Loet Leydesdorff

The operation of the social system in a model based on cellular automata

The technique of cellular automata can be used for the simulation of social phenomena by considering the cells as the actors and the resulting pattern on the screen as the social system of their interactions. Actor behaviour is then specified at the cell level (i.e. "genotypically"), while the operation of the social system can be observed "phenotypically". Thus, one is able to infer from the specification of individual behaviour to the dynamics of the social system. Additionally, subroutines can be attributed to different cells. For example, individual cells can be instructed to reflect on their environmental conditions and to act accordingly, by providing them with "if then" statements in addition to their regular behaviour ("do while"). Thus, the effects of social structure upon action can also be investigated. I argue that this methodology provides us with an instrument with which to relate social theory concerning the interplay between agency and structure to the formal analysis of social structure in terms of networks.

Theoretical relevance

The sociologist is often caught in a methodological dilemma: one is able to observe the behaviour of actors, but any reconstruction of the social system provides one with a hypothesis among a range of other possible hypotheses (Hinton et al., 1986). While human

Social Science Information (SAGE, London, Thousand Oaks, CA and New Delhi), 34, 3 (1995), pp. 413–441.

actions and interactions can be directly observed, the resulting social systems remain constructs which should not be reified. The sociologist has to infer the operation of the social system on the basis of a local reconstruction (see, e.g., Knorr-Cetina, 1981).

How might one be able to predict the operation of social patterns if the latter are so inherently uncertain? Can one ever use a hypothetical operation to provide a convincing explanation of observable behaviour? The social system is additionally complex because human actors are sometimes able to change the situation reflexively (cf. Henschel, 1990). But even without this complication, the operation of a hypothetical system has to remain a second-order hypothesis. Our imagination is easily confused when we wish to specify the possible operations of "virtual" systems (Giddens, 1979).

By using computer simulations, one is able to compare expectations with respect to hypothetical systems in terms of probabilities. Thus, an algorithmic approach can help one to study social structure in terms of ranges of possible operations. The ensemble of logical possibilities spans a phase space; substantive specifications restrict the number of possible transitions. Moreover, the range of possible interactions at each moment in time is conditioned by the previous state(s) of the hypothesized super-system (cf. Pearl, 1988). Previous states of the super-system can be specified by studying its assumed "macro"-history (cf. Giddens, 1984).

This model of social systems can be visualized by extending Burt's (1982) model of social action with a time axis as exhibited in Figure 1: structure is decomposed and recomposed by actions; actions are partly conditioned and partly determined by structure at a previous moment (Leydesdorff, 1991; Kaufer and Carley, 1993).[1] Thus, the social system, which itself remains "virtual" during the operation (Giddens, 1979), exhibits continuity and change: change as a result of various interactions, and continuity with reference to its previous state.

A traditional approach to this problem would require the specification of a system of partial difference equations. However, such a system or its continuous equivalent – a system of partial differential equations – is usually difficult to solve algebraically. The cellular automaton provides us with a methodology to simulate this problem. In this study, the social system is defined by considering the 25 lines and the 80 columns of a computer screen as $25 \times 80 = 2000$ actors who change their behaviour (in terms of their colour on the screen) in relation to the colours of their neighbours and

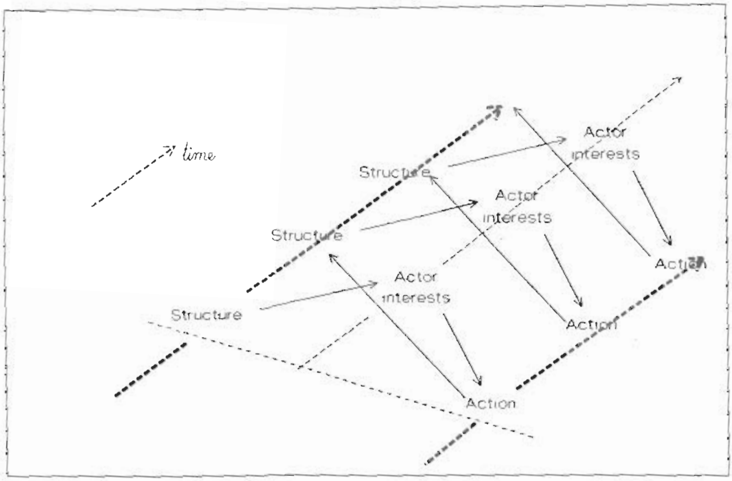


FIGURE 1
Dynamic extension of Burt's (1982) model of structure/action contingency relations
Source: Burt (1982: 9) and Leydesdorff (1991: 341).

according to relatively simple rules. The behavioural subroutines followed by the actors lead to overall patterns at the level of the observable super-system that can be exhibited on the screen. Among other things, the effect of providing the actors with some reflexive capacity will be discussed. In a final section, I return to the question of how this methodology provides us with an instrument to relate social theory with social network analysis.

Cellular automata as a method

With the advent of the computer, the cellular automaton has become increasingly popular in simulation studies. The technique was introduced by Von Neumann and his co-workers when they were searching for the specification of self-reproducing automata (Ulam, 1962; Von Neumann, 1966). Ever since, it has been well established in the natural sciences (e.g. Wolfram, 1983, 1984a, 1984b) and in biology (e.g. Hogeweg, 1988).

Biologists have used cellular automata for studying population dynamics both in "natural" evolution and in "artificial life" (e.g. Langton, 1989; Langton et al., 1992). Well-known computer games such as LIFE allow the user to watch the simulation of evolutionary processes (cf. Kauffman, 1991). The underlying models of "artificial life" have a format similar to those of connectionist models used in neural network research (e.g. Rumelhart et al., 1986; Pearl, 1988): the analyst specifies the micro-operations of the system at the "genotypical" level, and then evaluates the macro-outcome at the "phenotypical" level, while the in-between process is specified only in terms of possible structures and procedures.

Dewdney (1988) reported on the use of a cellular automaton model for studying chemical processes by Gerhardt and Schuster (e.g. 1989). These authors called their model "a hodgepodge machine", since it allowed them to simulate classes of cellular automata by varying the values of the parameters in the machinery. In this study, I use this hodgepodge model for the simulation, since it allows me to vary the behaviour of individual cells both in terms of individual routines and in terms of interaction parameters.

In *the social sciences*, the use of the computer for simulation purposes is now widely accepted (cf. Forrester, 1971; Hanneman, 1988). Sophisticated simulation packages (e.g. STELLA and DYNAMO) are available which allow for the deconstruction of complex systems into subroutines. However, the idea of constructing "social realities" by simulating a considerable number of lower-order ("actor") subroutines *concurrently* has seldom been applied to sociological problems (Leydesdorff, 1993).

Recently, a number of authors have drawn attention to the use of cellular automata for studying the diffusion of technologies in different geographical areas (e.g. Bhargava et al., 1993; Bhargava and Mukherjee, 1994). Zuyderhoudt (1990) has used a hodgepodge machine for studying the development of patterns in organizations. Others have proposed the use of cellular automata for studying structure/action contingency relations (e.g. Grasman, 1994; Parisi, 1994), but these studies did not yet contain simulation results.

At the theoretical level, Luhmann (1984) hypothesized that social systems be considered as networks of communication which are added to the actors at the nodes. These systems can be modelled as neural networks (cf. Leydesdorff, 1992a). However, Luhmann also emphasized that the system of reference — and thus the substance of communication — in a social system is different from the substance of a psychological system. Therefore, it remains metaphorical to study society *as if* it were a neural net. The cellular automaton provides us with a more adequate model for studying *social* systems:

the cells are allowed to behave (partially) independently and the hodgepodge model enables us to vary both the behavioural and the interaction parameters.

The model

Our model is based on the hodgepodge as described by Dewdney (1988) and Zuyderhoudt (1990 and personal communication). As noted, we use a standard computer screen with 80 columns and 25 rows, and thus 2000 cells. Since one can provide each cell with its own programme, the model allows for the simulation of a social network of 2000 actors who run their own (sub)routines. For the purpose of making our argument, such a simple model is sufficiently complex. (Note that one could define the hodgepodge at the lower level of the pixels on a computer screen; then one would have, in the case of a standard VGA screen, 640 times 480 pixels, i.e. >300,000 units. Furthermore, the relations between cells and pixels can provide us with a model for nested structures in an even more complex design.)

In the simplest case, each cell is instructed to compute its value in the next round in relation to its so-called Von Neumann neighbourhood, consisting of the four cells that share the cell's edges. For example, it may take the average of this neighbourhood. Additionally, a parameter D is defined with which all cell values are increased in each iteration. When a cell exceeds the value of 100, it "falls back" to the value of 1 again. Or, in a more formalized terminology:

$$\text{NEW VALUE} = \text{Int}\ [D + \{\Sigma(\text{OLD VALUES neighbouring cells})/4\}]$$

$$\text{If NEW VALUE} > 100, \text{then NEW VALUE} = 1$$

In addition, one can vary the relative weights of the four neighbouring cells so that the general formula will be:[2]

$$\text{Value}_{t(1)} = \text{Int}\{D + (\text{Value}_{t(0)}{}^{\text{right}}/a) + (\text{Value}_{t(0)}{}^{\text{left}}/b) + (\text{Value}_{t(0)}{}^{\text{top}}/c) + (\text{Value}_{t(0)}{}^{\text{bottom}}/d)\}$$

$$\text{If Value}_{t(1)} > 100, \text{then Value}_{t(1)} = 1$$

On the screen, values of cells are related to screen colours for each 10.

Furthermore, the left edge of the screen is linked to the right edge, and the bottom edge to the top, in order to prevent complex boundary distortions. The resulting screens are saved in sets of 25 screens, which can later be exhibited as in a film. (The two programs are listed in the Appendix.)

The simulations

The simulations begin with a disturbance by a single action in the middle of the screen. I have arbitrarily chosen a value of 75 for this seed cell in all examples which are discussed below. Obviously, if D is equal to 100 and a, b, c and d are all equal to 4 – so that an average is taken of the Von Neumann neighbourhood – the disturbance ("infection") disappears in the next iteration, since all the cell values then are set back to 1. In other words: the "infection" does not "survive," or one might also say that "it has been selected away" by the operation of the emerging super-system. Thus, playing with the value of D one has a mechanism for selection, and for periodicity, since this parameter also determines the maximum number of iterations that an infected cell can "survive".

For example, if we set D at the value of 34, the initial distortion (of 75) will be selected away in the third iteration when all cells will simultaneously reach a value larger than 100. (At this stage, some infected cells have reached the threshold for the second time.) The algorithm thus synchronizes the disappearance of the infection. If we subsequently lower D to 33, we obtain screens with an overall periodicity of 3. These screens will be symmetrical in the vertical and horizontal direction, since we have not yet differentiated in value between the parameters a, b, c and d. If we increase the influence of each of the neighbouring cells by a factor of 2 (setting a, b, c and d equal to 2 instead of 4) the system dies out even with $D = 33$. Changes in parameter values lead to different periodicities and patterns.

By experimenting with these parameters, a recognizable stable pattern can be found, for example, at the values $D = 31$, $a = 1$, $b = 3$, $c = 2$, $d = 4$. This pattern can be maintained for more than 1000 screens. (Figures 2a and 2b exhibit the 300th and the 500th screen respectively.) At each moment, the pattern collapses in some places, but is restored at others. The pattern also moves over the screen, but an average observer is not able to determine the periodicity of this movement by visual inspection.

A more precise study of the resulting periodicity at the level of the screens leads to the graph in Figure 3. In this picture the difference between the distribution of the cell values of each screen (between screens 450 and 500) and its 50 precursors is plotted in terms of bits of information as a measure of the difference (Theil, 1972; Leydesdorff, 1991). Thus, screen 451 is compared with screens 401 to 450. The resulting difference from screen 401 is indicated as a value at "−50" on the x-axis, while the comparison with screen 402 is plotted at the value of "−49". This procedure is repeated for 50 consecutive screens (451 to 500) so that an average with an error-bar can be exhibited.

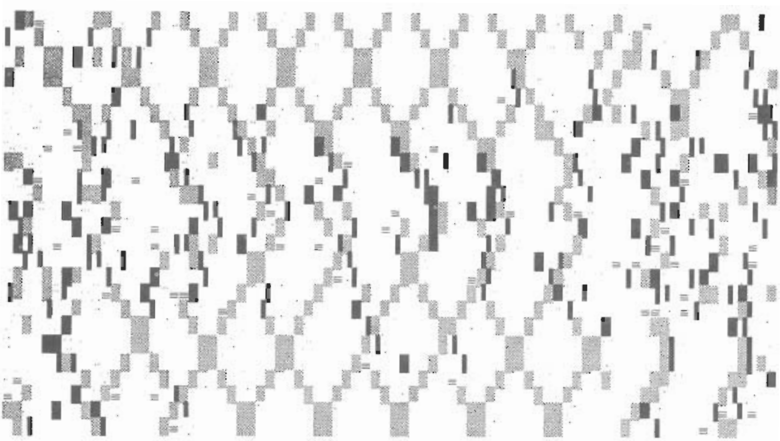
The graph in Figure 3 shows periodicities of 8 screens. The periodicity of 8 fades away after approximately 40 screens. Note that a periodicity of 8 cannot usually be distinguished by a human observer visually.

