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Approaching Agent-Based Simulation

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Origins of Social Science Simulation

Computer simulation in the social sciences has at least two types of origins: **equation-based modelling** *vs.* **agent-based modelling** [Parunak/Savit/Riolo 1998:10]

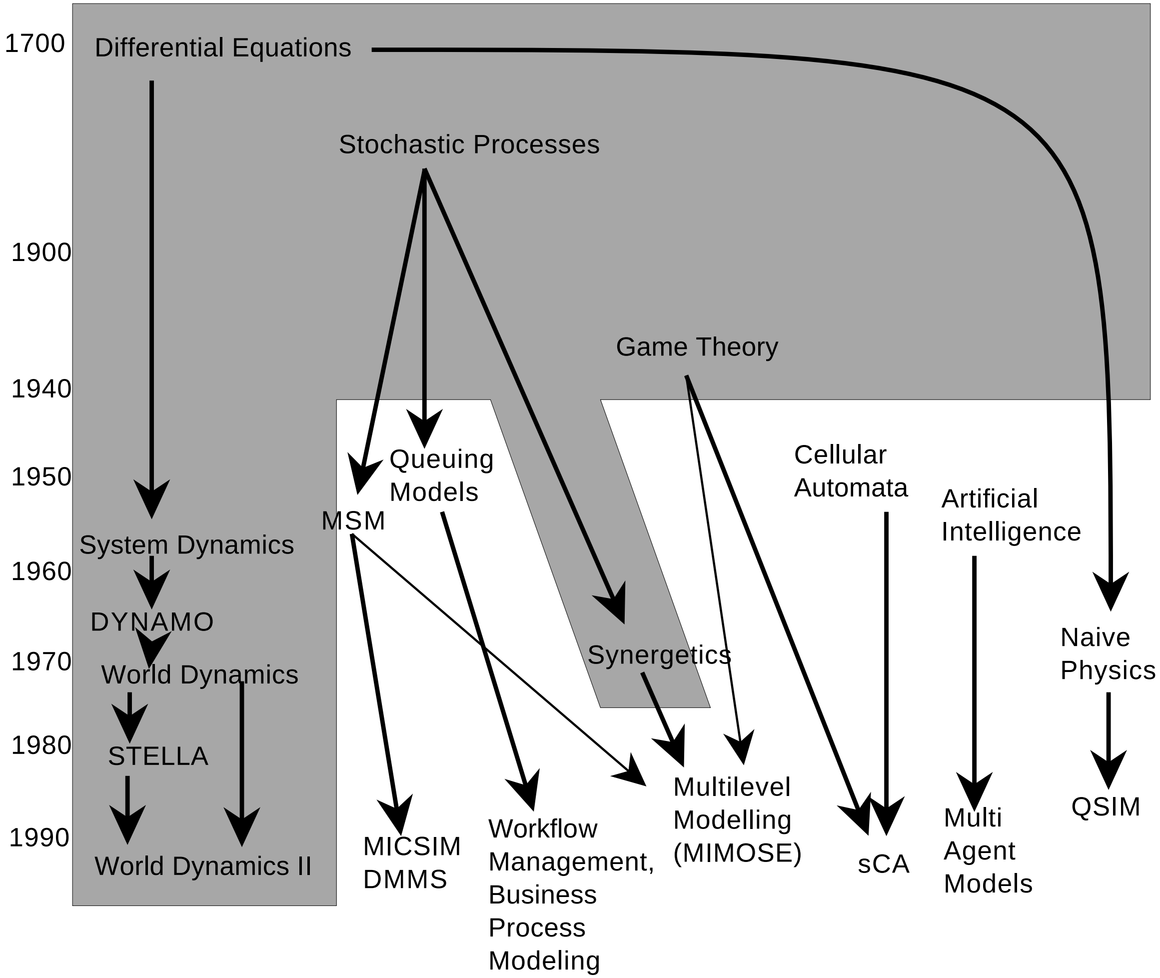
$\Rightarrow$ On the one hand, it continues mathematical modelling and is no more than the numerical treatment of difference equations or the various kinds of differential equations (including partial and stochastical differential equations). Here, a machine is used to manipulate the symbols of the symbol system of mathematics, and this manipulation is more or less restricted to numerical treatment (although some computer help in symbolic computation is sometimes desirable, too).

