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Integrating Agent-Based Models with Quantitative and Qualitative Research Methods

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Abstract: This paper will describe a mixed methodology that combines Agent-Based models of human behaviour with quantitative and qualitative research methods. A decision matrix for selection of a research method for education studies will be presented.

The methodology of social and behavioural research has undergone dramatic changes over the last 50 years. For most of the 20th century, social and behavioural research has been dominated by quantitative methods which relied heavily on objective measures and numbers.

Researchers dissatisfied with this dominant methodology have developed qualitative research methods to study humans in a natural setting. Research studies using this method analyse words not numbers to give a complex, holistic picture based on the narrative information from the study. As a result of the discussions and controversies between the two camps a mixed methodology has evolved as a way of using the strengths of both approaches.

Agent-based modelling is a new way of doing science that has developed form the concepts and techniques of complexity theory. It involves the study of many actors and their interactions. The models start with simple rules of learning and assumptions but will display complex behaviours. This tool is compatible with quantitative and qualitative research methods.

Key Words: Agent-Based Models, Philosophy of Social Science, Mixed Research Methods

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A third way of doing Science

Robert (Axelrod, 1997) has described Agent-Based Modeling as the third way of doing science in contrast with the two standard methods of induction and deduction.

Deduction involves specifying a set of axioms and proving consequences that derive from the assumptions. For example, thermodynamics is a formal system that allows us to deduce interesting consequences from a few simple laws.

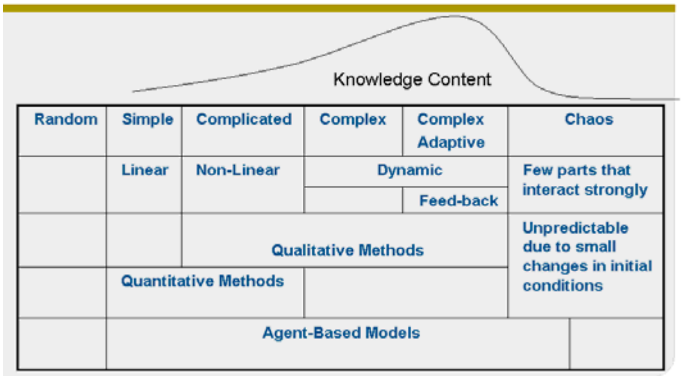
Induction is the discovery of patterns in empirical data. In the social sciences induction is used in the analysis of surveys and interview data.

Agent-Based Modeling is like deduction by starting with explicit assumptions (rules). The model then generates simulated data to be analyzed inductively using quantitative and qualitative tools. Its purpose is to aid intuition and is of value in education research. Joshua Epstein argues that this distinctive approach should be called Generative Social Science (Epstein, 1999).

Agent-Based Models were developed as a tool for complexity theory research. They are used to explore 'complex' systems where the whole is greater than the sum of the parts (Lewin, 1992) (Holland, 1995).

The researcher must understand the basic nature of the systems to make a good choice of research methods. Complexity theory defines phenomenon and systems into six categories that differ on linear, dynamic and knowledge factors (figure 1). Most social systems are complex-adaptive and are at the edge of chaos. Systems in chaos have a few parts that interact strongly. They can be explained by taking a global view but, they are unpredictable due to small changes in initial conditions producing dramatic outputs.

Figure1: Research Method Choice



Complex-Adaptive systems are dynamic and involve feed-back between interacting parts. Experimental results can be explained and used for prediction.

The goal of science is to explain 'causes' by encoding data into simpler 'Laws of Nature' that are easer to understand than the original data (Cornwell, 2004). Random data can not be recoded into a simpler form than the original. Qualitative methods encode the rules using narratives while quantitative methods works with numbers and Agent-based Models define the rules using computer code. A mix of methodologies is of benefit when used for data from complex and complex-adaptive systems.

