Modelling complex social systems: opportunities and challenges

Nigel Gilbert

University of Surrey
Guildford
UK

http://cress.soc.surrey.ac.uk
Overview

• Social systems are complex...
  ✦ non-linear
  ✦ multi-level
  ✦ emergent
  ✦ open systems

• but are not the same as complex physical systems
  ✦ second-order emergence
  ✦ social construction

• We can use agent-based models to understand complex social systems

• These models provide lots of opportunities but also some challenges
Complex systems are non-linear

- A simple forest fire model
  - Forest
    - 2-d grid network of trees
  - Fire
    - Wall of flame along left edge at start
    - Fire ignites any neighbouring trees

- Related to all kinds of spreading phenomena:
  - Disease networks
  - Word-of-mouth advertising in social networks
  - Impact of changes in an organisation consisting of interdependent parts
Complex systems are non-linear
Complex systems are non-linear

- Vulnerability to fires undergoes a phase transition

- There is an optimal initial density for post-fire density

Percent burned by Initial tree density

Final density by Initial tree density
Social Systems are non-linear

• Power law relationships (Pareto distribution, Yule distribution, Matthew effect) are straight lines when plotted on a log-log scale

• They are everywhere, once you start looking!
  ♦ distribution of wealth (Pareto)
  ♦ word frequency (Zipf)
  ♦ citations (Simon, de Solla price)
  ♦ web site popularity
  ♦ size of human settlements
  ♦ rail traffic through railway stations
Multi-level
• The scientific community
• Disciplines
• Specialties
• Papers
• Citations/references
Modelling knowledge: Kenes

• Kene: an idea which can evolve and mutate into other ideas
  ♦ each paper has one kene
  ♦ a new paper combines the kenes of the papers it cites + some mutation (new ideas)

• New papers are ‘rejected’ if they are not original (a paper with the same or very similar kene has already been published)

• Old papers generate (potential) new papers with uniform probability

• New papers choose a new author with some probability, or an existing author at random with uniform probability

• Authors stop publishing (stop being in the pool of potential authors) at random with a fixed probability
A picture of science
Model and reality

Comparing data about the journal *Research Policy* with the mean of 30 runs of the model.
Emergent
Emergence

http://www.traffic-simulation.de/
Path dependent

Central London:
Poverty 1896 (deep red = poorest)
Poverty 1991 (deep red = poorest)
Standardised mortality ratio, 1991 (~ lifespan)

Open systems
Open systems

World energy supply and demand, from
But...

- But while these are also features of many biological and even some physical systems, social systems have their own characteristics
  - these mainly arise from the fact that people can think and talk!
    - categories are constructed
    - analyses are reflexive
    - second-order emergence
- Consequently, methods of analysis imported from the natural sciences should be applied with caution in the social sciences
### Complex systems

<table>
<thead>
<tr>
<th>Physical systems</th>
<th>Living systems</th>
<th>Social systems</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>particles</strong> which</td>
<td><strong>living things</strong> which</td>
<td><strong>human actors</strong> which</td>
</tr>
<tr>
<td>• obey natural laws</td>
<td>• are partly autonomous</td>
<td>• are autonomous</td>
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<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
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<tbody>
<tr>
<td>• interact only in a few different modes</td>
<td>• interact in several different modes</td>
<td>• interact in numerous different modes</td>
</tr>
<tr>
<td>• have no roles</td>
<td>• can play different roles</td>
<td>• take on different roles even at the same time</td>
</tr>
<tr>
<td></td>
<td>• are only partly conscious of their roles and interactions</td>
<td>• are conscious of their interactions and roles</td>
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<tr>
<td>• do not communicate</td>
<td>• communicate only in a very restricted manner (and never about counterfactuals)</td>
<td>• communicate in symbolic languages even about counterfactuals</td>
</tr>
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</table>
Social construction

- e.g. labelling theory
  - the labels applied to individuals influences their behaviour, often towards making their behaviour more like that implied by the label

- e.g. the reflexive nature of social indicators
  - the police collect statistics on crime by locality
  - some areas seem to have more criminality than others
  - hence these areas are policed more heavily than lower crime areas
  - hence the amount of detected crime in these areas remains high
  - then social scientists point this out
  - ....
London burglary crime map
Second order emergence