The addition of a conservative trait to the cells' subroutines

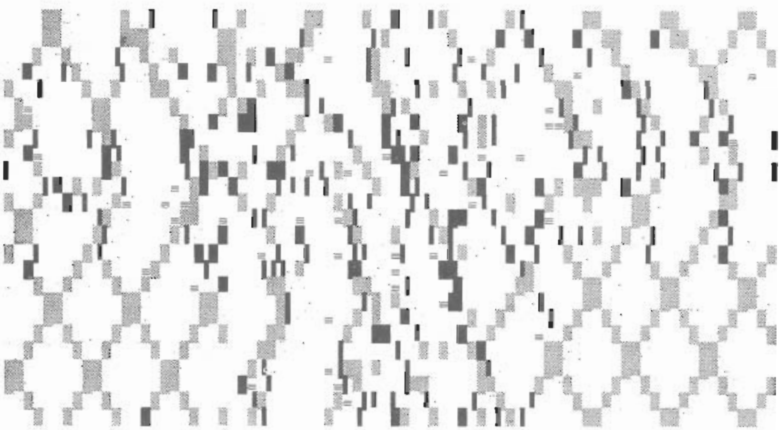
We experimented by providing cells with the instruction to keep their value if the pattern surrounding each cell was sufficiently stable in comparison to the previous screen. An analyst can appreciate this mechanism as a kind of "reflexive conservatism", i.e. the individual actors are allowed to keep their previous value if an update would bring them "out of line" with their neighbours.

Let us apply this reasoning to the interactive pattern shown in Figure 2. We instructed the cells that if the pattern of the following 8 cells in a row "■   " (corresponding to the numerical values: 59, 51, 33, 33, 1, 1, 1, 1) was maintained in 7 of them, the one remaining cell should adjust to the pattern and keep its value from the previous iteration.[3] Thus, this subroutine favours the conservation of the indicated pattern at the screen level by running an additional check as an "if then" statement in the subroutine.

Counter-intuitively, the result is a discontinuity in the maintenance of the noted pattern. Figure 4 exhibits the scrambling of the picture on the screen after 500 iterations. This figure can be compared with the screen exhibited in Figure 2b above, which was the result of a similar simulation without this additional subroutine.



(a) Screen 300



(b) Screen 500

FIGURE 2

The explanation is that the reflexive correction at the cell level *disturbs* the maintenance of the pattern at the level of the super-system. This conclusion can be illustrated by using the graph in Figure 5. This picture is superimposed on Figure 3 in order to facilitate the comparison. It shows that the periodicity is dampened much more in this case than in the previous one. Thus, reflexive capacity at the cell level disturbs not only the pattern but also the dynamics of the super-system upon which it *counter*-acts.

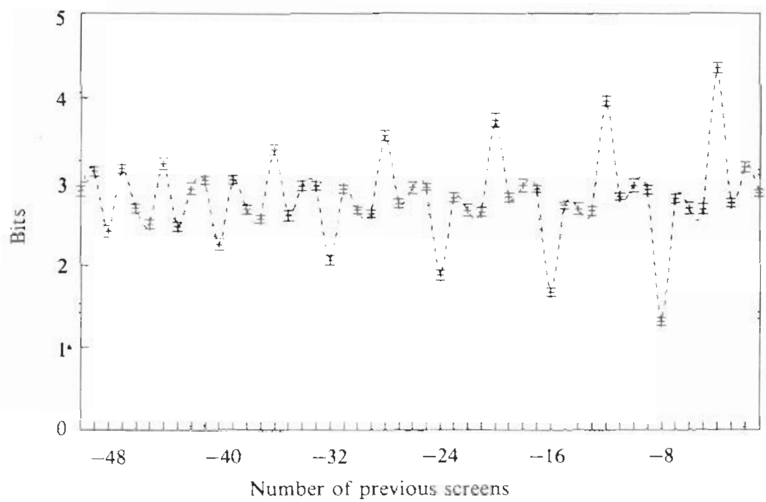


FIGURE 3
Average expected information values of 50 screens versus 50 previous ones

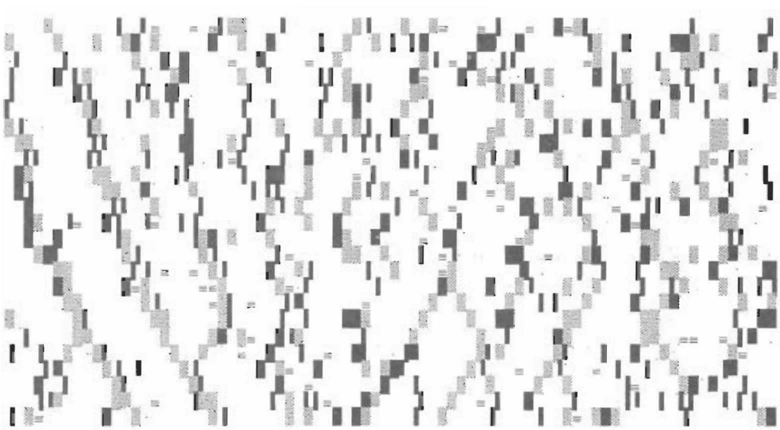


FIGURE 4
Screen 500 with correction for pattern maintenance at the cellular level

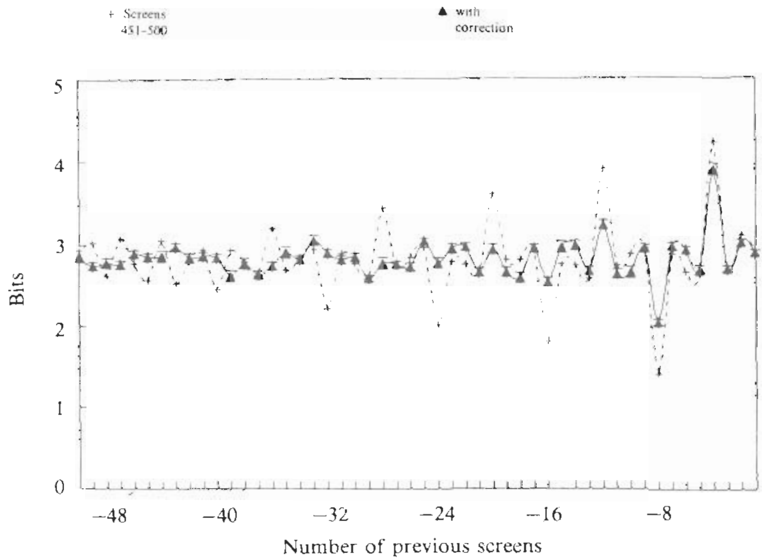


FIGURE 5
Average expected information values among screens after 500 screens

This conclusion may come as no surprise to the theoretically informed sociologist. But it remains noteworthy that these theoretical insights can be demonstrated with these relatively simple simulations. Complex behaviour can be the result of recursive interactions between relatively simple rules (see, e.g., May, 1976; Lewin, 1992). Additionally, the simulation results suggest that periodicities of a higher order than is intuitively appreciable can be expected to reign in a social system. While Giddens (1979) argued that social structure contained a "duality" in its operation, this simple system, for example, exhibited already an "octality".

