Simulating Human Behaviour: the Invisible Choreography of Self–Referential Systems

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Abstract: Challenges arise when it comes to capturing complex patterns of human behaviour in agent-based simulations. For example, human beings are not limited to one identity, to local levels of awareness or to acting on predetermined rules. Seemingly immune from these difficulties are some *self-referential* problems – situations where agents' forecasts act to create the world they are trying to forecast. The emergent complexity in these systems results more from ways in which agents interact and react rather than from their individual idiosyncrasies. A well-known example is the Bar problem, whose collective regularities are relatively insensitive to the vagaries of individuals. Some other socio-technical, socio-economic and socio-ecological systems of a self-referential nature are discussed. Many self-referential systems are intriguing because there is an air of inevitability about them. They seem to co-evolve in prearranged ways, as if under the spell of an invisible choreographer.

Keywords: Agent-based models; Bar problem; Self-referential behaviour; Sheep and explorers

1. INTRODUCTION

The pace of development in agent-based simulation models linking social, economic and ecological interactions has been rapid. Many simulation models representing facets of human behaviour have emerged [Arthur, 1994; Axelrod, 1997; Gilbert and Troitzsch, 1999, Barreteau and Bousquet, 2000]. Social scientists use simulation for several purposes, including discovery of collective regularities. Some have been built on strong behavioural foundations, where the mental models of the artificial agents are supported by empirical data or stakeholders' views. In others, agents' strategies have been chosen arbitrarily or stochastically and the outcomes tested in computational experiments. Both approaches have yielded interesting results.

In a recent paper to the IBM Systems Journal, Kurtz and Snowden [2003] assert that there are some important contextual differences between the behaviour of human and ant colonies, making it difficult to simulate humans using computer models. Unlike social insects, we are not genetically hardwired for cooperative behaviour. They list several challenges when it comes to capturing complex patterns of human behaviour in agent-based simulations:

(1) Humans are not limited to one identity or any common set of emotions;
(2) Humans are not limited to acting in accordance with predetermined rules;
(3) Humans are not limited to acting on local patterns.

On first sight, such challenges look daunting. Clearly it is difficult to consider all scales of human awareness simultaneously, instead of choosing one circle of influence when devising mental models to represent human behaviour in a specific context. On further reflection, however, these challenges may not be critical for simulating certain social collectives. One class of social systems that seems relatively immune is *self-referential* systems – situations where the forecasts made by agents serve to create the world they are trying to forecast. The emergent complexity in these systems arises more from ways in which the agents interact and affect each other and less from each agent's individual idiosyncrasies.

The purpose of this paper is to look at one self-referential system (the Bar Problem) and show that its collective outcomes are insensitive to the vagaries of individuals. Although it does not necessarily follow that all self-referential systems have this property, there is a similar air of inevitability about many of them. They appear to co-evolve in prearranged ways, as if under the spell of an invisible choreographer.

2. THE HUMAN IDENTITY PROBLEM

2.1 K&S Argument Number 1

K&S stress that "In a human complex system, an agent is anything that has identity, and we constantly flex our identities both individually and collectively." We play different roles at the same time – e.g. parent, spouse, employee or neighbour – and will behave differently depending on the context. Collectively, we might belong to a dissenting community group. When faced with a common threat, however, we might change this identity and throw our support behind the same government that prompted our dissent. Their key point is that it is often impossible to know in advance which unit of analysis we are working with. K&S are critical of several attempts to overcome this "unit of analysis" problem in the social simulation literature:

(1) They argue that identity goes deeper than *norms*, a concept often used to explain group behaviour [Axelrod, 1997];
(2) They argue that much internal diversity and patterning is suppressed if individuals are modelled as agents;
(3) They argue that use of an idea or "meme" as the unit of analysis is insufficient to capture the dynamics of multiple identities [Dawkins, 1976].

Despite the weight of their arguments, the identity problem may not always be as serious as K&S suggest. Who a person is may not be as vital for exploring the emergent properties of certain human collectives as representing the heterogeneous mix of agents' behavioural strategies and their interactions in the appropriate co-evolutionary context. When a mix of strategies co-evolves over time, any flexing of individual identities is unlikely to have much impact on collective outcomes. One setting where individual identities play a limited role is the bar problem, an early agent-based simulation of a complex adaptive system reported by Brian Arthur [1994].

2.2 The Bar Problem Defined

Consider a system of N = 100 agents deciding independently each week whether or not to go to their favourite bar next Thursday. Space is limited, so the evening is enjoyable only if the bar is not too crowded (say $N_{max} = 60$). There is no collusion or prior communication among agents. Knowing the bar attendance over the past few weeks, each bar-loving agent simply decides independently to go if he expects less than N_{max} to attend and to stay home if he expects more than N_{max} to go.

