

# Agent-Based Modeling and Simulation


## Analyzing and Understanding ABMs

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- ▶ These slides are based on the book of Railsback and Grimm [2], chapter 22.
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# Experimenting

- ▶ Once we have built a new ABM, even a preliminary version of one, it becomes another piece of software that we want to **understand**:
  - ▶ What **results** does the model produce, under what **conditions**?
  - ▶ How do results **change** when parameters, input data, or initial conditions change?
  - ▶ And most importantly, **why** does the model produce the results it does?
  - ▶ What is the model trying to tell us about **how** it works, and how the real system works?

# Scientific Method

- ▶ To turn experimentation into a scientific method, we make our experiments **reproducible** by:
  - ▶ **Completely describing** the model just as empirical scientists describe the materials and methods used in a laboratory or field study;
  - ▶ **Precisely documenting** all the parameter values, input data, and initial conditions we use; and
  - ▶ **Documenting and analyzing** the results of our experiments.

# Controlled Experiments

- ▶ Controlled simulation experiments are also **key** to analyzing and understanding what models do.
- ▶ “Controlled” does not, however, imply that a **simple protocol** for analyzing models exists.
- ▶ Rather, how we analyze a model still depends on the model, the question and system it addresses, our **experience**, and the problem-solving **heuristics** we know and prefer.
- ▶ Heuristics, or rules of thumb, for problem solving are characterized by the fact that they are often useful, but **not always**: we simply have to try them.
- ▶ Using heuristics does not mean that modeling is unscientific: heuristics are the basis of any **creative** research.



# Objectives

1. Understand the **purpose** and **goals** of analyzing full ABMs, including both “finished” models and preliminary versions of models that you plan to develop further.
2. Learn and try ten **heuristics** –techniques or tricks that are often useful– for analyzing ABMs.
3. Become familiar with common ways that **statistical analysis** is used to understand ABMs.



# Introduction

- ▶ The **segregation model** in the Social Science section of NetLogo's Models Library was inspired by a simple model by the Nobel laureate Thomas Schelling [3, 4].
- ▶ Following is an ODD description of this model.



# Purpose

- ▶ The model addresses **segregation** of households in cities: why do members of different groups, e.g., racial, ethnic, religious, tend to occupy different neighborhoods?
- ▶ The model explores the relationship between segregation patterns and the **tolerance** of individuals for unlike neighbors.





# Entities, State Variables, and Scales I

- ▶ The model entities include turtles that represent **households**, and patches that represent **houses**.
- ▶ Households are characterized by their **location** (which patch they occupy) and their **color**, which represents the group they belong to, either blue or red.
- ▶ Households also have a state variable `happy?`, a boolean variable set to false if the household has more **unlike neighbors** than it tolerates.
- ▶ The grid cells make up a **square** of  $51 \times 51$  cells, with no depiction of roads or other spaces between them. The space is **toroidal**.



# Entities, State Variables, and Scales II

- ▶ The length of a time step is unspecified but represents the time in which a household would decide **whether to move**.
- ▶ The number of time steps in a model run is an **emergent** outcome: the model runs **until all households are happy** and, therefore, stop moving.

# Process Overview and Scheduling

- ▶ The following **actions** are executed, in this order, once per time step:
  - ▶ If all households are happy (`happy?` is true) then the model **stops**.
  - ▶ The households that are not happy (`happy?` is false) execute the submodel **move**. The order in which these households execute is **randomly shuffled** each time step.
  - ▶ All households **update** their `happy?` variable.
  - ▶ Outputs for system-level results are **updated**.

# Design Concepts I

- ▶ The **basic principle** of segregation is the question of whether strong individual behaviors are necessary to produce striking system patterns –does the presence of strong segregation mean that households are highly intolerant– or can such strong patterns emerge in part from the system's structure?
- ▶ The key **outcomes** of the model are segregation patterns –especially, how strongly segregated the entire system is; these outcomes emerge from how households respond to unlike neighbors by moving.
- ▶ The households' **adaptive behavior** is to decide whether to move: they move when their objective –to live in a neighborhood with the fraction of unlike neighbors below their intolerance threshold– is not met.



