Social and Economic Complexity: the co-evolution of Reality, Knowledge and Values

Peter M. Allen and Liz Varga, School of Management, Cranfield University, MK43 0AL, for the Social and Economic Modelling Session, the ONCE Conference, Oxford

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Abstract: In this paper we consider the complexity of social and economic systems. In particular, we look at the importance of the ideas of co-evolution in which the aims and goals (axiology), and knowledge of agents (epistemology) essentially constitutes their identities, and the diversity and heterogeneity of these are the driving force of co-evolutionary change of reality (ontology). We use a simple example illustrating how experience leads to beliefs, beliefs direct actions which in turn lead to experience, creating a fundamentally, circular co-evolutionary potential for new elements and structure. This is the core of complexity that underlies social systems and undermines the application of the traditional scientific method, which supposes an objective, external reality.

1. Introduction

If epistemology is about what we know and how we know what we know – what is inside - and ontology is about what there is to know – what is outside – then the most fundamental challenge that complexity makes is that these can no longer be considered as separable. Axiology is the theory of values, and values are the background to behaviour that emerged during evolution giving us aims, goals and opinions which through our knowledge direct our actions. But in turn, values create our intentions and desires, and these in turn drive changes in our epistemologies, since they determine what it is that we wish to achieve, and therefore what seek to know in order to do this. Ontology - reality is therefore made up of an underlying physical and ecological system that is inhabited by individuals whose opinions are based on their values, which are affected by their experiences, and which also lead them to seek out knowledge in order to achieve their wishes. A fundamental circularity occurs because the actions that provide experience are guided by the epistemology, knowledge, of the individuals, and these are used to translate an individual's aims into actions and activity, that produce the experiences that lead to values. Not only is there no longer an "inside" and "outside", since other individuals "insides" are outside any particular "inside", but experiences are made up of the dynamic interactions of peoples' actions on each other, and these experiences are causing changes to values and epistemologies and therefore making it impossible to interpret our experiences in any definitive way. The underlying causes and meaning of experiences are changing.

Traditional science was based on the idea that there was an objective reality outside, and that we could study it and do experiments on it that allowed us to build, cumulatively, an increasingly accurate picture of that reality. Whilst for simple physical problems and for planetary motion this was a reasonable working hypothesis, for biological and social systems this has always been a problem. Many experiments involving whole organisms or social groups are not repeatable or transferable, situations are historically evolved involving local, co-evolving contexts, and therefore can potentially all be unique and lacking in any generic behaviours or laws. Complexity science brings us face to face with this elusive reality. It tells us that we must accept uncertainty and admit that our cognition, our descriptions and our models are necessarily incomplete and temporary props to our current functioning. They help us make some sense of the past and the present, and are all we have to help us in taking steps into the future.

In reality, complex systems thinking offers us a new, integrative paradigm, in which we retain the fact of multiple subjectivities, and of differing perceptions and views, and indeed see this as part of the complexity, a source of creative interaction and of innovation and change. The underlying paradox is that knowledge of any particular individual, social group or discipline will necessarily imply “a lack of knowledge” of other points of view and aspects. But all the different perspectives, disciplines and domains of “knowledge” will interact through reality – and so actions based on any particular view, although seemingly rational and consistent within that view, will necessarily be inadequate. Wisdom requires a broader view and these new ideas encompass evolutionary processes in general, and apply to the social, cultural, economic, technological, psychological and philosophical aspects of our realities.

2. The Science of Evolved and Evolving Systems

We may like to think that it is essentially human to consider that values are of vital importance for understanding the behaviour of the organisms, but in fact this has been important even for the evolution of simple organisms. Even ants decide to go for the more concentrated sugar source, and any species (if it is persistent) must actually “like” what it hunts and eats, and must also live in terrain where its prey occurs. Similarly, prey species must know that they should avoid things that resemble their predators, and so they must in fact have internal persistent signal “patterns”, that drive their behaviour. Any population will have a variety of internal images around some average, which will constantly allow its evolution with any changing behaviour or appearance of its prey or predators. This shows us that even for animal and marine ecologies, axiology, epistemology and ontology will co-evolve.

