

# Agent-Based Modeling and Simulation

## Patterns for Theory Development


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# The Problem

- ▶ As we design a model's structure and formulate its schedule, the overview part of the ODD protocol, we identify **which** processes we need without bothering yet about **how** they work.
- ▶ Then, to get the modeling cycle going, we start with a **very simple**, often obviously wrong, representation of the model's processes.
- ▶ **Example.** We often just assume that agents make decisions randomly.
- ▶ However, after we have a first implementation of the entire model, we need to unsimplify and come up with **sufficiently realistic** and useful representations of key processes.
- ▶ How can we do this?



# Minor and Major Processes

- ▶ First of all, we do not want to consider all the processes in a model with the **same level of detail**.
- ▶ ABMs typically include a number of relatively **minor processes** that can be represented simply or by using sub-models from the literature.
- ▶ Results of the model are unlikely to be **too sensitive** to the details of such sub-models.
- ▶ But ABMs also typically have a few processes, in particular agent behaviors, that seem **most important**.
- ▶ **Agent behaviors** are especially important because they are the reason we use an ABM in the first place and also because we are **less likely** to find a useful way to represent them in the literature.



# Questions

- ▶ What is the **most important agent behavior**, and
- ▶ How do we identify or invent a **good sub-model** to represent it?

# Model Development

- ▶ We call this stage of model design **theory development**.
- ▶ A **theory** being a sub-model for some particular **agent behavior** that has been tested and proven useful for **explaining** how the system works in a particular context
- ▶ The goal is to find models of key agent behaviors that are simple, but complex enough to produce **useful** system behaviors.



# Testing

- ▶ How do we **test** models of agent behavior to know which to accept as theory?
- ▶ The answer of course is via **pattern-oriented modeling** (POM): we accept models of agent behavior as theory when they cause the ABM to reproduce the set of patterns that we chose to characterize the system's dynamics.
- ▶ We introduce here the use of ABMs as **virtual laboratories** where you test and improve submodels for key behaviors.



# Motivation

- ▶ Theory development is the most unique, important, and **academically fertile** part of agent-based modeling.
- ▶ How to model key agent behaviors is obviously **fundamental** to agent-based simulation, and there are many important discoveries to be made.
- ▶ Currently, almost every ABM requires **new theory** for a new behavior or context, and developing the theory will often be as important as anything else learned in the modeling study.
- ▶ This stage of modeling is, more than any other, about basic **scientific discovery**.



# Objectives

- ▶ Understand the general concept of developing theory by posing **alternative hypotheses**, conducting **controlled experiments** to identify the most **useful hypothesis**, then **revising them** and conducting more experiments.
- ▶ Understand that theory in agent-based science includes models of **agent behavior** that **explain** important system behaviors; and that we develop this theory via pattern-oriented testing of hypothesized sub-models.
- ▶ Develop **experience** with this theory development process.

# Virtual Labs

- ▶ We can consider an ABM a **virtual laboratory** where we test alternative submodels for key behaviors.
- ▶ We do so by plugging these alternative sub-models into the ABM and testing how well the ABM then **reproduces patterns** observed in the real system.
- ▶ Through a cycle of **testing** and **refining sub-models**, perhaps combined with **research** on the real system to find additional patterns, we exclude (**falsify**) unuseful sub-models and home in on useful ones that we can treat as theory.

# Strong Inference

- ▶ Contrasting **alternative theories**, or hypotheses, is the foundation of what is simply called scientific method.
- ▶ Platt [6] rephrased this approach and called it **strong inference**.
- ▶ He wondered why some fields of science move forward **so much faster** than others. His answer was that progress depended largely on how systematically people **used this method**.



# Steps

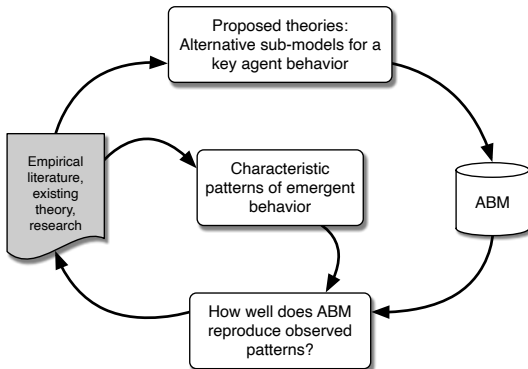
1. Devising **alternative hypotheses**;
2. Devising a **crucial experiment** (or several of them), with alternative possible outcomes, each of which will, as nearly as possible, **exclude** one or more of the hypotheses;
3. Carrying out the **experiment** so as to get a clean result;
4. **Recycling the procedure**, making sub-hypotheses or sequential hypotheses to refine the possibilities that remain, and so on.