# Design Concepts II

- ▶ The behavior does not involve **learning**, or prediction other than the implicit prediction that moving might lead to a neighborhood where the tolerance objective is met.
- ▶ Households **sense** the color of households on the eight surrounding patches.
- ▶ **Stochasticity** is used in two ways:
  - ▶ to initialize the model so that it starts unsegregated, and
  - ▶ to determine the new location of households when they move, because modeling the details of movement is unnecessary for this model.
- ▶ **Observations** include a visual display of which color household is on each grid cell, and two numerical results: the mean percentage (over all households) of neighbors of similar color and the percentage of unhappy households.



# Initialization

- ▶ A **user-chosen number of households** (typically 2000, out of the 2601 patches that represent houses) are initialized.
- ▶ They are each **placed** on a random empty grid cell and given a color randomly, with equal probability of red and blue.
- ▶ The variable `happy?` is then calculated for all households.

# Input Data

- ▶ The model **does not use input** from external models or data files.

# Submodels I

**Move** is performed by individual households if they are unhappy. The household chooses a direction randomly from a uniform continuous distribution between 0 and 360 degrees, then moves forward a distance drawn randomly from a uniform continuous distribution of 0 to 10 grid cell widths. If there is already a household on the grid cell at this new location, the household moves again with a new random direction and distance. If the new grid cell is empty, the household moves to its center.



# Submodels II

**Update** is conducted by all households to determine whether they tolerate their neighborhood. The tolerance of households is determined by a parameter `%-similar-wanted`, which can range from 0 to 100 and applies to all households. A household's neighbors are all households on the eight surrounding patches. The household's variable `happy?` is set to false unless the number of neighbors with the household's color is greater than or equal to `%-similar-wanted` divided by 100 and multiplied by the number of neighbors.



# Experiment

- ▶ Start NetLogo and **open** the segregation model.
- ▶ Press the **setup** and **go** buttons.
- ▶ With the density of turtles set to 80% and %-similar-wanted set to 30%, it takes about **14 ticks until everybody is happy**.
- ▶ The average similarity of neighborhoods is about 70%, *i.e.*, turtles have on average **70% neighbors of the same kind**.
- ▶ The View shows **relatively small clusters** of red and blue households, mixed with smaller clusters of empty patches.



# Results

- ▶ The model thus demonstrates, in the current settings, the point Schelling [3] wanted to make: even **relatively small intolerance** to unlike neighbors can lead, without any other mechanism, to **segregated neighborhoods**.
- ▶ Do we **understand** the results of our first experiment?
- ▶ It is not entirely clear why the small intolerance of 30% gives rise to an average similarity of 70% or more.
- ▶ Let us see how model output changes if we chose **extreme values** of `%-similar-wanted`.

# H1. Try extreme values of parameters.

- ▶ When parameters are set to the extremes of their range, model outcome often is **simpler to predict** and understand.
- ▶ Set %-similar-wanted to small values (5%) and large values (90%).
- ▶ Before you press the go button, try to **predict the outcome** of these experiments!

# Low Intolerance

- ▶ If intolerance is very low, most households are happy in the initial random distribution, and it takes only a **few** time steps until they are all happy.
- ▶ The **average similarity** among neighbors is near 50%, which might seem surprisingly high until we remember that, with only two colors, average similarity should be near 50% even when households are randomly distributed.
- ▶ This is an important realization already: that the final average similarity is always **at least 50%** no matter how low %-similar-wanted is.

# High Intolerance

- ▶ If intolerance is very high, almost all households are unhappy at the beginning, but the **simulation never stops** and the **average similarity never changes much from 50%**.
- ▶ The first result is easy to understand; the second is less clear: why does the average similarity among neighbors not just increase with %-similar-wanted?
- ▶ We can only assume that there is a **critical value** of %-similar-wanted above which it becomes very unlikely that moving households ever will find a neighborhood that suits their tolerance. Let us test this hypothesis.



## H2. Finding tipping points.

- ▶ If a model shows qualitatively different behaviors at different extreme values of a parameter, vary the parameter to try to find a tipping point: a parameter range where the **behavior suddenly changes**.
- ▶ This is an extremely important heuristic because it helps us understanding different **regimes of control**: below a critical parameter value, process A may be dominant and control the behavior of the system, but above that tipping point control is taken over by process B.
- ▶ Identifying regimes of control and understanding how they emerge reveals a great deal about how a model works.



