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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 $\neq$ 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

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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

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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?

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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.

Validation

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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.”

— 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

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5. **Synergies between Simulation and Conventional Theory.**

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Four lessons:

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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 2006.)

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