2. Simulation

The Five Functions of Simulations:

(from Hartmann 1996)

1. **As a Technique — to investigate the detailed dynamics of a system.**
2. **As a Heuristic Tool — to develop hypotheses, models, and theories.**
3. **As “Experiments” — perform numerical experiments, Monte Carlo probabilistic sampling.**
4. **As a Tool for Experimentalists — to support experiments.**
5. **As a Pedagogic Tool — to gain understanding of a process.**

1. Technique

- **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 patters in empirical data**
- **Simulation: assumptions $\rightarrow$ data for inductive analaysis**

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

S permits increased understanding of systems through controlled computer experiments

Emergence of self-organisation

Examples: ice, magnetism, money, markets, civil society, prices, segregation.

Defn: emergent properties are properties of a system that exist at a higher level of aggregation than the original description of the system

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 condistions/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”

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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