# Proposed POM approach

1. Identify alternative sub-models (hypotheses) for the **behavior**;
2. **Implement** the alternative sub-models in the ABM, **testing** the software carefully to get **clean results**;
3. Test and **contrast** the alternatives by seeing how well the model reproduces the characteristic patterns, falsifying sub-models that cannot reproduce the patterns; and
4. **Repeat the cycle** as needed: revise the behavior sub-models, look for (or generate, from experiments on the real system) additional patterns that better resolve differences among alternative submodels, and repeat the tests until a submodel is found that adequately reproduces the characteristic patterns.

# Graphically

- ▶ The approach we use to developing theory for agent behavior is a sub-cycle of the **modeling cycle**, and closely follows Platt's steps:



# Finding Alternative Theories

- ▶ Sometimes rules for key behavior have **already been proposed** by others or identified as the model was conceived.
- ▶ However, often it is not at all clear how to model behavior, so we start with both **empirical data** and **existing theory**.
- ▶ Are there **sufficient observations** of the real world to develop statistical and **stochastic sub-models**?
- ▶ Is there **decision theory** for the kinds of agents and decisions being modeled?
- ▶ It is always important to understand **existing theory** as a starting point, and in some fields quite useful kinds of theory can be adapted to ABMs.



# Behavioral Sciences

- ▶ Many scientific fields include a sub-discipline focused on the **behavior of individuals**.
- ▶ **Example.** Cognitive psychology, behavioral ecology.
- ▶ They include theory for how individuals make **complex decisions** that include trade-offs among competing objectives.
- ▶ **Example.** How people or businesses choose among investments that provide different expected payoffs and risks.
- ▶ **Example.** How animals select among alternative strategies (for foraging, mating, etc.) that affect both growth and survival.



# Optimization

- ▶ This classical individual-level theory often uses optimization: if we assume that an agent knows the **future payoffs** and **risks** associated with each alternative behavior, it can mathematically calculate the behaviors that **maximize an objective** such as net income or reproductive output.
- ▶ Optimization approaches have been very **successful** at producing realistically complex behaviors, so this kind of theory is very appealing for ABMs.
- ▶ But agents cannot know the future payoffs and risks of alternative behaviors, or sometimes even the alternatives available, because those future conditions depend on how all the **other agents** behave.

# Goal

- ▶ Your goal is not to reproduce **all behaviors** that your agents are known to exhibit! If you try to do so, you will never finish.
- ▶ Instead, remember that you seek theory that is just realistic enough to **reproduce the patterns** of interest, and make sure you have a clear limit on what patterns you need to reproduce.

# Null Theories

- ▶ You should always **start** with null theories, that is, theories that do not use any **specific mechanism** or assumption.
- ▶ Typical null theories are to just assume that agents **make decisions randomly**, and (the opposite) to assume agents always do exactly the **same thing**.
- ▶ Why start with null theories?
  - ▶ It allows you to develop and test the rest of the ABM **before focusing** on behavior sub-models.
  - ▶ It helps you learn how **sensitive** the output of the ABM is to how you represent the key behavior.

# Expected Results

- ▶ You might find that some key patterns emerge robustly even **without detailed behavior**; then you will have learned that the behavior in fact is not key to explaining the patterns; or
- ▶ You might learn that some important patterns are **not reproduced**, showing that the theory development exercise is in fact important.

# A final methodological comment

- ▶ Remember that exploring and testing sub-models **independently before** you put them into the ABM for pattern-oriented evaluation, is a useful technique.
- ▶ Your progress in theory development will be much **faster** if you implement hypothesized sub-models **separately**, e.g., in a spreadsheet, and understand them thoroughly before plugging them into the ABM.