Ecologies and social and economic systems are the result of evolutionary processes, in which microscopic deviations in individual characteristics are constantly produced at all levels in the system. Those characteristics that have not yet been eliminated constitute the evolving system. This means therefore that although there will be a variety of possible simplified descriptions of evolving systems in terms of interacting population types, depending on the level of detail used in the classification, the real underlying processes that will shape its evolution reside both in the precise spectra of internal individual diversity that actually make up each of these population types and any new individual characteristics that arise over time. A “system dynamics” descriptive model of a real evolved system in terms of the interacting population types will, unlike reality, simplify down to just a few populations. For example, when we run a mechanistic model of an ecosystem - with the fixed birth, death capture and escape rates that we have found on average in the real system - then one particular food chain simply eliminates all the others(Allen, 1994; Allen, 1999; Allen, 2002). In other words, selection between metabolic chains operates simplifying the ecosystem leaving only the highest performing chain. However, this is not what happens to the real ecosystem, which remains complex and capable of further evolution. What is it therefore that makes the real ecosystem and its complexity resilient, and stops it simplifying down to just a few populations?

The answer comes by considering the series of assumptions that must make in order to create a mechanical model of an evolved system. These are shown below and in Figure (1).

Number	**Assumption Made**	**Resulting Model**	**Characteristics**
1	Boundary assumed	Some local sense-making possible – no structure supposed. Post-Modern	Subjective experiences
2	Classification assumed	Strategic, Open-ended Evolutionary – structural change occurs. Qualitative research is relevant.	Evolutionary models, creative destruction, qualitative change
3	Average Types	Operational, stochastic non-linear differential equations – assumed structurally stable	Spontaneous switching from one attractor basin and regime to another

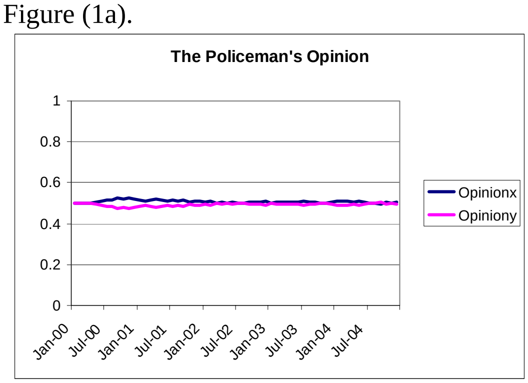
4	Average events	Operational system dynamic equations – assumed structurally stable	A deterministic, predictable trajectory to a particular attractor

Table (1). Successive assumptions used to create a descriptive, mechanical model of an evolved system,

It is the third assumption of a description in terms of "average types" that loses the evolutionary capacity. This tells us that it is evolution is generated by the internal diversity of the population types, and the mechanisms that generate new characteristics and behaviours. There are multiple dimensions of possible difference, firstly in location, but also in age, size, strength, speed, colour etc. and also in skills, knowledge, experience and axiology so this means that behaviours that are less successful in any particular situation will tend to decline while those with high pay-offs will be amplified. Of course, this is only a tendency and not an absolute rule, and in human systems would depend on people defining success according to their axiology and correctly associating successful outcomes with particular aspects of behaviour. Providing this occurs to some degree then the population will evolve both their aims and goals as well as the capacity to satisfy them, leading over time to a community, culture or society with mutual, co-evolved roles and behaviours. Evolution will create patterns in the different dimensions of diversity that the individuals inhabit. But neither we, nor the individuals concerned need know what these dimensions are. It just happens as a result of evolutionary dynamics.

3. The Science of Social Systems

Let us consider a very simple social science example that will illustrate the co-evolution of the ontology, epistemology and axiology of interacting individuals. It will illustrate how the non-linear responses involved can generate new knowledge (that may be true or false), and can provoke symmetry-breaking changes that can drive history onto new paths, with new qualities, problems and consequences. Let us consider how we all try to gain knowledge and modify our actions to make them more effective. The problem we shall briefly study is that of "targeting" or "profiling" by policemen or security officials, something that is of great interest at the moment because of terrorism as well as general crime. We shall initially assume that policemen move randomly around the town, and stop and search people when they appear to be acting suspiciously. We shall further suppose that there are two populations in the city – pink and blue people – which could stand for different ethnies, races, religions, age groups or any other potential characteristic of classification. In reality, these two populations actually commit crime to exactly the same average rate (3% crime rate/person/year), and hence policemen acting randomly find just as many criminals that are blue or pink. In our model of this situation, we find a result of 3% with the "sampling" noise around it. Figure (1a).