- Interaction at the individual (‘micro’) level yields patterns at the global (‘macro’) level
- These patterns remain even though the individuals come and go
- The patterns are recognised by people, who name them and respond to them
  - So the macro feeds back onto the micro: second-order emergence

Schelling residential segregation model, but with desired locations influenced by the predominant ethnicity of the neighbourhood/cluster
Models
Agent-based models

- **Agents** are units that have behaviour
- They act within a (simulated) **environment**
- Agents have
  - **perception**
  - **performance**
  - **policy**
  - **memory**
- **Macro-level features** can emerge from the interaction of agents
Agents

• Distinct parts of a computer program, each of which represents a social actor
• Agents may model any type of social actor
  ✦ Individuals
  ✦ Firms
  ✦ Nations
  • etc.
• Properties of agents:
  ✦ Perception
  ✦ Performance
  ✦ Policy
  ✦ Memory
Environment

• Options:
  ✦ Geographic space
  ✦ Analogues to space e.g. knowledge space
  ✦ Network (links, but no position)

• The environment provides
  ✦ Resources
  ✦ Communication medium
Interaction

- Information flows or is passed from one agent to another through
  - (coded) messages
  - direct transfer of knowledge
  - by-products of action
ABM methodology

• Find or develop a theory
• Propose some agent actions and the contexts in which they occur
  ✦ ‘micro foundations’
• Create a model
  ✦ representing agents and their interactions in an environment
• Observe the behaviour of the model
  ✦ macro behaviours
• Compare the output of the model with observations of the social world
The Growth of Agent-Based Computational Experiments

data from searches of Web of Science

with thanks to James Kitts
Opportunities
Opportunities arising from adopting an ABM approach

• provides a way of thinking about the ‘micro-macro link’ which dissolves some of the historical puzzles

• encourages a greater focus on process and dynamics
  ✦ much social science is too concerned with ‘now’, to the neglect of how we got to where we are
  ✦ cf correlational analyses of one-shot surveys

• encourages a greater focus on geography and network links
  ✦ taking into account spatial and network interaction
  ✦ cf structural equation/econometric modelling

• demands greater attention to identifying ‘mechanisms’
  ✦ cf cause and effect induced from correlations
Peer reviewed articles

**Why Bother with What Others Tell You? An Experimental Data-Driven Agent-Based Model**
Riccardo Boero, Giangiacomo Bravo, Marco Castellani and Flaminio Squazzoni

**When Does a Newcomer Contribute to a Better Performance? A Multi-Agent Study on Self-Organising Processes of Task Allocation**
Kees Zoethout, Wander Jager and Eric Molleman

**Leadership in Small Societies**
Stephen Younger

**A Tag-Based Evolutionary Prisoner's Dilemma Game on Networks with Different Topologies**
Jae-Woo Kim

**Interorganizational Information Exchange and Efficiency: Organizational Performance in Emergency Environments**
Adam Zagorecki, Kilkon Ko and Louise K. Comfort

**Co-Operation, Punishment and Group Size: Social Cohesion**
Meyer, Matthias, Lorscheid, Iris and Troitzsch, Klaus G. (2009). ‘The Development of Social Simulation as Reflected in the First Ten Years of JASSS: a Citation and Co-Citation Analysis’. Journal of Artificial Societies and Social Simulation 12 (4)12 <http://jasss.soc.surrey.ac.uk/12/4/12.html>. 

JASSS co-citation network, 2002 - 2007
Current foci

- Diffusion over networks
- Modelling pitfalls
- Model alignment
- Simulation and social theory
- Cognitive agents
- Reputation
- Reciprocity and altruism
- Opinion dynamics
- Environment and resource management
- Norms
- Social order and social systems
- Behavioural economics
- Evolution and learning
Challenges
Challenges

• **Prediction**
  - what can we predict, in principle?
  - what can we predict, in practice?
  - how can predictions be made believable?

• **Scale**
  - simple versus complicated models
  - are there qualitative differences between the behaviour of models with 10 and millions of agents?

• **Validation**
  - how do we validate complex models?
  - where do we get large scale, temporal, individual data from?