This problem is a metaphor for a broad class of social situations: e.g. urban traffic congestion, canteen crowding, queue lengths at big events, fishing strategies and many other commons or coordination problems. It has some interesting properties. First, if a decision model existed that agents could rely upon to forecast attendance, then a deductive solution would be possible. No such model exists. Irrespective of past attendance figures, many plausible hypotheses could be adopted to predict future attendance. Because agents' rationality is bounded, they are forced to reason *inductively*. Second, any shared expectations will be self-defeating and broken up. If all agents believe *most* will go, then *nobody* will go. By staying home, that common belief will be destroyed. If all agents believe *few* will go, then *all* will go, thus undermining that belief. The result is that agents' expectations must always differ.

Perplexed by the intractability of this problem, Arthur created a computer simulation in which his agents were given attendance figures over the past few months. Also, he created an "alphabetic soup" of several dozen predictors replicated many times. After randomly ladling out k of these to each agent, each kept track of his k different predictors and decided whether to go or not according to a preferred predictor in his set. This preferred predictor could be chosen in a variety of ways, although Arthur adopted the currently most accurate predictor for each agent in his simulations.

Each predictor is a means of deciding between two simple alternatives: GO or DON'T GO. It could be tied to a much richer set of decision criteria, including an agent's multiple identities or moods. When deciding whether to go to our favourite bar, for example, our simultaneous roles as a parent, a spouse or employee impact differently on our decision at different times. Provided the desire is to go to an <u>uncongested</u> bar each week, however, a richer soup of identity-flexing hypotheses is unlikely to alter the results of Arthur's simulations (see the next section) in any qualitative way.

3. THE INTENTIONALITY PROBLEM

3.1 K&S Argument Number 2

K&S argue how difficult it is to simulate free will and complex intentionality. Simulations have addressed cooperation, reputation, gossip, reciprocity, lying and trust, but are yet to address other aspects – like duplicity, rumour, self-deception, manipulation, stress, confusion, ambiguity and charisma. Although the list is challenging, not all of it is relevant to the aims of those engaged in agent-based simulation. Whether humans do act in accordance with certain predetermined rules or not is not the primary question, but rather can we identify certain patterns when agents behave *as if* governed by predetermined mechanisms (such as certain cognitive processes). In this respect, human being and ants are similar. We still do not know if ants behave according to certain predetermined mechanisms, but at least we can model and study them as if this is the case.

A key difference between the strong-AI school of the seventies (hoping to reproduce human intelligence) and those doing agent-based simulation is that the latter are not expecting to simulate how people will behave in every instance [Gilbert and Troitzsch, 1999]. Their main aims are: (1) to show how heterogeneous micro-worlds of individual behaviours interact to generate macroscopic regularities, and (2) to show how alternative collective outcomes may evolve under different conditions. Both are sensitive to *interactions between agents*, rather than to the agents' individual predilections.

3.2 The Bar Problem Simulated

Once decisions have been made in Arthur's simulated bar, agents learn the new attendance figure, updating the accuracy of their own set of predictors. Then decisions are made for the following week. In this kind of problem, the set of predictors acted upon by agents – called the set of *preferred* predictors – determines the attendance. But the attendance history also determines the set of preferred predictors. We can think of this set as forming a kind of *ecology* (John Holland's term). Of interest is how this ecology evolves over time.

The simulations show that weekly attendance fluctuates unpredictably, but mean attendance always converges to sixty in the long run. The predictors self-organize into an equilibrium pattern or ecology in which (on average) 40% of the preferred predictors forecast above sixty and 60% below sixty. This 40/60 split remains although the population of preferred predictors keeps changing in membership forever. The emergent ecology is rather like a forest whose contours do not change, but whose individual trees do. Similar results appeared throughout Arthur's experiments, robust to changes in the types of hypotheses (read identities or moods). There is another intriguing result. Although, the computer-generated attendance results look more like the outcome of a random process rather than a deterministic one (see Figure 1), there is no inherently random factor governing how many people attend. Weekly attendance is a deterministic function of the individual predictions, themselves being deterministic functions of the past attendance figures.

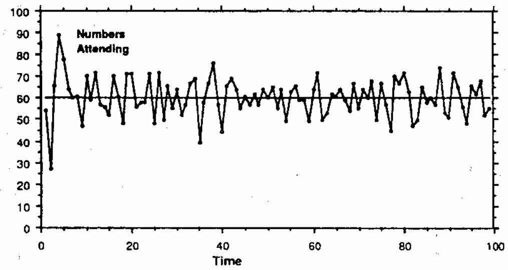

Fig. 1. A simulated 100-week record of attendance at El Farol.

