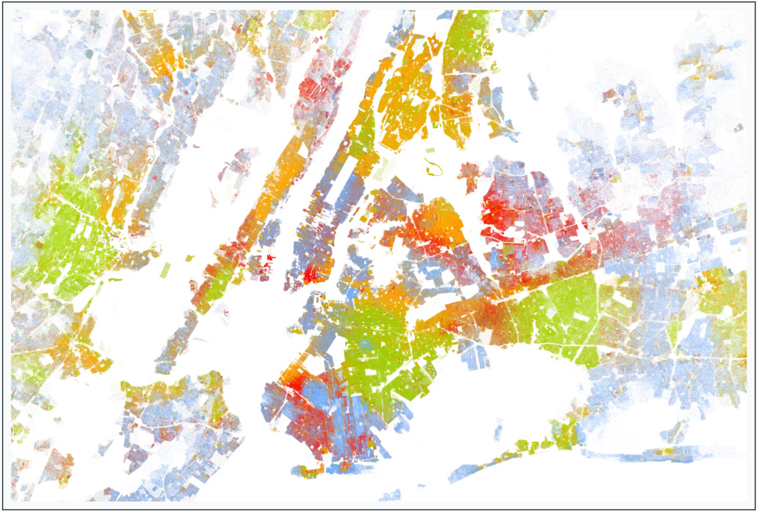
Classic Models

Segregation (Schelling 1971)

