Detecting Emergence in the Interplay of Networks

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Abstract

We present a formal framework for the identification and interpretation of emergent properties in environments where agents participate in distinct kinds of relations or networks. We focus here on the interplay between social and geographic relations in the behavior of our agents. The method we present provides a way to detect emergent properties in the interaction of distinguishable forms of network. Our initial models suggest that characterizing the emergent properties of the behavior of a complex communication network allows for the explanation of dynamics in geographic and other dimensions. Additionally, we hypothesize the emergence of territory-like features which have consequences for the behavior of agents at both social and spatial levels. We distinguish our approach from what we call macro-level accounts of emergence and present two case studies in which we apply some of the formal strategies discussed.

1. Introducing the inter-network analysis of emergent properties

In this paper, we discuss our initial findings concerning the identification and interpretation of emergent patterns in the interplay between social and physical dimensions of agency.[1] We also present some of the formal techniques which may serve as part of a generic framework for a new approach to the characterization of emergent properties. Our approach is intended to supplement traditional cellular automata models and to offer an alternative to the part-whole or macro-property conception of emergence which dominates the computational literature.

Among metaphysicians, the core conceptual challenge to a viable account of emergent properties relates to the contradictory implications of permitting emergent properties to have downward causal power over their constituents. [Kim, 1999] In response to the difficulty of individuating emergent properties in a way which overcomes the challenge of causal preemption, philosophers have distinguished types of emergent properties. These properties are ordered from weakly to strongly emergent and philosophers have argued over their relative metaphysical acceptability. Weakly emergent properties are those which are understood relative to our epistemic capacities (predictability, compressibility etc.). [Bedau, 1997] Strongly emergent properties, by contrast, have intrinsic ontological properties such that they have unique causal powers over and above the powers of their constituents. [Symons, 2001]

Weak and strong emergence are not clearly distinguished in the computer science and engineering literature where emergent properties are understood, in very general terms, to appear as a macro-property within a system in virtue of the interaction of more basic components of that system. [Symons, 2008]

Our approach to emergence offers an alternative to the macro-properties model of emergence. Emergence, we suggest, is not restricted to macro-phenomena, but can appear at the intersection of relations or networks. Rather than attempting to account for some macro-property of a system, we examine the interplay between distinguishable dimensions of the behavior of some set of objects. We assume that objects or agents can be involved in distinguishable systems or networks simultaneously. Our assumption is that an agent may participate in social, political, economic and other networks simultaneously. In some cases these distinct sets of relations have no effect on one another. Fred's being a nephew may have no relevant bearing on his participation in some non-familial networks, say for example, his activities as a member of a university committee.

[1] We would like to thank Paul Humphreys and two anonymous referees for excellent critical comments on an earlier draft of this paper.

Alternatively, it may be that the influence from the agents behavior in one network acts on its behavior in another network in a uni-directional manner. Let's assume, for instance that being a physical object can be understood as being part of a network of objects governed by physical laws. Most philosophers regard physical laws as fundamental and maximally general. On the traditional mereological view of part-whole relations, participation in all other networks would supervene on the agent's place within the physical network. Belief in what philosophers call strong supervenience is equivalent to the claim that the agent's place within a physical network fixes its place within all other networks such that any object having the same place in the physical network as some object *a* would hold the same place in all networks as *a*. This would be the case for most of the macro-properties under consideration in traditional cellular automata models. Macro-properties in these contexts do not act on their constituents. Like properties supervening on their basal physical properties, the patterns that are sometimes called emergent in cellular automata models do not have the power to modify their constituents. More precisely, as modeled by traditional cellular automata, there is no way to model such powers.

Our view is that the mereological approach to emergence fails to capture some important features of the natural world and that it is especially inadequate in the social sciences. An agent can be a member of a distinct set of networks governed by a variety of different rules, and in some contexts, by virtue of being involved in these distinct networks, agents can occasionally serve as the site for productive interplay between networks. In this interplay, we claim that one can sometimes find emergent properties. These properties are not always best characterized as macro-properties of one system in particular.