$\Rightarrow$ On the other hand, computer simulation is used in its own right, not as a substitution for more elegant mathematical solution algorithms, but as a means of manipulating the symbols of the symbol system of programming languages.

Simulation approaches as they are being used in social science nowadays have different origins, as this figure may show. Three of the lines — those starting before the computer era — represent simulation techniques derived from mathematics, while the younger lines come from computer science, especially from artificial intelligence and automata theory. The dividing line between both groups is not that sharp — “cellular automata may be considered as an alternative ⟨to differential equations⟩ and in some respects complementary basis for mathematical models of nature” (Wolfram 1984, vii), so one can be in doubt whether cellular automata is a mathematical or a non-mathematical alternative to (partial) differential equations. If one keeps to Ostrom’s (1988) idea of three different symbol systems used in the social sciences — verbal argumentation, mathematics, computer simulation —, CAs are very likely to be allotted to the third symbol system.

The mathematical means of describing deterministic and stochastic processes (represented by “differential equations” and by a very general “stochastic processes” in that figure) necessitated very different kinds of numerical treatment from their very beginning; game theory did only do so when it was applied to the analysis of processes.

Historical Development of Contemporary Approaches



Common Approaches

Systems Dynamics makes heavy (and, at times, problematic) use of large systems of equations which in some respect resemble differential equations, but which may contain arbitrary discontinuous and non-differentiable functions (which may also be given as tables). Solutions are found, or, rather, trajectories are calculated, by rather coarse-grained algorithms.

Microanalytic simulation models, queuing models, and stochastic multilevel models have in common that analytic solutions do exist for very simple cases. “Solution” here means a stable distribution.

Cellular automata, Distributed Artificial Intelligence, and qualitative simulation models have so far been examined only by means of computer simulation.

Computer simulation as a means to find solutions to mathematical models

Cases:

- Mathematics does not yield a closed analytical solution — which is most often the case in nonlinear, partial, and stochastic equations.

- Mathematical treatment of such equations would lead to a very complicated solution formula which would contribute less to understanding than a graphical representation of selected trajectories of an equation system (or less even than the problem itself).

Computer simulation in its own right

Soon after computer simulation became available to social scientists, they, too, started their first experiments with non-numerical models. But only when in the eighties powerful computing machinery became accessible, the third symbol system could really be used — although there are impressive examples from the early sixties (election and referendum campaigns simulated — an early example of stakeholder orientation!).

(Sola-Pool & Abelson 1962; Abelson & Bernstein 1963; Abelson & Carroll 1965; Abelson 1968)

On the other hand, as Alker (1974) put it in a seminal article, simulation was sometimes found “inelegant” and “atheoretical” as compared to mathematical models.

Alker's position

- "Computer representations can be and have been developed quite closely to contemporary verbal social science theories. . . . These formalizations help the investigator to check for consistency, to test for empirical fits and to derive new theoretical and practical implications. . . . Social simulations are no more valid and, if poorly formalized, they are probably even less valid than the theories they embody.

- Such simulations should not be automatically debunked as inelegant mathematics. . . . Social systems are open systems. . . . An open simulation is bad mathematics even if it is a good social system representation.

- If synthetic computer representations allow for a larger class of theoretical manipulations than previous analytic exercises, this does not mean that higher orders of mathematical analysis and insight are not called for as well."

(Alker 1974, 152–154)

Ostrom's Third Symbol System

Computer simulation is a third symbol system in its own right and an alternative to mathematical formalization of social science theories.

$\Rightarrow$ Simulation is neither good nor bad mathematics, but no mathematics at all. The confusion might have come from the fact that computer simulation has also been used and is still being used as a means to apply numerical treatment to mathematical models.

