

# *Agent-Based Modeling (Master SIED)*

Andrea G. B. Tettamanzi  
I3S Laboratory – SPARKS Team  
`andrea.tettamanzi@univ-cotedazur.fr`



# Unit 1

## Introduction

# Objectives of the Course

- Provide a friendly introduction to the fascinating field of agent-based modeling
- We will study how to use agent-based modeling to understand and examine a wide range of complex problems related to Economics and beyond.
- We will also see how to build a model from the ground up using the Python programming language and how to analyze its results.

# Course Structure

- Introduction
- Building a Simple Model
- Extending Models
- Creating Agent-Based Models
- The Components of an Agent-Based Model
- Analyzing the results of an Agent-Based Model
- Verification, Validation, and Replication
- The ODD Protocol
- History of ABM and Classic Models
- Advanced Agent-Based Modeling

# Suggested Readings

- Eric Bonabeau. Agent-based modeling: Methods and techniques for simulating human systems. PNAS May 14, 2002 99 (suppl 3) 7280-7287.
- Norman Ehrentreich. Agent-Based Modeling. Springer 2008.
- Uri Wilensky and William Rand. An Introduction to Agent-Based Modeling. MIT Press, 2015.

# Credits

- I'm indebted to many colleagues
- Main sources of inspiration
  - Bill Rand (North Carolina State University)
  - Janusz Szwabiński (Wrocław University)

# What is a Model?

- A simplified representation of a phenomenon (process, object, or event)
  - Focuses on relevant aspects
  - Abstracts away non-relevant aspects
- “Essentially, all models are wrong, but some are useful” (George Box, 1987)

# Agent-Based Modeling

- A tool for studying complex systems
  - Alternative/complementary to mathematical tools
  - Advantage : more realistic description
- Agents
  - Discrete, autonomous entities
  - Have goals and behavior
  - May be heterogeneous
- Basic assumptions
  - Key aspects of behavior, interaction can be described
  - We can (re-)construct complex processes and systems bottom-up
- Simulation is the main tool to test models (= theories)



# Reactive vs. Cognitive Agents

- Reactive Agents
  - Input-output mapping (sensors → actuators)
  - Simple behavior (described by fixed rules or math equations)
  - No or limited internal state
- Cognitive Agents
  - S/w artifacts that exhibit intelligent behavior in complex domains
  - Autonomous, responsive, proactive, goal-oriented, co-operative
  - Deliberation
  - Established cognitive architecture (e.g., the BDI Model)

# Complex Systems

- A system composed of many interacting parts in which the **emergent** outcome of the system is a product of the interactions between the parts and the **feedback** between that emergent outcome and individual decisions
- Emergence: “the action of the whole is more than the sum of the parts” (Holland, 2014)
- Feedback: The effect of the emergent result on the decisions of the individuals

# How do you understand Complex Systems?

- Complex Systems can be difficult to predict, control and manage, which in many ways is the goal of public policy
- Agent-Based Modeling and Complex Systems analysis is to provide a “flight simulator” rather than a perfect prediction

# What Makes Complex Systems Complex?

- Path dependence
- Sensitivity to initial conditions (→ chaos)
- Non-linearity and dynamics
- Diversity and heterogeneity
- Interconnectedness and interactions

# A Third Way of Doing Science

- Two traditional ways of doing science
  - Induction - inferring a general theory from particular data
  - Deduction - reasoning from first principles to prove a general theory
- Third Way
  - Generative - using first principles to generate a particular set of data that can create a general theory

(Axelrod, 1997)

# When to Use ABM?

- Medium Numbers
- Heterogeneity
- Complex but Local Interactions
- Rich Environments
- Time
- Adaptation

# Medium Numbers

- Too few agents and the simple may be too simple
  - Game theory and ethnography work well
- Too many agents and means may describe the system well
  - Mean-field approaches and statistical descriptions
- The key is that the number of agents that can affect the outcome of the system be a *medium number*

# Heterogeneity

- Agents can be as heterogeneous as they need to be
- Many other approaches assume homogeneity over individuals



# Complex but Local Interactions

- ABM can model complex interactions
  - History dependent
  - Property dependent
- The assumption is that these are local
  - No global knowledge

# Rich Environments

- The environment the agents interact in/with can be extremely rich
  - Social Networks
  - Geographical systems
- The environment can even have its own agent-like rules