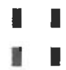
Variation in the interactive parameters

The macro-system (which is made visible on the screen) is highly sensitive to variation in the different parameters. As noted, a change in parameter choice may easily lead to the extinction of the original "infection" so that the macro-system vanishes. In other words, the definition of the system in terms of parameters and routines constitutes a phase space which can be investigated in terms of its properties (e.g. Kampmann et al., 1994). I return to these more abstract considerations in the next section, but let me first discuss one more example of an important social phenomenon, i.e. *morphogenesis* as a result of (in this case, social) interaction.

Figure 6 exhibits various stages of a process of morphogenesis produced by a run with parameter values $D = 31$, $a = 1$, $b = 1$, $c = 2$ and $d = 2$. (In other words, the communication is spreading horizontally twice as fast as vertically.) Figure 6a exhibits the unit which emerges after a number of iterations and Figure 6b exhibits the generation of a mutant which is formed between these two "parent" figures. This mutant is selected away in the next iteration (Figure 6c).

The creation of the mutant between each couple, however, can have an effect on another unit when a density of the more stable units on the screen has been reached (Figure 6d). At this point, in a few iterations a network pattern emerges among the hitherto loose units. Shortly thereafter, all units have become part of this network (Figure 6e), and in a next stage, the super-system begins to grow according to a completely different pattern (Figure 6f). Note that this can be considered as the *morphogenesis* at the level of the higher-order system (cf. Maruyama, 1963): while the mutant itself was not stable in the original configuration, at a certain stage its generation appears conditional on the emergence of a pattern at a next higher level. Thereafter, the development pattern of the super-system changes. If we pursue the metaphor of considering the super-system on screen as a representation of the social system, this mechanism explains why social systems may exhibit reorganizations without causes that can be identified in terms of actor behaviour. Not only is structure latent for action (Lazarsfeld and Henry, 1968; Burt, 1982), but action can also be latent for structural developments at the level of the social system.

Let me finish this discussion of simulation results with Figure 7. While the series of Figure 6 may have given the impression that the network in a cellular automaton is locally constructed, Figure 7 (which is based on a run with parameters $D = 28$, $a = 1$, $b = 3$, $c = 2$ and $d = 4$) shows that the effects of disturbance by infection are not necessarily local. The existence of a single infection may affect the whole system, as is manifested in each third screen of this run: all units above the infection take a different colour from all

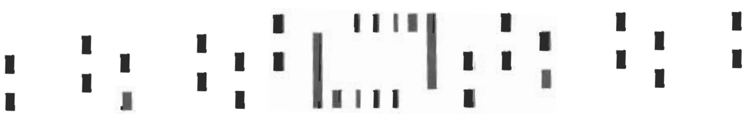


(a) The original unit

(b) The formation of a mutant

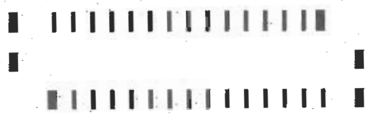
FIGURE 6

(c) The multiplication of the original unit

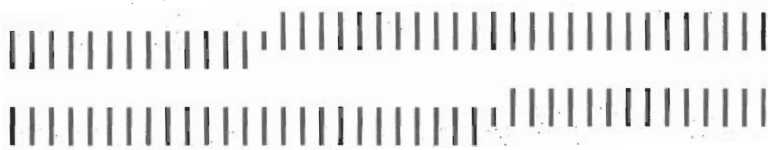


(d) Emergence of an interactive network

FIGURE 6 (contd)



(e) The new structure has emerged



(f) A new pattern of development has been developed (screen 186)

FIGURE 6 (contd)

units vertically below it, and all units to the left and to the right of the infection are again differently affected. Thus, the super-system is immediately – i.e. at the third screen – globally affected.

In summary, these results teach us that the locality of an action should never be taken at its face value. Any action can have a different impact on all other systems involved.

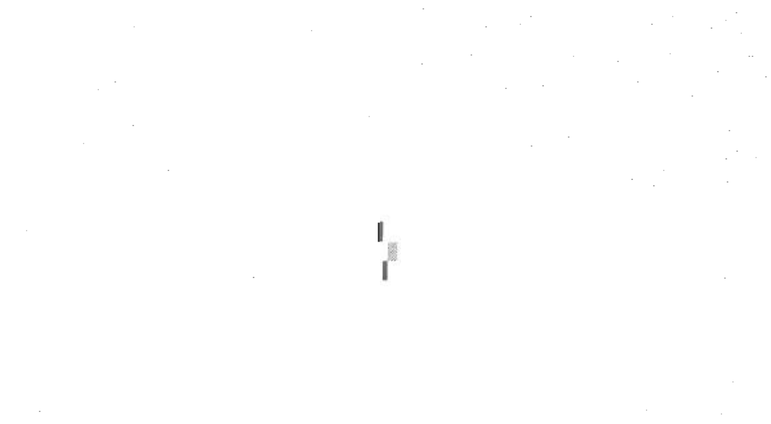
Patterns of interaction among discrete systems

Obviously, the emergence of the complex "order out of chaos" on the screen is a result of the interaction among relatively simple computational subroutines. How can one understand these phenomena?