# Observation

- ▶ To put this heuristic into practice, we would usually program some **quantitative outputs**, and then run **sensitivity experiments**.
- ▶ However, Segregation is such a simple model that it is sufficient to simply **watch the View** while we change the value of **%-similar-wanted**.





# Experiment

- ▶ Set %-similar-wanted to 90%; click setup and then go.
- ▶ Then, use the slider to **slowly decrease** this parameter –slowly, because it might take some time until the system responds.
- ▶ Bang! Very abruptly, when %-similar-wanted reaches 75%, model behavior changes and **segregation occurs**.

# Results

- ▶ Note that the system needs **quite a long time** for all households to become happy (about 150 ticks).
- ▶ Another difference are the **much larger clusters** of households of the same color.
- ▶ And a striking feature of the final distribution of households is that regions of different colors are separated by **strips of empty patches**. Why?
- ▶ One of the things we need to understand about a model is how it got to its current state as a **consequence** of what happened over time.
- ▶ How could we do this without visualizing the current state from many different perspectives?

### H3. Try different visual representations.

- ▶ To better understand an ABM, we often look at different visual outputs to **detect patterns** and establish **causal relationships**.
- ▶ Kornhauser, Wilensky, and Rand [1] list many useful ways to change the View of NetLogo models to reveal hidden structures and correlations.
- ▶ With the Segregation model, **the ability to tell happy from unhappy** households would allow us to better understand why and where clusters of happy households form or dissolve.



# Experiment

- ▶ Select the square-x visualization in the Interface. Now unhappy households are drawn as x while happy ones are squares.
- ▶ Repeat the experiment described before, where you start with  $\% \text{-similar-wanted} = 90\%$  and slowly decrease it as the model runs.

# Results

- ▶ With high intolerance (90%), we **never see any clusters of happy households**.
- ▶ With lower %-similar-wanted, more and **more small clusters of happy blue or red households occur but never persist**.
- ▶ At the very sharp **transition point (75%)** clusters start to persist and grow slowly, with **a lot of dynamics going on at their boundaries**.
- ▶ But still, the simulation runs too fast to really understand what happens.



## H4. Run the model step-by-step.

- ▶ Stepping through a simulation, tick by tick, is crucial because it allows us to look at the **current state** of the model, predict what will **happen next**, and see whether we were right.
- ▶ Add a button step to the Interface and make it call the go procedure, but with the **forever** option off.

# Experiment

- ▶ Now, by stepping through the simulation at the critical parameter value  $\% \text{-similar-wanted} = 75\%$ , we see that **clusters of happy households tend to grow**.
- ▶ We understand that **inside such clusters there cannot be any dynamics**: everybody is happy, so nobody moves.
- ▶ And the clusters **do not contain any isolated empty patches** for long.
- ▶ Why? (We leave answering this question to you.)



# Observations

- ▶ What we see is that the driving dynamics are going on at the **boundaries of clusters**.
- ▶ We realize that a household's decision to move affects not only its **own happiness** but also that of its old and new **neighbors**, *i.e.*, the movement of households can sometimes turn other happy households into unhappy ones.
- ▶ Now, how do the boundaries between blue and red clusters emerge?





## H5. Look for striking patterns in the output.

- ▶ Patterns are key to discovering important **mechanisms** and the **internal organization** of complex systems.
- ▶ With %-similar-wanted set to 75%, **run the model several times**.

# Observations

- ▶ The clusters of blue and red households are quite clear, but the pattern is **not yet clear enough** to indicate anything particular.



## H6. Parameter experimentation.

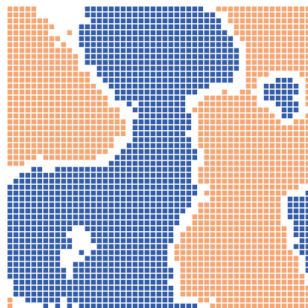
- ▶ At an interesting point in parameter space, **keep the controlling parameter constant** and **vary other parameters**.
- ▶ A parameter space is the set of **all possible values** of model parameters.
- ▶ A point in this space corresponds to one specific **set of parameter values**.