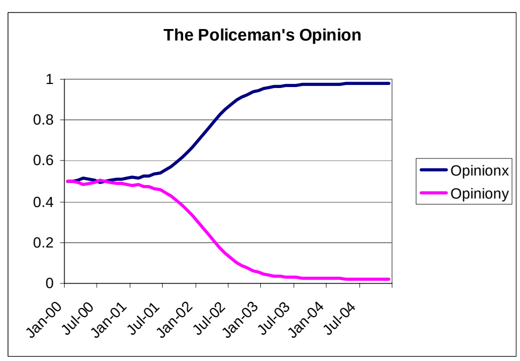


Figure (1). Are pink or blue people more likely to be criminals? (a) Low Targeting (Neither) (b) High Targeting (Either Blue or Pink are seen as highly criminal)

However, in order to improve performance the police authorities may decide that policemen will be promoted and rewarded according to their relative success in arresting criminals. The only way that policemen can improve their arrest rate per hour, is if they can anticipate which population commits more crimes, and then to target them instead of simply moving randomly. Over time, if the targeting is sufficiently strong, the policeman will become convinced that one or other of the populations is highly criminal, and the other is not. A typical result is shown in figure (1b). This result occurs because the strong targeting amplifies whichever initial fluctuation in the successful stop and search happens to occur first. The choice of which population to target grows and self-reinforces as increased convictions for one population lead to greater targeting, and in turn to a further increase in convictions of that population.

The mathematics captures the targeting which reflects the accumulated view of the policeman as a result of the convictions that he has obtained. This however, in itself already reflects the history of his targeting. The apparent crime rate is given by a moving average of actual convictions of x C(x) or y, C(y). This reflects the length of time of the moving average, and either could reflect a long term judgement or a fairly rapid response to changes in convictions. This leads to a theoretical targeting rate of given by the relative “attractivity” of stopping and searching x out of the both x and y:

$$\text{Theoretical Targeting} = \text{encounter rate.}\ \frac{\exp(r.C(x)}{(\exp(r.C(x)+\exp(r.C(y))}$$

Here “r” represents the degree of rationality of the policeman, in the degree of response to his own current opinion concerning the probability of criminality of x, based on his past experience. If “r” is 0, then the targeting remains completely even but the larger the value of “r” the greater the level of targeting for any recorded difference in criminality recorded in the past. As the policeman walks around however, the encounters they have will naturally reflect some level of randomness. This means that the actual stop and searches that occur are:

$$\text{Actual Stop and Search of x} = \text{encounter rate.}(1 + \text{Noise})^{*}\ \frac{\exp(r.C(x)}{(\exp(r.C(x)+\exp(r.C(y))}$$

By multiplying this by the rate of criminality of the population concerned, we will arrive at the value for the observed rate of criminality of x and y, which will affect the policeman’s view of their criminality through the moving average that he uses.

The actual arrests over time therefore will depend on the length of the moving average that the policeman’s opinion follows, the degree of randomness in the encounters with the population and also on the value of “r”. This can give rise to a positive feedback loop that can amplify chance fluctuations in his experience of criminality, and hence to a rapidly growing belief that either x or y are far more criminal than the other. Which population appears to be more criminal than the other is just a matter of chance.

Of course, a single policeman may not form his opinion entirely alone, based on his own experience, but often may be influenced by colleagues. Obviously, policemen in a given locality will talk between themselves, and may mutually suggest different reasons for targeting one or another population type. This could either lead to a statistical damping of single opinions based on short term experience, but it could also spread a particular prejudice. However, it is also true that if targeting is introduced as part of a performance package, then policemen will be put into competition with each other, and may tend not to share their own opinions freely, because these opinions will be their ways of targeting, and of improving their own performance relative to the others.

A vital point however, is that the increased levels of **apparent** criminality on the part of one population is a completely false result, since the **actual** criminality of both x and y remain the same. All that changes are the opinions of policemen and the apparent criminality. The knowledge used to target action is actually false, and is an artefact of the policeman’s own method of theorizing and of “testing” his theory. In reality, there would be no overall increase in arrests, only in the identities of those arrested, which would simply reflect the bias in the targeting. But, in the real world, as opposed to the calm of a laboratory experiment, the failure of the theory may not be so obvious, particularly when the policemen concerned may consider it as being their theory, and wish to defend it, and exaggerate its success.

More importantly, although the "knowledge" generated is false, it can nevertheless have a real effect on society as the targeted, population respond to the injustice of the situation. Two things can happen. First, the targeted population becomes resentful and ceases to feel an equal part of society, leading to anti-social behaviour, and to a fulfilment of the initially incorrect targeting, and an increase in crime of the targeted population. Second, the population that is not targeted may begin to assume that whatever they get up to, they will not be suspected, and they can get away with all kinds of things. This may lead to an increase in crime on the part of the untargeted population. In this way, pressure to increase police performance and to reduce crime could actually increase it.

