Agent-Based Modeling and Simulation Emergence

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- These slides are based on the book of Railsback and Grimm [2], chapter 8.
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Ideas

- The most important and unique characteristic of ABMs is that complex, often unexpected, dynamics at both the individual and system levels emerge from how we model underlying processes.
- The behavior of the whole system emerge from the rules given to the agents for adapting to changes in their environment and to what the other agents do.
- Emergence, therefore, is the most basic concept of agent-based modeling.



Questions of interest

- What dynamics of the system and its agents emerge, *i.e.*, arise in relatively complex and unpredictable ways, from what adaptive behaviors of the agents and what characteristics of their environment?
- What other behaviors and model dynamics and outcomes are instead imposed, *i.e.*, forced to occur in direct and predictable ways, by the model's assumptions?



Qualitative criteria

- There is no simple way to classify some particular outcome of an ABM as emergent versus imposed, but we can think about these qualitative criteria for a model result being emergent:
 - It is not simply the sum of the properties of the model's individuals;
 - It is a different type of result than individuallevel properties or decisions; and
 - It cannot easily be predicted from the properties of the individuals.
- Example. The corridor-width in the butterflies model. Really?



Amount of emergency

- The extent to which ABM results are emergent can vary widely, and having more emergence does not necessarily make a model better.
- The best level of emergence is often intermediate.
- Models with highly imposed results are often not very interesting, and sometimes their problem can be solved with a simpler mathematical model.
- A model with too many of its results emerging in complex ways from too many complex individual behaviors and mechanisms can be very hard to understand and learn from.



Objectives

- Understanding what makes the results of ABMs emergent.
- Designing and analyzing simulation experiments to test hypotheses and develop understanding about how an ABM works and how well it reproduces the system it models.
- Use of BehaviorSpace [4], NetLogo's tool for automatically running simulation experiments and producing output from them.
- Analyze output produced by NetLogo models by importing results to other software for graphing and statistical analysis.



The Simple Birth Rates Model

- The Biology category of NetLogo's Models Library includes a model called Simple Birth Rates.
- It is a very simple model, designed to simulate how the difference in birth rates between two co-occurring species (red and blue turtles) affects each population.
- The two species differ only in the number of offspring each individual produces each time step; the probability of death is the same for both species and is adjusted so that the total number of individuals is approximately constant.
- Exercise. Open this model, read its Info tab, and play with it a bit.



Addressed Question

- How does the time until extinction of one species depend on the relative birth rates of the two species?
- If we hold the birth rate of the red species (global variable red-fertility) constant at 2.0 and vary blue-fertility from 2.1 to 5.0, how does the number of ticks until extinction of the red species change?



Expectations

- When birth rates of the two species are close, they should coexist for a long time.
- As the difference in birth rates increases, the time to red extinction should decrease rapidly.
- But no matter how rapidly the blue reproduce, it seems unlikely that the reds will go extinct immediately, so the time to red extinction will probably never get as low as one time step.
- We thus expect a curve that starts high when blue-fertility is 2.1, drop rapidly, then flatten out at a value above 1 as blue-fertility increases.
- Exercise. Are these expectations correct?



Experiment

- To see how the time to extinction of red turtles varies with the fertility parameter of blue turtles, we need to run the model over a wide range of bluefertility values and record the time (tick number) at which the number of red turtles reaches zero.
- But there is a complication: this model is stochastic, producing different results each time we run it because the turtles that die each tick are chosen randomly (see the grim-reaper procedure).
- Because the model produces different results each run, to really understand it we need to estimate the average results and the variability around those averages.



Methodology

- Modelers often do this the same way that scientists study real systems that are highly variable: by executing experiments that include replicates of several different scenarios.
- A scenario is defined by a model and one set of parameters, inputs, and initial conditions; if a model has no stochastic elements, it produces exactly the same results each time it executes the same scenario.
- Replicates are model runs in which only the stochastic elements of the model change.



Back to the Birth Rates

- To analyze how blue fertility affects the time to extinction of red turtles, we will use a simulation experiment that varies blue-fertility from 2.1 to 5.0 in increments of 0.1, producing a total of 30 scenarios.
- Further, we will run 10 replicates of each scenario.
- Each model run will continue until there are no more red turtles and then will output the tick number at which this extinction occurs.
- These results need to be recorded in a file that we can then import to a spreadsheet or statistical software and, finally, calculate the mean and standard deviation of time to red extinction and graph how they vary with blue-fertility.