While we regard our approach as having general applicability to interactions between networks, at present, our research is focused on the interplay between social communication networks and geographical location. Specifically, we are interested in the reciprocal relations between an agent's social/communication networks and its spatial location. We have modeled these relations in our case studies on cicada mating behavior and human smart mobs. [Louçã *et al.*, 2007] While there is an obvious "bottom-up" effect from spatial relationships to communicative relationships, our working hypothesis is that social factors can have a causal effect on the spatial locations of agents. What we mean by social factors here is left deliberately non-specific. In our study of cicada behavior for instance, the factors we considered were related to species-specific constraints on the communications network. We studied the relationship between the species movement in geographical space and alternative sets of constraints on the cicadas' communication systems. However, a range of alternative applications can be explored wherein the effects of varying constraints on social or communications networks are observed on geographical, economic or other forms of network.

2. First steps in the application of the approach: *Cicada barbara lusitanica*

Our first case study derived from experimental results concerning live experiments on the stereotyped singing response behaviors of cicadas. [Fonseca & Revez, 2002] [Louçã *et al.*, 2007] By observing the relationship between constraints on communications networks and the resulting geographical patterns in the movements of the cicadas, we were able to conclude that insect songs encode specific information about the identity of species, which are used by individuals to discriminate conspecific from heterospecific sympatric species.

In their empirical study of cicadas, Fonseca and Revez argued that both the frequency spectrum of the male cicadas' signal and its temporal pattern carries information about the species-identity of the singer. By modeling the interplay between alternative types of song patterns and their resulting georgraphical patterns we provide further support to the empirical findings of Fonseca and Revez, showing why the use of only one parameter in the cicada song is suboptimal.

The pre-copulatory isolating mechanism based on song analysis, used to maintain species integrity, uses one or/and another parameter according to the species environment. In our simulations, we compare the input communication patterns, based on frequency spectrum or time pulse, and resulting emergent movement patterns in a community of insects. Sample results from our model of the geographical movement of the cicadas are depicted in Figures 1 and 2.

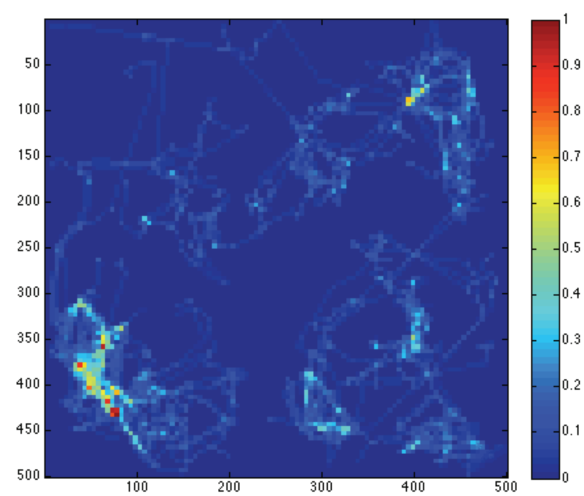

Figure 1: The *Cicada Barbara lusitanica* model: trails of cicadas considering no input patterns.

In our model, cicadas use song recognition patterns, to guide their motion towards males through the environment. Their motion exhibits a structure depending on the system of recognition in use. The movement of cicadas covers the space with clear tracks. As we can see in figure 2, the particular case of simultaneously using both recognition patterns results in a thin network, with more tracks and more rapid access to males of the corresponding species (image on the right). On the other hand, when there is no use of recognition patterns, dislocations are short and their direction is random, with no clear existence of tracks (figure 1). We can also model alternative strategies for pattern recognition in cicadas in order to exhibit their macro features.

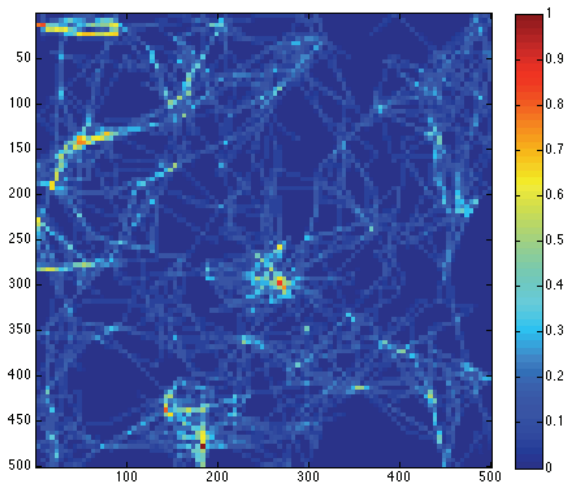

Figure 2: The *Cicada Barbara lusitanica* model: trails of cicadas considering both time and frequency patterns.

