Agent Based Models

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Prologue

With many calculations one can win; with few one cannot.

—Sun Tzu, The Art of War

Scientific laws have conventionally been constructed in terms of a particular set of mathematical functions and constructs, and they have often been developed as much for their mathematical simplicity as for their capacity to model the salient features of a phenomenon.

—Stephen Wolfram, “Computer Software in Science and Mathematics”

Outline

- Introduction
- Implementation
- Example 1: Artificial Life
- Example 2: Financial Crisis
- Example 3: Schelling Model
- Disadvantages and Advantages
- Methodological Challenges

The World’s Favorite ABM: The Sims

What is an Agent Based Model?

Computer simulation of the global consequences of local interactions of members of a population

"Microscale model" – simulate interactions of multiple agents to re-create and predict complex phenomena

Types of agents:

- Plants and animals in ecosystems
- Vehicles in traffic
- Political actors

What is an Agent Based Model?

Agent Based Models (ABMs) aim to provide an in silico lab, where we can:

1) Capture our understanding of systems.

2) Test that understanding of the systems for coherence and comprehensiveness.

3) See how theory at the individual level creates aggregate patterns.

4) Validate that theory against real data at the aggregate and individual scale.

5) Make predictions about the system.

6) Test "what if?" scenarios to inform planning.

Purposes

Derive findings for the system’s behavior (“macro level”) from the agents’ behavior (“micro level”) (Bonabeau 2002; Epstein 2006a).

“Generative social science” (Epstein 2006a) or to “social science from the bottom-up” (Epstein and Axtell 1996).

Several purposes like, for example, predicting consequences, performing certain tasks (which is typically the case in the domain of artificial intelligence), or discovering theory.

Some regard simulation as a third research methodology which has in common with deduction the explicit set-up of assumptions (though it does not prove theorems by the “classical” mathematical techniques) and which generates data from a set of rules (rather than from measurement of real world data as it is typical for induction).

ABM Components

1. Agents specified at various scales (agent-granularity)

2. Decision-making heuristics

3. Learning rules or adaptive processes

4. Interaction topology

5. An environment

KISS and Gestalt

"Keep it simple, stupid."

Tenet: Simple rules generate complex behavior

Tenet 2: Gestalt – the whole is greater than the sum of its parts

Core assumption: bounded rationality. Agents act in their own interests.

Modeling Process

Three core ideas: objects, emergence, and complexity

Emergence – generative. Potential to generate system equilibrium is the biggest benefit of ABM.

Inductive modeling process

- Modeler makes assumptions believed to be most relevant and observes behavior.

Implementation

Originally designed for serial von-Neumann computer architectures

Limits to speed and scalability

Recent development – data-parallel algorithms on GPUs for simulation

Artifiical Life

Studies fundamental processes of living systems in artificial environment

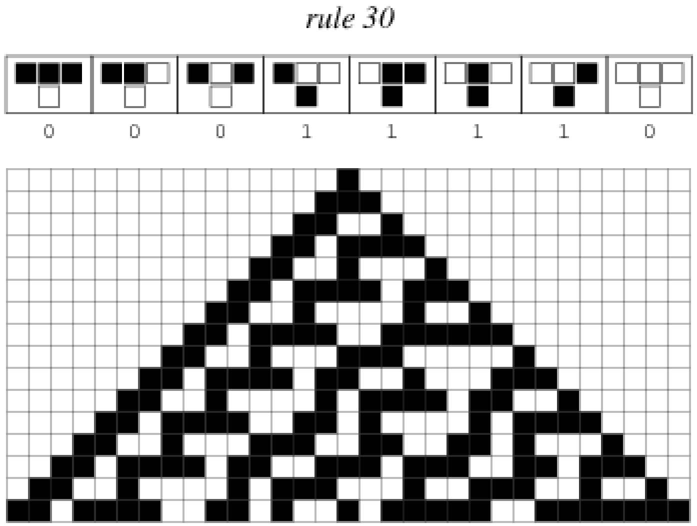
The modeling philosophy of artificial life strongly differs from traditional modeling by studying not only "life-as-we-know-it" but also "life-as-it-might-be".