• **Agent Learning** and adaption

• **Cumulation**
  - building on others’ work
The limits of prediction

• What, in principle and in practice, can we predict?
  ✦ NO
  • the FTSE index next year
  • the weather in a month’s time
  ✦ YES
  • it will not be 40 degrees Celsius in São Paulo in November 2010

• Challenge: formalise what we can and cannot expect to predict

• How can predictions be made believable?
  ✦ The modeller’s “Catch-22”
    • If the model predicts a situation already anticipated, the model is of little practical value
    • If the model predicts a situation not already anticipated, the model must be wrong.
Validation

Convert the model to a black box:

Experiment design
Genetic algorithm
Equation-free methods
Theorem-proofing methods

Challenge: understand the behaviour of models of complex systems
Scale

• **Tools for thinking**
  - relatively simple models
  - few parameters
  - usually highly abstract
  - emergence of social regularities from individual action is the focus

• **Tools for doing**
  - relatively complicated
  - fitted to specific domains, localities or scenarios
  - many parameters

• **Challenge**: clarify the difference between these and their methodologies
Abstract models

• Aim: demonstrate some (probably emergent) social process or mechanism
• No corresponding specific empirical case
• Example:
  ✦ Models of opinion dynamics
  ✦ Evolutionary game theory
• Validation criterion:
  ✦ Does it generate macro-level patterns that seem plausible?
• Problem:
  ✦ Gap between model and empirical data
Example: Opinion dynamics

• Studies of opinion dynamics
  • How (political) opinions change due to people influencing each other

• Agents have
  • An opinion (-1 to +1)
  • An uncertainty about their opinion (0 to \(\infty\))
  • An opinion segment (opinion \(\pm\) uncertainty)

• Agents meet randomly and if their opinion segments overlap, their opinions influence each other, by an amount proportional to the difference between the opinions, and inversely proportional to the influencing agent’s uncertainty. So uncertain agents influence little, and certain ones influence a lot.
Deffuant model of opinion dynamics

Facsimile models

- **Aim:** provide an exact reproduction of some target phenomenon
- **Often intended to provide predictions**
- **Example:**
  - a model of the traffic in a city, used to predict locations of potential jams
- **Validation criterion**
  - does it lead to accurate predictions?
- **Problem:**
  - accurate predictions may be impossible for complex systems; implicit ceteris paribus may be untenable
Middle range models

- **Aim:** understand the generative mechanisms that lead to a particular social phenomenon
- **Should be applicable to many specific cases**
- **Example:**
  - models of epidemics, innovation networks, utility markets
- **Validation criteria:**
  - qualitative resemblance
  - similar dynamics

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*Fig. 6.3-2. The density of infected locations on day 128 of the base case epidemic, when the epidemic is at its peak, for 10 a.m.*

From [http://public.lanl.gov/stroud/LACaseStudy5.pdf](http://public.lanl.gov/stroud/LACaseStudy5.pdf)
Middle-range agent-based models are good for communication

• The housing model incorporates elements from the disciplines of:
  † economics
  † sociology
  † social policy
  † urban planning
  † geography
  † ....

• and possibly hydrology, geology, ...
Learning

- People learn
  - Most agents don’t (yet)
- Individual learning
  - Reinforcement learning
    - trial and error
    - reinforce actions that led to success, penalise error
  - Evolution
    - Natural selection at the population level
- Learning and teaching
  - first, a language is needed to communicate
- Challenge: build good models with learning
Cumulation

• Must every model be different? Are we always condemned to re-invent the wheel?

• No!
  
  ✦ Methodology
  - a gradually improving understanding of how to design, build and validate models

  ✦ Composition
  - ABM building blocks
  - Abstract social processes or social mechanisms
Summary

• Social systems are complex
  ✦ To understand complex systems, one needs computational methods
  ✦ Agent-based models are a useful tool
  ✦ But people are not particles

• There are huge opportunities for computational social science

• And some interesting challenges
More information

http://www.jiscmail.ac.uk

http://jasss.soc.surrey.ac.uk/JASSS.html

http://www.openabm.org/
Thank you

n.gilbert@surrey.ac.uk