"Any theory that can be expressed in either of the first two symbol systems can also be expressed in the third symbol system." (Ostrom 1988, 384)

$\Rightarrow$ Thus, there might be verbal theories which cannot be adequately expressed in the second symbol system of mathematics, but can be in the third.

Advantages of an Object-/Agent-Oriented Approach

While classical simulation models are restricted

⇒ to the macro level in that

⇒ it models a part of reality (the ’target system’) as an undifferentiated whole,

⇒ whose properties are then described with a multitude of attributes in the form of ’level’ and ’rate’ variables representing the state of the whole target system and its changes, respectively

multilevel object-oriented or agent-based models

⇒ show much more structural correspondence between the ‘target system’ and the model representation,

⇒ are understood much more easily by a non-mathematician and

⇒ may be maintained and refined much more simply.

Modelling Strategy

⇒ identify some part of reality as a ‘real system’ consisting of elements of **different** ‘natural kinds’ [Bunge 1977, p. 143] and represent them by model objects,

⇒ identify relations defined on the ‘natural kinds’ of these elements (‘what depends on what?’),

⇒ identify their properties and represent them by model object attributes.

These three steps — steps two and three are easily interchangeable — are, by the way, also covered by the static entity-relationship approach to database modelling [Chen 1976] in computer science.

⇒ detect — or rather reconstruct — the laws governing that part of reality we are about to model (‘what are the dependences like?’, ‘system representation’ [Kreutzer 1986, p. 2];

⇒ combine our notions of the laws governing reality into a model written down in a formal language (a computer programming language), thus representing real world elements and their properties with (programming language) objects and their attributes, and empirical laws with program invariants;

⇒ run the simulation program.

Purposes: Understanding *vs.* Prediction

Simulation may be seen as a thought experiment which is carried out with the help of a machine, but without any direct interface to the target system: We try to answer a question like the following.

Given our theory about our target system holds (and given our theory is adequately translated into a computer model), how would the target system behave?

The latter has three different meanings:

- ⇒ Which kinds of behaviour can be expected under arbitrarily given parameter combinations and initial conditions?
- ⇒ Which kind of behaviour will a given target system (whose parameters and previous states may or may not have been precisely measured) display in the near future?
- ⇒ Which state will the target system reach in the near future, again given parameters and previous states which may or may not have been precisely measured?

What kinds of behaviour can be expected?

Answers to the first type of question apply to explanatory models in the sense of Casti. They could be like the ones given by, e.g. Dynamic Social Impact Theory: This theory answers the question

- “What if we have a population of people, each influenced by and influencing each other?”

  ⇒ “The system achieved stable diversity.

  ⇒ The minority was able to survive, contrary to the belief that social influence inexorably leads to uniformity. . . .

  ⇒ Attitudes have become spatially clustered, not through individuals changing their location, but simply through the attitude change process.”

(Latané 1996, 292, 294)

Which kind of behaviour will a given target system display in the near future?

Answers to the second type of questions could be like the ones given by the simple opinion formation model of Weidlich and Haag (1983) in which individuals change their (binary) attitudes toward two alternatives (say computer operating systems — or water usage strategies) with a transition probability which depends on the prevailing majority in the population they belong to:

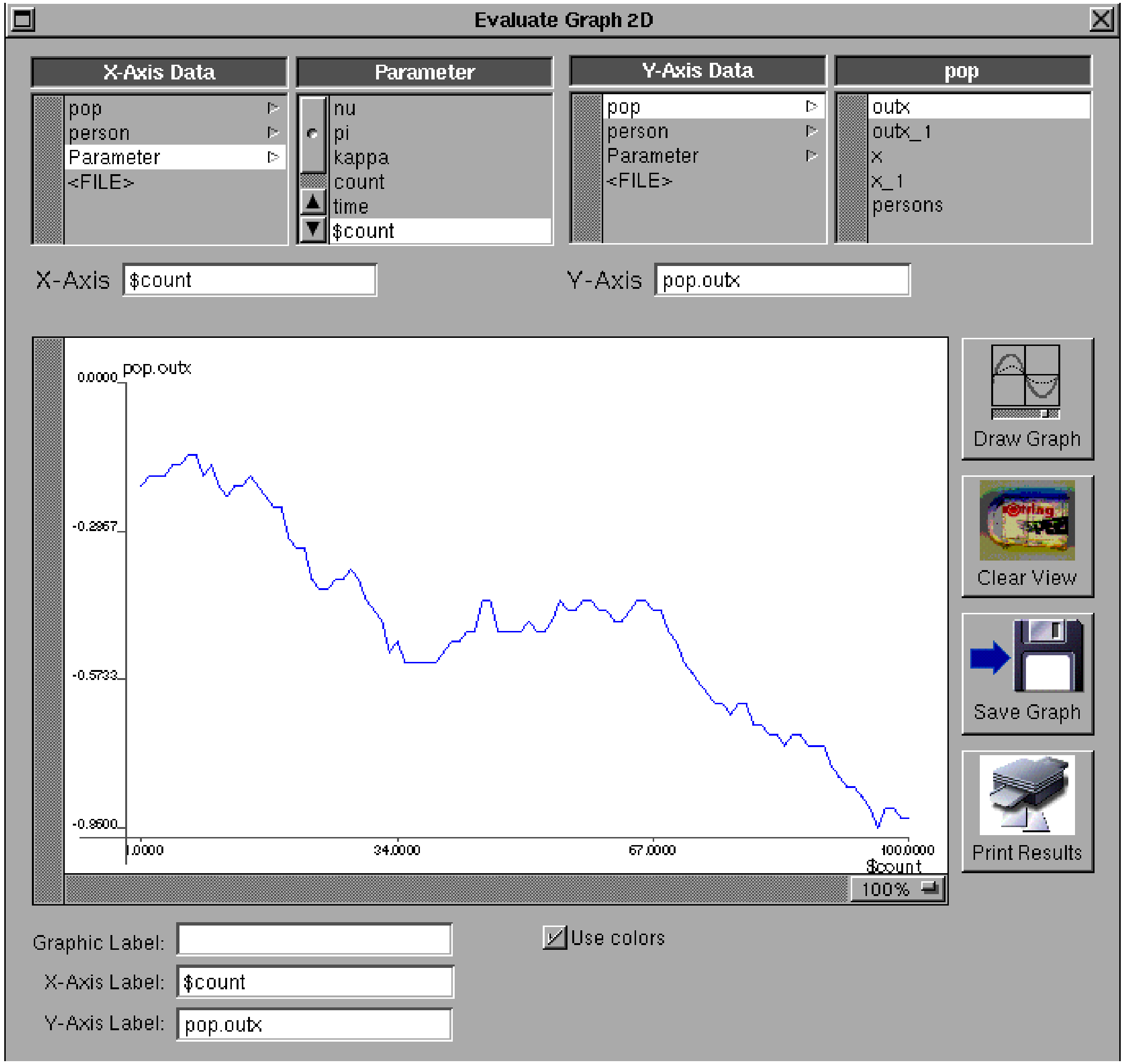
$\Rightarrow$ Given low compatibility demands, both of two products will survive, and both market shares will be of approximately equal size for a very long time, but

$\Rightarrow$ given high compatibility demands,

- $\Rightarrow$ one of the two products will acquire an overwhelming market share,
- $\Rightarrow$ the other being reduced to an extremely low minority, but nonetheless being able to survive in a niche;

from an initial state with equal chances for both products, no prediction is possible whether of the two will win or lose.

Simulation output for one population



Which state will the target system reach in the near future?