These results illustrate the interplay between spatial location, usage of energy and the features of social or communications network in cicadas behavior. This interplay is, of course directly related to the preservation of their species. This is a very simple model which relates constraints at the level of the communication network with movement through space. Our next model involves a slightly more complex social network.[2]

3. Social networks and their spatial dynamics: *Smart Mobs*

Howard Rheingold introduced the expression "smart mob" to describe the concept of a "mobile ad hoc social network". [Rheingold, 2002] Smart mobs are social networks where people communicate using mobile and wireless internet technologies. Smart mobs are becoming increasingly familiar for their role in social and political expression. For example, SMS communication was used to organize mass protests all over Spain in the aftermath of the Madrid train bombings of March 11th 2004. Viral communication strongly spread through social networks mainly composed of friends, where trust between members of the network is extremely high.

We have designed a generic model of smart mob dynamics, where the viral propagation of communication through the social networks of individuals coexists with the coordinated movements of individuals to some meeting point. Our model of smart mobs comprises two types of agents, individuals and attractors. Very briefly, when an individual finds an attractor, he propagates this information to all his friends; consequently, they will then move towards the attractor. Some results of the simulation can be observed in the following images:

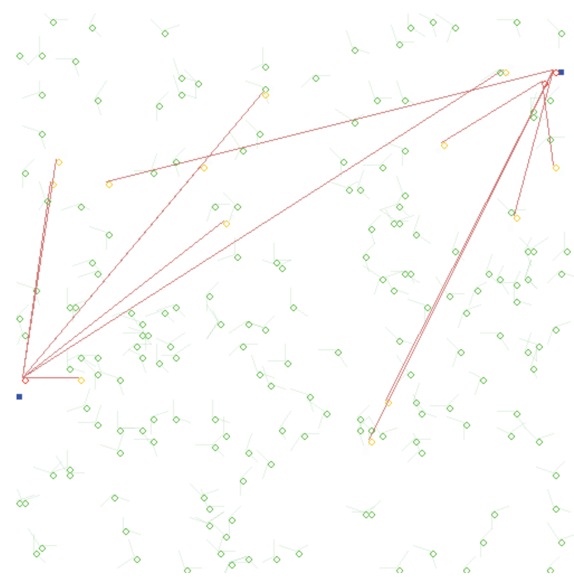

Figure 3: The Smart Mobs model: showing a sample of a communication network

Figure 3 represents communications between individuals in a social network. In this portion of the social network two individuals are acting as attractors. By contrast, figure 4 (below) depicts the physical movement of the individuals. Our experiments showed that the trace of the movement of the individuals through physical space

[2] Supporting documentation and simulations for both the cicadas and the smart mobs models can be found at: http://www.listaweb.com.pt/projects/cells

indicates geographic characteristics of specific configurations of the social network in its interplay with some physical constraints.

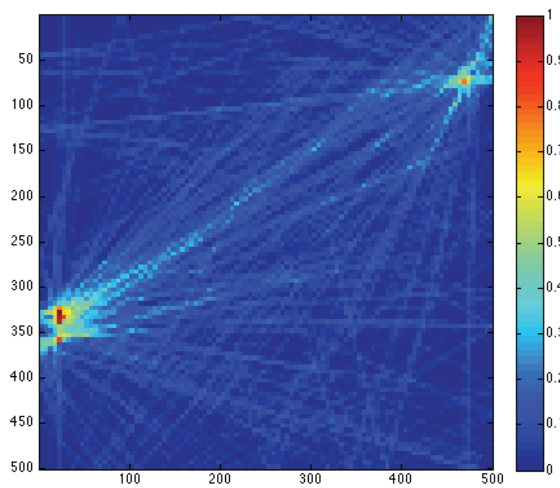

Figure 4: The Smart Mobs model: The same two attractor sample, showing the territorial movements of individuals towards the two attractors.

In future work we will apply the methodology described above to the analysis of community relations and territoriality in smart mobs models. The tools we developed in the smart mob and cicada models form the basis for the inter-network analysis of emergence described here.

4. Formalizing the interplay

Our case studies provide some insight into the manner in which collective behavior of the system in geographical space is shaped by constraints on communication. The next step is to provide a general formal framework for detecting emergence between networks.