4. SCALES OF AWARENESS PROBLEM

4.1 K&S Argument Number 3

The third challenge raised by K&S is the fact that it is difficult to consider all scales of human awareness simultaneously, instead of one circle of influence when devising a set of mental models to simulate human behaviour in a specific context. Although true, it evokes an earlier statement: people engaged in simulation are not expecting to represent what people may think, feel and do in every context. Instead they aim to explore the co-evolutionary space under "as if" scenarios – collective results that may emerge under particular conditions only. Such conditions are described in terms of the state of the agents, the environment in which they interact and the sets of rules that govern both agents and environment. Since the agents are interacting in or on this environment, the rules and state of the environment play a key part in focusing each agent's mind on the decision at hand and the choice of a pragmatic predictor or heuristic to apply to it.

Part of the art of agent-based simulation lies in identifying settings where the agents' decision criteria are focused and limited in number (e.g. fast and frugal), less emotive or theoretical. Heuristics allow agents to make smart choices quickly in the face of limited information, by exploiting the way that information is structured in some environments [Gigerenzer and Selten, 2001]. In many settings, there is little scope for sophisticated decision tools or emotive states because the decision itself is of a simple, binary kind – "GO or DON'T GO". In these situations, recollections of earlier experiences of a similar kind tend to combine with our current predisposition towards the event, leading to a final decision.

4.2 The Bar Problem Interpreted

The bar problem is a situation where a system of interacting agents can develop collective properties that are not at all obvious from our knowledge of the agents themselves. Even if we knew all agents' individual idiosyncrasies, we are no closer to anticipating the emergent regularities. In the absence of communication between the agents, individually subjective, boundedly rational expectations self-organize (under the influence of a strong aggregate *attractor*) to produce "collectively rational" behaviour [Arthur, 1994]. If we allow the agents to learn and communicate using an evolutionary process (a genetic programming algorithm), heterogeneity among the agents emerges in the form of role-playing and non-uniform social structures [Edmonds, 1999]. All these collective properties are features that emerge purely from the micro-dynamics.

Is the bar problem important? From several perspectives, it would seem to be. First, like the Prisoners' Dilemma, it is receiving more attention outside economics – as a metaphor for learning and bounded rationality. It has inspired a new literature in statistical physics on a closely related problem known as the Minority Game. In this game, each agent chooses one out of two alternatives every turn and those who end up in the minority are the winners. Like in the bar problem, numerical simulations of this game have displayed a remarkably rich set of emergent, collective behaviours [Challet and Zhang, 1998].

Second, the bar problem contains all the key elements of a *complex adaptive system*. It involves a *medium* number of agents, a number too large for hand-calculation or intuition but too small to use statistical methods applicable to very large populations. These agents are *intelligent* and *adaptive*, making decisions on the basis of rules of thumb or heuristics (like the bar predictors). Needing to modify these rules or come up with new ones if necessary, they reason *inductively*. Importantly, no single agent knows what all the others are (thinking of) doing, because each has access to limited information only.

Third, the bar problem is *self-referential* – a situation where forecasts made by individual agents act to create the world they are trying to forecast. Such systems have also been called *reflexive* or *co-evolutionary* [Batten, 2000]. In self-referential systems, the "best" thing to do (e.g. GO or DON'T GO) depends on what everyone else is doing. Since no single agent knows that, the best thing that they can do is to apply the predictor or heuristic that has worked best so far. The remainder of this paper will be devoted to a discussion of other self-referential systems and some examples of their nonlinear, dynamic properties.

5. SELF-REFERENTIAL SYSTEMS

What do these self-referential situations have in common? First, they are "GO or DON'T GO" decision problems at specific locations in space and time. Second, the best thing to do depends on what everyone else is doing at that time. Third, since no agent knows what all the others are doing, agents must decide using a predictor or heuristic that has worked well for them earlier. Finally, there is a risk that agents may be caught up in an undesirable collective outcome – such as congestion.

5.1 Socio-Technical Systems

Many examples of self-referential problems lie in the socio-technical arena. Socio-technical systems are ones in which human beings interact with each other in a physical environment built by humans. Situations of a qualitatively similar kind to the bar problem arise, such as canteen crowding, queue lengths at cinemas, crowds at sporting stadiums, and traffic congestion during peak periods on our roads and at our airports.

Like agent numbers turning up at the bar each Thursday night, the number of vehicles turning up on a specific road each day is unpredictable. If the traffic density is pushed beyond critical levels, however, it triggers unexpected phase changes in the traffic's collective behaviour. Simulation work using Cellular Automata has shown that the average speed drops rapidly once the density passes a critical value – corresponding to a jamming transition from free-flow to start-stop waves. Fluctuations in travel time from vehicle-to-vehicle go up very quickly, reaching a peak near the point of critical density. This emergent behaviour is quite striking.