# Observations

- ▶ This heuristic allows us to explore how our controlling parameter, or the process represented by it, is **affected by other processes** in the model.
- ▶ Trying to understand a model includes trying to understand the interactions of **mutual controls**.

# Experiment

- ▶ With %-similar-wanted set to 75%, decrease the number of households, for example a density of 70% and then increases it to, say, 90%.
- ▶ Now you can see that the pattern becomes much clearer and more striking if we increase the number of households.



# Observations

- ▶ It is also striking that the system now usually segregates into only **one cluster of each color**. What might be the reason for this?
- ▶ Note that small clusters, with their strongly curved boundaries, usually do not survive unless they manage, by chance, to develop **longer sections of their boundary that are more or less straight**.
- ▶ This suggests a **hypothesis**: straight boundaries create spatial configurations that make the nearby households less sensitive to the influence of single neighbors of the opposite color; there will always be enough of one's own kind to keep the proportion of unlike neighbors below the intolerance level.

# Testing the Hypothesis

- ▶ Measure (and visualize), in detail, the similarity of neighbors as perceived by **households at the boundary**.
- ▶ This would be easier if we set up specific configurations in a much **smaller system** of, say,  $5 \times 5$  patches.
- ▶ If our hypothesis is correct, then straight boundaries should become **less important** when **intolerance is less**, because then curved boundaries can also survive the influence of single unlike neighbors.
- ▶ We can **predict** that when we slowly decrease %-similar-wanted, clusters should increase in numbers, decrease in size, and have more curved boundaries.



# Experiment

- ▶ Study segregation patterns for %-similar-wanted smaller than 75%, keeping the number of households at 90%.
- ▶ Our prediction turns out to be correct!
- ▶ We still did not explain why for %-similar-wanted = 75% (and also down to about 58%), empty patches are only found between the boundaries of the red and blue clusters. We leave explaining this to you.





# Final comments

- ▶ The Segregation model is admittedly **very simple** and not that hard to understand.
- ▶ Nevertheless, we applied **heuristics** that are useful for analyzing any model.
- ▶ Note that Schelling's model of segregation –which, ironically, was only verbally formulated and never implemented by Schelling himself– was and still is **highly influential**.
- ▶ Myriad **modifications** of this model have been made because real cities and households are of course much more complex, e.g., larger neighborhoods, social networks, spatial barriers, housing prices, and variable intolerance levels.



## H7. Use Several Currencies for Evaluations I

- ▶ ABMs are rich in structure, including many agents and spatial units, all in different states. It is impossible to take all this information into account.
- ▶ We therefore need to find **currencies**, *i.e.*, summary statistics or observations, that capture an important property of the model system in a single number.
- ▶ Currencies correspond to the things empirical researchers **measure** (or wish they could measure) in the real system.
- ▶ **Example:** In population models an obvious currency is population size: the total number (or weight, or wealth, etc.) of all agents.



## H7. Use Several Currencies for Evaluations II

- ▶ We therefore could analyze the **time series** of population size produced by the model. But even time series can contain too much detailed information, so we often look at even **coarser** currencies, e.g., the **mean** and **range of values** over time.
- ▶ Often, finding useful currencies is a nontrivial and important task of the modeling process. This is why **Observation** is included in the Design Concepts section of the ODD protocol.
- ▶ Usually, we try **several currencies** and see how **sensitive** they are and how much they help us **understanding** the model.
- ▶ In most cases, one currency **is not sufficient**, and we need to view the model from different perspectives.



# Currencies Used in the Course

Model	Currencies
Butterfly Hilltopping	Corridor width Final cumpling of butterflies
Culture Dissemination	Mean similarity of sites with neighbors
Simple Birth Rates	Time to extinction
Flocking	Number of turtles who have flockmates Mean number of flockmates per turtle Mean distance between turtles and its nearest neighbor Standard deviation in heading
Wild dogs	Frequency of extinction within 100 years
Woodhoopoes	Shape of the group size distribution Mean number of birds Standard deviation among years in number of birds Mean percent of territories vacant
Segregation	Time steps until stasis Size and shape of homogeneous groups



# Kinds of Currencies I

- ▶ The patterns defined in the ODD element **Purpose and patterns** which are by definition key currencies for use in model analyses. However, they are often not sufficient to fully understand the model.
- ▶ Standard measures of the **statistical distribution of results**, whether distributions among agents of their state variables or distributions over time of system-level results, including:
  - ▶ The mean and median,
  - ▶ The standard deviation or variance,
  - ▶ The minimum and maximum,
  - ▶ And whether they fit theoretical shapes (normal, exponential, power law, etc.) and, if so, the distribution coefficients.