In our research, we have focused on formalizing the process of identifying emergent properties which result from the interaction of communications networks and geographical movement. In more concrete terms, by associating patterns in different kinds of system we hope to connect the notions of place, movement and territory to social relationships represented in social networks. To this end, we develop hybrid models which combine multi-agent social simulation, cellular automata and social network analysis. This allows us to propose a way of representing the effects of social relations or communication on physical location.

Our goal is to develop techniques which permit us to relate patterns from distinct networks and to model the appearance of new features which emerge from their interaction. An operational goal of this research is to provide a generic framework (a set of tools composed by a methodology, algorithms and a programming library) for the analysis of networks and for the identification of emergent properties or fingerprints. The framework aims at providing formal characterization of the following main notions:

- *communication network* – a set of nodes and links, excluding the semantics of communication acts. Communication networks can be very broadly construed to include a wide variety of dynamic systems of rule governed relations between agents;
- *emergent fingerprint* within a communication network or at the intersection between systems. We leave the notion of emergent fingerprint deliberately vague. We simply mean, the appearance of a pattern in the system which has salient and stable features such that it can play a role in the causal economy of the set of objects under consideration. We have been using the intuitively accessible notion of territory in our exposition, but one important role of our approach would be the discovery of previously undetected emergent properties;
- *algorithms* to identify emergent fingerprints in a communication network model. These algorithms may be based, for example, on the frequency paths of communication flow in a simulation after *n* iterations.

The Z language [Spivey, 2006] is used to formally characterize the approach. This specification language allows, on the one hand, the formalization of a set of concepts and the relations between those concepts, and on the other hand the possibility of straightforwardly converting the formal model into programming code.

We formalize the following major steps within the framework: the pattern detection mechanism applied to social networks (*ComNet*); the pattern detection mechanism applied to cellular automata (*GeoNet*); and the identification of links between patterns that were detected at different levels.

From here, we plan to track the properties of these links, sifting through them in order to determine whether they constitute a causally or at least an explanatorily relevant system of their own. For example, the notion of territory results from the interplay of social networks and geographical space. However, territories play a role in modifying both geographical and social relationships. In this sense, territories have causal consequences in the structure of both networks.

By formalizing the process of discovering links between patterns at distinct levels, we hope to provide a general approach to the identification of previously unrecognized emergent phenomena. While in the models discussed above, the cellular automata are our way of representing the spatial or geographical dynamics of the agents in question, alternative interpretations of what it is that the cellular automata are representing could be introduced. The interpretation of the dynamics of the cellular automaton will be dependent on what it is that the researcher is attempting to model.

A variety of systems of relations can be characterized as communications networks and our approach is intended to be as generally applicable as possible.

ComNet. The pattern detection mechanism applied to social networks follows the detection of the group in a topological space. This strategy was initially proposed by Feldman et al. [2007] and was developed by Morais. [2007]

$$
\begin{array}{l}
\textit{FindNodeMaxDegree}[network, resultNode] \\
\hline
network? : Network \\
\Delta resultNode? : Node \mid resultNode \in network?.nodeList \\
\hline
\forall node \in network?.nodeList : \\
\# node.edgesOut > resultNode.edgesOut \Rightarrow node = resultNode
\end{array}
$$

Figure 5: Formal representation of the function detecting the node of maximal degree

Figures 5 and 6 present the formal description of the algorithms isolating communities in a social network.

$$
\begin{array}{l}
\textit{IsolateCommunities}[network] \\
\hline
network? : Network \\
\Delta structure : Structure \\
tempNetwork : Network \mid tempNetwork = network? \\
tempNode : Node \\
tempNode2 : Node \\
tempMap : Map \\
tempCommunity : Community \\
\hline
\forall edges \in tempNetwork.edgeList \\
\bullet FindNodeMaxDegree(tempNetwork, tempNode) \wedge \\
\textbf{if } tempNode \notin structure.mapping.nodeName \\
\ \textbf{then } \forall tempNode2 \in \{tempNode \cup GetNeighbours(tempNode)\} \\
\bullet \Delta structure.mapping \cup \{tempMap : \\
tempMap.nodeName = tempNode2.name \wedge \\
tempMap.communityName = \# \Delta structure.data\} \\
\wedge \Delta structure.data \cup \{tempCommunity : \\
tempCommunity.network \cup tempNode2 \\
\wedge tempCommunity.name = \# \Delta structure.data\} \\
\ \textbf{else } \forall tempNode2 \in GetNeighbours(tempNode) \\
\bullet \Delta structure.mapping \cup \{tempMap : \\
tempMap.nodeName = tempNode2.name \wedge \\
tempMap.communityName = \# GetCommunityName(tempNode)\} \\
\wedge \Delta structure.data \cup \{tempCommunity : \\
tempCommunity.network \cup tempNode2\}
\end{array}
$$