Answers to the third type of questions would be of the kind

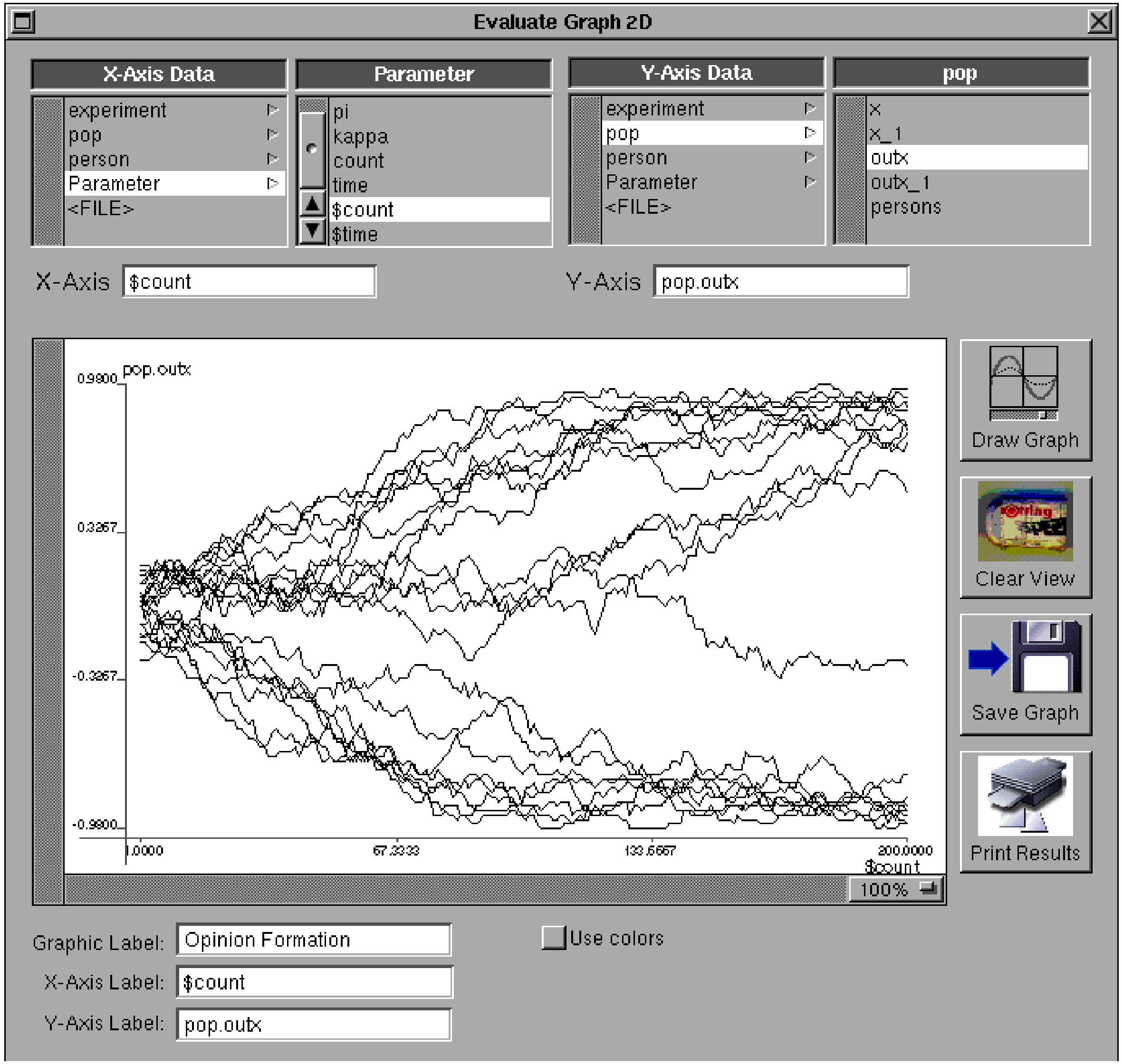
$\Rightarrow$ “after n time steps (years) product no. 1 will have an expected market share of p %, with a 95 % confidence interval of q percentage points”.

Note that in the case of the opinion formation model cited above, with high cohesion it is not even necessary to measure a majority above 75 % exactly:

$\Rightarrow$ if a population reaches this state, it will quite inevitably end up with an overwhelming majority of the same kind, and the 25 % minority has only a tiny chance to take over, instead, it will shrink further.