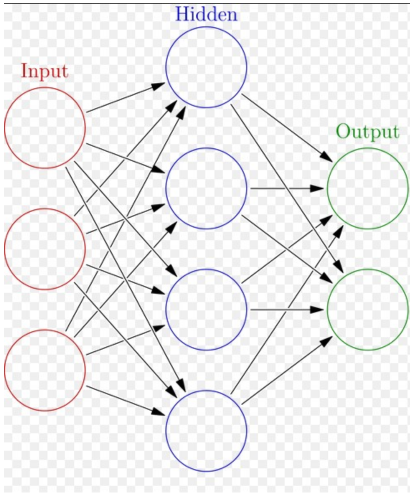
A traditional model of a biological system will focus on capturing its most important parameters.

In contrast, an alife modeling approach will generally seek to decipher the most simple and general principles underlying life and implement them in a simulation.

Alife Techniques

Cellular automata





Artificial neural networks

Cellular Automata

A collection of "colored" cells on a grid of specified shape that evolves through a number of discrete time steps according to a set of rules based on the states of neighboring cells. The rules are then applied iteratively for as many time steps as desired.

Von Neumann was one of the first people to consider such a model, and incorporated a cellular model into his "universal constructor."

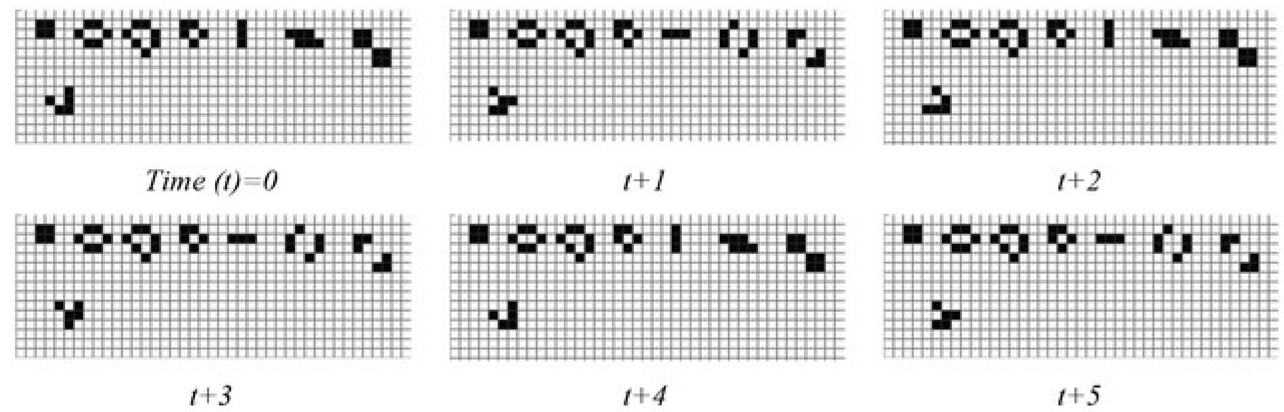
Studied in the early 1950s as a possible model for biological systems.

Comparison of CA vs ABM

CA and ABM are similar but not interchangeable!

In CA, cells do not move. ABM, they can.

The only requirement for an agent-based model is that the agents have individual properties that are tracked over time. Rules of interaction between agents and groups, inheritance of properties over time, or spatial context can vary over different types of agent-based models.



Criticisms of Alife simulation

Alife simulation – focuses on the investigation of emergent phenomena in the natural world.

Difficult to explain; simulation provides a means to view the origin of these phenomena from the behaviour of low-level component parts

Lacks in its ability to explain the overall behaviour of that higher-level emergent order.

A Novelty or a Copy?

Can a simulation create novel datasets which allow us to discover new things about natural systems, or are simulations based on the natural world destined to be mere facsimiles of the systems that inspire them?

"Life-as-we-know-it" or "life-as-it-might-be"?

