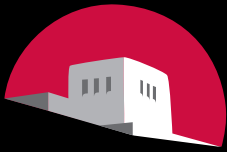


CS 365

Introduction to Scientific Modeling
Lecture 1: Modeling

Stephanie Forrest
Dept. of Computer Science
Univ. of New Mexico
Fall Semester, 2014



THE UNIVERSITY *of*
NEW MEXICO

Introduction

- Three legs of science
 - Experiment
 - Mathematical theory
 - Simulation and modeling
- What are models good for?
 - Tools for analyzing data
 - Methods for discovering new knowledge (3rd leg)
 - Understanding nature as an information-processing system
 - Explaining how something works---mechanisms

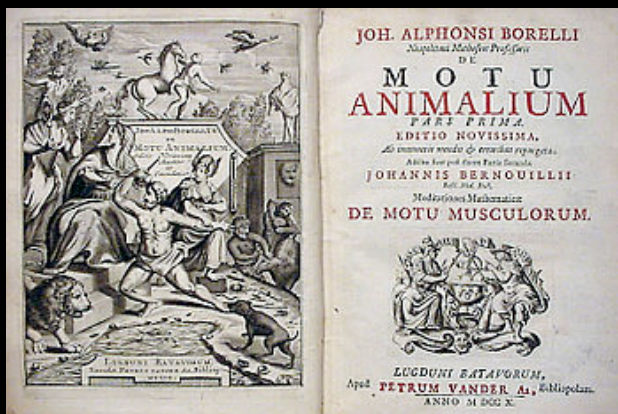
What is a model?

- A hypothetical **description**, often based on an analogy, used in analyzing something.
- A **representation** of something in which we are interested.
- The representation is **reduced**---what to throw away?
- Examples?



Giovanni Alfonso Borelli (1608-1679)

- Father of biomechanics and an early modeler
- Related animals to machines and used mathematics to prove his theories
- *Likened* the action of the heart to that of a piston and reasoned that arteries must be elastic



Representation: Models are expressed in different ways

- Verbal descriptions, e.g.,
 - The “invisible hand” in economics
 - Clonal selection theory in immunology
 - Bohr’ s model of the atom
- Pictures
- Mathematical equations
- Computer programs (model vs. simulation)

EXAMPLES ??

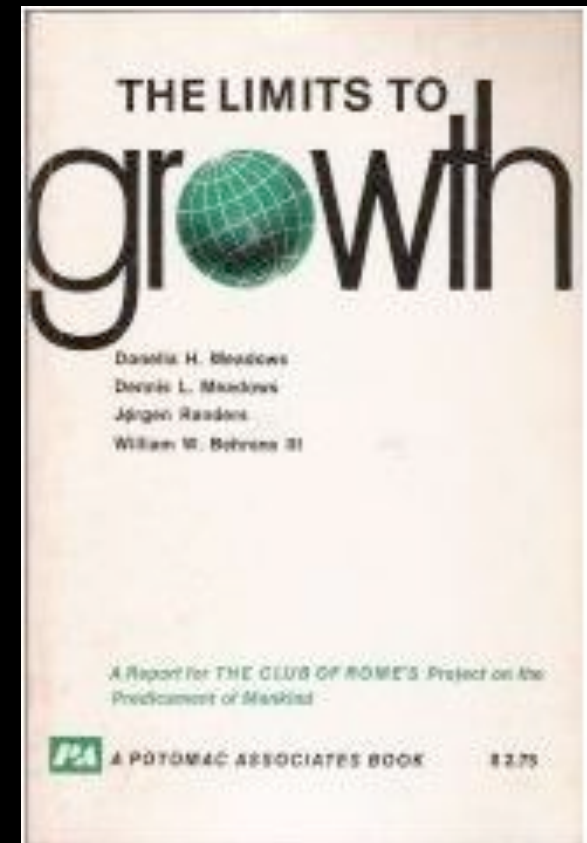
Examples

- A genetic algorithm is a model of Darwinian evolution
- Stock market simulation
- Crash test dummies (model humans)
- Social network models of social relationships
- The carbon cycle: a compartment model (air, ocean, terrestrial ecology, fossil fuels)