Figure 6: Formal representation of the function isolating communities

These algorithms serve to process the data produced initially by the cellular automata in order to establish the character of the social network. From this network we isolate communities by analyzing the network of relations. We start by quantifying the degrees of relationships between neighbors for each node in the network and from there we find the node with maximum degree of connectivity. This node and all the nodes directly connected to it will belong to one community. Afterwards all connections to this node are removed. This procedure is continued until there are no connections left in the network.

$$
\begin{array}{l}
\textit{ModularizeCommunities}[structure] \\
\hline
\Delta structure? : Structure \\
\Delta phi : phi \in R \\
\hline
\forall \textbf{ bag } community : \textbf{ bag } community \in \mathbb{P} \Delta \text{structure?.data} \\
\mid \# \textbf{ bag } community = 2 \wedge \\
\{\forall community : community \in \textbf{ bag } community \\
\bullet community \notin \textbf{ bag } community \uplus community\} \\
\bullet analysis = MaxPhiPQ(\textbf{ bag } community) \\
\wedge \textbf{if } analysis.phi > 0 \\
\ \textbf{then } \bigcup analysis.communitiesToMerge \\
\wedge \Delta phi = analysis.phi
\end{array}
$$

Figure 7: Formal representation of the function detecting social structures

This is a relatively simple strategy for determining distinct communities within social networks. Based on the previously determined community structure we find the pair of communities that could be merged to increase the overall modularity of the network (see Figure 7). This is determined by calculating the value for *Phi*, meaning the modularity change resulting from such merger. This procedure is carried until no such pair exists. The result is a group of sub-networks, representing communities.

The resulting communities which our analysis extracts demonstrate that there exists a previously unrecognized level of organization in the data. We begin from data that is organized merely by the structure of respective interconnections. These interconnections are derived from the modeled behavior and, therefore, the organization of elements in sub-networks is a property of a macro-level.

The fact that elements within these sub-networks or communities have more connections to one another than to elements that are not in the same group is, in part random and in part a result of additional constraints, including, in some of our models a set of general physical or spatial constraints on the formation of new friendships. Constraints at the level of spatial relations led us to consider the interplay between the communicative and geographical constraints that act on social agents.

To characterize the territories of sub-groups, we can map our social or communication networks to the physical location of the agents, thus determining whether some group behavior exists that may be characterized as governed or influenced by the existence of a specific territory. In this sense GeoNet is an essential part of this project since it allows us to build social networks from the spatial patterns of specific models.

GeoNet. The concept of pattern detection in cellular automata targets what we call 'fingerprints' in a set of tracks left by agents as they move through some defined spatial region. We propose to convert the spatial pattern of these fingerprints to a social network in order to apply social network metrics. To do this, we define the *GeoNet* mechanism to map a geometrical model to a topological one.

$$
\begin{array}{|l}
\multicolumn{1}{l}{Normalized[trails]} \\
\Delta trails? : Trails \\
\hline
\Delta trails? = normalize(\Delta trails?)
\end{array}
$$

Figure 8: Formal representation of the function normalizing trails

From the trails left by agents in geometrical space the first step involves the normalization of data, represented in Figure 8, to allow comparison between different data sets.

$$
\begin{array}{|l}
\multicolumn{1}{l}{CutOff[normalized, cuttOffValue]} \\
\Delta normalized? : Trails' \\
cutOffValue? \in R \\
\hline
\Delta normalized? = cutOff(cutOffValue?)
\end{array}
$$

Figure 9: Formal representation of the function eliminating irrelevant values

From the normalized data, a threshold is defined to eliminate irrelevant values that arise in the data set. This allows the selection of the strongest features present.