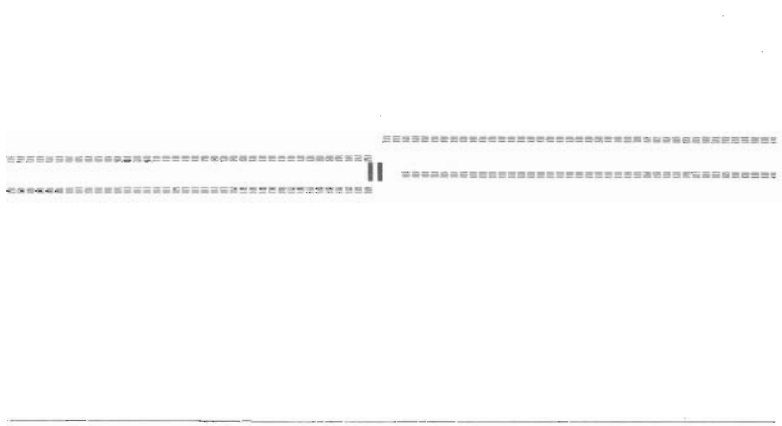
By using the specified algorithm, waves of disturbance are sent through the system in the four directions of a Von Neumann environment. By varying the parameters, one changes frequencies and amplitudes of the waves in the various directions. Thus, the outcome can be considered as an *interaction among* frequencies (cf. Smolensky, 1986). Remember from physics that an interaction among continuous frequencies can sometimes be stabilized on an oscilloscope as a so-called *Lissajous* figure. Lissajous figures may have all kinds of shapes and periodicities.

In other words, what we have actually produced in the above simulations are discrete and dissipative equivalents of Lissajous figures. Figure 8 illustrates the point. It shows the frequency distributions of the cell values for screens 201 to 300 and screens 401 to 500, respectively. The bars inform us that discrete values are reproduced by this interaction, e.g. at the values of 1, 33, 51 and 59. Indeed, these were also the values of the string that we assessed previously for its persistence.[4] Given other parameters of the system, other values would become pronounced. However, the figure informs us that the pattern slowly degenerates over time.

Lissajous figures are electronically driven by fixed oscillations, and therefore they can be stabilized as resonances. The patterns which have been discussed above, however, are the results of semi-resonances among discrete frequencies: these systems vibrate in a non-equilibrium state and the quotient of the interacting frequencies is normally not an integer. Thus, the frequencies can be considered as "failing" to resonate. The visible stabilization of a pattern is the result of a specific semi-resonance state, which can be temporarily maintained despite the absence of equilibrium. A resonance would



(a) The infection (screen 2)



(b) The infection has a global effect (screen 3)

FIGURE 7

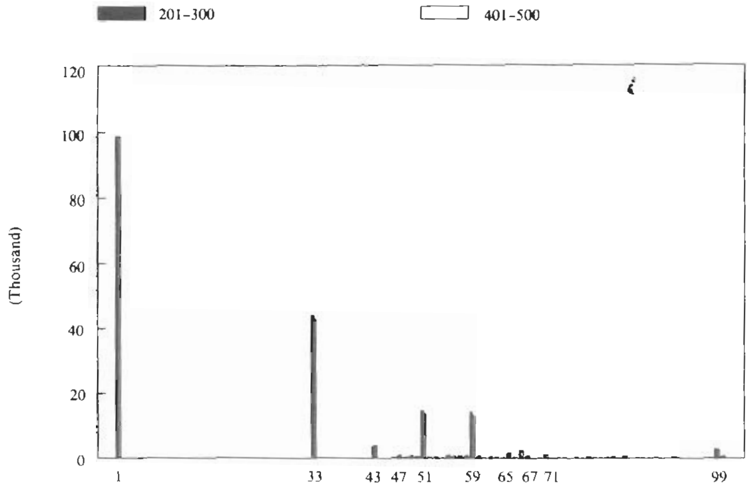


FIGURE 8
Frequency distributions of cell values

completely filter the noise, but since the system is only in a semi-resonance, its dynamics are suboptimal. Consequently, this system is not able to fully recover its pattern and therefore the semi-resonance is expected gradually to deteriorate (as was shown above).

As early as 1969, Herbert Simon argued convincingly that evolutionarily complex systems are *nearly* decomposable, and therefore in a suboptimal state. The interaction terms between the composing frequencies are structural, and the virtual dimensions of the system cannot completely be orthogonal (cf. Simon, 1973). In other words, evolutionarily complex systems manifest the suboptimal specification that has been achieved historically. A reflexive analyst can use the observable phenomena to develop a theoretical reconstruction in terms of composing dynamics. The subsequent translation of these theoretical specifications into algorithmic code allows us to explore the phase space of other possible recombinations beyond the phenomena which have historically occurred.

Theoretical specifications, however, remain hypotheses (Popper, 1934/1959). Formalized into computer code (for example, as conditional statements that operate as selectors on the variation) the specifications span a phase space of possible variations. The specifications limit the number of possible combinations.[5] By virtue of the simulation the analyst can tinker with various specifications and observable effects. Using the technique of cellular automata, we have shown that in this way a research strategy can be developed for studying a social system despite its "virtual" existence.

This research strategy can be recapitulated as follows. First, a complex phenomenon has to be deconstructed in terms of its presumed underlying ("genotypical") mechanisms. Second, these specifications are translated into a computer model. Third, one is able to explore the structural characteristics of the macro-system using simulations. Fourth, the appreciation of the "phenotypical" behaviour of the model (i.e. the simulation results) can be used recursively to improve the model gradually with reference to insights in the weight and the probability of the theoretically specifiable subdynamics.

Theoretical implications

Theoretical interpretation is needed both at the "genotypical" and at the "phenotypical" level. The two levels of theorizing refer to different systems, and thus one expects them to behave substantively differently (cf. Luhmann, 1984). Since the super-system remains emergent from the perspective of the lower-level system, discursive reflections on the behaviour of lower-level units are not sufficient for the specification of the higher-order system. One has to distinguish between the hypothesized subcybernetics (at the lower level) and their interactions (at a next higher level): both the aggregation of actions and their interactions play a role in composing the complex result. Consequently, theoretical interpretations are expected to vary with the focus chosen for the analysis (e.g. Hinton et al., 1986; Shinn, 1987; Haraway, 1988).

Note the epistemological consequences for the sociological analysis: the geometrical metaphors provide us with partial perspectives. But these partial perspectives no longer have to remain juxtaposed; they can be nested as subroutines, "genotypically" highlighting different aspects and different stages of the system. Additionally, the algorithmic model provides us with the possibility to relate the "phenotypically" visible results of the simulation on the screen unambiguously to changes in the values of (sets of) parameters at each moment (cf. Langton, 1989). In principle, improvements in theoretical specifications can therefore be assessed algorithmically in terms of their consequences. In the longer run, one may even be able to compare the differences in possible perspectives in terms of the percentages of dynamic variation (i.e. probabilistic entropy) that can be explained (cf. Swenson, 1989; Leydesdorff, 1995).