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The BehaviorSpace

- BehaviorSpace runs simulation experiments on your model and saves the results in a file for you to analyze.
- By filling in a simple dialog, you can:
 - Create scenarios by changing the value of global variables;
 - Generate replicates (called repetitions in NetLogo) of each scenario;
 - Collect results from each model run and write them to a file;
 - Determine when to stop each model run, using either a tick limit (e.g., stop after 1000 ticks) or a logical condition (e.g., stop if the number of red turtles is zero); and
 - Run some NetLogo commands at the end of each model run.
- The information that you enter in BehaviorSpace to run experiments is saved as part of the model's NetLogo file.
- Work on a renamed copy of the Library models.

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The BehaviorSpace Dialog

The menu Tools/BehaviorSpace opens the dialog:

xperiments.		
New	Edit Duplicate	Delete

You can create new experiments, edit previously saved ones, or copy or delete experiments.

Experiment Dialog

- Create a new experiment by clicking on the New button.
- The Experiment Dialog is open:

Welcome to the new BehaviorSpac We added some new features to this you can hover over the labels or clic read our updated documentation.	ce experiment editor! window. If you would like to learn more about them .k the "Help" button at the bottom of the window to
Experiment name experiment	
Vary variables as follows (note bra	ckets and quotation marks):
["carrying-capacity" 1000] ["red-fertility" 2] ["blue-fertility" 2]	
Repetitions 1	
Execute combinations in sequences	ential order
Measure runs using these reporte	rs as metrics:
Run metrics every step	
Run metrics when	
Run metrics when	
Kun metrics when Pre experiment commands: Setup commands:	Go commands:
Run metrics when Pre experiment commands: Setup commands: setup	Go commands: 02
Stop condition:	Go commands: 90 J/Post run commands:
A fun metrics when Pre experiment commands: Setup commands: Setup Stop condition: Post experiment commands	Go commands:
Iden metrics when If the metrics when If the experiment commands: Setup commands: Setup Stop condition: If Post experiment commands Time limit 0	Go commands:



Setting the experiment I

- Give a more significant name to the experiment, e.g., Blue_fertility_effect_on_red_extinction.
- You can create scenarios varying blue-fertility from 2.1 to 5.0 in increments of 0.1 by entering in the Vary variables as follows field:

```
1 ["blue-fertility" [2.1 0.1 5.0]]
```

It is a very good idea to also include the model variables you want to hold constant:

```
1 ["carrying-capacity" 1000]
2 ["red-fertility" 2]
```

► For the replicates, set the Repetitions value to 10.



Setting the experiment II

- Now you can tell NetLogo what results you want by filling in the field labeled Measure runs using these reporters.
- You can tell BehaviorSpace to stop the model when the number of red turtles is zero and output the tick number when this happens (turn off run metrics at every step).
- Recall that red-count is defined and computed in the plot.



Resulting Experiment Dialog

	Experiment
Welcome to the new Behavio We added some new features t you can hover over the labels read our updated documentati	orSpace experiment editor! to this window. If you would like to learn more about then or click the "Help" button at the bottom of the window to on.
Experiment name Blue_fertili	ity_effect_on_red_extinction
Vary variables as follows (not	te brackets and guotation marks):
["carrying-capacity" 1000] ["red-fertility" 2] ["blue-fertility" [2.1 0.1 5	5.0]]
Repetitions 10	
✓ Execute combinations in	sequential order
Measure runs using these re	porters as metrics:
Run metrics every step Run metrics when	
Run metrics every step Run metrics when > Pre experiment commands	S.
Run metrics every step Run metrics when JPre experiment commands Setup commands: setup	x Go commands: 99
Run metrics every step Run metrics when > Pre experiment command: Setup commands: setup	s Go commands: 00 1) Post run commands:
Run metrics every step Run metrics when JPre experiment commande Setup setup 	s Go commands: 90 1/Post run commands:
Run metrics every step Run metrics when) Pre experiment commands Setup commands: setup -Stop condition: red-count = 0) Post experiment command	s Go commands: 90 JPost run commands:
Run metrics every step Run metrics when Pre experiment command: Setup commands: 	S Go commands: 00 JPost run commands:



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Run Options

Spreadsheet out	tput oyt	put-spread	dsheet	Browse	Disable
Table output o	utput-ta	ble		Browse	Disable
Stats output				Browse	Disable
Lists output				Browse	Disable
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ind you will not be at	ble to toggle	II be better. Ho e plots in the "F	wever, no plo Running Expe	t data can be e: riment" window	kported,
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Observations I

- BehaviorSpace produces a runtime error (see issue #2322 in NetLogo's Github repository) when:
 - 1. The user specifies a Run metrics when reporter,
 - 2. The reporter is never true, and
 - 3. The user has specified both Table and Spreadsheet output.
- Since the reporter red-count is computed in a plot, the option Update plots and monitors must be turned on.
- The setup procedure must be tuned to avoid interference with the Behavior Space, *e.g.*, resetting variables set by the later.



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Observations II

- For this, consider that global variables in the interface tab can not be initialized by the setup procedure.
- Since we are running experiments in parallel, the lines capturing the output might be unordered. You must order them as post-processing, e.g., by [run number].
- More details in the book of Railsback and Grimm [2], pages 108-109.



The Output Table

```
"Behaviorspace results (NetLogo 6.4.0)", "Table version 2.0"
1
    "Simple Birth Rates.nlogo"
    "Blue fertility effect on red extinction"
3
    "09/27/2024 20:06:09:743 -0600"
4
    "min-pxcor", "max-pxcor", "min-pycor", "max-pycor"
    "-50", "50", "-50", "50"
6
    "[run
    → number]","carrying-capacity","red-fertility","blue-fertility","[step]","tick
    "1", "1000", "2", "2.1", "117", "117"
8
    "2", "1000", "2", "2.1", "171", "171"
9
    "3", "1000", "2", "2.1", "166", "166"
10
11
    . . .
```



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Scripts

- Copy the table to a new file, e.g., rates.csv and delete the initial lines using:
- 1 sed -i '' 1d rates.csv
- The following R code sorts and plots the data:

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The plot

Time to red extintion vs. Blue fertility



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Using R

You can extract the replicates using R, e.g., for blue-fertility of 2.5 we can use:

```
> data[data$blue.fertility == 2.5, ];
1
       X.run.number. carrying.capacity red.fertility blue.fertility X.step.
2
       \hookrightarrow ticks
                     41
                                          1000
                                                                                 2.5
   42
                                                                                             56
3
   \rightarrow 56
   41
                     42
                                          1000
                                                                2
                                                                                 2.5
                                                                                             41
Λ
   \hookrightarrow 41
5
   . . .
```

Or summarize the ticks statistics for this replicate:

 1
 > summary(data[data\$blue.fertility == 2.5,]\$ticks)

 2
 Min. 1st Qu. Median
 Mean 3rd Qu. Max.

 3
 33.00
 40.25
 43.00
 43.70
 45.00
 56.00

Observations

- While it seems reassuring that the model produced results that were quite as we expected, it also makes us wonder what the value of building an ABM was if it produces results we could easily anticipate.
- This model is a clear example of an ABM whose dynamics are strongly imposed by its very simple, rigid agent behaviors: the agents make no decisions, they have no individual state variables, and their very few behaviors (reproducing, dying) are tightly specified, or imposed, by the global parameters.
- It is not a good example of the kind of problem that requires an ABM to understand, but a good one for using the BehaviorSpace.



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- The Flocking model [3], also in the Biology section of the Models Library, is the classical example of emergent complex and realistic dynamics in ways that could not be completely predicted.
- Schools of fish and flocks of birds can be thought of as emergent properties of how the individual animals move in response to each other.
- A school or flock can appear as a coherent entity, but it can also break up and re-form, and its shape changes continually.
- See the original video in YouTube.



Individual Behavior I

- Individuals have one behavior: adjusting their movement direction in response to the location and direction of other nearby individuals, *i.e.*, their flockmates, which are all other turtles within a radius equal to the vision parameter.
- They make this decision considering three objectives:

Align. Moving in the same direction as their flockmates;Cohere. Moving toward the flockmates ("cohere"); andSeparate. Maintaining a minimum separation from all other individuals.