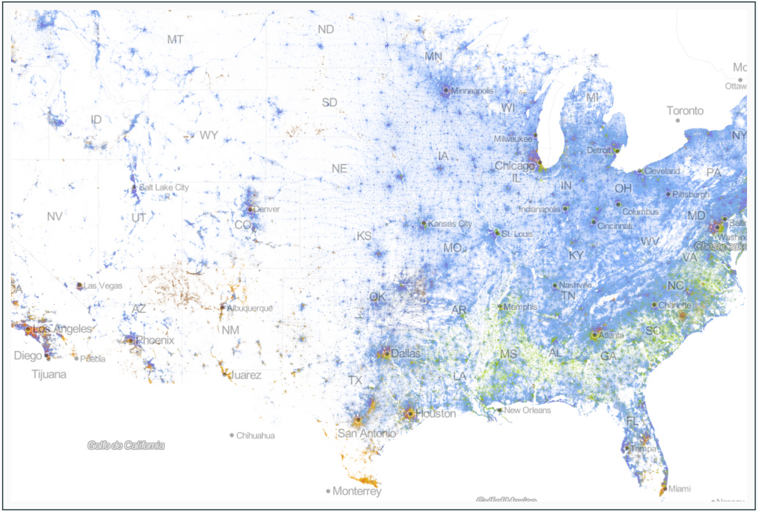
Segregation



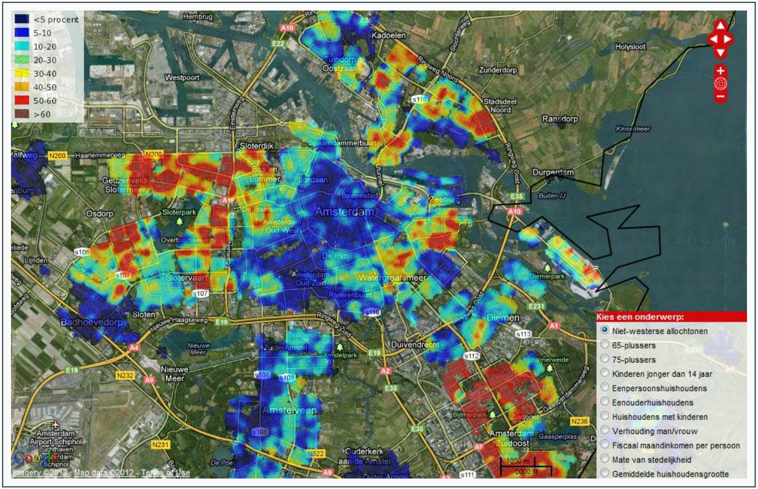
Segregation



Segregation

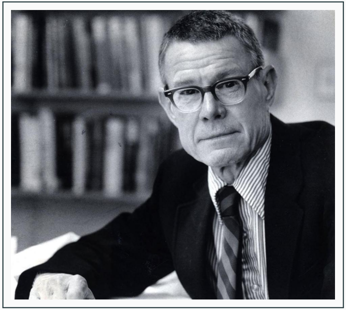


Segregation



Schelling Segregation Model

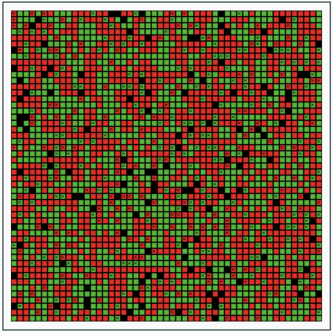
It represents one of the first constructive models of a dynamic interacting-agent system explicitly designed to explore an important social issue ***white flight***
Originally done with manual simulation. He used coins on graph paper to demonstrate his theory by placing pennies.



Schelling Segregation Model

The neighbourhood is stylised as an $N \times N$ lattice. Every space of the lattice is a housing lot. Lots can be occupied (coloured) or empty (black). There are *red* and *green* agents that are considered different (racially, culturally, financially, etc.)

An initial population of agents (households) is placed on the board - this is normally balanced and some unoccupied lots are left.



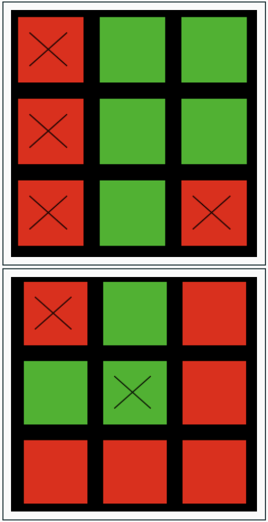
Schelling Segregation Model

Every agent has a local neighbourhood consisting of the 8 surrounding cells.

Each agent is considered unhappy if:

$$\theta_s < \frac{N_s}{N}$$

Where θ_s is a threshold for the fraction of neighbours I want to be the same as me, N_s is the number of neighbours the same as me, $N = 8$ is the number of total neighbours.
An unhappy agent moves to the nearest available spot



Segregation - Θ

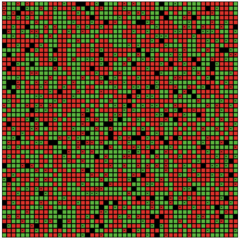


Figure 4: $\theta = 0.7$

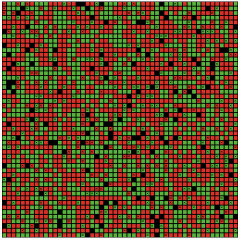


Figure 5: $\theta = 0.5$

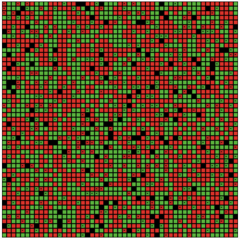


Figure 6: $\theta = 0.3$

Segregation - Continued

There has been a lot of further work on the Schelling Model and a number of researchers have tried to verify the model using real data:

- (W. A. V. Clark 1991)
- (William A. V. Clark and Fossett 2008)
- (Hatna and Benenson 2012)

Again, the model is not intended to be predictive - the main purpose, which it achieved, was to illuminate the core dynamics of the segregation process.

Even at very, intuitively, tolerant θ, you would still say significant segregation.

Classic Models

El Farol (Arthur 1994)

Inductive Reasoning and Bounded Rationality - El Farol

Brian Arthur wanted to understand the assumption of rational behaviour used in economic thinking (game theory). With rational agents you can more easily reason about another's behaviour, and thereby better predict the system behaviour. Arthur argues that humans are in fact limited:

- We are *bounded* - when things get too complex we find it hard to reason - this may lead to 'irrational actions'
- Humans do not assume others are rational - so we instead guess what others might do, we do *inductive reasoning*

El Farol is bar in Santa Fe where Arthur was working. On Thursday's it played Irish music, Arthur is Irish – but doesn't like overcrowded bars.
There are $N = 100$ agents, each agent picks each week if he will go to the bar. They make a prediction about how many agents go to the bar, if more than 60 are predicted the agents stays at home. Otherwise the agent goes to the bar and enjoys their time.
Note: If all believe few will go, all will go. But this would invalidate that belief. Similarly, if all believe most will go, nobody will go, invalidating that belief. Expectations will be forced to differ. (Arthur 1994)

El Farol

The Model has each agent use the attendance of the previous weeks to make their decision:

$$\{\ldots, 45, 65, 68, 93, 45, 33, 35, \ldots\}$$

Agents have different possible prediction strategies:

- Last weeks (35)
- Average of last 3 weeks (37.6)
- Same as 4 weeks ago (93)
- etc.