# Kinds of Currencies II

- ▶ Characteristics of **time series** such as:
  - ▶ Positive or negative trends.
  - ▶ Auto-correlation.
  - ▶ The time until the system reaches some state such as having no more agents or becoming static.
- ▶ Measures of **spatial distributions** and patterns such as:
  - ▶ Spatial auto-correlation.
  - ▶ Fractal dimensions.
  - ▶ Point pattern metrics.

# Kinds of Currencies III

- ▶ Measures of **difference among agents**:
  - ▶ Whether the distribution among agents of some state variable is uni- or multi-modal, e.g., is wealth distributed normally among agents or are there distinct groups of rich and poor?
  - ▶ Whether different kinds of agents are segregated over time or space.
- ▶ **Stability properties**, which can provide insight into a system's internal mechanisms and be important for management problems:
  - ▶ How quickly the system returns to some “normal” state after a disturbance?
  - ▶ How large the “domain of attraction” spanned by two or more state variables is?
  - ▶ What buffer mechanisms damp the system's dynamics.

## H8. Analyze Simplified Models

- ▶ Once we have chosen our first currencies, we proceed to the most important approach for analyzing models: **Simplify!**
- ▶ ABMs (and other models) can be **hard to understand** because so many different factors affect model behavior.
- ▶ Often, it is relatively easy to reduce this complexity and make understanding what mechanisms cause what results much more **feasible**.



# Kinds of Simplifications I

- ▶ Make **environment** (and input data) **constant**.
- ▶ Make **space homogeneous** (all patches are the same, and constant over time).
- ▶ **Reduce stochasticity**, e.g., by initializing all agents identically or by replacing random draws with the mean value of their distribution
- ▶ **Example**. Replace **set size 2 + random-float 10** with **set size 6**).
- ▶ **Reduce the system's size** by using fewer turtles and patches.



# Kinds of Simplifications II

- ▶ Turn off some actions in the model's schedule (comment them out).
- ▶ Manually create simplified initial configurations and states that allow you to check whether a certain mechanism works as you assume.

# Observations

- ▶ When you make these kinds of simplifications, the model version will **no longer be a good representation** of the system you want to understand.
- ▶ You create, so to say, **simplified worlds** that are unrealistic but easier to understand.
- ▶ Many developers did not systematically simplify their models for analysis, perhaps because of a **psychological barrier**: if you spent so much time developing a model that seems to represent a real system reasonably well, should you then make this model extremely unrealistic?
- ▶ Yes, definitely! Modeling includes as much **deconstruction** as construction!



## H9. Bottom-up Analysis

- ▶ Any system that requires an agent-based modeling approach is very difficult to understand without first understanding the behavior of its parts: **the agents** and **their behavior**.
- ▶ It is important that we **test and understand these behaviors first**, before we turn to the full model.
- ▶ That is why we emphasize **analyzing sub-models independently** before putting them in an ABM and systematically **developing theory for agent behaviors**.
- ▶ Even more of these kinds of **low-level analysis** may be needed to understand the full model, especially if unexpected dynamics seem to emerge.



# H10. Explore Unrealistic Scenarios

- ▶ The idea of this heuristic is to simulate scenarios that could **never occur in reality**.
- ▶ Why? Because a simple and direct way to see the effect of a certain process or structure on overall model behavior is to just **remove it**.
- ▶ **Example:** The analyses of how **investor behavior** affects double-auction markets provides an interesting contrast: models that deliberately used unrealistically simple investment behaviors were shown to produce system-level results that were not so unrealistic. Complex agent behavior **might not be the mechanism generating complex market dynamics** after all; the market rules themselves might be more important than anticipated.