Individual Behavior II

- Parameters control the relative strength of these objectives by limiting the maximum angle a turtle can turn to align, cohere, and separate.
- The minimum-separation parameter sets the distance at which turtles try to separate from each other.



Observations

- The Flocking model's results are in fact complex.
- The turtles form flocks that continually change characteristics, and these characteristics change as you vary the parameters.
- Further, parameters seem to interact *i.e.*, the effect of one parameter depends on the value of another.
- Example. See what happens when you vary max-cohere-turn when minimum-separation is low, then high. (To speed up the model, use the comments in the go procedure to make turtles move forward one unit instead of making five short moves.)



Characteristics of Emergent Behavior

- The most important and interesting results of the model seem qualitative and hard to describe with numbers.
- Example. Whereas the state of the Simple Birth Rates model can be described by two numbers (how many red and blue turtles are alive), the characteristics of the emergent flocks clearly change as you vary parameters but in ways that are not easy to quantify.
- It takes some time before the flock characteristics emerge, both when the model starts and when you change parameter values in the middle of a run. ABMs often have a warm-up period in which their dynamics gradually emerge.



Use of the Model

- Flocking is a fascinating simulator: we specify some simple agent rules and observe the complex flocking dynamics that emerge.
- But when we do science we are instead trying to do the opposite: we identify some complex dynamics observed in the real world and then try to figure out what behaviors of the system's agents explain those emergent dynamics.



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Measures

- Huth and Wissel [1] combine ABMs with studies of real fish to address the question- What assumptions about movement of individual fish explain the emergent characteristics of real schools of fish?
- We can use statistics on properties analog to those proposed by them, e.g., how close the individuals are to the nearest other fish and how much variation there is in the direction they move:
 - The number of turtles who have flockmates;
 - The mean number of flockmates per turtle;
 - The mean distance between a turtle and the nearest other turtle; and
 - The standard deviation in heading, over all turtles –an imperfect but simple measure of variability in direction.



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Experiment I

- We do not want to vary any of the parameters, so we will set up no scenarios other than the baseline scenario with default parameter values.
- But we will run ten replicates of this scenario.
- The configuration of the experiment is shown in the next slide.



Experiment II

elcome to the ne	w BehaviorSpace ex	periment editor!
e added some ne	v features to this wind	low. If you would like to learn more about them,
ou can nover over	the labels of click the	Help button at the bottom of the window to
au our upuateu u	ocumentation.	
periment name	flock-experiment	
ry variables as f	ollows (note bracket	s and quotation marks):
nax-cohere-turn'	3]	
nax-separate-tur	mr 1.5J	
minimum-separati	lon" 1]	
population" 300]		
petitions 10		
Execute combi	nations in sequentia	l order
easure runs usin	g these reporters as	metrics:
unt turtles with	[any? flockmates]	
an [count flockm	ates] of turtles	tustles] of tustles
an [min [distand	he mysetri of other	curries] of turries
		-
Run metrics ev	ery step	
n metrics when		
Pre experiment	commands:	
tup commands:		Go commands:
tup		go
Stop condition:		▶ Post run commands:
Post experiment	commands	
me limit 500		
		Cancel Hein OK



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R Script I

You can plot the mean number of flock mates over time:

```
setwd("~/Documents/cursos/abms/code/abms-07/flocking")
2
    data <- read.csv("flocking-experiment-table.csv", header = TRUE, sep = ",",</pre>
3
    \hookrightarrow skip = 6)
4
    data <- sort by(data, data$X.run.number.)</pre>
    flocking_means <- aggregate(data$mean..count.flockmates..of.turtles,</pre>
7
    → list(data$X.step.), FUN=mean)
    flocking_sds <- aggregate(data$mean..count.flockmates..of.turtles,</pre>
8
    \rightarrow list(data$X.step.), FUN=sd)
9
    flocking means <- flocking means [-1,]
10
    flocking means$Group.1 <- flocking means$Group.1 - 1</pre>
11
    flocking_sds <- flocking_sds[-1,]</pre>
12
13
    plot(flocking means, type = "1",
14
         main = "Mean Number of Flockmates over Time",
15
         vlab = "Mean Number of Flockmates",
16
                                                              (4 何) トイヨト イヨト
```