Financial Crisis Example

The financial crisis, and the related real crisis, were unpredictable, and are only partially understood, using available economic models

Unpredictable refers to Knightian uncertainty, where risk cannot be measured (not a wrong guess on a probability distribution)

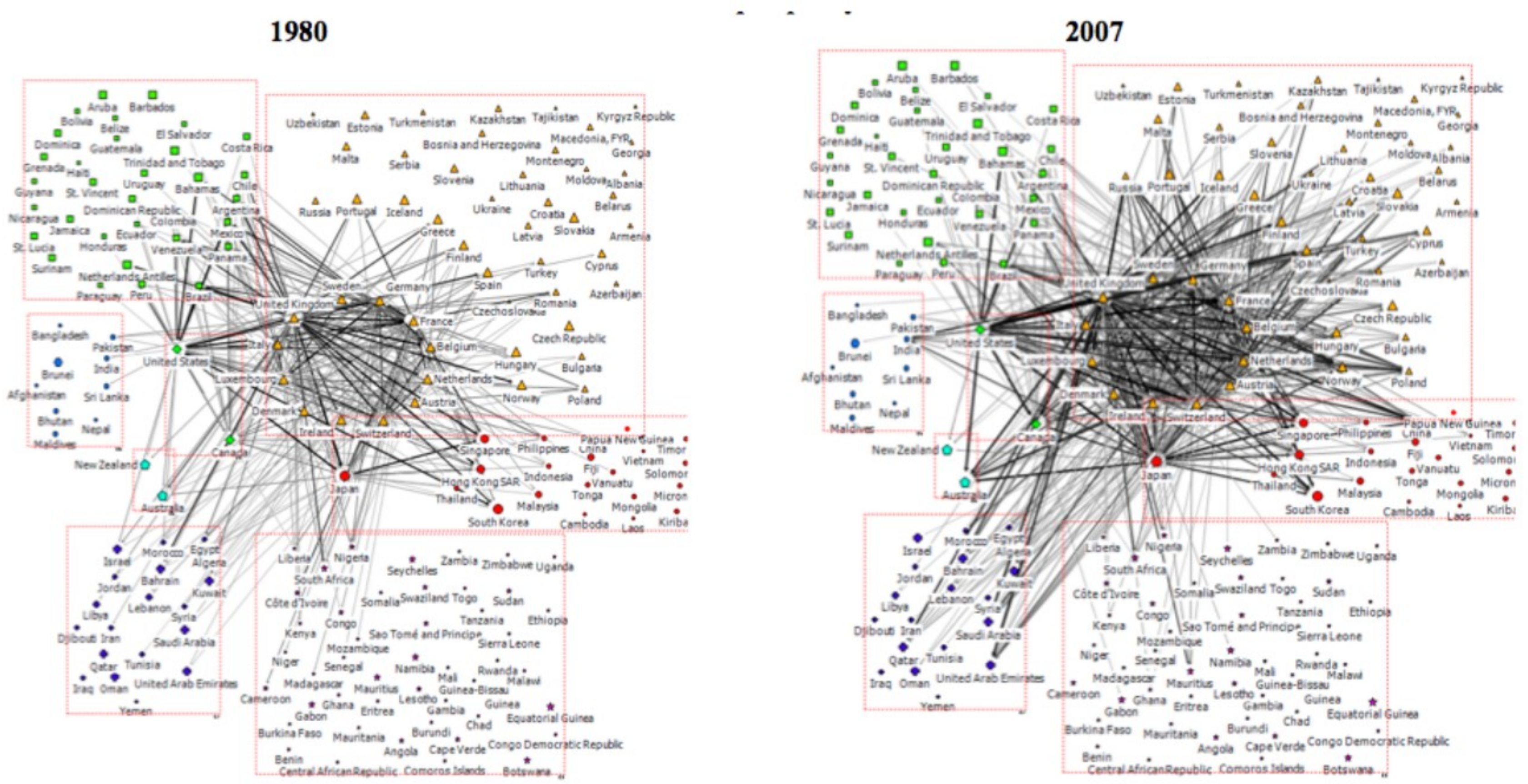
Why?

