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5. **As a Pedagogic Tool** — to gain understanding of a process.
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- Solution of a set of equations describing a complex (e.g. bottom-up) interaction.
- *Discrete* (CA): if the model behaviour ≠ empirical, it must be because of the transition rules.
- *Continuous*: not so clear-cut: background theory v. model assumptions

Q: does more realistic assumption → more accurate prediction?

“A simulation is no better than the assumptions built into it” — Herbert Simon
2. Heuristic Tool

Where the theory is not well developed, and the causal relationships are not well understood:

- theory development = guessing suitable assumptions that may imitate the change process itself
- but how to assess assumptions independently?

3. Substitute for Experiment

When actual experiments are perhaps:

- \textit{pragmatically} impossible: scale, time
- \textit{theoretically} impossible: counterfactuals
- \textit{ethically} impossible: e.g. taxation, no minimum wage

\textit{or} to complement lab experiments
Agent-Based Models v. Economic Experiments

Hailu & Schilizzi (2004, p.155) compare and contrast ABMs with experiments using human subjects, under the headings:

- Approach to inference, or micro-macro relationship
- Specification of behavioural rules
- Informational problems
- Degree of control
- Explanation of agents’ choices
- Temporal length of analysis
- Representativeness / realism
- Data
- Cost
4. Tool for Experimentalists

- to inspire experiments
- to preselect possible systems & set-ups
- to analyse experiments
  (statistical adjustment of data)
5. For Learning

A pedagogic device through play ...


Play with NetLogo models, and experience emergence: Life is famous, and others too.
Summary

A simulation imitates one process by another process

With Social Sciences: few good descriptions of static aspects, and even fewer of dynamic aspects
(Remember: existence, uniqueness, stability)
Robust Predictions from Simple Theory
(from Latané, 1996)

Four conceptions of simulation as a tool for doing social science:

1. As a scientific tool: theory + simulation + experimentation
2. As a language for expressing theory:
   — natural language,
   — mathematical equations (i.e., closed form), and
   — computer programs, such as C++, Java, etc.
3. As an “easy” alternative to thinking: robust coding
4. As a machine for discovering consequences of theory: if this, then that.
A Third Way of Doing Science
(from Axelrod & Tesfatsion 2006)

Deduction + Induction + Simulation.

• Deduction: deriving theorems from assumptions
• Induction: finding patterns in empirical data
• Simulation: assumptions $\rightarrow$ data for inductive analysis

S differs from D & I in its implementation & goals.
S permits increased understanding of systems through controlled computer experiments
Emergence of self-organisation
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Examples: ice, magnetism, money, markets, civil society, prices, segregation.
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Adam Smith’s Invisible Hand $\rightarrow$ prices

Schelling’s segregation model:
People move because of a weak preference for a neighbourhood that has at least 33% of those adjoining the same (colour, race, whatever) $\rightarrow$ segregation.

Need models with more than one level to explore emergent phenomena.
Families of Simulation Models

1. System Dynamics SD  
   (from differential equations)

2. Cellular Automata CA  
   (from von Neumann & Ulam, related to Game Theory)

3. Multi-agent Models MAM  
   (from Artificial Intelligence)

4. Learning Models LM  
   (from Simulated Evolution and from Psychology)
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G & T compare these (and others):

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So “agent-based models” excludes Systems Dynamics models, but can include the others.
Simulation: The Big Questions

- What is a simulation?
- What is a model?
- What is a theory?
- How do we test the validity of any of the above?
- When do we trust them, what sort of understanding do they afford us?
- What is an experiment? What does it mean to experiment with a simulation?
- What is the role of the computer in simulation?
- How does general systems dynamics influence simulations?
- How do we handle sensitivity to initial conditions?
- How precisely can a simulation approximate real life / a model?
- How do we decide whether to use a theory / model / simulation / lab experiment / intuition for a given problem?
- Does a simulation have to tell us something?
- How complex is too complex, how simple is too simple?
- How much information do we need to (a) build and (b) test a simulation?
- How/when can the transition from a quantitative to a qualitative claim be made?
Verification & Validation

Verification (or internal validity): is the simulation working as you want it to:
— is it “doing the thing right?”
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To Verify: use a suite of tests, and run them every time you change the simulation code — to verify the changes have not introduced extra bugs.
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Use Sensitivity Analysis, to ask:

• robustness of the model to assumptions made
• which are the crucial initial conditions/parameters?

use: randomised Monte Carlo, with many runs.
Judd’s ideas (2006)

“Far better an approximate answer to the right question ... than an exact answer to the wrong question.”

That is, economists face a tradeoff between:

the numerical errors of computational work and
the specification errors of analytically tractable models.
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Several suggestions:

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5. Synergies between Simulation and Conventional Theory.
Axelrod on Model Replication and “Docking”

Docking: a simulation model written for one purpose is aligned or “docked” with a general purpose simulation system written for a different purpose.

Four lessons:

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4. Minor procedural differences (e.g. sampling with or without replacement) can block replication, even at (b).
Reasons for Errors in Docking

1. Ambiguity in published model descriptions.
2. Gaps in published model descriptions.
3. Errors in published model descriptions.
4. Software and/or hardware subtleties.
   e.g. different floating-point number representation.

(See Axelrod 2006.)
References:


