Prospects (and perils) of modeling
“Idea” models

• Show that a proposed mechanism for a phenomenon is plausible

• Explore general mechanisms underlying behavior

• Explore effects of topology, parameters, etc. on behavior
Examples:

• “What are the logical requirements for self-reproduction? (Von Neumann, 1966)

• “Under what circumstances will population growth be predictable?” (May, 1976)

• “Does distributing a population of Prisoner’s Dilemma agents in space cause them to cooperate without requiring iterated games?” (Nowak and May, 1992)
Advantages of idea models

• Notion of “intuition pump” (Dennett, 1984)

• Allows exploration and understanding of core ideas of highly complicated systems

• Allows possibility for mathematical analysis

• Provides inspiration for new kinds of technology and computing methods
<table>
<thead>
<tr>
<th>Technique</th>
<th>Originating idea model</th>
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<tbody>
<tr>
<td>Programmable computers</td>
<td>Turing (&quot;Turing machine&quot;) model of human mathematical thought</td>
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<tr>
<td>Cellular automata</td>
<td>Von Neumann self-reproducing automaton (1966)</td>
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<td>Neural networks</td>
<td>McCulloch &amp; Pitts &quot;logical calculus&quot; of neural activity (1943)</td>
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<td>Genetic algorithms</td>
<td>Holland model of adaptation (1975)</td>
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<td>Artificial immune systems</td>
<td>Minimal models of immune system</td>
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<td>(Farmer, Packard, and Perelson, 1986; Forrest et al. 1993)</td>
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<td>Swarm intelligence</td>
<td>Deneubourg, Bonabeau, Theraulaz, minimal models of insect behavior (1996)</td>
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Perils of complex systems modeling

• Every modeling project has “perils”.

• Let’s look at two examples of the possible perils in minimal models.

  (Chosen for pedagogical reasons, not to criticize anyone in particular. Examples of these perils are in many, if not most computer models.)

• Then let’s summarize the lessons learned.
Hofstadter’s “Luring Lottery”

From Hofstadter’s *Metamagical Themas* column in *Scientific American*:

"This … brings me to the climax of this column: the announcement of a Luring Lottery open to all readers and nonreaders of *Scientific American*. The prize of this lottery is $1,000,000/N, where N is the number of entries submitted. Just think: if you are the only entrant (and if you submit only one entry), a cool million is yours! Perhaps, though, you doubt this will come about. It does seem a trifleiffy. If you'd like to increase your chances of winning, you are encouraged to send in multiple entries without limit. Just send in one postcard per entry. If you send in 100 entries, you'll have 100 times the chance of some poor slob who sends in just one."
Come to think of it, why should you have to send in multiple entries separately? Just send one postcard with your name and address and a positive integer (telling how many entries you're making) to:

Luring Lottery
c/o Scientific American
415 Madison Avenue
New York, N.Y. 10017

You will be given the same chance of winning as if you had sent in that number of postcards with ‘1’ written on them. Illegible, incoherent, ill-specified, or incomprehensible entries will be disqualified. Only entries received by midnight June 30, 1983 will be considered.”

What do you guess happened?
<table>
<thead>
<tr>
<th>Number of entries submitted</th>
<th>Number of participants submitting</th>
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</thead>
<tbody>
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<td>2</td>
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<td>602 300 000 000 000 000 000 000 000 000 000 000 000 (Avogadro's number)</td>
<td>1</td>
</tr>
<tr>
<td>$10^{100}$ (a googol)</td>
<td>9</td>
</tr>
<tr>
<td>$100^{10^{100}}$ (a googolplex)</td>
<td>14</td>
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Example 1: Prisoner’s Dilemma

- Prisoner’s Dilemma:

<table>
<thead>
<tr>
<th>Player 1</th>
<th>Player 2</th>
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</thead>
<tbody>
<tr>
<td>cooperate</td>
<td>3, 3</td>
</tr>
<tr>
<td>defect</td>
<td>5, 0</td>
</tr>
</tbody>
</table>

- One of the most famous and influential idea models in the social sciences

- Meant to model social dilemmas, arms races, etc.

- Invented by Flood and Dresher in 1950s

- Studied most extensively by Axelrod (e.g., *The Evolution of Cooperation*, 1984)
• Dilemma: It’s better for any particular individual to defect. But in the long run, everyone is better off if everyone cooperates.

• So what are the conditions under which cooperation can be sustained?

  – This has been investigated by many people using agent-based models:
    • Iterated games
    • Norms and metanorms
    • Spatial distribution of players
Iterated games

Example game

See Netlogo model (PD two-person iterated)

Axelrod’s tournament

Axelrod’s genetic algorithm

How to represent strategies?
Norms

• “Norm”: Behavior prescribed by social setting. Individuals are punished for not acting according to norm.

• Examples:
  – Norm against cutting people off in traffic.
  – Norm for covering your nose and mouth when you sneeze
  – Norm for governments not to raise import taxes without sufficient cause
Axelrod’s (1986) Norms model

Norms game: $N$-player game.

1. Individual $i$ decides whether to cooperate ($C$) or Defect ($D$).

   - If $D$:
     - Individual gets "temptation" payoff $T=3$
     - Inflicts on the $N-1$ others a "hurt" payoff ($H=-1$).

   - If $C$, no payoff to self or others.
2. If \( D \), there is a (randomly chosen) probability \( S \) of being seen by each of the other agents.

Each other agent decides whether to punish the defector or not.

Punishers incur “enforcement" cost \( E = -2 \) every time they punish a defector with punishment \( P = -9 \).
**Strategy** of an agent given by:

- **Boldness** (propensity to defect)

- **Vengefulness** (propensity to punish defectors).

\[ B, V \in [0,1]. \]

\( S \) is the probability that a defector will be observed defecting.

An agent defects if \( B > S \) (probability of being observed).

An agent punishes observed defectors with probability \( V \).
• A population of 20 agents play the Norms game repeatedly.

• **One round:** Every agent has exactly one opportunity to defect, and also the opportunity to observe (and possibly punish) any defection by other players that has taken place in the round.

• **One generation:** Four rounds.

• At beginning of each generation, agents’ payoffs set to zero.

• At end of generation, new generation is created via selection based on payoff and mutation (i.e., genetic algorithm).
Axelrod’s results (Norms)

- Axelrod performed five independent runs of 100 generations each.

- **Intuitive expectation for results:** Vengefulness will evolve to counter boldness.
Actual results (Norms model)

(From Axelrod, 1986)
Actual results (Norms model)

- = results of one run

: Take all 100 generations for all 5 runs, yielding 500 populations. Group populations with similar average B and V, and measure average B and V one generation later.

(From Axelrod, 1986)
Actual results (Norms model)

“This raises the question of just what it takes to get a norm established.”

(From Axelrod, 1986)
Metanorms model

- On each round, if there is defection and non-punishment when it is seen, each agent gets opportunity to meta-punish non-punishers (excluding self and defector).

- **Meta-punishment payoff** to non-punisher: -9

- **Meta-enforcement payoff** to enforcer: -2 every time it meta-punishes
Results (Metanorms model)

(From Axelrod, 1986)
“[T]he metanorms game can prevent defections if the initial conditions are favorable enough.“ (i.e., sufficient level of vengefulness)

(From Axelrod, 1986)
• Conclusion: “Metanorms can promote and sustain cooperation in a population.”
Re-implementation by Galan & Izquierdo (2005)

- Galan & Izquierdo showed:

1. Long term behavior of model significantly different from short term.

2. Behavior dependent on specific values of parameters (e.g., payoff values, mutation rate)

3. Behavior dependent on details of genetic algorithm (e.g., selection method)
Re-Implementation results

(From Galan & Izquierdo, 2005)

Norms model: Norm collapse occurs in long-term on all runs.

(Norm collapse: average $B \geq 6/7$, average $V \leq 1/7$
Norm establishment: average $B \leq 2/7$, average $V \geq 5/7$)
Metanorms model: Norm is established early, but collapses in long term on most runs.
(From Galan & Izquierdo, 2005)

**Metanorms Model: Mutation Rate = 0.001**

- **Norm Collapse**
- **Norm Establishment**

*Graph showing the proportion of norm establishment and collapse over generations.*
Proportion or runs where the norm has collapsed

(From Galan & Izquierdo, 2005)
Conclusions from Galan & Izquierdo

• Not intended to be a specific critique of Axelrod’s work.

• Analysis in G&I paper required a huge amount of computational power, which was not available in 1986.

• Instead, re-implementation exercise shows that we need to:
  – Replicate models (Axelrod: "Replication is one of the hallmarks of cumulative science."
  – Explore parameter space
Conclusions from Galan & Izquierdo

- Run stochastic simulations for long times, many replications
- Complement simulation with analytical work whenever possible
- Be aware of the scope of our computer models and of the conclusions obtained with them.
Example 2: Spatial games and chaos


- Experimented with “spatial” Prisoner’s Dilemma to investigate how cooperation can be sustained.
Spatial Prisoner’s dilemma model

- Players arrayed on a two-dimensional lattice, one player per site.

- Each player either always cooperates or always defects. Players have no memory.

- Each player plays with eight nearest neighbors. Score is sum of payoffs.

- Each site is then occupied by highest scoring player in its neighborhood.

- Updates are done synchronously.
NetLogo PD Basic Evolutionary model
Nowak and May’s results

Sample of patterns that arise from different initial conditions.

Blue: cooperator at a site that was a cooperator in previous generation.
Red: defector following a defector.
Yellow: defector following cooperator.
Green: cooperator following defector.
• In general, different initial configurations and different payoff ratios can generate oscillating or “chaotically changing” patterns in which cooperators and defectors coexist indefinitely.

• Contrasts with non-spatial multi-player Prisoner’s Dilemma in which defectors dominate without special additions (e.g., metanorms).
Interpretation

• Motivation for this work is “primarily biological”.

• “We believe that deterministically generated spatial structure within populations may often be crucial for the evolution of cooperation, whether it be among molecules, cells, or organisms.“

• "That territoriality favours cooperation...is likely to remain valid for real-life communities“  (Karl Sigmund, *Nature*, 1992, in commentary on Nowak and May paper)
Re-implementation by Glance and Huberman (1993)

• “There are important differences between the way a system composed of many interacting elements is simulated by a digital machine and the manner in which it behaves when studied in real experiments.”

• Asked: What role does the assumption of synchronous updating have in the behavior observed by Nowak and May?

• "In natural social systems... a global clock that causes all the elements of the system to update their state at the same time seldom exists."
Glance and Huberman’s results

**Synchronous**

Same initial configuration: a single defector in the center.

**Blue:** cooperator at a site that was a cooperator in previous generation.

**Red:** defector following a defector.

**Yellow:** defector following cooperator.

**Green:** cooperator following defector.

**Asynchronous**
Glance and Huberman’s conclusion

"Until it can be demonstrated that global clocks synchronize mutations and chemical reactions among distal elements of biological structures, the patterns and regularities observed in nature will require continuous descriptions and asynchronous simulations."

Note: Show model with “nonlocal” interactions
Nowak, Bonhoeffer, and May response (PNAS, 1994)

• Huberman & Glance performed simulation for only one case of the “I defect, you cooperate” payoff value $p$.

• Sequential, rather than synchronous, updating of sites, still leads to persistence of both cooperation and defection for a range of $p$ values.

Behavior with other forms of asynchronous updating (e.g., random)?
Summary

Some prospects for idea models:

– Often no other way to make progress!

– “All models are wrong. Some are useful.”

– All the ones I talked about here were useful and led to new insights, new ways of thinking about complex systems, better models, and better understanding of how to build useful models.
Some perils for minimal models:

– Hidden unrealistic assumptions

– Sensitivity to parameters

– Unreplicability due to missing information in publications

– Misinterpretation and over-reliance on results

– Lack of theoretical insight
Summary

How to overcome perils:

1. Replicate, replicate, replicate!

   Independent replication of computer models is essential for progress is complex systems

   Community of scientists and funding agencies needs to recognize this as a worthwhile, publishable, fundable activity

2. Write your own code.
3. Question assumptions of models

4. Explore parameter space

5. Complement simulation with analytical work

6. Understand and emphasize limitations of your model.

7. Give enough details in your paper that someone else can replicate your experiments!
The ‘edge of chaos’ in cellular automata
(C. Langton, 1992)

• Langton devised an “order parameter” for cellular automata

\[ \lambda = \frac{\text{number of non-quiescent states in rule table}}{\text{length of rule table}} \]

• Building on Wolfram’s classes of behavior for CA, Langton found evidence that cellular automata can be “ordered” or “chaotic” roughly according to \( \lambda \).
• Langton gave some evidence that the “complexity” of patterns formed by cellular automata is maximized at the transition between order and chaos

• He argued that the potential for computation must be maximized at this “phase transition”. (Need long transients, information carrying signals, etc.)
The ‘edge of chaos’ in cellular automata (Packard, 1988)

• Packard used a genetic algorithm to evolve cellular automata to perform a computation (the “density classification task”):

• Hypothesis: Resulting CAs will end up at a $\lambda$ value near the “edge of chaos”.
Gamma: measure of chaos at each $\lambda$ value

Packard’s GA: fraction of rules at each $\lambda$ value
**Gamma:** measure of chaos at each $\lambda$ value

**Packard’s GA:** fraction of rules at each $\lambda$ value

**Mitchell, Hraber, & Crutchfield (1994):** fraction of rules at each $\lambda$ value
What caused the discrepancies?

• Theoretical result (Das, Mitchell, & Crutchfield, 1994) shows $\lambda$ has to be 0.5 to do well on this task.

  (Note that $\lambda \approx 0.5$ does not mean chaotic here.)

• Via personal communication, we found out that the original GA included injections of many random CAs with various densities into the population at each generation, in order to prevent convergence.
• It seems that this, and other non-standard details of the GA, were the cause of the behavior Packard observed, rather than any intrinsic advantage of particular $\lambda$ values.

• In fact, not clear that particular $\lambda$ values were correlated with high fitness CAs.