In other models, the final outcome may depend on initial or later conditions much more sensitively, and also in this model, for an initial 51 % majority no quantitative prediction is possible.

Simulation output for several populations



Drawing conclusions from complex antecedents (1)

If the representation is in the form of verbal argumentation,

$\Rightarrow$ only rather simple target systems may be analyzed, and
$\Rightarrow$ hidden antecedents may perhaps fail to be detected during the argumentation.

If the representation is in mathematical form, there are no hidden antecedents, but still we have the case that only simple representations have their mathematical solutions:

$\Rightarrow$ We cannot tell from a potential function which is a polynomial up to the fourth degree in two dimensions whether it has one or two or three or four local minima if we only look at the values of the parameters of the polynomial.

Even simulation may fail in finding all of the possible conclusions — visualization may help here.

Drawing conclusions from complex antecedents (2)

The opinion formation model gave an example what drawing conclusions from complex antecedents means.

We had a system of very modest complexity consisting of a large number of "identical" members of a homogeneous population acting according to simple transition probabilities which depend on the actual state (market shares) of the population.

The question was:

Which are the possible futures of such a target system?

Drawing conclusions from complex antecedents (3)

There were two different qualitative outcomes:

Either the population ends up in more or less equal market shares.

Or a large majority of users of one product develops in the population whereas the other product is used only in a very small niche.

Detecting the limits of a model

In the case of one homogeneous population with only two products to choose between, even an approximate closed solution can be derived with the tools of mathematics.

A heterogeneous population or several interacting populations are far more difficult to treat mathematically ($\Rightarrow$ Lotka-Volterra models).

And if the individual transition does not only depend on the overall market share, but on the decisions of other individuals in a friendship network or in local neighbourhoods, simulation is often the only tool available.

Detecting and extending the limits of a model

Computer assisted theory building is always a process of refinement of models which leads us, step by step, to more and more understanding of the target system or of a class (“natural kind”) of target systems.

$\Rightarrow$ We could start with one element of a class of objects — the target system as a whole (say a forest).

$\Rightarrow$ In further steps we would identify the target system as composed of elements of different ‘natural kinds’ of objects (say trees and game and hunters and the environment of the forest).

But the forest would still be represented as an object in our model, otherwise “we won’t see the forest for the trees . . . ”

Qualitative prediction

This is the prediction which of several possible modes of behaviour a particular target system will have in the near future, provided the theory we have in mind holds for this target system.

- Will this system stabilize or lock in (and in which of several stable states will it do so), will it go into more or less complicated cycles, will it develop chaotic behaviour (such that long-time quantitative predictions are impossible)?

- Will this system display some emergent structures like stratification, polarization, or clustering?

Note: Most quantitative social simulation aims only at qualitative prediction. And: Most qualitative prediction is done by quantitative simulation.

Will this system stabilize or lock in or . . . ? (1)

To answer this question, we must measure at least some of the parameters and initial states of the target system, namely the ones to which the system would react sensitively.

Mathematical analysis is possible in certain simple cases, not only in deterministic, but also in stochastic models, but models of this kind are, as a rule, too simple as to allow an adequate measurement of parameters — and this is because parameters are conceived of as fixed:

The theory behind these models assumes that parameters (cohesion, compatibility prerequisites, fertility rates, . . .) do not change over time, thus if we find different parameter values for different times of measurement, then the theory and its models are not applicable any more.

Will this system stabilize or lock in or . . . ? (2)

Here, too, an extension of the model will be necessary, making parameters endogenous — which results in a model which can no longer be treated mathematically.

And here is where simulation comes in: the simulation model will have to be run with a possibly large number of combinations of parameters — some parameters will still be constant — and initial states in a neighbourhood of the actual state of the particular target system under consideration.

Will this system display some emergent structures . . . ?

To answer this question, we must also measure the target system, but here mathematical analysis will be of little help.