Some fundamental features of economic systems

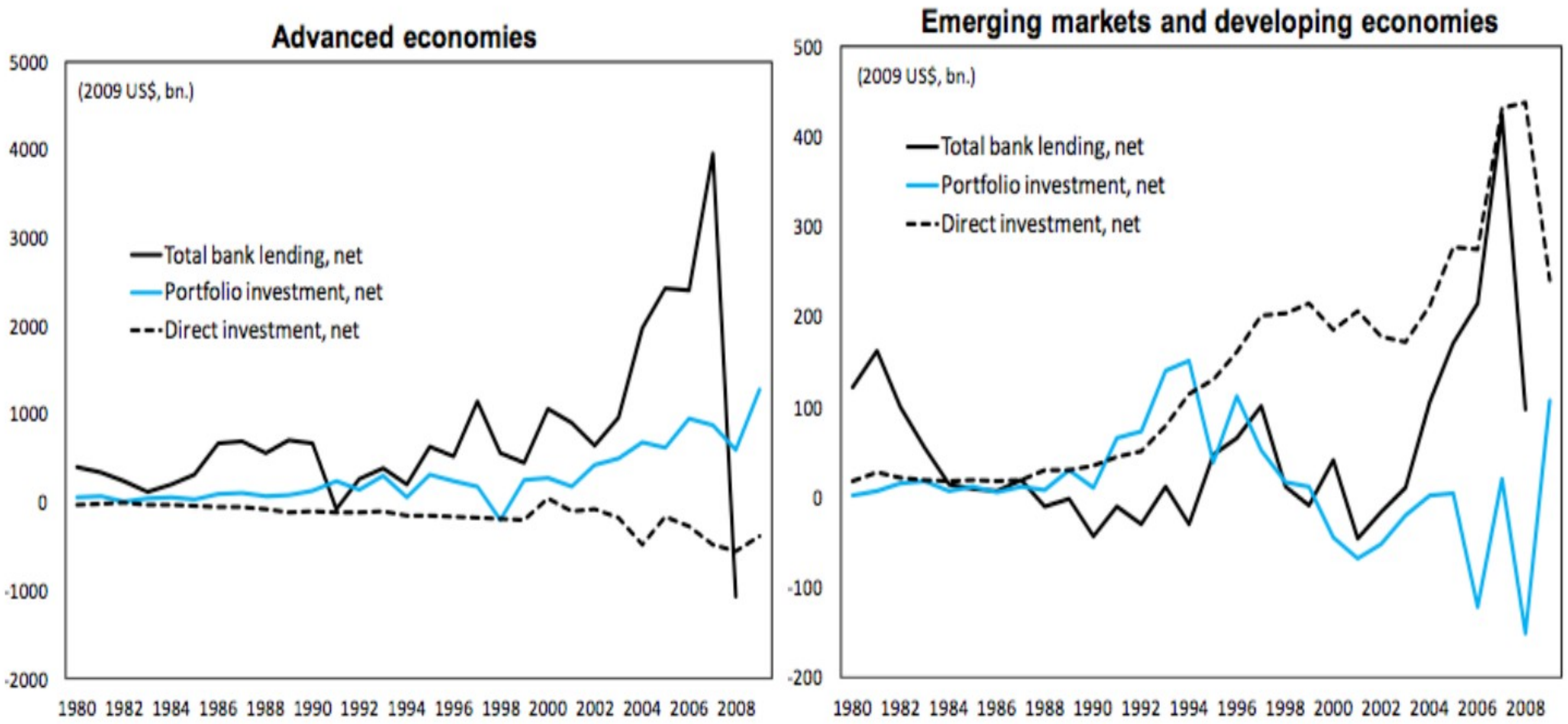
- network structure – banks, users and countries
- individual's beliefs and expectations – satisficing, partly adaptive, and heterogeneous
- interdependent behaviour – contagion

⇒ Features of a complex system

Network: Cross-border Banking Network



Network: Cross-border Flows



(a) To advanced economies (b) To emerging and developing economies

Contagion in Financial Crisis Model

Market signals adjust through time.

Information mediated by other actors locally.

Cumulative actions of others contain so much information that individuals ignore his own information (“information cascade”).