# ABM and Statistics

- ▶ Many scientists automatically think of **statistics** when they think about analysis and understanding.
- ▶ The goal of statistics is to extract understanding, and perhaps infer causal relations, from a **fixed and usually limited set of data**.
- ▶ Agent-based modeling, in contrast, can produce **as many data as we want**, and offers additional ways to develop understanding and deduce mechanisms.
- ▶ If a simulation experiment does not provide a clear enough answer, we **manipulate the model world** further and run **new experiments** until we get clear results.
- ▶ The purposes, and underlying mind-sets, of statistics and simulation modeling are thus **quite different**.



# Summarizing Results

- ▶ Aggregating model output into statistics such as the mean and standard deviation is useful and often unavoidable, but remember that in model results, **extreme** or **unusual values** are often important clues to understanding.
- ▶ They should not be thrown away as **outliers** as they often are in statistical analysis of empirical data.

# Contrasting Scenarios.

- ▶ Statistics can be used to **detect** and **quantify differences** between simulation scenarios, much like testing for differences among laboratory treatments.
- ▶ This analysis often requires arbitrary assumptions that affect results –especially, the **Number of replicates** for each treatment and the statistical definition of “different”.
- ▶ While the same is true for laboratory and field experiments, it is **easier to change these assumptions** when analyzing model results.



# Quantifying correlative relationships. I

- ▶ **Regression analysis** can be used to see **which inputs have strongest effects** on which model outputs, and whether there are interactions among factors.
- ▶ The approach is simply to look for **statistical relationships** among inputs (here, including parameter values and initial conditions as well as time-series inputs) and outputs.
- ▶ This approach can be very useful, in particular if a model is complex and we initially have **no idea** where to expect causal relationships.
- ▶ These regression methods do not directly identify **causal relationships**, but they can provide important clues by revealing the relative importance of different factors.



# Quantifying correlative relationships. II

- ▶ As detectives trying to understand why an ABM behaves as it does, we should consider such statistical **meta-models** as a starting point, not the end, of our analysis.
- ▶ The meta-model points to factors that we should **explore** in more detail using simulation experiments.
- ▶ Statistical models of ABM results can summarize insights from complex simulation experiments in a way that is **familiar** to many scientists;

# Comparing model output to empirical patterns.

- ▶ During **calibration** and other times when we want to compare model results to observed patterns quantitatively, there is a wide variety of statistical approaches that can be useful.
- ▶ The extensive literature on model calibration, **fitting of models to data**, and **model selection** is applicable.



# Detectives

- ▶ To understand **what** an ABM does and **why**, we must again be detectives—as we were when searching for programming errors.
- ▶ Good detectives combine reasoning and strong inference, systematic analysis, intuition, and creativity.
- ▶ Obviously, we cannot teach you how to reason logically, be creative, and have good intuition. You have to develop your intuition through **experience**.
- ▶ Thus, the key messages of this session are that once we build an ABM, or even the first time we freeze the design, we need to try to understand what it does; and **controlled simulation experiments** are how to do it. Now try it!



# Publications

- ▶ In addition to the analysis heuristics presented here, you should try to learn from **published analyses**.
- ▶ If you read a publication that presents some exciting **new insights** using an ABM, ask yourself: how did they do that?
- ▶ The **key experiments** presented in a publication can give you a good idea what techniques and heuristics the authors used to obtain their insights.

# Heuristics

- ▶ You can try them into the following sequence:
  - ▶ Analyzing from the bottom up.
  - ▶ Define and test several currencies for evaluating your simulation experiments.
  - ▶ Try different views (visual outputs).
  - ▶ Run the model step-by-step.
  - ▶ Analyzed simplified versions of your model.
  - ▶ Try extreme values of parameters.
  - ▶ Look for striking, or strange, patterns in the model output.
  - ▶ Find tipping points in model behavior.
  - ▶ From an interesting point in parameter space, keep the controlling parameter constant and vary other parameters.
  - ▶ Explore unrealistic scenarios.



# Suggestion

- ▶ Add your **own heuristics** to ours.
- ▶ Intuition is important, but **critical reflection** on how your intuition, and heuristic approaches, work is no less important.
- ▶ Good science always is based on a mixture of **creativity**, which can include quite chaotic, unsystematic things, and **rigorous methods**, which can be pedantic and boring.
- ▶ Switch between these two attitudes, try looking at your model from different perspectives, and you will quickly learn—how to learn from ABMs!

# Referencias I

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