4. Conclusions

This illustrates the main contention of the paper that reality, knowledge and intentions all co-evolve, even on the basis of false inferences. Since we cannot do repeatable experiments on social or economic systems, we are forced to build interpretations of the past, a past that consists of our own experiences and experiments. The fact is that this loop of self-reinforcing learning is a very general property and in reality probably underlies much of what we call "tacit knowledge". Obviously, we learn most things from experience, and clearly science is not a necessary approach for many everyday tasks. But nevertheless, whenever we engage in attempting to "improve" our performance, we naturally attempt to identify which characteristics are significant indicators, and to use these as a guide to our actions. Experience is made up of an accumulation of such sequences, and many of them are probably useful. However, those made under pressure and formed and acted upon rapidly may well be nonsense.

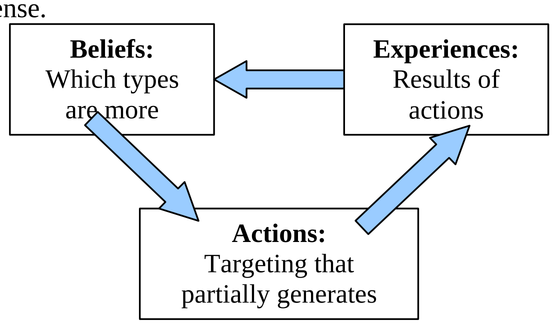


Figure (2). Epistemology and axiology arise from experience, but guide actions, which in turn generate the ontology experienced, creating a positive feedback loop.

Clearly, intelligence is about the ability to formulate possible theories and ideas about how things work and then checking which ones are really true. In science the theory may be a possible mechanism or process, and it should lead to a prediction that at least can be invalidated. But in normal life the criteria are less rigorous and correct tests are not necessarily applied to possible theories, providing a kind of "satisficing" model of peoples "beliefs". However, as we see here is that implementing theories, whether about stop and search, company strategy, possible new products etc. can actually change reality in social systems. This is because each agent, policeman and citizen, producer and customer, designer and shopper, is continually responding to their experiences by reinforcing or modifying their own theories and beliefs, which form the basis for their actions and responses. This means that our beliefs lead to our actions and experiments, providing our individual experiences, and leading to our particular beliefs, within a sea of different perspectives and incommensurable aspects. Only the simple physical aspects of the world may be viewed objectively and the scientific method applied unambiguously. In social systems, we cannot perform strictly repeatable experiments or define completely comparable situations, and this is why complexity science is of vital importance in providing a new basis for action.

In general, an individual with a slow response rate to "theories" will be less likely to adopt a false and potentially provocative path of action, and therefore wisdom is more associated with a "slow" response, allowing a greater "integration" of noisy signals. Inertia can be virtuous, at least more virtuous than jumping on to a fashionable notion, and then not testing it correctly.

The important point for complexity science however, is that self-organising systems can beak symmetry and create real behavioural differences between populations that were hitherto identical. This means that a system with internal diversity can evolve qualitatively over time, and this diversity doesn't even need to be real. It only needs to be a "speculation" in an actor's mind which leads to some experiment and that may be enough for non-linear interactions to amplify into a real presence.

Several different multi-agent models have been developed which show how these same principles apply to the management of natural resources (Allen and McGlade, 1987a), economic markets (Allen, 1994, 2001, 2004), distribution systems and organizational forms (Baldwin et al, 2003). In these models both the beliefs and goals of the agents change over time, as do their actions and as does the ontology they experience. These systems do not run to any pre-determinable equilibrium but exhibit an on-going path-dependent evolution of qualitative change and emergent properties, reflecting the details of particular circumstances, timings and contingencies. They correspond in the social sciences to the emergence of hypercycles in the work of Eigen and Schuster, 1979, in bio-chemistry, but recognise the importance of emergent collective attributes and dimensions. Evolutionary Drive (Allen and McGlade, 1987b) describes how underlying micro-diversity drives systems forward through successive emergent dynamical systems. Essentially, this fulfils the early vision of dissipative structures (Nicolis and Prigogine, 1977;:Prigogine and Stengers, 1987), in that their existence and amplification depend on the internal agents or elements "learning" how to access energy and matter in their environment, and this brings intentionality, whether well-informed or not, into the dynamics of micro-diversity generation.

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