While the theoretical specifications can be improved at each moment in time, they remain by definition "situated" and time-stamped. Additionally, evolution theory enables us to specify a dynamic expectation with respect to the global direction of the system's development. In general, two mechanisms drive the further development of the "nearly steady" state of the super-system along the time axis. On the one hand, the semi-resonances partly filter the noise. On the other hand, the system is left free to develop according to its structural parameters, and therefore it drifts. More specifically, the complex dynamic system tends to drift towards a critical state (Swenson, 1989; cf. Leydesdorff, 1994). In the critical state each disturbance may create an avalanche of further disturbances (Bak and Chen, 1991). However, more often than not, systems which have hitherto "survived" will be sufficiently buffered by semi-resonances so that the previous patterns are restored. The nearly differentiated systems are expected to be reproduced after the interaction most of the time.

If a system is locked into a semi-resonance – and thus temporarily stabilized – the frequencies of the interaction are expected to be nearly discrete (see Figure 8), i.e. characteristic for the structure and functional for its further development as an evolutionary system (Simon, 1973; cf. Arthur, 1989). A fully differentiated system would have orthogonal axes, but then it would risk disintegration. The more a dissipative system approaches this potentially resonating state, however, the better it will be able to use its resources (e.g. energy) for its further development (cf. Freese, 1988; Swenson, 1989; Lee, 1994). Thus, the system drives itself toward a critical state.

Structural constraints disturb this movement towards equilibrium (cf. Schumpeter, 1939), while local disturbances tend to enforce the dynamics of the system in the sense of providing it with opportunities to change its developmental pattern (Allen, 1994). As noted, a theoretical appreciation of the phenotypical manifestations remains needed for the attribution of functions to structural constraints and observable differentiations. But in contrast to Parsons's model of structural-functionalism, the functions of a model of operations may have to be specified in terms of interactions at the network level; one does not expect that the functions are fully decomposable in terms of actions over any stretch of time (cf. Leydesdorff, 1993).

The recursive and interaction terms at the network level generate what Giddens (1979) has called the "unintended consequences" of human actions. The specification of these unintended consequences, and vice versa of the ways in which action is "conditioned and enabled" by "virtual structure", requires a probabilistic apparatus that can be used for the systematic exploration of the various options of semi-resonances in the phase space spanned by the model specifications. Consequently, the appreciation of the macro-level system can no longer be firmly founded in a micro-level understanding; the systems are expected to feed back on each other. In general, any attempt discursively to reduce the one level of theoretical specification to the other unnecessarily sacrifices explanatory power.

Relevance to sociological research

As noted, the cellular automaton is primarily a methodological tool: it enables us to simulate *developments* at the network level while formal network analysis has focused on the study of networks at specific moments in time. In social theory, however, one is interested in explaining *why* the system has changed (e.g. Burt, 1982; cf. Leydesdorff, 1993). In other words, formal network analysis provides us with insights into the multivariate structure of a social system at different moments in time, while social theory tends to focus on issues of change and continuity in these structures in terms of recurrent patterns of behaviour.

The cellular automaton enables us to combine these two perspectives. It goes beyond the framework of this paper to provide the reader with empirical examples (cf. Leydesdorff, 1992b and 1995), but the methodological advancement over (formal) network analysis can now be specified. First, social theories provide us with hypotheses about the mechanisms of change in social systems. The formulation of this specification in terms of behavioural routines ("do while") and interactive triggers ("if then") at the cellular level allows for the mathematical specification of a probability distribution of possible states of the network in a next stage. These expectations vary with the theoretical specifications that go into the construction of the model. Subsequently, one is able to find confirmation for the various theoretical insights by measurement of the relevant networks.

Depending on the empirical research question, one may wish to make further assumptions in order to reduce the complexity or add other (e.g. stochastic) sources of variation. For example, the researcher may assume that it matters whether an actor (i.e. a cell in this representation) interacts with a man or a woman when choosing among routines available for exhibiting behaviour ("if then else"). Thus, reflexive layers can be added to the communications under study by nesting (sub)routines.

While behaviour can be independently specified, the overall effects are dynamic when the cells operate concurrently. Because of the interaction terms, actions are expected to have "unintended consequences" at the level of social structure: social systems behave according to their own (recursive) logic as soon as they are constructed as a system.[6] As shown above, these patterns are rapidly more complex than "dual". The formalization, however, enables us to backtrack from overall effects in the model (on the screen) to precise specifications in the computer code. Each subroutine represents a theoretical insight about dynamic sources of change ("action"). The substantive assumptions which go into the construction of the model limit the number of possible states of the macro-system. The feedback of the results of the simulation may challenge the reflexive theories to improve on their respective specifications.

Loet Leydesdorff is Senior Lecturer in the Department of Science and Technology Dynamics at the University of Amsterdam. He has published extensively in scientometrics, philosophy of science and sociology. His most recent book is: *The Challenge of Scientometrics: The Development, Measurement and Self-Organization of Scientific Communication* (1995). *Author's address*: Science and Technology Dynamics, Nieuwe Achtergracht 166, 1018 WV Amsterdam, The Netherlands.