What are Agent-based Models?
Agent-Based Models (ABM) are computer simulations that represent individual actors in a dynamic system (Gilbert & Troitzch, 1999). Agent-based simulation can capture "real life" social systems on a computer by replicating the behaviors of heterogeneous participants and modeling the interactions between them.

The models of actors are software ‘Agents’ that have:

1. Internal data representations (*memory* or *state*)
2. Means for modifying their internal data representations (*perceptions*)
3. A fixed set of rules which they must follow (*behaviors/decision making*)

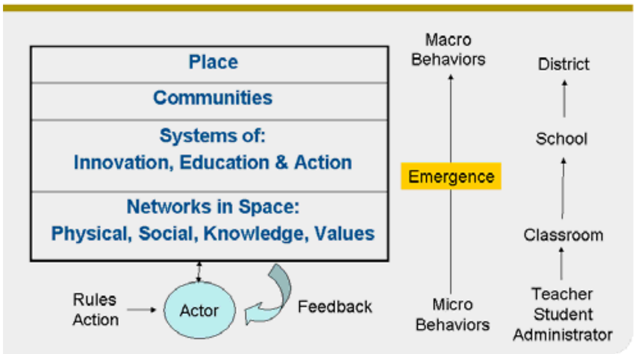
‘Agents’ represent heterogeneous individuals who interact with each other and/or their environment based on a pre-defined set of rules. Agents can be very simple with few rules or complex with many rules. From these interactions, macro-scale behaviors may emerge.

The movement from the low-level rules to higher-level sophistication is called emergence (Holland, 1998). It is a bottom-up not a top-down view of science. For example, the properties of water emerge from the interaction of hydrogen and oxygen atoms not from the sum of the properties of the two gases.

In figure 2 we can see an example from education. Macro behaviors within Communities and Place will emerge from the interactions of actors within networks under systems of innovation, education and action. ABM permits the study of how rules of individual behavior give rise to macroscopic regularities.

Agent-Based Modeling is meant to complement and enhance rather supplant traditional approaches but it is a new way of doing science

Figure 2: Emergence



When to use ABMs
ABMs can become a learning tool for understanding a system under a variety of conditions by simulating the nature of the interactions between the agents in a system. They are particularly useful for evolving/dynamic systems. ABM can be used in a scientific research project or in a classroom as a tool to teach science. The NetLogo web site has 140 models that can be used by students to experiment in a simulated world.

ABM is of use for problems where:

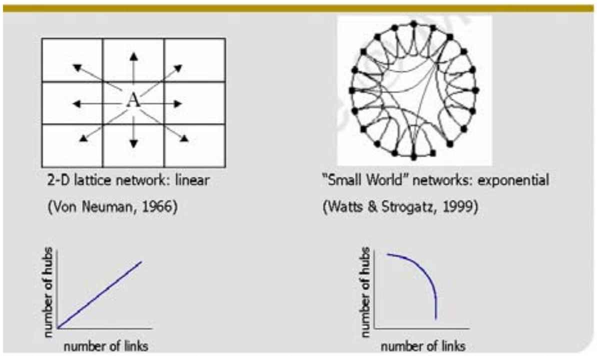
- There are many interrelated factors, high uncertainty, and where a novel approach with competitive differentiation is the goal.
- Emergent behaviors are to be modeled.
- Interactions between agents are complex, nonlinear, or discontinuous
- Spatial issues are of interest, i.e. social networks.
- The population is heterogeneous.
- Agents exhibit learning and adaptive behaviors, i.e. dynamic strategies

Spatial ABMs
ABM consists of a space, framework or environment where interactions take place. Behaviors for this space are defined for the agents with a basic set of rules and by characteristic parameters.

The aim of ABM is to look at global consequences of individual or local interactions in a given space. Agents are seen as the generators of emergent behavior in that space.

Many of the agent models use a 2-D lattice network to represent space (figure 3). The structure of the network over which actors interact in the real world has a significant impact on the efficiency of the communication (Watts & Stogatz, 1998) (Buchanan, 2002).