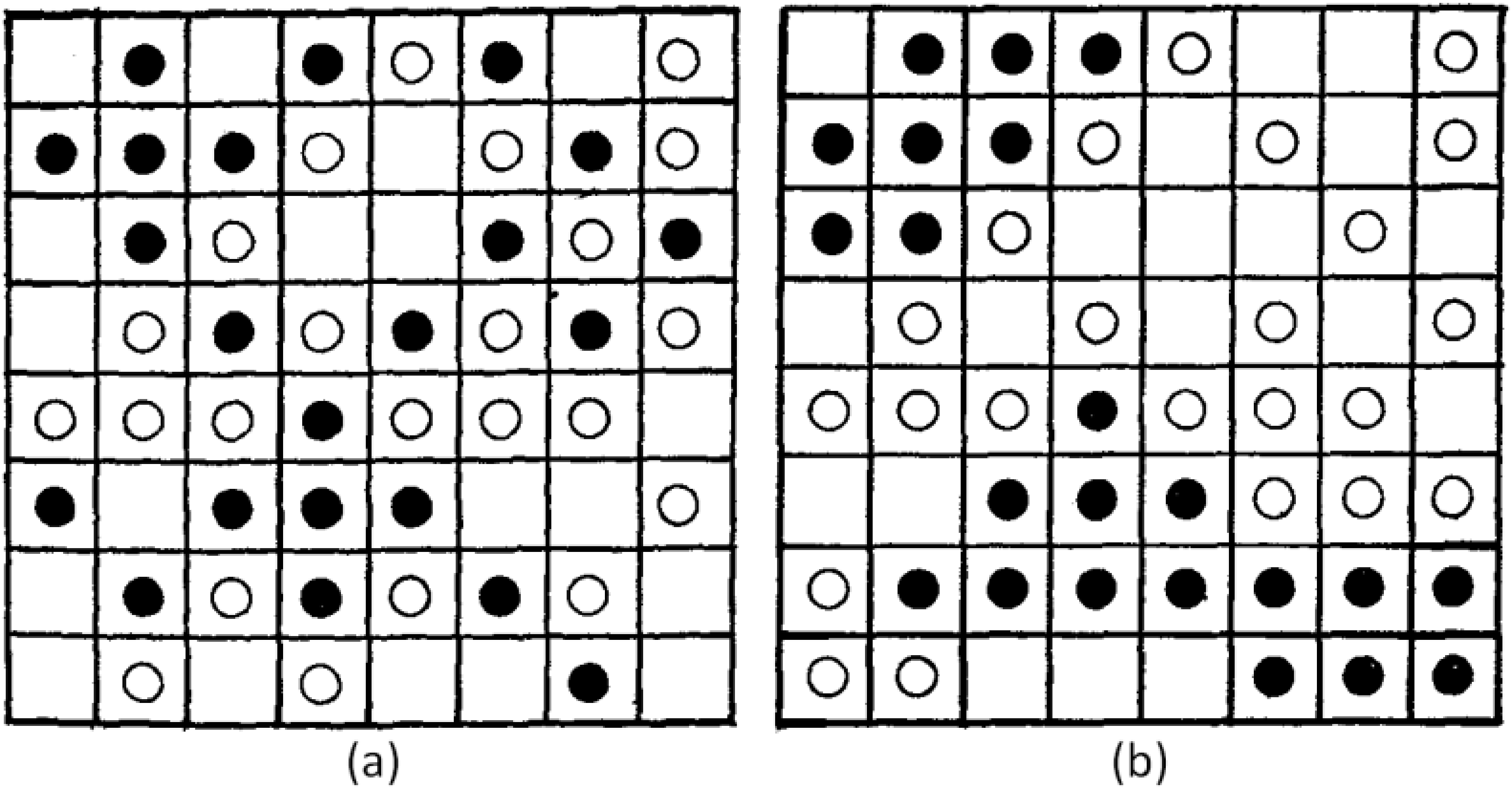
Schelling’s Model

Demonstrates individual tendencies regarding neighbors can lead to segregation. The model is especially useful for the study of residential segregation of ethnic groups where agents represent householders who relocate in the city.

In the model, each agent belongs to one of two groups and aims to reside within a neighborhood where the fraction of 'friends' is sufficiently high: above a predefined tolerance threshold value F. It is known that depending on F, for groups of equal size, Schelling's residential pattern converges to either complete integration (a random-like pattern) or segregation.

Reality is more complicated than this simple integration-segregation dichotomy: some neighborhoods are ethnically homogeneous while others are populated by both groups in varying ratios.

Schelling's Model



(a) initial condition of one of Schelling's experiments;
(b) stable segregated pattern obtained in several iterations

Why not a formal or statistical model?