APPENDIX

```
** Basic routine for the construction of the HODGEPODGE
** (using clipper '87: HODGEPOD. PRG)

clear all
declare old[2000], new[2000]
```

```
afill (old,1)
afill (new,1)

clear screen
set cursor on
store 12 to v1
store 40 to v2
store 1 to v3
store 4 to v5a
store 4 to v5b
store 4 to v6a
store 4 to v6b
store 219 to v7
store 1 to n
store 1 to counter
store "N" to v4
@ 10,1 say "Change options ? (Y/N) " get v4 picture "!"
read
clear screen
if v4 = "Y"
   @  7,1 say " Seed row ?       (1-24) " get v1
   @  8,1 say " Seed column ?  (1-80) " get v2
   @  9,1 say " D-value ?                    " get v3
   @ 11,1 say " New value = int(D + right/a + left/b + above/c + under/d) "
   @ 13,1 say " relative weight of cell on the right        (a) " get v5a
   @ 14,1 say " relative weight of cell on the left          (b) " get v5b
   @ 15,1 say " relative weight of cell above                (c) " get v6a
   @ 16,1 say " relative weight of cell under                (d) " get v6b
   @ 17,1 say " start iteration              " get n
   @ 18,1 say " ASCII character             " get v?
   read
endif

** generation of the infection
v1 = v1 * 80 + v2
new[v1] = 75
do CORE
set cursor on
clear all
return
***


Procedure CORE
set cursor off
clear screen
do while lastkey( ) < > 27
   ** construction of screens
   vcol = 0
```

```
vrow = 0
v__count = 1
do while v__count < 2001
  do case
    case new [v__count] < 10
      set color to N
    case new[v__count] > = 10 .and. new[v__count] < 20
      set color to B
    case new[v__count] > = 20 .and. new[v__count] < 30
      set color to G
    case new[v__count] > = 30 .and. new[v__count] < 40
      set color to BG
    case new[v__count] > = 40 .and. new[v__count] < 50
      set color to R
    case new[v__count] > = 50 .and. new[v__count] < 60
      set color to RB
    case new[v__count] > = 60 .and. new[v__count] < 70
      set color to GR
    case new[v__count] > = 70 .and. new[v__count] < 80
      set color to W
    case new[v__count] > = 80 .and. new[v__count] < 90
      set color to N+
    case new[v__count] > = 90
      set color to GR+
  endcase
  @ vrow, vcol SAY chr(v7)
  v__count = v__count + 1
  vcol = vcol + 1
  if vcol > 79
    vcol = 0
    vrow = vrow + 1
  endif
enddo
```

```
** saving of screens
vscreen = "S" + ltrim(str(n))
save screen to &vscreen
if counter = 25
  save to &vscreen all like S*
  release all like S*
  counter = 0
endif
counter = counter + 1
```

```
** preparing for the next iteration
```

```
  set color to W
  acopy(new,old)
  v__count = 1
  do while v__count < 2001
    ** control of boundary effects at the edges
    v__left = v__count - 1
    if v__left = 0
      v__left = 2000
    endif
    v__right = v__count + 1
    if v__right = 2001
      v__right = 1
    endif
    v__above = v__count - 80
    v__below = v__count + 80
    do case
      case v__above < 1
        v__above = v__above + 2000
      case v__below > 2000
        v__below = v__below - 2000
    endcase



    ** difference equation
    new[v__count] = int(v3 + old[v__left]/v5b + old[v__right]/v5a +;
      old[v__above]/v6a + old[v__below]/v6b)
    if new[v__count] > 100
      ** selection step
      new[v__count] = 1
    endif
    v__count = v__count + 1
  enddo
  n = n + 1
enddo
clear all
return
** eof( )
```

**** Routine for showing the results (SHOW.PRG)**

```
clear all
n = 25
v__count1 = 1
v__count2 = 1
x1 = 1
x2 = 1000
v1 = "N"
clear screen
@ 10,1 Say " Change defaults ? (Y/N) " get v1 picture "!"
```

```
read
if v1 = "Y"
  clear screen
  v1 = "S"
  @ 10,1 Say " delay in seconds or in counts ? (S/C) " get v1 picture "!"
  read
  clear screen
  if v1 = "S"
    @ 10,1 Say " delay in seconds " get x1
  else
    @ 10,1 Say " delay in counts " get x2
  endif
  read
else
  v1 = "S"
endif
DO scherm
clear all
return



***
Procedure SCREEN
do while lastkey( ) < > 27
  vscreen = "S" + ltrim(str(n))
  vtemp = vscreen + ".mem"
  if .not. file(vtemp)
    exit
  endif
  restore from &vtemp additive
  do while v_count < = 25
    vscreen2 = "S" + ltrim(str(v_count2))
    restore screen from &vscreen2
    if v1 = "S"
      if x1 < > 0
        inkey(x1)
      endif
    else
      h = 1
      do while h < x2
        h = h + 1
      enddo
    endif
    if lastkey( ) = 28
      inkey(0)
    endif
    v_count1 = v_count1 + 1
```

```
    v__count2 = v__count2 + 1
    release all like &vscreen2
  enddo
  n = n + 25
  v__count1 = 1
enddo
inkey( )
clear all
return
** eof( )
```

Notes

1. By definition, two interacting factors determine each other in the co-variation while conditioning each other in the remaining parts of the uncertainty. Giddens (1979) noted that the determining and conditioning functions of structure upon action are provided with a meaning by reflexive actors in terms of "enabling and conditioning" structures.

2. For the case of $a = b = c = d = 4$, the two formulations lead to similar results.

3. The pattern was defined not in colours but in terms of the numerical values underlying the colours. The procedure checks whether seven of these eight values correspond with values in the previous iteration, and in this case only the eighth value is adjusted.

4. The predominance of the value of 1 is a consequence of the selection mechanism: once a cell grows larger than 100, it is reset to 1 before the next iteration.

5. Without theoretical specifications the problem would rapidly become non-computable (e.g. Ebeling, 1991).

6. One can, for example, use the Markov property for testing the extent to which the emerging network of interactions has obtained "systemness" (Leydesdorff, 1992b; cf. Theil, 1972).

References

Allen, P.M. (1994) "Evolutionary Complex Systems: Models of Technology Change", in L. Leydesdorff and P. Van den Besselaar (eds), pp. 1–17.

Anderson, E.S. (1994) *Evolutionary Economics. Post-Schumpeterian Contributions*. London: Pinter.

Arthur, W.B. (1989) "Competing Technologies, Increasing Returns, and Lock-In by Historical Events", *Economic Journal* 99: 116–31.

Bak, P. and Chen, K. (1991) "Self-Organized Criticality", *Scientific American* 246(1): 46–53.

Bhargava, S.C., Kumar, A. and Mukherjee, A. (1993) "Stochastic Cellular Automata Model of Innovation Diffusion", *Technological Forecasting and Social Change* 44: 87–97.

Bhargava, S.C. and Mukherjee, A. (1994) "Evolution of Technological Growth in a Model Based on Stochastic Cellular Automata", in L. Leydesdorff and P. Van den Besselaar (eds), pp. 55–62.

Burt, R.S. (1982) *Towards a Structural Theory of Action*. New York: Academic Press.

Dewdney, A.K. (1988) "Computer Recreations: The Hodgepodge Machine Makes Waves", *Scientific American* (August): 86–9.

Ebeling, W. (1991). *Chaos – Ordnung – Information*. Thun/Frankfurt a.M.: Deutsch.

Forrester, J.W. (1971) "Counterintuitive Behavior of Social Systems", *Technology Review* 73(3): 52.

Freese, L. (1988) "Evolution and Sociogenesis", in E.J. Lawler and B. Markovsky (eds) *Advances in Group Processes*, vol. 5, pp. 53–118. Greenwich, CT: JAI Press.

Gerhardt. M. and Schuster, H. (1989) "A Cellular Automaton Describing the Formation of Spatially Ordered Structures in Chemical Systems", *Physica D* 38: 209–21.

Giddens, A. (1979) *Central Problems in Social Theory*. London: Macmillan.

Giddens, A. (1984) *The Constitution of Society*. Cambridge: Polity.

Grasman, J. (1994) "Mathematische sociologie, simulatie en het prisonersdilemma", in C. van Dijkum and Dorien de Tombe (eds) *Simulatie in Nederland: Een stand van zaken*, pp. 21–30. Amsterdam: SISWO.

