

2. Simulation

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(from Hartmann 1996)

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4. As a **Tool for Experimentalists** — to support experiments.
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 \neq empirical, it must be because of the transition rules.
- *Continuous*: not so clear-cut: background theory v. model assumptions

Q: does more realistic assumption \rightarrow 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?

Durlauf: Is there an underlying optimisation by agents?
(Complexity and Empirical Economics, *EJ*, 2005)

3. Substitute for Experiment

When actual experiments are perhaps:

- *pragmatically* impossible: scale, time
- *theoretically* impossible: counterfactuals
- *ethically* impossible: e.g. taxation, no minimum wage

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 ...

See Mitchell Resnick. *Turtles, termites, and traffic jams: Explorations in massively parallel microworlds*. MIT Press, 1997.

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 → data for inductive analysis**

S differs from D & I in its implementation & goals.

S permits increased understanding of systems through controlled computer experiments

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Adam Smith's Invisible Hand → 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) → 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)

Comparison of Simulation Techniques

G & T compare these (and others):

Technique	Number of Levels	Communication between agents	Complexity of agents	Number of agents
SD	1	No	Low	1
CA	2+	Maybe	Low	Many
MAM	2+	Yes	High	Few
LM	2+	Maybe	High	Many

Number of Levels: “2+” means the technique can model more than a single level (the individual, or the society) and the interaction between levels.

This is necessary for investigating emergent phenomena.

So “agent-based models” excludes Systems Dynamics models, but can include the others.

Simulation: The Big Questions

from: www.csse.monash.edu.au/~korb/subjects/cse467/questions.html

- 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?”

Validation: is the model used in the simulation correct?

— is it “doing the right thing?”

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.

Validation

Ideally: compare the simulation output with the real world.

But:

1. *stochastic* ∴ complete accord is unlikely, and the distribution of differences is usually unknown
2. *path-dependence*: output is sensitive to initial conditions/parameters
3. test for “retrodiction”: reversing time in the simulation
4. what if the model is correct, but the input data are bad?

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.”

— John Tukey, 1962.

That is, economists face a tradeoff between:

**the numerical errors of computational work
and**

the specification errors of analytically tractable models.

Judd on Validation

Several suggestions:

- 1. Search for counterexamples:**
If found, then insights into when the proposition fails to hold.
If not found, then not proof, but strong evidence for the truth of the proposition.
- 2. Sampling Methods: Monte Carlo, and quasi-Monte Carlo** → standard statistical tools to describe confidence of results.
- 3. Regression Methods:** to find the “shape” of the proposition.
- 4. Replication & Generalisation:** “docking” by replicating on a different platform or language, but lack of standard software an issue.
- 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:

- 1. Not necessarily so hard.**
- 2. Three kinds of replication:**
 - a. numerical identity**
 - b. distributional equivalence**
 - c. relational equivalence**
- 3. Which null hypothesis? And sample size.**
- 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 2003.)

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