Each agent keeps a set of k individual prediction strategies, they have an active strategy which is the best performing strategy from last week.
What is of interest is how the set of active strategies evolves over time, and how this impacts the attendance.

El Farol - Model

In this version of the model an agent has some parameter:

Memory : How many previous weeks the agent remembers, m

Strategies : How many strategies the agent should keep, k

The agents strategies are generated randomly as a list of weights of size m, where each entry in the vector represents the weight associated with that week.

$$p(t) = [x(t-1) \times a(t-1)] + [x(t-2) \times a(t-2)] + \ldots.. + [x(t-m) \times a(t-m)] + c \times 100,$$

where $p(t)$ is the prediction at time t, $x(t)$ is the attendance of the bar at time t, $a(t)$ is the weight for time t, c is a constant representing a guess in the absence of data, and m is the memory size.

El Farol

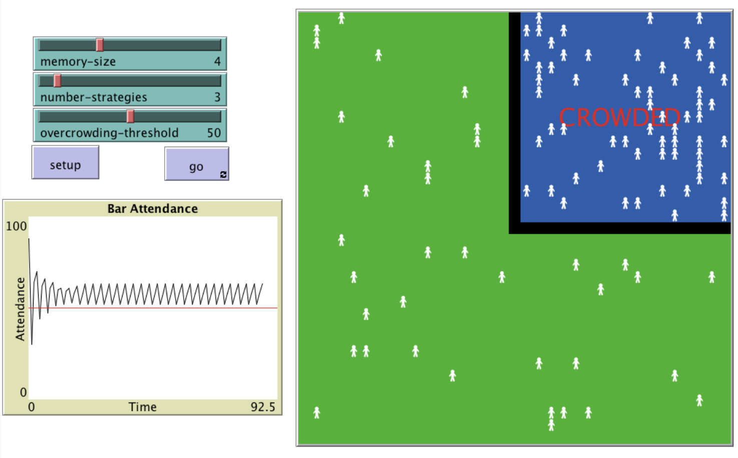


Figure 7: El Farol Model in Netlogo

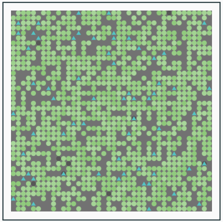
Classic Models

Civil Violence (Joshua M. Epstein 2002)

In this model a central authority attempts to suppress civil violence among agents (variation include ethnic groups). Agents have political grievance and rebel

It operates on an $N \times N$ lattice and contains agents (activists) and police (cops).

Agents can be active or quiescent, cops arrest active agents and place them in jail for some time.



Agents have two attributes that describe political grievance

Hardship H : a value drawn from $U(0,1)$ - indicating economic of physical privation

Legitimacy L : perceived legitimacy of the regime - a parameter that changes between $[0,1]$

Grievance G of an agent is the defined as:

$$G = H(1 - L)$$

Agents have other parameters:

Risk Aversion R : Riskier agents are more likely to rebel, again sampled from U(0,1)

Vision v : How far an agent can see on the lattice, they use this to estimate probability of arrest P

$$P = 1 - \exp^{-k(C/A)_v}$$

Where $(C/A)_v$ is the cop-to-active ratio within vision v and k is a constant chosen to have $P = 0.9$ when $C = A = 1$. Note that $A \geq 1$, the agent includes himself as an active within vision.

There is a deterrent in the system, being prison

Net Risk N : $N = RP$, the net risk of the agent given riskiness of agent and the likelihood of arrest. Or $N = RPJ^{\alpha}$ where J is the jailterm and *alpha* is influence of Jail, in case $N = RP$ $\alpha = 0$

Agents have a simple rule

```
if (G − N) > T
  be active
else
  stay quiet
```

$G - N$ is the expected utility of publicly expressing one's private grievance, and T is the expected utility of not expressing it.

Civil Violence - Cops

Cops have a vision $v*$ and they arrest any active agent that they can see within $v*$. Once they arrest an agent they move the empty space where the agent was.

Civil Violence - Movement & Jail

Agents move randomly within the vision range (both cops and agents) at each step where there is space.

When arrested, agents are removed from the environment - jail has no impact on their grievance.