Hanneman, R. (1988) *Computer-Assisted Theory Building: Modeling Dynamic Social Systems*. Newbury Park, CA: Sage.

Haraway, D. (1988) "Situated Knowledges: The Science Question in Feminism and the Privilege of Partial Perspective", *Feminist Studies* 14: 575–99.

Henschel, R.L. (1990) "Credibility and Confidence Loops in Social Prediction", in F. Geyer and J. Van der Zouwen (eds) *Self-Referencing in Social Systems*, pp. 31–58. Salinas, CA: Intersystems.

Hinton, G.E., McClelland, J.L. and Rumelhart, D.E. (1986) "Distributed Representations", in D.E. Rumelhart, J.L. McClelland and the PDP Group *Parallel Distributed Processing*, vol. I, pp. 77–109. Cambridge MA: MIT Press.

Hogeweg, P. (1988) "Cellular Automata as a Paradigm for Ecological Modeling", *Applications in Math. and Computation* 27: 81–100.

Kampmann, C., Haxholdt, C., Mosekilde, E. and Sterman, J.D. (1994) "Entrainment in a Disaggregated Economic Long-wave Model", in L. Leydesdorff and P. Van den Besselaar (eds), pp. 109–24.

Kaufer, D.S. and Carley, K.M. (1993) *Communication at a Distance*. Hillsdale, NJ: Erlbaum.

Kauffman, S.A. (1991) "Antichaos and Adaptation," *Scientific American* (August): 64–70.

Knorr-Cetina, K.D. (1981) "Introduction. The micro-sociological challenge to macro-sociology: towards a reconstruction of social theory and method", in K.D. Knorr-Cetina and A.V. Cicourel (eds) *Advances in Social Theory and Methodology: Toward an Integration of Micro- and Macro-Sociologies*. London: Routledge & Kegan Paul.

Langton, C.G. (1989) "Artificial Life", in C.G. Langton (ed.) *Artificial Life*, pp. 1–47. Redwood City, CA: Addison-Wesley.

Langton, C.G., Taylor, C., Farmer, J.D. and Rasmussen, S. eds, (1992) *Artificial Life II*. Redwood City, CA: Addison-Wesley.

Lazarsfeld, P.F. and Henry, N.W. (1968) *Latent Structure Analysis*. Boston, MA: Houghton Mifflin.

Lee, M.E. (1994) "The Evolution of Technology: A Model of Socio-ecological Self-organization", in L. Leydesdorff and P. Van den Besselaar (eds), pp. 167–79.

Lewin, R. (1992) "Life and Death in a Digital World", *New Scientist* 133(22 February): 36–9.

Leydesdorff, L. (1991) "The Static and Dynamic Analysis of Network Data Using Information Theory", *Social Networks* 13: 263–8.

Leydesdorff, L. (1992a) "Knowledge Representations, Bayesian Inferences, and Empirical Science Studies", *Social Science Information* 31: 213–37.

Leydesdorff, L. (1992b) "The Impact of EC Science Policies on the Transnational Publication System", *Technology Analysis and Strategic Management* 4: 279–98.

Leydesdorff, L. (1993) " 'Structure'/'Action' Contingencies and the Model of Parallel Distributed Processing", *Journal for the Theory of Social Behaviour* 23: 47–77.

Leydesdorff, L. (1994) "The Evolution of Communication Systems", *International Journal of Systems Research and Information Science* 6: 219–30.

Leydesdorff, L. (1995) *The Challenge of Scientometrics: The Development, Measurement, and Self-Organization of Scientific Communication*. Leiden: DSWO Press Leiden University.

Leydesdorff, L. and Van den Besselaar, P., eds (1994) *Evolutionary Economics and Chaos Theory: New Directions in Technology Studies*. London: Pinter.

Luhmann, N. (1984) *Soziale Systeme. Grundriss einer allgemeinen Theorie*. Frankfurt a.M.: Suhrkamp.

Maruyama, M. (1963) "The Second Cybernetics: Deviation-amplifying Mutual Causal Processes", *American Scientist* 51: 333–57.

May, R. (1976) "Simple Mathematical Models with Very Complicated Dynamics", *Nature* 261: 459–67.

Parisi, D. (1994) "Science as History", *Social Science Information* 33: 621–47.

Pearl, J. (1988) *Probabilistic Reasoning and Artificial Intelligence: Networks of Plausible Inference*. San Mateo, CA: Morgan Kaufman.

Popper, K.R. (1934) *The Logic of Scientific Discovery*. London: Hutchinson, 1959.

Rumelhart, D.E., McClelland, J.L. and the PDP Group (1986) *Parallel Distributed Processing*. Cambridge, MA/London: MIT Press.

Schumpeter, J.A. (1939) *Business Cycles: A Theoretical, Historical and Statistical Analysis*. London: Allen & Unwin.

Shinn, T. (1987) "Géometrie et langage: la structure des modèles en sciences sociales et en sciences physiques", *Bulletin de Méthodologie Sociologique* 1(16): 5–38.

Simon, H.A. (1969) *The Sciences of the Artificial*. Cambridge, MA/London: MIT Press.

Simon, H.A. (1973) "The Organization of Complex Systems", in H.H. Pattee (ed.) *Hierarchy Theory: The Challenge of Complex Systems*, pp. 1–27. New York: George Braziller.

Smolensky, P. (1986) "Information Processing in Dynamical Systems: Foundations of Harmony Theory", in D.E. Rumelhart et al. (eds), vol. I, pp. 194–281.

Swenson, R. (1989) "Emergent Attractors and the Law of Maximum Entropy Production: Foundations to a Theory of General Evolution". *Systems Research* 6: 187–97.

Theil, H. (1972) *Statistical Decomposition Analysis*. Amsterdam: North-Holland.

Ulam, S. (1962) "On Some Mathematical Problems Connected with Patterns of

Growth of Figures", *Proceedings of Symposia in Applied Mathematics* 14: 215–24.

Von Neumann, J. (1966) *Theory of Self-reproducing Automata*. Edited and completed by A.W. Burks. Urbana: University of Illinois Press.

Wolfram, S. (1983) "Statistical Mechanics of Cellular Automata", *Review of Modern Physics* 55: 601–44.

Wolfram, S. (1984a) "Universality and Complexity in Cellular Automata", *Physica D* 10: 1–35.

Wolfram, S. (1984b) "Cellular Automata as Models of Complexity", *Nature* 311: 419–24.

Zuyderhoudt, R.W.L. (1990) "Chaos and the Dynamics of Self-Organization", *Human Systems Management* 9: 225–38.