# Time

- Almost all agent-based models feature time
- ABM is a model of process
- Nearly necessary
- There are exceptions
  - Solving complex equilibrium problems

# Adaptation

- Adaptation is when an agent's actions are contingent on their past history
- An agent may take different actions depending on its own past experience
- Usually sufficient
- Very few modeling approaches besides ABM feature adaptive individuals

# Agent-Based Modeling (ABM) vs. Equation-Based Modeling (EBM)

- Many EBMs make the assumption of homogeneity
- EBMs are often continuous and not discrete
- The nano-wolf problem (Wilson, 1998)
- EBMs require aggregate knowledge in many cases
- Ontology of EBMs is at a global level
- EBMs do not provide local detail
- EBMs are Top-Down, ABMs are Bottom-Up
- EBMs are generalizable, but restricted
- ABM can be built from analytical models, and can complement EBMs



# ABM vs. Statistical Modeling

- Hard to link to first principles and behavioral theory
- Need to have the right kind of data
- ABM can complement by building from first principles to statistical results

# ABM vs. Lab Experiments

- Lab experiments can generate theory
- Lab experiments are rarely scaled up
- ABM can be created from lab experiments
  - ABM can explore macro-implications of lab experiments
  - ABM can generate new hypotheses
  - ABM can determine sensitivity of results
  - ABM can compare generative principles

# Limitations

- High Computational Cost
  - Benefit of more insight and data to intermediate stages
- Many Free Parameters
  - Simply exposing parameters that other models assume
- May Require Individual-Level Behavioral Knowledge
  - Provides better insight



# Uses of ABM

- Description
- Explanation
- Experimentation
- Analogy
- Education / Communication
- Touchstone
- Thought Experiments
- Prediction

# Description

- An ABM is a description of a real-world system
- A simplified description but still a description
- Models that are not simplified are useless
- “Make your model as simple as possible but no simpler.” - Albert Einstein

# Explanation

- An ABM provides an explanation of potential underlying phenomenon that control a system
- They are a proof-of-concept that something is possible
- They illuminate the power of emergence

# Experimentation

- ABMs can be run repeatedly under slightly different conditions to observe the resultant changes
- We can change the model and see what happens
- We can then go back to the real-world and validate these experiments

# Analogy

- ABMs help us to understand other system with similar patterns of behavior
- For instance, a model of flocking birds can help us understand fish and even locusts
- They can even help us understand engineered systems, e.g., drones

# Education / Communication

- ABMs help us communicate our results to others
- They encapsulate knowledge in a way that is easily transferable
- They encourage exploration about different theories

# Touchstone

- ABMs create a focal object
  - Papert (1980) calls them an object to think with
- They give us a common language to describe a phenomenon and to argue about its causes
- They turn complex systems into a set of simple rules

# Thought Experiments

- ABMs can explore things that may not even exist in the real world, or are very idealized examples of the real world
- ABM gives us the power to say what will happen if we assume a few basic rules


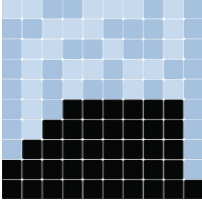


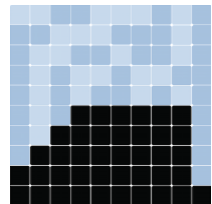
# Prediction

- ABM is often used to think about possible future scenarios
- But the validity of a prediction is determined by how well the model has been validated
- It is difficult to assess the validity of any model for an event that has not yet occurred
- Prediction can often be reduced to description and explanation

# ABM Tool Kits



- NetLogo 
  - Easy to learn
  - Logo-based
- MASON
  - fast, flexible, portable
  - Java-based
- Recursive Porous Agent Simulation Toolkit
  - GIS support
  - Java-based
- Mesa 
  - Python 3-based
  - Web GUI



# Mesa Tutorial

- Must have Python 3+ and Mesa installed
- Go to <https://mesa.readthedocs.io>
- Follow the link to the “Mesa Introductory Tutorial”
  - Based on the Boltzmann Wealth Model
  - The code should be in the Examples folder of your local Mesa installation
  - We will write the code from scratch, step by step

# The Boltzmann Wealth Model

- Simple model from econophysics
- A statistical mechanics approach to wealth distribution
  - There are a number of agents.
  - All agents begin with 1 unit of money.
  - At every step, an agent gives 1 unit of money (if they have it) to some other agent.
- Despite its simplicity, interesting results