Comparison with formal models:

Same mathematical abstraction of a given problem, but uses simulation rather than mathematics to “solve” model and derive comparative statistics

Comparison with statistical models:

Same attempt to analyze data, but uses simulation data rather than real data

Advantages of Agent Based Models

Formal – assumptions laid bare

Flexible – agents can be rational or adaptive

Tractable – easier to deal with complexity

Generative – can develop new hypotheses

Disadvantages

Models too simple
- Could be solved in closed-form
- Closed-form solution always preferable

Models too complicated
- Not possible to assess causality
- What use is an existence proof?

Coding mistakes
- Many more lines of code than lines in typical formal proof

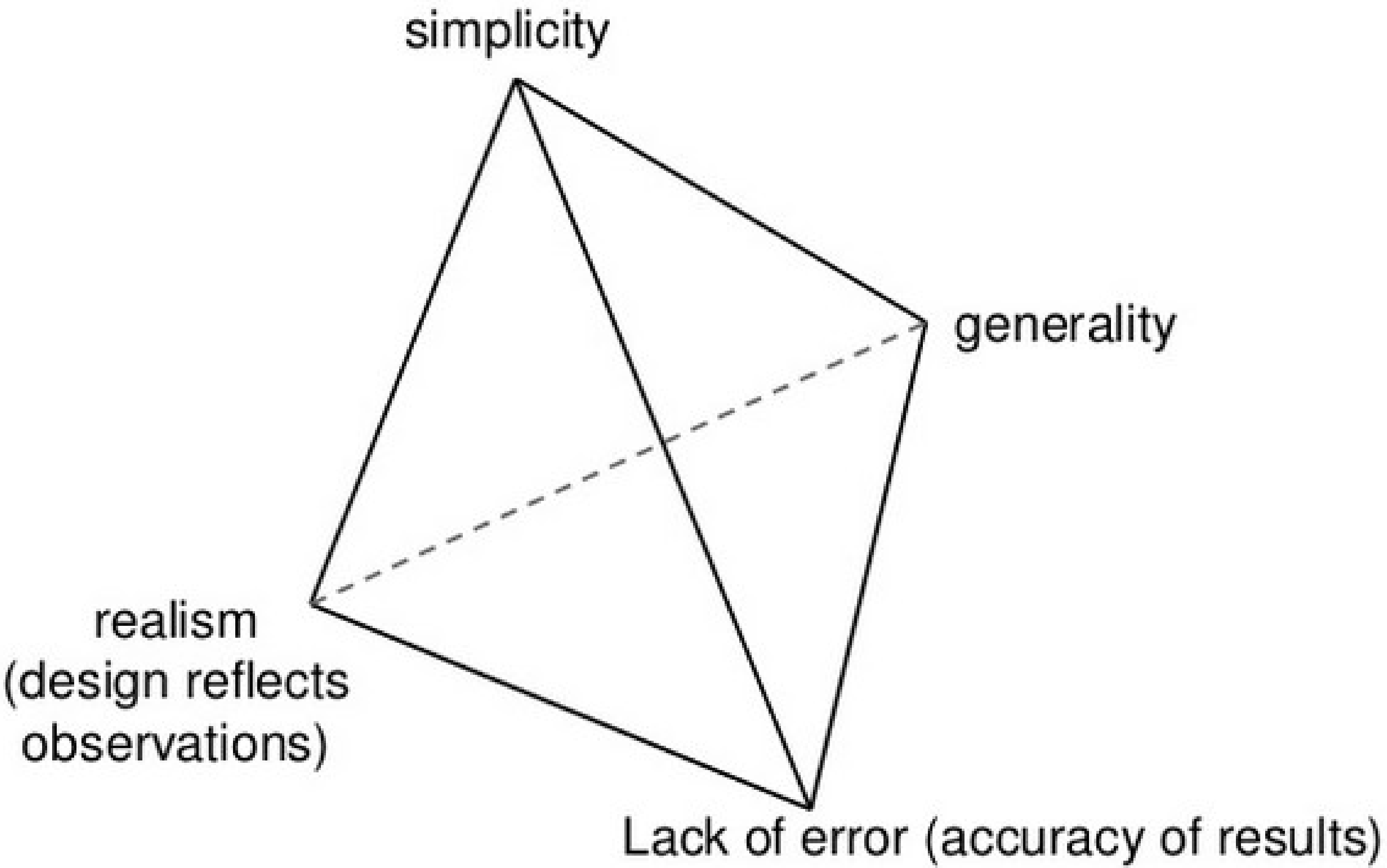
Data analysis
- What part of the parameter space to search