Civil Violence Analysis

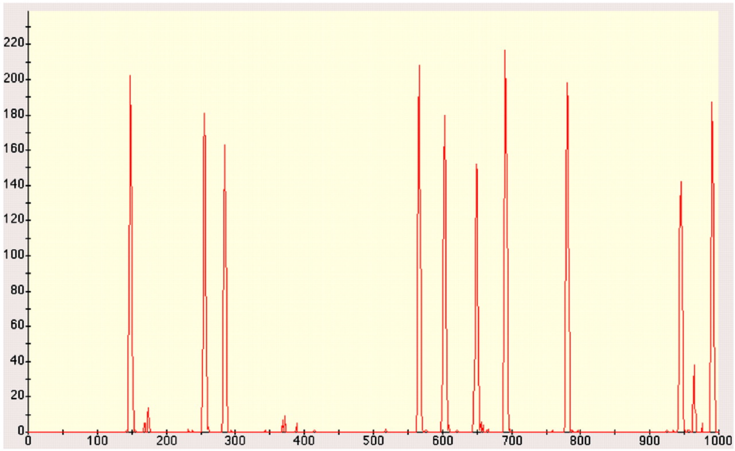


Figure 8: Punctuated Equilibrium

Civil Violence Analysis

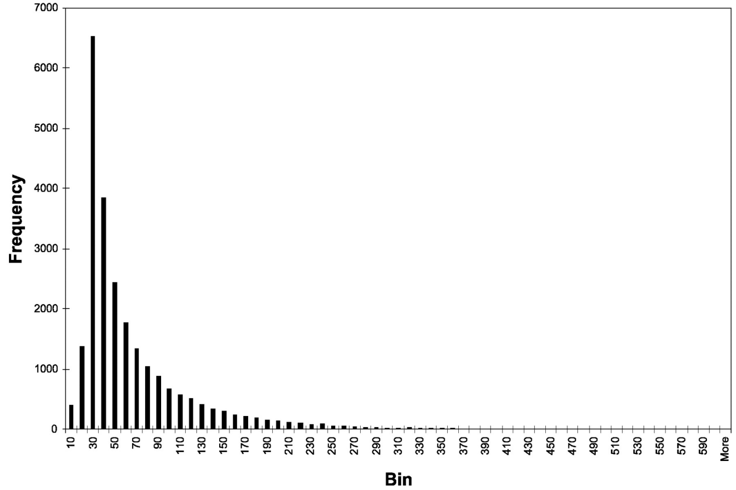


Figure 9: Waiting Time Distribution

Civil Violence Analysis

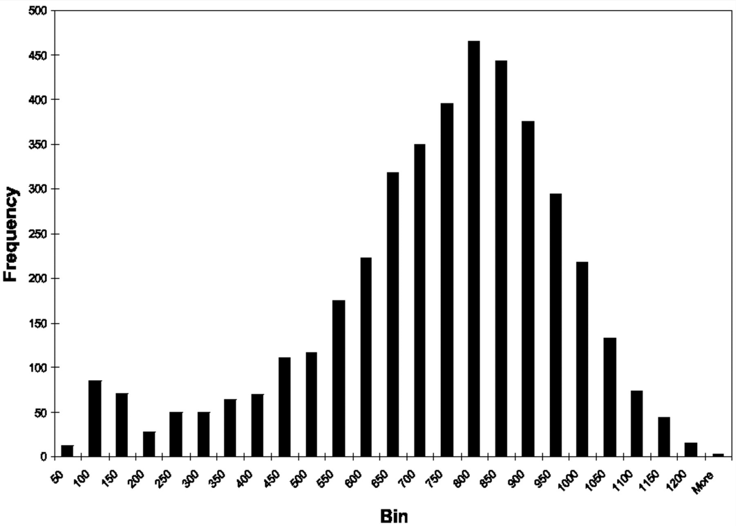
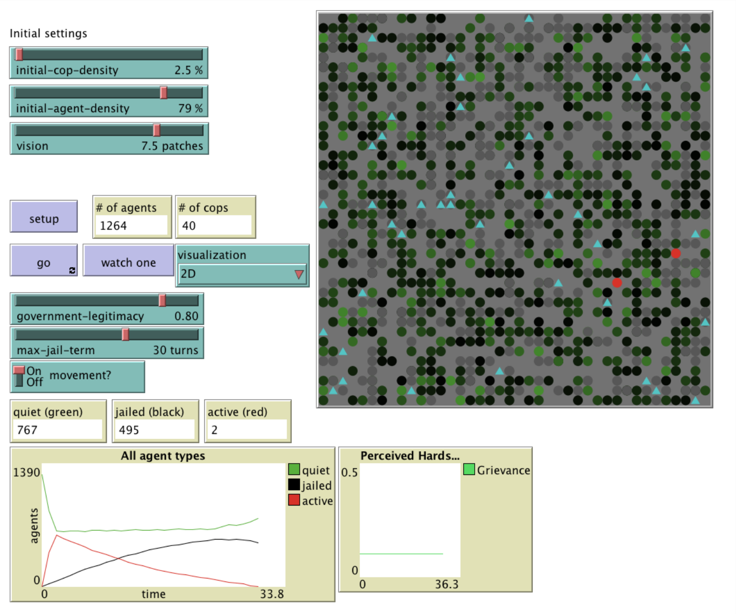