Example: Limits to growth model

Meadows et al. 1972

- Computer model:
 - 5 variables: population, industrialization, pollution, food production, resource depletion
- Goal: **Not to make specific predictions, but to explore how exponential growth interacts with finite resources.** Because the size of resources is not known, only general behavior can be explored.
- This process of determining behavior modes is "prediction" only in the most limited sense of the word. ... These graphs are *not* exact predictions of the values of the variables at any particular year in the future. They are indications of the system's behavioral tendencies only.

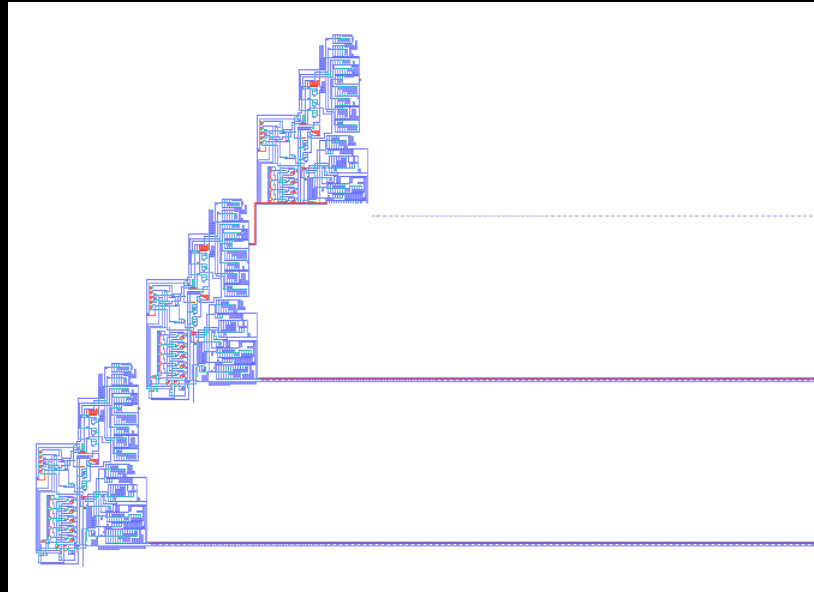


How do we use models?



- Making predictions (conventional use)
 - Quantitative (most analytical models)
 - Qualitative, e.g., critical parameters, regions of stability or instability
 - Validation: Accurate predictions

How do we use models?

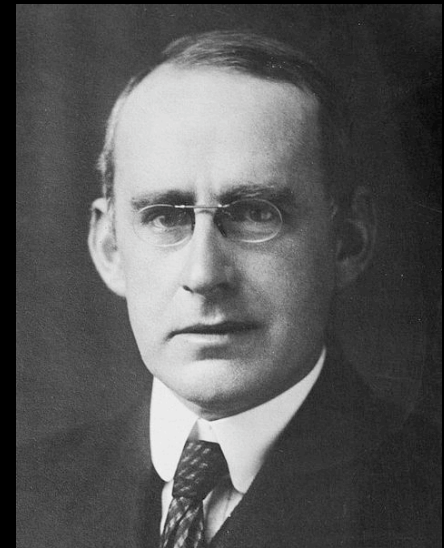


<ftp://ftp.ira.uka.de/pub/cellular-automata/jvn>

- Existence proofs
 - Demonstrate that something is possible (e.g., von Neumann's self-reproducing automaton, patents)
 - Validation: it works

How do we use models?

- Building intuitions about how complex systems work (**exploratory**):
 - Examples: Flight simulators, Sim City.
 - Study how patterns of behavior, how resources flow, how co-operation arises, arms races.
 - Sensitivity analysis.
 - Discovering lever points for intervention, e.g., vaccines
 - Validation? (Trust, allows a pilot to land safely).



“The contemplation in natural science of a wider domain than the actual leads to a far better understanding of the actual.” A.S. Eddington. (first test of Einstein's Theory of Relativity experimentally)

Not everyone agrees

- Def. “Modeling is the application of methods to analyze complex, real-world problems in order to make predictions about what might happen with various actions.” [Shiflet and Shiflet, 2006]
- “Models are metaphors that explain the world we don’t understand in terms of worlds we do. They are **merely analogies**, provide partial insight, stand on someone else’s feet. Theories stand on their own feet, and rely on no analogies.” [Emanuel Derman, 2012]

How do we evaluate a model?

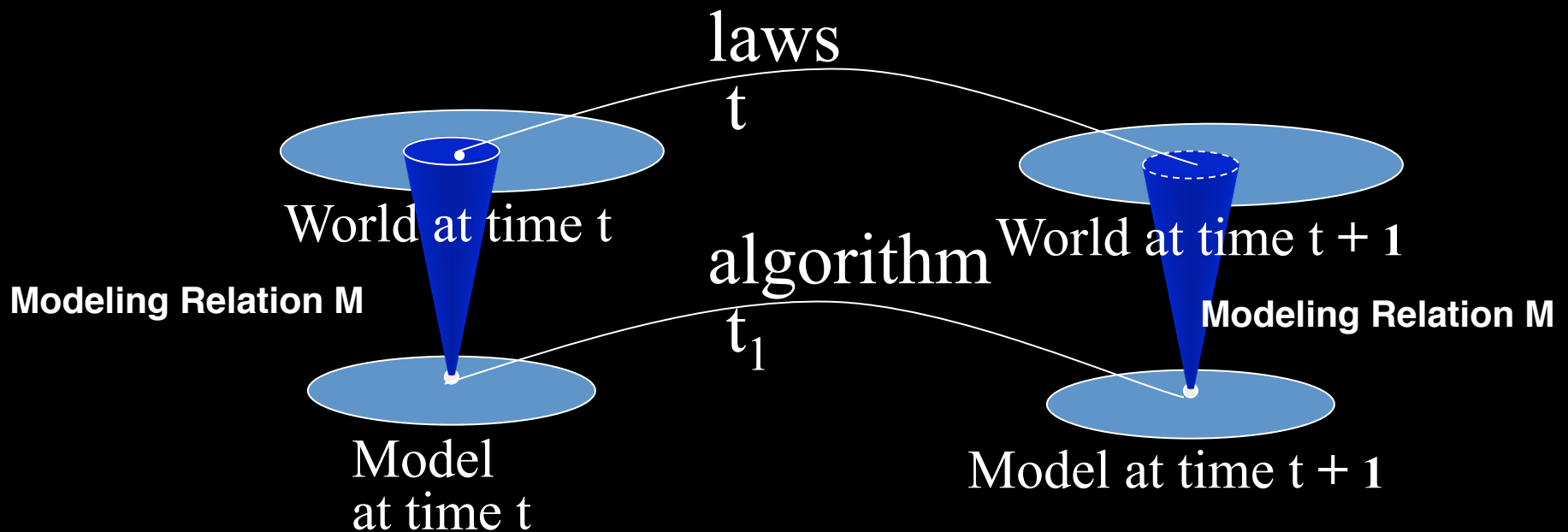
- Parsimony and simplicity
 - Occam's Razor (select the competing hypothesis that makes the fewest new assumptions, when the hypotheses are equal in other respects)
- Accuracy of predictions
 - R^2 and other statistical tests
- Dynamical model works as claimed:
 - Run it. E.g., patented devices.
- Cogency and relevance of ideas that they produce.
- Falsifiability.
- Consistency---formalize notion of model as a *homomorphic map*.

A Framework for Modeling *based on homomorphic maps*

- From An Introduction to Cybernetics by Ross Ashby (1957)
- The black box (from electrical engineering)
 - Given a sealed box that has terminals for input and terminals for output
 - Determine the contents (internal rules) of the box
 - Applies to any system whose internal mechanisms are not fully open to inspection, e.g., the brain
 - How should the experimenter proceed to understand the black box?
 - What properties of the box are discoverable and which are not?
 - What is the most efficient way to investigate the properties of the box?
- Scientists study only a small fraction of a complex system
 - To what extent can systems justifiably be simplified?
 - How to distinguish good simplifications (models) from bad ones?

Models as Homomorphic Maps

Commutativity of the Diagram



M is an equivalence relation

Model M is valid iff this is a homomorphic map:

$$M(t(x)) = t_1(M(x)), \text{ for all } x$$

Remarks

- What if the inside of the box is not deterministic?
 - Search set of inputs/outputs that take more variables into account (**refine the model**) and see if the results is deterministic. **OR**
 - Look for statistical determinacy, i.e., determinacy in the averages, as in Markov chains.
- Models themselves are seldom regarded in all their detail
 - Only aspect of the model is related to system of study
 - E.g., a tin mouse may be a satisfactory model of a living system, if we ignore the “tinniness” of the model and the “proteinness” of the living mouse
 - Thus, two systems (the system of study and the model) are often related such that a homomorphism of one is isomorphic with a homomorphism of the other.

Common Modeling Assumptions

- Homogeneity (all agents are identical / stateless)
- Equilibrium (no or very simple dynamics)
- Random mixing
- No feedback (learning)
- Deterministic
- No connection between micro and macro phenomena

Models with these assumptions can produce some interesting features, e.g., tipping points (R_0).

Features of Complex Systems

- Heterogeneous agents
- Non-equilibrium (non-linear dynamics)
- Contact structure (networks, nonrandom mixing)
- Learning / Feedback (agents can change behavior)
- Stochastic behavior (interesting behavior in the tails)
- Emergence (multi-scale phenomena)

Modeling Complex Systems is Difficult

- Closed form solutions rarely exist:
 - Features from previous slide
- Detailed simulations are problematic:
 - Can never hope to get all the details correct.
 - Because systems are nonlinear, small errors can have large consequences.
- Evolution is key:
 - Basic components change over time.
 - Individual variants matter (hard to do theory).
- Discreteness (e.g., time, state spaces, and internal variable values)
 - Techniques developed to study nonlinear systems are not always directly applicable
- Spatial heterogeneity

Scientific Models

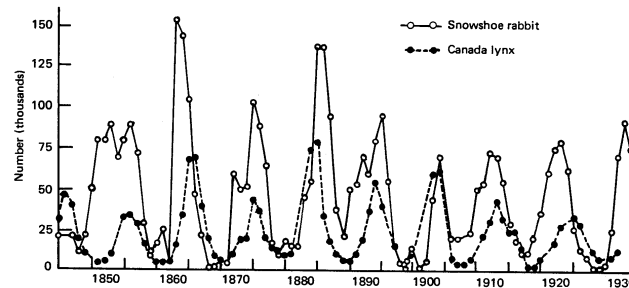
- Continuous vs. Discrete
 - E.g., Differential equation vs. Cellular automaton
- Deterministic vs. Probabilistic
 - Dynamical system vs. Markov chain
 - Cellular automaton vs. genetic algorithm
- Spatial vs. nonspatial
- Data-driven vs. theory-driven
 - Bayesian networks vs. expert system

Classical ODE

(ordinary differential equation)

- Represent how a process changes through time as a differential (difference) equation
 - Time is continuous (discrete)
 - Model components are continuous (density)
 - Deterministic
 - Nonspatial (in standard case)

$$\frac{dx}{dt} = Ax - Bxy$$
$$\frac{dy}{dt} = -Cy + Dxy$$



ODE Characteristics

- Describes the global behavior of a system
- Averages out individual differences (stateless)
- Assumes infinite size populations of model components
 - E.g., all possible genotypes always present in population
- Spatial homogeneity
- Easier to do theory and make quantitative predictions
- Examples
 - Maxwell's equations
 - Mackey-Glass systems
 - Lotka-Volterra systems

Cellular Automata (CA)

- Basic model
 - Regular arrangement (lattice) of cells
 - Cells are in one of a finite number of states each time step
 - All cells have the same synchronous update rule
 - Cells have a local interaction neighborhood

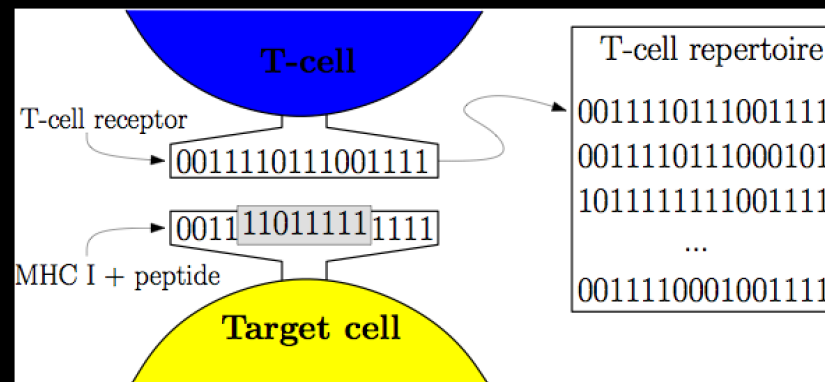


CA Characteristics

- Naturally spatial and discrete
- Individuals have state
 - But all cells have the same rule set
 - Cleverness required to design the uniform rule set
 - Correspondence: What does each cell represent?
- Mathematical analysis is challenging
- Examples
 - Hydrodynamics, fluid dynamics
 - Forest fire simulation
 - Ferro magnetic modeling (ISING models)

Agent-based Models (ABM)

- A computational artifact that captures essential components and interactions (I.e. a computer program)
 - Each component represented explicitly
 - Aids visualization
- Study the behavior of the artifact, using theory and simulation:
 - To understand its intrinsic properties, and wrt modeled system.
- CAs are a kind of minimal ABM



ABM Characteristics

- Encodes a theory about relevant *mechanisms*:
 - Mechanisms give rise to macro-properties without being built in from the beginning
 - Very different kind of explanation than simply predicting what will happen next
 - Example Cooperation emerges from iterated PD model
 - Simulation as a basic tool
 - The mechanistic theory cannot always be stated cleanly
- Many contingent behaviors
- Limited scalability (time, error rates, population sizes)
- No single answer, how to interpret results?
 - Observe distribution of outcomes
- Examples:
 - Cellular automata
 - Genetic algorithms
 - Digital immune systems
 - Sugarscape
 - Stock market models

Studying Complex Systems with ABM

(taken from Axelrod, 2005)

- Can address problems that are fundamental to many disciplines:
 - Path dependency
 - Effects of adaptive vs. rational behavior
 - Effects of network structure
 - Cooperation among egoists
 - Diffusion of innovation
- Facilitate interdisciplinary collaboration:
 - “A prosthesis for interaction”
- Useful tool when closed form mathematical analyses are intractable
 - E.g., the evolution of sex
- Can reveal unity across disciplines
- Can be a “hard sell”
 - Reality vs. clarity

How do we build models?

- Three elements in a computational model:
 - The system of interest
 - The model
 - The computer
- Modeling: The relationship between the real system and the model
- Simulation: The relationship between the computer and the model

Basic Modeling Approaches

- Top-down
 - Analyze problem / system of interest
 - Collect data: Live with your data!
 - Formulate a model
 - Make simplifying assumptions
 - Determine variables and model relationships between them, and submodels
 - Solve/run model
 - Compare to data
- Bottom-up
 - Collect data (training data)
 - Formulate a model to account for the data
 - Test model on additional data for goodness of fit