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Complexity and Limits to Knowledge: The Importance of Uncertainty

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INTRODUCTION

This chapter examines how complexity science faces up to the material fact of uncertainty and the very real limits to knowledge. Indeed it shows how ignorance, the impossibility of having full knowledge and the inevitability of uncertainty, are both the result of, and the driving force behind, evolution and change. The chapter will review how this affects the exploration of complex problems and in particular the approaches to the mathematical modelling of their embedded but often un-defined limitations. This involves examining the assumptions that are necessary in order to represent a 'situation' in terms of changes in the values of a particular set of variables and the ways this whole structure moves forwards over time. Our feeling of 'understanding' seems to correspond to the degree of predictability such methods imply, since we feel that we do not 'understand' a situation when we are unable to predict future behaviour. This definition of 'understanding' is questionable, however, since it assumes that the future already exists within the present and that it can therefore be determined. But this does not allow for learning, adaptation, change, exploration or creativity of any kind. In short it corresponds to an assumption of the stability and fixity of:

- the initial system – the mechanisms that link the variables
- the internal responses inside each individual element
- the system's environment

In other words we 'understand' things by assuming that they will continue to do what they are doing; we pay less attention to how, why or when they came to be like this, and to what they may do, individually and collectively, in the future.

In addition to this great simplification that assumes fixity and unchanging behaviour, often a further assumption is made of dynamic 'equilibrium' whereby even the trajectory of the system of fixed mechanisms is supposed to have run itself to a stationary state, independent of the particular history or movements that actually took place. So we assume that it is generally appropriate and possible to understand most situations through investigating a static end point rather than by exploring how things change. Clearly this is an even-more-unlikely assumption than believing in fixed, deterministic dynamics; but nevertheless this idea has been dominant in economics, creating a false impression of certainty and of the existence of a deterministic relationship between the state of a market and the external conditions in which it sits.

Complexity, and indeed the presence of coupling and feedback between interacting elements, shows the limits of these simplifying assumptions. The sources of uncertainty are manyfold-:

- Uncertainty in the behaviour of individual elements inside the system
- Uncertainty in the collective behaviour of the system
- Uncertainty in the way the system interacts with other systems
- Uncertainty in the boundaries of what we define as a system or systems
- Uncertainty in the environment in which the system is immersed and the way the system responds to changes in this
- Uncertainty in how any description of elements, systems or the environment may change over time

We argue that, in the real world, uncertainty is a real experience and 'exists'; and this embracing of uncertainty is the fundamental underpinning of complexity science. It is the science that arises when the questionable, even incredible, simplifications that lead to assumptions of determinism and prediction cannot be made.

In this chapter we explore the ontology of uncertainty, from ancient cosmologies through Darwin to Prigogine and the beginnings of complexity theory. We then transfer our interest to the epistemological questions as to how you explore, or indeed ignore, uncertainty. We take an overview of ways of exploring complex problems, focusing in particular on mathematical modelling; we look at how uncertainty is handled or ignored or even denied through the use of various simplifying assumptions.

We then move our focus more specifically to human systems and take the example of economics; we consider how uncertainty has been considered, historically, in the field of economics. Finally, we present an example of the impact of including uncertainty in an evolutionary model of a market.

THE HISTORICAL ROOTS OF UNCERTAINTY

The pre-Socratics and 'becoming'

Our current dominant worldview which underpins most mainstream schools of thought in economics, policy-making, management, education and development still centres on the mechanistic idea that the world is objective, measurable, predictable and controllable and that is despite almost overwhelming evidence to the contrary. Uncertainty has not had a place in this view, apart from as a limiting irritation, to be overcome by increasing knowledge and greater scholarship. Has this always been the case? Early philosophers in both the East and West held a much more sophisticated position: they have seen the world as changing and flowing, but yet with a degree of order and patterning that arose intrinsically, from within.

This image of flow and change is captured in the following fragment, part of the few remaining writings of Heraclitus (Kirk et al., 1957).

> Upon those that step into the same rivers different and different waters flow … They scatter and … gather … come together … and flow away … approach and depart.