$$
\begin{array}{|l}
\multicolumn{1}{l}{HotSpots[cutOff, normal, network]} \\
cutOff? : Trails'' \\
normal? : Trails' \\
\Delta network? : Network \\
\Delta nodeList : \mathsf{seq}\ Node \mid nodeList = \Delta network?.nodeList \\
\Delta edgeList : \mathsf{seq}\ Edge \mid edgeList = \Delta network?.edgeList \\
\hline
\Delta nodeList : getMaximums(cutOff?) \\
\Delta edgeList : connectNodes(cutOff?, \Delta nodeList, normal)
\end{array}
$$

Figure 10: Formal representation of the function reconnecting selected nodes

In the normalized and selected data determined previously, we define the nodes and connections so that this data may be analyzed as a network.

To these networks generated by the *GeoNet* algorithm we can now apply the *ComNet* algorithms to try to identify the communities that where formed. In this way, we can map the communities to the territories occupied by each of them in the cellular automaton space.

This allows us to validate the *ComNet* algorithm as a process of identifying communities since in our experimentation we are privy to knowing which community an agent belongs ahead of time. In the construction of the model this process is repeated to find the optimal parameters for the *GeoNet* algorithm that will then be used to create the relations between the patterns observed from *GeoNet* and *ComNet*.

Relating Patterns. Finally, patterns derived from *ComNet* and *GeoNet* can be associated to relate patterns characterizing different levels of analysis.

The dynamics of each simulation is analyzed by determining the number of times each pair of structure and trail map occurs. We start by combining all possible tuples of specific trail maps and structures. Then we count how many times each tuple occurred. This allows us to infer a causal effect between the two levels of analysis.

$$
\begin{array}{l}
\mathit{History}[\mathit{trailmap}, \mathit{structuremap}] \\
\hline
\mathit{trailmap?} : \mathsf{seq}\ \mathsf{bag}\ \mathit{Trails} \\
\mathit{structuremap?} : \mathsf{seq}\ \mathit{Structure} \\
\Delta \mathit{counter} : \Delta \mathit{counter} \in \mathbb{N} \\
\Delta \mathit{sortedMap} : \mathsf{seq}\ (\ \mathsf{bag}\ \mathit{Trails}, \mathit{Structures}, \mathit{counter}) \\
\mathit{tuple} : (\ \mathsf{bag}\ \mathit{Trails}, \mathit{Structures}) \\
\mathit{triple} : (\ \mathsf{bag}\ \mathit{Trails}, \mathit{Structures}, \mathit{counter}) \\
\hline
\forall \mathit{tuple} \in \mathbb{P}(\mathrm{trailmap?} \times \mathrm{structuremap?}) : \\
\exists \mathit{triple} : \mathit{triple} \in \Delta \mathit{sortedMap} \\
\wedge \mathit{first\ triple} = \mathit{first\ tupple} \wedge \mathit{second\ triple} = \mathit{second\ tupple} \\
\wedge \mathit{third\ triple} = \mathit{CountOccurrences}(\mathit{trailmap}, \\
\mathit{structuremap}, \mathit{first\ tupple}, \mathit{second\ tupple}))
\end{array}
$$

Figure 11: Formal representation of the function relating trail and social structure patterns

Simulations where there is a salient effect between the two levels of analyses will present a larger number of occurrences when compared to pure random simulations.

It could be argued that this result is obvious as it arises from the rules of the model. Although the rules are programmed, they aren't used to predict or to map the results and are used only for the training of the algorithms. After that they are forgotten and the analysis is directed solely towards patterns at the network and trail levels.

The methodology formally depicted above was developed out of a series of case studies [Louçã *et al.*, 2007; Rodrigues, 2007; Morais, 2007] wherein we developed the representation of geometrical patterns and the relationship of geometrical patterns to topological patterns.

5. Contrasting macro-property and inter-network analyses of emergent properties

Classic cellular automata models of emergence, like John Holland's for example, are meant to provide formal accounts of the appearance of macro-level patterns of collective behaviour within a particular system. Macro-properties appear from the interaction of rules governing the basic constituents of a system. As such, Holland regards emergence as "the obverse of reduction". [1997, 38] This is what philosophers would call a mereological or part-whole conception of emergence.