## ... and Fish Schooling

- ▶ You already have experience doing **theory development** in section 8.4 (stochasticity).
- ▶ We discussed the simulation experiments that Huth and Wissel [4] used to find a model of individual behavior that explains how **groups of fish form schools**.
- ▶ A suggested exercise asks to **contrast some alternative sub-models** for how animals form schools and flocks.
- ▶ This work on fish schools was one of the **earliest** examples of theory development for ABMs

# Assumptions

- ▶ Individual animals **adapt** their movement direction and speed to match those of their neighbors, and move toward their neighbors while maintaining a minimum separation distance and avoiding collisions.
- ▶ Huth and Wissel [4] identified two alternative assumptions, **potential theories**, for how fish adapt their movement:
  1. One theory was that fish react to **only the nearest** other fish;
  2. a second was that fish adapt to the **average direction and location** of several neighbors.

# Contrasting alternatives I

- ▶ Huth and Wissel simulated them and compared the results to several **observed patterns**.
- ▶ One pattern was simple and **qualitative**: Did the model fish look like a school of real fish?
- ▶ Other patterns were quite quantitative, using **measures** of how compact and coordinated real fish schools are:
  - ▶ the mean distances between fish and their nearest neighbor,
  - ▶ the mean angle between a fish's direction and the average direction of all fish, and
  - ▶ the root mean square distance from each fish to the school's centroid.





# Contrasting alternatives II

- ▶ The theory that fish adapt to the average of several neighbors **reproduced** these patterns robustly over a wide range of parameter values.
- ▶ The alternative of following one nearest neighbor did not reproduce the patterns and was hence **falsified**.

# Observations

- ▶ The experiments of Huth and Wissel considered only the most **basic patterns** of schooling and focused on fish.
- ▶ However, pioneering studies such as theirs started the modeling cycle, and subsequent studies have produced more detailed models, more **quantitative data** on real animals, and much more refined theory.
- ▶ The theory that birds always respond to six or seven neighbors (Ballerini et al. [1]) created a **more realistically cohesive** model flock than did the alternative that birds respond to all neighbors within a fixed distance.

# Double-Auction Markets

- ▶ Double-auction markets include agents who are either **buyers** or **sellers**, with buyers buying goods from those sellers who **ask for a price** lower than the buyer's value of the good.
- ▶ **Example.** Stock markets.
- ▶ They are governed by rules (**protocols**) that serve **purposes** such as:
  - ▶ Letting buyers know the best **available price** and sellers know what buyers are **willing to pay**.
  - ▶ Determining the **exact price** at which trades are made (trades occur only when a buyer is willing to pay more than a seller is asking, so the trading price is between these two values); and
  - ▶ Updating this information as trades are **executed** and participants adjust their prices and willingness to pay.



# Patterns

- ▶ Duffy [2] describes a series of experiments, using both ABMs and real people, to develop theory for how traders **decide** when to buy or sell.
- ▶ The exact **theory question** is, What assumptions about trader intelligence are sufficient to reproduce patterns observed in double-auction markets operated by real people?
- ▶ Double-auction markets have been simulated with ABMs many times, and the obvious theory question is how to represent the elaborate ways that people make trading decisions in sufficient detail so that market models produce **realistic dynamics**.
- ▶ What are realistic dynamics?



# Human-based Experiments

- ▶ A number of **empirical experiments** have used real people to represent buyers and sellers in game-like artificial markets that are **simplified** in the same ways that the ABMs are.
- ▶ These experiments have identified patterns such as that people rapidly converge on a very efficient solution, the **equilibrium price** where the number of willing buyers equals the number of willing sellers.

# Agent-based Experiments I

- ▶ Duffy started with a **null theory** that is extremely simple.
- ▶ Gode and Sunder [3] simulated a market with **zero-intelligence traders**, *i.e.*, traders decided randomly (within very wide bounds) the price at which they would buy or sell.
- ▶ Traders could make trades that **lose** instead of make money. However, the market rules that link the highest offer to buy with the lowest selling price were still in effect.
- ▶ As expected, this null theory resulted in **wild fluctuation** in the market's exchange price.