Of interest are the adaptive strategies of drivers exposed to regular traffic jams. Downs [1962] identified two behavioural classes of driver: those with a low propensity to change their mode or route strategy, called *sheep*, and those with a propensity to change, called *explorers*. Explorers search for alternative options to save time. They are quick to learn and hold several heuristics in mind simultaneously. Sheep are more conservative and prone to following the same option. Empirical work in North America has confirmed the presence of sheep and explorer behaviour in real traffic [Conquest et al, 1993]. Sheepish drivers, who are unwilling to modify their commuting behaviour, made up about one-quarter of the sample.

5.2 Socio-Economic Systems

Socio-economic systems are ones in which human beings interact with one another in an economic environment designed by humans. Examples are stock and commodity exchanges, labour markets and trade networks. Adopting the "Santa Fe" complexity approach highlights their self-referential character. Because agents derive their expectations from an imagined future that is an aggregate result of other agents' expectations, there is a self-referencing of expectations that leads to deductive indeterminacy. As with the above-mentioned traffic example, agents' forecasts combine to create the very same world that they are trying to forecast.

Collections of beliefs and heuristics co-evolve in simulation experiments, revealing emergent features of socio-economic systems. Markets tend to mimic traffic systems. The beliefs and expectations of drivers are constantly being tested in a world that forms from their and others' beliefs and actions [Batten, 1998]. A confused investor is akin to a confused driver! Prediction for each means a beat-the-crowd anticipation of tomorrow's situation (stock prices or travel times). How individual agents decide what to do matters little. What happens depends more on the interaction structure through which they act, that is, who interacts with whom according to which rules.

In real and simulated stock markets, agents' expectations continually react and adapt to a market they create together. Observable states are often poised between the deterministic and the seemingly chaotic (i.e. between simple and complex). Given sufficient homogeneity of beliefs, for example, the standard equilibrium of the literature is upheld. As we turn the dial of heterogeneity of beliefs up, the market undergoes a phase transition and "comes to life" developing a rich psychology. It displays phenomena regarded as anomalies in the standard theory but observed in real markets – speculative bubbles, crashes, technical trading and persistent volatility [Arthur, Durlauf and Lane, 1997].

If we label these two regimes *simple* and *complex*, there is growing evidence that real markets live in the complex regime. There is also evidence that sheep and explorers co-exist in populations of trading agents. Such systems have been called *adaptive nonlinear networks* [Holland, 1988]. There are many such systems in nature and society, such as nervous systems, immune systems, ecologies and economies.

5.3 Socio-Ecological Systems

Socio-ecological systems are ones in which human beings interact with one another and other living systems in a natural environment. Self-referential problems of the "GO/DON'T GO" type arise in these systems, but are rarely recognized as such. Most are commons dilemmas in which agents are over-exploiting natural resources. Examples are degradation of national parks, overfishing of fisheries and destruction of coral reefs.

In fisheries, for example, the "best" thing to do in a fishing vessel definitely depends on what everyone else is doing. Allen and McGlade [1986] explored the implications of different fishing strategies and information flows among vessels. They found that such vessels exhibit one of two strategies – *Cartesian* or *Stochast*. Like sheepish drivers on our roads, Cartesians are risk-averse agents who choose well-known sites with the best possible return. Risk-taking Stochasts direct their search more randomly.

Using agent-based models, information flow among fishing vessels can be shown to have important effects on the dynamics and resource exploitation of a simulated fishery [Little et al, 2004]. Some vessels interact by obtaining information about where other vessels are fishing. Whether they share reliable catch information is unclear, but agent-based models can help to clarify the collective value of information-sharing. Also, they can be used to explore self-administered solutions that do not involve the market or the state.

Since commons problems are management or coordination problems, agent-based models can provide decision support on sustainable management strategies for them. For a review of such models, see Hare and Deadman [2003]. Representing all the essential components of socio-ecological systems is a vastly more challenging task than doing the same for socio-technical or socio-economic systems. In the latter, the slower dynamics (of a road network or an exchange system) can be ignored and the physical or economic environment treated as a constant. In many socio-ecological systems, however, the dynamics cannot be simplified in such a way. Slower and faster processes must be addressed together.

6. CONCLUSIONS

In this paper, we have discussed some *self-referential* systems, a class of social systems to which objections raised by Kurtz and Snowden [2003] may not always apply. Part of the explanation for this lies in the emergent complexity of these systems. At least some of their emergent regularities are less sensitive to individual behaviours and more to ways in which agents interact and react in totality.

The fundamental class of properties of the social world that agent-based simulation is opening to new understanding is that which occurs only in the dynamics produced by the interactions of the agents making up the system. Emergent novelty derives mostly from accumulated interactions between agents and the co-evolutionary learning that it engenders. This reflexive process may induce the traits of agents to change over time. If the collective outcomes of these self-referential systems turn out to be insensitive to the rich spectrum of idiosyncrasies that human beings possess individually, then it is quite reasonable to disregard these idiosyncrasies as inputs to the simulations because they are not central to the context under investigation.

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