Holland's purpose in tracking the behaviour of cellular automata is to observe how the interactions of constituent level phenomena can give rise to emergent properties at the macro-level. He shows how critical these interactions are in the appearance of macro-properties of a system and he regards them as eluding a scientific study of the constituents in isolation; "A detailed knowledge of the repertoire of an individual ant does not prepare us for the remarkable flexibility of the ant colony." [Holland 1998, 130]

Our approach extends Holland's work insofar as it is not restricted to the analysis of a single system and its macroproperties. Instead, we consider a set of agents participating in a number of distinct systems or networks simultaneously. For example, an agent can be considered as part of a communications or social network and as a location in a geographical space. We have described how it is possible to link distinct networks and track novel features that appear at the intersection.

By way of an example of the kind of emergent property that we believe has an inter-network nature, we suggested that the interplay between social network dynamics and physical locations gives rise to the notion of territory. Consider the properties of a territory. One can regard territories as emergent properties which result from and in turn modify the spatial and social relations governing an agent. The strength of some social relations will be weakened or reinforced by territories while territories also have some role in modifying the probability of some physical movements of agents.

The process of finding territories and tracking their effects on the social and geographical networks is a non-trivial technical challenge. We have begun to show how it might be achieved in the previous section. However, given the difficulty of the project, it is worth contrasting the approach to the limitations of traditional cellular automata models in order to motivate researchers to consider our approach.

As we have discussed above, Holland and others treat emergence as a feature of a single system of agents and states and thus the formal representation of emergence involves specification of the possible mappings between the states of that system. These mappings can be captured via a transition function which maps the set of possible states of a system onto itself. Holland describes the characterization of the transition function along the following lines:

The set of states S $\{s1, s2, s3, \ldots\}$ is taken to be finite for the sake of computational tractability. A transition function takes as its argument some state of the system in combination with some input at a time and gives as a value a state of the system. For any input of type j there will be an associated set of possible input values Ij.

Thus,

$Ij = \{ij1, ij\,2, ij\,3, \ldots\}$

where $ij2$ names state number 2 of the input j. Given k types of input for the system there will be k sets of possible input values

$\{I1, I\,2, I\,3, \ldots Ik\}$.

The set of all combinations for the system is given as the product of the sets

$I1 \times I\,2 \times I\,3 \ldots \times Ik$.

Now, the transition function can be defined as

f: $(I1 \times I2 \times I3 \ldots \times Ik) \times S \to S$

and the temporal dynamic of the system can be defined as

$S(t+1) = f(I1(t), I2(t), I3(t), \ldots Ik(t), S(t))$.

The iteration of f generates the state trajectory of the system. [Holland 1998, 130-131] Thus, the core methodological assumption in traditional cellular automata approaches to emergence is the idea of functions mapping the set of states of a system onto itself. By contrast, our approach involves a single set of objects which are seen as participating in two distinct networks or systems of relationships. The emergent features which we hope to understand and detect cannot be characterized in the manner described by Holland. In part, this is because what we are calling the emergent properties will (in Holland's terms) modify the transition functions acting on the initial specification of the possible states of the system in each of the interacting levels in a way that is not dependent on the rules governing that initial specification of states. For instance, in the example mentioned previously, we hypothesize that the transition functions which act on the set of possible states in the social network will not accurately capture the temporal dynamic of the system once one takes account of the interaction with the agents' geographical location. This is simply because, the social dynamic in which an agent participates will be the subject to the effects of emergent territorial properties. In addition, territories will play a role in the physical location of an agent in a specific social network.

6. Conclusion

Traditional cellular automata models illustrate the idea that the interaction of transition functions may give rise to behaviours that are not captured by the transition functions in isolation. This is an important insight which our approach preserves. As described in the previous section, emergence via constrained generating procedures is such that given a deterministic system governed by more than one kind of rule ranging over the behaviour of a simple set of elements we can often find a contingent set of initial conditions such that some a macro-property is generated by the system in question. Such models resolve puzzles concerning how it is that specific macro-properties might have come into being by modelling the interaction of transition functions given some specific set of initial conditions.

Our approach extends traditional cellular automata accounts of emergence insofar as we aim to study the appearance of emergent properties in contexts where agents are governed by different systems of interacting relations. In our initial modelling projects, we highlight the interplay between social and spatial relations. The broader purpose of this work is to suggest new approaches to the study of emergence and to present an alternative to the macro-properties approach which has dominated traditional cellular automata accounts of emergence.

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