# Agent-based Experiments II

- ▶ Then Gode and Sunder add the **smallest bit of intelligence** by constraining the random trades to exclude those that lose money.
- ▶ Now, the result was surprising: the simulated market rapidly converged, just as the human market did, on an **efficient equilibrium price**.
- ▶ In fact, these minimal-intelligence trader agents made **more total profit** than the humans did.



# Observations I

- ▶ One conclusion is that theory for trading decisions in a market ABM might not need to be elaborate at all, because much of the system's behavior **emerges** instead from the market's elaborate trading rules.
- ▶ However, the results of this experiment triggered so much interest that a number of subsequent studies identified **additional patterns** and tested whether they could be reproduced using minimally intelligent trader behavior.
- ▶ At least one of them, the effects of a **price ceiling** imposed on the market, was reproduced by the minimal-intelligence trading theory.





# Observations II

- ▶ As markets are made more complex and realistic, human traders produce **less efficient** results but minimal-intelligence agents do far worse.
- ▶ And even the original experiment of Gode and Sunder identified one pattern of the human market, **low price volatility** that was not reproduced by the ABM.
- ▶ By using zero-intelligent agents as a baseline, the researcher can ask: what is the **minimal additional** structure or restrictions on agent behavior that are necessary to achieve a certain goal.

# Common Resources

- ▶ Understanding how people make decisions about harvesting a **common resource** is important for diverse problems.
- ▶ **Example.** How to **manage** natural resources, e.g., air quality, public land, water.
- ▶ **Example.** Understanding how **cooperative societies** first started.
- ▶ In these problems, individual people or businesses consume a resource that is shared by many; if individuals **maximize** their own short-term gain, the common resource is quickly **used up**.
- ▶ Janssen, Radtke, and Lee [5] used an ABM, laboratory experiments, and POM to study how people make one **particular kind** of common resource decision.



# Human-based Experiments

- ▶ They modeled a laboratory experiment in which human subjects harvested a shared resource in a **computer game**.
- ▶ Players moved an avatar around a resource grid, **harvesting tokens** that grew on each cell; players were actually paid for each token they harvested.
- ▶ To produce **negative feedback** between harvest rate and resource availability, which makes total harvest much more sensitive to harvest behavior, the time until a cell grew a new token after being harvested was made to increase with the number of neighbor cells that were also harvested.
- ▶ People **compete** on the same grid for the available tokens, experiencing the consequences of each other's decisions.



# ABM-based Experiments

- ▶ The ABM of Janssen et al. then simulated those movements as a way of **quantifying** the participants' harvest behavior.
- ▶ Three **patterns** that characterized the laboratory experiments with real people.
- ▶ The patterns are the range (mean  $\pm$  1 standard deviation) over time of three **metrics**:
  1. The number of tokens available for harvest,
  2. The inequality of harvest among the participants, and
  3. How often participants changed direction as they moved their avatar through the grid.
- ▶ A pattern was assumed to be matched by the ABM if the ABM's results fell within the **observed range**.



# Theories I

- ▶ Janssen et al. tested **alternative theories** for how people moved to harvest the tokens. The first two were **null theories** embodying two extremes:
  1. Making decisions for no reason, e.g., making the avatars to move randomly; and
  2. Always using the same decision, e.g., making them to always move toward one of the nearest tokens.
- ▶ The third one included some mechanisms **observed** in the human experiment:
  - ▶ Avatars tend to move toward closer tokens,
  - ▶ To avoid tokens that are closer to the avatars of other participants, and
  - ▶ To prefer continuing in their current direction.

# Theories II

- ▶ The relative strength and exact effects of these three tendencies were controlled by **seven parameters**.
- ▶ When **testing** the third theory Janssen et al. ran their model with 33,000 combinations of values for these parameters.

# Results

- ▶ Janssen et al. found that the **null theories** reproduced only the second observed pattern.
- ▶ The third theory reproduced the **second pattern** under most parameter combinations, and reproduced **the other two patterns** for only a few parameter combinations.
- ▶ Janssen et al. concluded that their second pattern, **inequality of harvest**, seemed **built into the system** because it was produced by even the null theories.
- ▶ They also concluded that harvesting tokens close to the avatar and moving in a constant direction seem to be particularly important parts of the **human behavior**.

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