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Embracing social uncertainties with complex systems science

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Abstract

Human ecosystems are real-life systems characterized by very strong and longterm interactions between human communities and their environment; as such they constitute an expansion of the ecological concept of ecosystem. According to Stepp and colleagues (2003), human ecosystems not only process matter and energy flows, but - and more specifically - information flows as well. Therefore, they display very specific characteristics due to our ability to communicate and learn from others, creating the conditions for co-evolutionary processes in which chance lends a hand to necessity. Bradbury (2006) argues that, until recently, human beings had been able to adapt to changes and to cope with co-evolution through rather simple heuristics. But human activities have gradually strengthened the links globally between loosely connected environments and societies. More information, more interactions and shorter communication paths tend to create intractable dependencies between events and to generate deeper uncertainties overall

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Embracing Social Uncertainties with Complex Systems Science

Pascal Perez

Human Ecosystems are Inherently Uncertain

Human ecosystems are real-life systems characterized by very strong and long-term interactions between human communities and their environment; as such they constitute an expansion of the ecological concept of ecosystem. According to Stepp and colleagues (2003), human ecosystems not only process matter and energy flows, but – and more specifically – information flows as well. Therefore, they display very specific characteristics due to our ability to communicate and learn from others, creating the conditions for co-evolutionary processes in which chance lends a hand to necessity. Bradbury (2006) argues that, until recently, human beings had been able to adapt to changes and to cope with co-evolution through rather simple heuristics. But human activities have gradually strengthened the links globally between loosely connected environments and societies. More information, more interactions and shorter communication paths tend to create intractable dependencies between events and to generate deeper uncertainties overall.

Batten (2000) relates the uncertainty of human ecosystems to the idiosyncratic nature of human decision-making processes. People, as cognitive beings, constantly shift from deductive to inductive reasoning in order to solve daily problems or to assess complex collective situations. Deduction is reasoning from the general to the particular; a logical deduction yields a conclusion that must be true provided that its premises are true. Inductive reasoning, on the other hand, involves pattern formation and pattern recognition, aided by intuition and creativity. Clearly some people are more intuitive or creative than others. But we all share this capacity to adapt to complex situations through alternate inductive and deductive reasoning (Perez and Batten, 2006).

By recognizing that most human ecosystems are complex and adaptive, we acknowledge their inherent uncertainty. Thus we also accept that it may not be possible to understand the processes which underlie well-established facts and which are supported by social observations. For example, Durkheim (1979, p58), in his famous study of suicide, concluded that no matter how much a researcher knows about a collection of individuals, 'it is impossible to predict which of them are likely to kill themselves. Yet the number of Parisians who commit suicide each year is even more stable than the general mortality rate.' A process that seems to be governed by chance when viewed at the level of individuals turns out to be strikingly predictable at the level of society as a whole. Most human ecosystems – being complex and adaptive – display emergent properties such as these, challenging our hopes of understanding the workings of causation (Lansing, 2003).

Using Metaphorical Models to Track Uncertainty

During the late 1980s, research on complex and adaptive systems in biology and physics progressively permeated the social sciences. Concepts like emergence, path dependency, dynamic equilibrium and adaptation were directly transposed to studies of human ecosystems (Holland, 1995). In order to better identify and understand emergent processes within these real systems, scientists developed computer-based metaphors, called social simulations or artificial societies (Gilbert and Troitzsch, 1999).

Despite the fact that complex systems science does not present a homogeneous corpus of theories and methods, most of its models rely on an atomistic vision of human ecosystems. These atoms – called agents or nodes – are metaphorical representations of social entities and aim at reproducing plausible, and ideally realistic, behaviours (Perez, 2006). Numerous attempts to mimic reality via these computational metaphors, however, have sometimes resulted in erasing the distinctions between simulated and observed systems. Lissack and Richardson (2001, p101) criticize some complex systems modellers for not recognizing this duality:

> *The act of interpreting differs from the act of observing, and both may differ significantly from the underlying phenomenon being observed. In their failure to respect this distinction, [these scientists] are implicitly suggesting that the interpretation is reality. However, while a good model of complex systems can be extremely useful, it does not allow us to escape the moment of interpretation and decision.*

Nevertheless, a large majority of complex systems scientists safely use computer simulations as virtual laboratories where they can test, replicate and compare social theories in order to better understand reality. The types of uncertainties they have to face can be separated into two classes: (1) ill-defined predicates and (2) non-linear interactions.

Ill-defined predicates include cases where observed social patterns rely on unknown or largely implicit rules. Hence the modeller faces the challenge of inferring atomistic rules without calibrating observations in order to validate macro-level patterns. Recently, Perez and Dray (2005), supported by a trans-disciplinary team of experts, designed an atomistic model of illicit drug use and street-markets in Australia. Because of the illicit nature of the drugs industry, the simulated processes could only be hypothetical. Nevertheless their macro-patterns matched epidemiological observations. Similarly, any attempt to simulate Durkheim's findings on suicide would have to rely on a series of speculative predicates. Often, reliance on ill-defined predicates is a temporary limitation, lifted by new inductive evidence or innovative deductive theory. Hence, from this perspective, one might see uncertainty attached to simulated emerging phenomena as an indicator of our incomplete understanding of social reality.