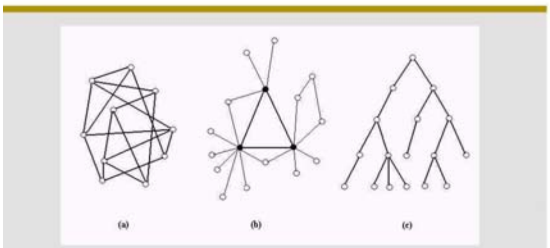
Figure 3: Types of Networks



Actors use different types of networks in space (figure 4). Agents in our models must reflect this complexity.

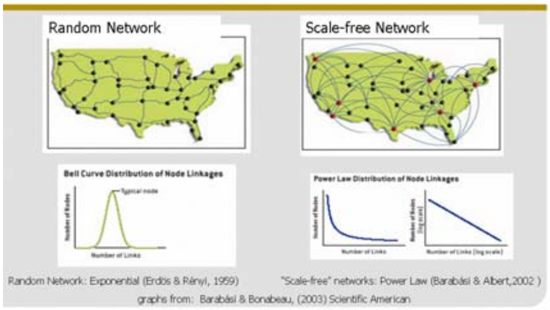
Networks can be classified by looking at the distribution of the number of hubs (agents) that have a set number of links (Barabasi, 2002). The form of this graph is different for each network type, see figure 3 and 5. Scale-free networks, with a power law distribution, are the most efficient structure and are common in biological and social networks. They are networks with a few hubs having many connections but with most hubs having only a few links. The example shown is for the air lines in USA.

Figure 4: Different types of Networks (Space)



Representation of network structures: (a) random, (b) scale-free and, (c) hierarchical

Figure 5: Types of Networks



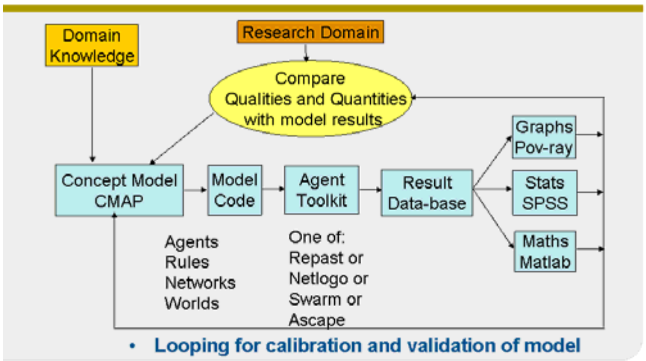
Goals of Good ABM Programming
The starting point is a clear map of the knowledge of the problem area. Tools like Cmap can be used to define this concept model. Agents, rules and networks are defined for the model using If-Then-Else rules and messages (codes, or words) between the agents. This is then translated to the computer code like java.

Validity, usability and extendibility issues have to be addressed during the process. Validity is difficult because the problem is to know whether an unexpected result is a reflection of a mistake in programming or a surprising consequence of the model itself. In validating the program, check micro-dynamics, not just aggregate results. Follow Occam's razor in building models – the simpler, the better. It is easer to use commercial programs for data analysis (for example: Excel, SPSS, and NUD-IST).

The process of building an Agent-based Model is shown in figure 6 and is as follows:

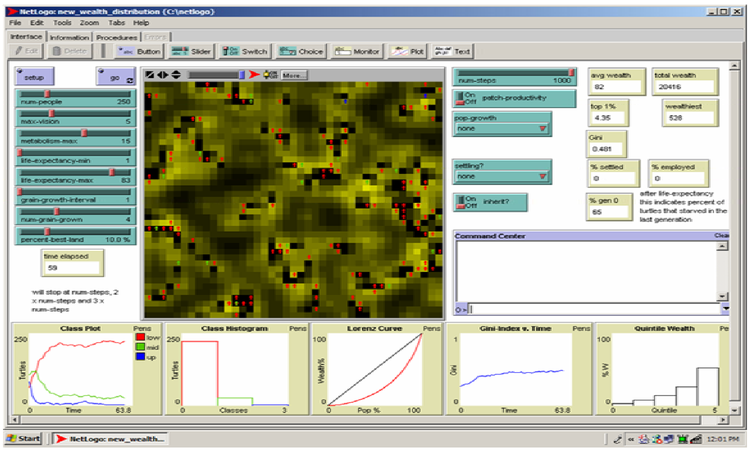
1. Define a concept model using your knowledge of the research domain. This concept map defines the types of agents and their rules; networks, spaces and rules of interaction; rules for worlds and levels of the research domain.
2. Define the quantitative and qualitative data to gather for each time interval.
3. Code rules from the concept model into the computer language of the selected Agent Toolkit (Java or C++).
4. Run the model and compare the results with a calibration data set.
5. Repeat 1 to 4 until model is calibrated.
6. Validate the model using data from the research domain.

Figure 6: Agent-Based Modeling System



Wealth model example: NetLogo

This model simulates the distribution of wealth. "The rich get richer and the poor get poorer" is a familiar saying that expresses inequity in the distribution of wealth. In this simulation, we see Pareto's law, in which there are a large number of "poor" or red people, fewer "middle class" or green people, and many fewer "rich" or blue people.



This model is adapted from Epstein & Axtell's "Sugarscape" model. It uses grain instead of sugar. Each patch has an amount of grain and a grain capacity (the amount of grain it can grow). People collect grain from the patches, and eat the grain to survive. How much grain each person accumulates is his or her wealth.

Education example: SimEd Models

Sklar's Agents Lab at Columbia University has developed a multi-agent simulation of interactions between students, teachers, and administrators (Sklar, Davies, & Co, 2004). The model has three integrated levels: School district, schoolhouse and classroom. SimEd demonstrates how pedagogical and economic policy decisions reach the classroom and effect student learning.

The schoolhouse and school district model has agent rules that define interactions between students, teachers, parents and administrators. Rules model resource allocation and define links to classroom learning model. Factors considered are economic and demographic links to student and school performance.

In the classroom model, the student-teacher interaction is based on the Iterative Prisoner's Dilemma agent-based model of cooperation, (Axelrod, 1984, 1997).

There are two agents involves in a Meta-Game of Learning. The Teacher Agent provides both easy or hard questions and Student Agent respond with either right or wrong answers.

The goal is student learning when both agents cooperate.

The student agent has rules for factors of ability, emotional state and motivation while the model of teacher has factors for the decision of question type.

Figure 7: Meta-Game of Learning

Teacher	Student	
	Right Answer Cooperate	Wrong Answer Defect
Hard Question Cooperate	Learning	Frustration
Easy Question Defect	Verification	Boredom

Conclusion
Agent-Based based models are of value as a tool in education research. Areas like Knowledge Transfer, Diffusion of Innovations**,** Artificial Societies, Learning Organizations and Cultural Issues have active researchers using this methodology.

Resources
SimEd website:
http://agents.ca.columbia.edu/simed
Rauch (2002), 'Seeing Around Corners':
www.theatlantic.com/issues/2002/04/rauch.htm
Santa Fe Institute Working Papers:
www.santafe.edu
Brookings Institute:
www.brook.edu/dybdocroot/es/dynamics/ models/
Cambridge Colloquium on Complexity & Social Networks:
www.ksg.harvard.edu/complexity
Concept mapping tools
http://cmap.ihmc.us

Source of free open source ABM software Tool kits (all Java based)
Ascape:
www.brook.edu/dybdocroot/es/dynamics/models/ascape
RePast/Sugarscape REcursive *Porous Agent Simulation Toolkit*:
http://repast.sourceforge.net/
SWARM:
www.swarm.org/

Netlogo:

http://ccl.northwestern.edu/netlogo/models/community/

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