R Script II

```
xlab = "Ticks")
17
18
    lines(flocking means$x+flocking sds$x, lty=3)
19
    lines(flocking_means$x-flocking_sds$x, lty=3)
20
21
    heading_sds <- aggregate(data$standard.deviation..heading..of.turtles,
22
    \rightarrow list(data$X.step.), FUN=mean)
    heading_sds_sds <- aggregate(data$standard.deviation..heading..of.turtles,
23
    \rightarrow list(data$X.step.), FUN=sd)
24
    plot(heading sds, type = "1",
25
         main = "Standard Deviation of the Heading over time",
26
         ylab = "Standard Deviation of the Heading (deg.)",
27
         xlab = "Ticks")
28
29
    lines(heading sds$x + heading sds sds$x, lty=3)
30
    lines(heading sds$x - heading sds sds$x, lty=3)
31
```

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The plot



Mean Number of Flockmates over Time



- Do the same for the standard deviation of heading.
- Do this outputs seem to stabilize?



Plot







Experiment I

- Let's do an experiment similar to one performed by Huth and Wissel [1].
- What happens to the emergent schooling patterns if turtles adapt their direction considering only the one closest neighbor turtle?
- Modify the find-flockmates procedures as follows:

```
    to find-flockmates ;; turtle procedure
    set flockmates other turtles in-radius vision
    set flockmates flockmates with-min [distance myself]
    end
```

To see if these differences show up in the statistical output, repeat the BehaviorSpace experiment.



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Observations I

- This is an example of a second common kind of simulation experiment: contrasting alternative scenarios.
- The sensitivity experiment varies a parameter across a wide range.
- Scenario contrast experiments look at the differences between two (or several) distinctly different scenarios.
- Scenario contrasts are more similar to the experimental designs typically used on real systems.
- Example. Specifying two or more treatments, then using replicates of each to determine how different the treatments' effects are.



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Observations II

- Often, the different scenarios are different agent behaviors.
- Example. The difference is defining flockmates as all other turtles within a range versus only the closest other turtle.
- When we analyze scenario contrast experiments, we typically look at how different the results are between the two scenarios.



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Summary I

- ABMs are useful because they can reproduce how complex dynamics of real systems, and complex agent behaviors, emerge from the characteristics, behavioral sub-models, and interactions of the systems' members and their environment.
- ABMs can range from having relatively predictable results that are closely imposed by simple, rigid rules for agent behavior, to producing many kinds of complex results that are very difficult to predict from agent behaviors.
- When describing the emergent characteristics of an ABM, we can start by defining what the key outcomes of the model are and the agent behaviors that those outcomes emerge from.

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Summary II

- And we need to describe how model outcomes emerge from the environment, if they do.
- Example. In the Flocking and Simple Birth Rates models, results emerge only from agent behaviors; but the results of the Butterfly Hilltopping model depend qualitatively and quantitatively on behavior and on topography.



Summary III

We demonstrated two very common and important kinds of simulation experiments:

Sensitivity analysis. With the Simple Birth Rates model, we varied a parameter over a wide range and analyzed how model results changed in response, *i.e.*, how sensitive the model is to a particular parameter or input. Contrasting scenarios. With the Flocking model, we compared two different versions of the model, a contrast of alternative model scenarios or versions, *i.e.*, determining which alternative models cause the ABM to be better at reproducing system behaviors observed in the real world.



Conclusions I

- Making model results more emergent is not always better.
- Very simple ABMs with highly imposed dynamics may not be very different from an equation-based model of the same problem and hence not extremely exciting.
- But such simple ABMs can still be useful and appropriate for many problems, and can have advantages such as being easier and more intuitive to build and understand than equation-based models.
- An ABM with emergent outcomes so complex that they are completely unpredictable would be very hard to use for science because our goal is to figure out what underlying processes give rise to the emergent outcomes.



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Conclusions II

- We observed two common characteristics of emergent dynamics in the Flocking model:
 - Important emergent outcomes may seem more qualitative than quantitative, but we can find numerical outputs to describe them.
 - It often takes a considerable warm-up period before emergent outcomes become apparent and stabilize.



Referencias I

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