Figure 10: Active Distribution

Civil Violence



Summary

Summary

Common concepts in ABM

Agent Based Model

Agent-based models are *computational* simulation models that involve *many discrete* agents.

Computational

ABMs are usually implemented as simulation models in a computer, where each agent's behavioral rules are described in an algorithmic fashion rather than a purely mathematical way. This allows modelers to implement complex internal properties of agents and their nontrivial behavioral rules.

Analytical Tractability

Therefore, the analysis of ABMs and their simulation results are usually carried out using more conventional statistical analysis commonly used in social sciences, e.g., by running Monte Carlo simulations to obtain distributions of outcome measurements under multiple experimental conditions, and then conducting statistical hypothesis testing to see if there was any significant difference between the different experimental conditions. In this sense, ABMs could serve as a virtual replacement of experimental fields for researchers.

Many

Although it is technically possible to create an ABM made of just a few agents, there would be little need for such a model, because the typical context in which an ABM is needed is when researchers want to study the collective behavior of a large number of agents (otherwise it would be sufficient to use a more conventional equation-based model with a small number of variables). Therefore, typical ABMs contain a population of agents, just like cells in CA or nodes in dynamical networks, and their dynamical behaviors are studied using computational simulations.

Discrete

While there are some ambiguities about how to rigorously define an agent, what is commonly accepted is that an agent should be a discrete individual entity, which has a clear boundary between self and the outside.

Agent Based Model

Typical properties generally assumed in agents and ABMs

- Agents are discrete entities.
- Agents may have internal states.
- Agents may be spatially localized.
- Agents may perceive and interact with the environment.
- Agents may behave based on predefined rules.
- Agents may be able to learn and adapt.
- Agents may interact with other agents.
- ABMs often lack central supervisors/controllers.
- ABMs may produce nontrivial "collective behavior" as a whole.

Emergence: from chaos comes order!

- ABMs with few or no emergent outcomes tend to be less useful (and less interesting!)
- However, don't try to 'impose' emergence. Instead, look for the adaptation rules that might lead to it.

Adaptation: what decisions do agents make?

- Direct objective seeking: decisions maximize explicit estimates of an agent's future condition
- Indirect objective seeking: agents are given rules that mimic observed behavior, which are presumably contribute to their objectives

Interaction: local NOT global interaction

- Direct interaction: (example: wolf-sheep interaction in the predator-prey model)
- Indirect interaction: through the environment (competition between sheep for grass)

Sensing: what information do agents have?

- Is it realistic to assume that the agent knows a certain piece of information? Under what conditions?
- What is the effect of this "partial knowledge"? Bounded rationality (El farol model)

Conclusion

In order for an ABM to be scientifically meaningful, it has to be built and used in either of the following two complementary approaches:

- Build an ABM using model assumptions that are derived from empirically observed phenomena, and then produce previously unknown collective behaviors by simulation. micro-known to produce macro-unknown
- Build an ABM using hypothetical model assumptions, and then reproduce empirically observed collective phenomena by simulation. micro-unknown to macro-known
- Of course, a free exploration of various collective dynamics by testing hypothetical agent behaviors to generate hypothetical outcomes is quite fun and educational, with lots of intellectual benefits of its own.

Conclusion

- ABM is another tool in your toolkit as a Computational Scientist
- Experiment with other modeling approaches and use the one that fits best for or a combination of them – **smartly**!
- Challenge model boundaries and resolution and usual thinking by creating **hybrid models!**

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