Instead, again a large number of simulation runs will be necessary to explore the future behaviour of the model in order to draw conclusions with respect to the future behaviour of the target system.

This exploration might be done with the help of visualization tools, which, of course, should be included into simulation toolkits.

Quantitative prediction (1)

This is the prediction

- which state the system will reach after some time, given we know its actual state precisely enough.

- which state the system will acquire if we change parameters in a certain manner, i.e. if we control parameters to reach a given goal.

Here it is only possible to calculate trajectories starting from the measured initial state of the target system and using the parameters of the target system (which, too, must have been measured or adequately estimated beforehand).

Quantitative prediction is the field of microanalytic simulation models which are very often used for prediction in demography and policy making.

Quantitative prediction (2)

Two additional problems have to be kept in mind here:

- If sensitivity analysis has yielded the result that the trajectory of the system depends sensitively on initial conditions and parameters, then quantitative prediction may not be possible at all (which is a very valuable result!).

- And if the model is stochastic, then only a prediction in probability is possible, i.e. confidence intervals can be estimated from a large number of stochastical simulation runs with constant parameters and initial conditions.

Conclusion (1)

It should have become clear by now that social science simulation has at least two very different types of purposes.

- One of them might be called explanatory — this includes also teaching —, while
- the other comprises different types of prediction and prescription, including parameter estimation, retrodiction, and decision making.

In most cases, the explanatory type of simulation — exploring would-be worlds (Casti 1996) — has to be done before the prediction and prescription type of simulation can be accessed.

Conclusion (2)

Explanatory models (in the sense of Casti) are used “to account for *past* observations rather than to predict *future* ones”.

The example he uses to explain what an explanatory model is resembles many of the concept-driven models used in social science in the last twenty years:

It is a model of the process of planetary formation in early solar systems which allows us

> “to make predictions about the kinds of planetary systems that might be seen in the real universe under various physical circumstances surrounding the mass of the gaseous cloud, its composition, rate of rotation and so forth.”

(Casti 1996, 14)

Conclusion (3)

Nearly the same sentence

> "to make predictions about the kinds of social systems that might be seen in a real society under various social and psychological circumstances surrounding individual people, . . . , and so forth."

could be formulated about the cellular automata created by Hegselmann, Latané, Nowak and others, or about the artificial worlds created and described by Castelfranchi, Conte, Doran, Drogoul and others.

They all address the problem how patterns arise out of the actions of individual agents.

Conclusion (4)

And this is, according to an old saying by Hayek, at the core of all social sciences, since

> "the problems which they try to answer arise only in so far as the conscious action of many men produce undesigned results, in so far as regularities are observed which are not the result of anybody's design. If social phenomena showed no order except in so far as they were consciously designed, there could be no room for theoretical sciences of society. . . . It is only in so far as some sort of order arises as a result of individual action but without being designed by any individual that a problem is raised which demands a theoretical explanation."

(Hayek 1942, 288)

Hayek stresses "how patterns arise", but what about "the actions of individual agents"?

Emerging patterns

Even in the two simple models shown, the emergence of social order can be simulated. They show how “some sort of order arises as a result of individual action”, but this “action” is only poorly modeled. Deterministic and stochastic automata are “grey boxes” which behave as reactive agents who either follow strict and unchanging rules or cast dice, and it does not come as a surprise that the same techniques are applied to simulate the emergence of patterns in dead matter, in individual living organisms, and in societies.

But most of us are suspicious that we do not always cast dice and sometimes make up our minds and change our rules . . . .

So, shouldn’t we replace our deterministic stochastic automata in our multilevel models and cellular automata with models of intelligent and deliberative agents?

Mind is not enough — society is not enough

In the same way as Rosaria Conte stated some years ago that

- mind is not enough,

we can add that to understand human societies

- society is not enough.

We have to understand both: how social behaviour emerges in the individual, and how social order emerges in an undifferentiated population.

We have to understand how individuals learn social norms in particular environments and why they still apply these norms even in changed environments.