Unlike ill-defined predicates, uncertainty linked to non-linear interactions stems from purely deterministic rules. Complexity is generated from a large number of iterative and conditional interactions between social entities (atoms), the outcomes of which become rapidly intractable, leading to unexpected emergent phenomena. This second class of uncertainty has attracted a vast amount of literature since the 1990s (see, for example, Casti, 1999; Kauffman, 2000; Lansing, 2003). But the most striking evidence of the analytical value of atomistic simulations was given by Arthur (1994), with his well-known El-Farol metaphor. The author describes the dilemma of regular patrons and music lovers who have to decide, independently, each week, whether or not to go to their favourite bar on the following Thursday. Space is limited, so the evening is enjoyable only if the bar is not too crowded (the optimal capacity is 60 patrons). There is no collusion or prior communication among patrons. Knowing the bar attendance over the past few weeks, each patron decides to go if he or she expects fewer than 60 people to attend or stay home if he or she expects more than 60 people to go. Because of this self-referential condition, no decision model exists that could provide a deductive solution to the problem. Arthur therefore decided to create a simulation model composed of 100 computer agents forced to reason inductively, based on a given set of replaceable decisional rules. One intriguing result of the simulation is that – regardless of the ever-changing set of individual decisional rules – the average attendance at the bar fluctuated, albeit erratically, at around 60 people. The model shows that deterministic individual decisions – while totally unpredictable for an external observer – drive the entire system towards a stable state, due to its self-referential conditions. Though fascinating, this emerging simplicity should not be taken for granted. Indeed, most of the time, non-linear interactions drive social simulations towards highly unstable ground and emerging complexity. However, the conditions under which simplicity emerges from complex atomistic interactions are central to research on complex systems (Batten, 2006).

A Constructivist Viewpoint of Uncertainty

So far, I have asserted that human ecosystems are complex and adaptive, largely due to our individual cognitive capacities and communication skills, and pointed out that complex systems science tries to track uncertainties attached to these systems by exploring metaphorical models of reality. Here one can feel the potential tension between grounded reality and artificial metaphors; social sciences and computer engineering; constructivism and positivism.

As a matter of fact, mainstream research on artificial human ecosystems stems from 'distributed artificial intelligence', which has developed a very normative approach to human behaviour (Castelfranchi, 2001; Brazier et al, 2002). The advantage of a normative approach is to establish a consistent analytical framework in order to create and validate scientific knowledge. Its main limitation is that it relies on the assumptions that science is inherently objective and that scrutinized reality is unique. While perfectly suiting computer development principles, these assumptions become questionable when addressing issues of human cognition or social interactions.

Is there an objective way to describe decision-making processes? Maturana and Varela (1980) criticize the circularity in scientists' attempts to address, let alone explain, human cognitive abilities by using those same cognitive abilities. They argue that the primary response to this paradox has been to ignore it and proceed as if there is a fixed and objective reality, external to our act(s) of cognition. The authors dispute the very concept of objective reality by considering that:

- people operate in multiple 'worlds', particularly socio-cultural ones; and
- a 'world' is moulded by contextual factors intertwined with the very act of engaging with it.

Their theory (which they call autopoiesis) considers living beings as living systems embedded in larger systems constituted by themselves and the environment they interact with. Unlike other more positivist approaches to human ecosystems (Holling, 2001), their constructivist theory includes the observer in the analytical framework.

Despite its robust foundations, this theory has failed, so far, to translate into a pragmatic analytical framework. The main reason for this failure is that criticizing circularities is not sufficient to design concrete methodologies that overcome the paradox. Hence, validating atomistic models of human ecosystems might face a third type of uncertainties in addition to ignorance (ill-defined predicates) with experts and stakeholders. This co-construction process no longer aspires to provide normative models of reality. Instead it is meant to enhance discussion and collective decision-making around and about the topic being modelled (Lynam et al, 2002).

In these models, social entities (atoms) are designed according to the consensual information provided by the participants. Decisional rules and behaviours implemented in the simulations are the phenomenological expression of participants' perceptions (Becu et al, 2003; Dray et al, 2006). Hence, this constructivist and post-normal process deals with uncertainties in the following ways:

- ignorance (ill-defined predicates) is dealt with through individual contributions of experts on plausible atomistic features and processes (the populating process);
- complexity (non-linear interactions) is dealt with through consensus among participants on existing and plausible realities of the system under study (the framing process); and
- subjectivity (observer-dependency) is dealt with by fully acknowledging the inherent limitations of the designed model (the embodiment process).

D'Aquino and colleagues (2003) propose a formal approach of co-construction of social simulations aiming to support collective learning and decision-making. Acknowledging the complex and adaptive nature of human ecosystems, their 'companion modelling' approach requires a permanent and iterative confrontation between theories and field circumstances. Companion modelling deals with the dialectical confrontation between researchers, models and observed realities. The subjective and contextual nature of the models is fully acknowledged as the observer is considered as part of the experiment. Furthermore, companion modelling emphasizes the modelling process itself rather than concentrating solely on the model, embedding information gathering, model design and use of simulations into a collective process (Perez, 2006). Incomplete knowledge, contrasting viewpoints and limited capacities of prediction are inherent and explicit weaknesses of this approach. But the legitimacy of the outcomes, through social validation of the whole process, supports a more effective use of such models by decision-makers. Finally, companion modelling might help reduce the epistemological gap between science and policy described by Bradshaw and Borchers (2000). Far from reducing uncertainties (the policy standpoint) or relentlessly exploring them (the scientific standpoint), co-constructed social simulations tend to 'domesticate' uncertainty through the populating, framing and embodiment processes described above. But it must be clear that decision-makers have to satisfy themselves with 'what if' scenarios, inherently limited and uncertain. Hence decision-making has to become recognized as a risky business for professional and responsible gamblers. Under this condition only, a new kind of complex systems science can bring in reality-connected and fast-evolving support systems.

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