Versus Traditional Tools

Modeling Potential

Traditional Tools	*Agent-Based Objects*
Precise	Flexible
Little process	Process oriented
Timeless	Timely
Optimizing	Adaptive
Static	Dynamic
1, 2, or ∞ agents	1, 2, ..., N agents
Vacuous	Spacey/networked
Homogeneous	Heterogeneous

ABM Tradeoffs



Social vs Physical Systems

Assumptions about appropriate behavioral rules.

Physical system example: Quantum effects aside, all hydrogen atoms rely on a set of rigid external physical properties and forces.

Social agents, on the other hand, often alter their behavior in response to, and in anticipation of, the actions of others.

Social systems have an extra layer of complexity.

ABM vs Regression Model

Agent-based modeling vs. statistical regression models.

Regression model assumption: simplifying assumption: errors are iid.

Relax this assumption in ABM but gain model complexity – difficult to interpret.

Solution: Simplify on some dimensions!

Key Challenges

Results depend on the parameters' values under which the simulation was performed and also on the "internal" structure of the model.

Transparency

Variability

Reproducibility

Dependency Issues (w.r.t. Input Values)

Use of non-parametric iterative procedures that change the parameters’ values until the greatest proximity between the observed and simulated macroscopic structures is achieved

Calibration if one has empirical data, sensitivity analysis otherwise

Dependency Issues (w.r.t. Internal Structure)

Robustness analysis if the previous methods aren’t feasible.

We can adjust the following:

a) the form of probability distributions used for the stochastic parts of the model

b) the functional forms adopted to link the elementary entities’ attributes

c) the rules of behaviour of these entities

d) the structure of their interactions (which is often done by simulating the model under several network topologies)

e) the sequence followed to “call” each entity

f) the way in which the behaviours of elementary entities are adapted and updated from a temporal point of view

Variability of Results

Random elements contained in model is source of variability

Quantify variability by replicating simulation for each parameter set and describe central tendencies

If comparing simulated and real data, evaluate overlap between variability in simulation between repetitions and empirical variability between samples.

If interested in trajectories of each agent, this is very difficult to understand. Multi-level regression models suggested to deal with this variability.

When Sensitivity Analysis Fails

Error creep

Do nonlinearities in the models destroy their usefulness? NO.

Is there a stabilizing (homeostatic) process in the real system?

Processes like agent-to-agent negotiation, averaging, and aggregation will often dampen down error propagation.

Transparency

Sensitivity analysis may help develop intuitions (Railsback and Grimm, 2011)

Mathematical description of state sequences is helpful

Isolate effects of mechanisms on internal dynamic and aggregated results, ideally

Otherwise, ad-hoc measures needed – call the model's "currencies" (Railsback and Grimm, 2011) to study evolution of an aspect over time and its impact on results

Reproducibility

Two trends to deal with this:

Standardized presentation of ABMs (Richiardi et al., 2006; Grimm, Berger and DeAngelis, 2010).

Platforms for classification and sharing of models (Janssen et al., 2008)

Verificiation and validation

Verification – ensure model works correctly

Validation – check that the right model is chosen

Example: VOMAS (virtual overlay multi-agent system).

Recent work (2017) by Niazi, Hussain, Kolberg

https://arxiv.org/abs/1708.02361

VOMAS

Formal way of validation and verification

Design VOMAS agents alongside agents in simulation

Simulations are validated in simulation.

Conclusion

ABMs have their flaws but their advantages, particularly emergence, make them useful

Great complements to analytic methods

Next time: further discussion of agent based models in economics

Some References

Grimm, Volker; Railsback, Steven F. (2005). Individual-based Modeling and Ecology. Princeton University Press.

Silverman, Eric (2018). Methodological Investigations in Agent-Based Modelling. Springer International Publishing, Cham, Switzerland.