The Hindu Upanishads and the Dao de Jing present a similar sense of temporary patterning emerging without the need for extrinsic design or planning.

And Democritus (Monod, 1970) said:

> Everything existing in the universe is the result of chance and of necessity.

Plato, however, refused to believe that form or patterning could arise without external design and introduced the idea of a Creator who, guided by pre-existent perfect forms, created a world, which emulated and aspired to them. Uncertainty and fluctuations were seen as irritating limitations and something to be overcome; they were not seen to serve any useful purpose.

This theme of perfection and order then paved the way for the seizing of Newton's mechanics, in the seventeenth century, by French Enlightenment thinkers and became *the* dominant world view; where order, prediction and control are regarded as attainable and desirable and variation is viewed both as a nuisance and largely irrelevant. How did this happen? Why was Newton's theory of physics, which in fact applied, merely, to certain limited problems of interaction between discrete objects, seized on as *the* dominant worldview? Many authors (for example Toulmin, 2001) have written on this topic at length. In summary, Newtonian thinking supports the notion of 'the grand design', and of the view that logic and reason will lead to the 'right' answer; indeed it implies there *is* a predictable 'right' way and 'right' answer. So it represents a way, a rationale, to control chaos, to be efficient, to overcome superstition, to make things happen in a predictable fashion; this is very beguiling.

Darwin and variation

In contrast to this view of achievable perfection, stands the messy and inefficient and surprising process of evolution. It was Darwin (1859) who recognised that uncertainty is indeed *necessary* for change to happen. Whilst the realisation that animals and plants evolve had been recognised for decades before Darwin's expedition on the *Beagle*, indeed by his own grandfather (Darwin, 1794), Darwin's contribution was to suggest that variation was a fundamental part of how this happened.

Charles Darwin wrote (1978: 169):

> In 1838 … I happened to read for amusement Malthus on Population, and being well prepared to appreciate the struggle for existence which everywhere goes on …, it at once struck me that … favourable variations would tend to be preserved, and unfavourable ones to be destroyed. The results of this would be the formation of new species.

The notion of messiness as playing a useful role, *fundamental* to innovation, adaptability and change, is very significant. Despite its seeming acceptance there is still much resistance to its implications as evidenced by the continued focus on prediction, design, control, measurement and an endless search for certainty.

The idea that variation is a pre-requisite for evolution and change to happen was a Big Idea that subsequently captured the imagination of philosophers, psychologists, sociologists – and eventually physical and biological scientists. For example, the Pragmatist Charles Peirce (1955) was one of the first to recognise the wider implications of evolution as a worldview. In 1891, he wrote:

> Now the only possible way of accounting for the laws of nature and the uniformity in general is to suppose them results of evolution. This supposes them not to be absolute, not to be obeyed precisely. It makes an element of indeterminacy, spontaneity, or absolute chance in nature.

Equally, William James (1995) explains in 1884:

> Of two alternative futures which we conceive, both may now be really possible; and the one become impossible only at the very moment when the other excludes it by becoming real itself. … To that view, actualities seem to float in a wider sea of possibilities out of which they are chosen; and, ***somewhere***, indeterminism says, such possibilities exist, and form a part of truth.

So, the early philosophers noticed the world changed in an uncertain way but nevertheless had form; Darwin recognized that variation and uncertainty were in fact *central* to the emergence of new form; it was the physicist Prigogine (1947) who took the next step. He started to explore *how* uncertainty led to emergence and evolution, and how the future is *in principle* unknowable. This was the beginning of the new science of Complexity.

Prigogine's early insights into the relationship between function and variation

Prigogine (1997), in his autobiography, tells us that, in his adolescence, Henri Bergson's (1911) book 'L'évolution créatrice' cast a spell on him. Bergson posed the question as to why, if physics, in the form of the second law of thermodynamics, proposes that matter and form degrades into structureless dust, does life mount the incline that matter descends (Bergson, 1911: 245). He focused on the image of the universe as 'becoming' rather than 'being' and recognized that *what is real is the continual change of form: form is only a snapshot view of a transition* (Bergson, 1911: 301).

Prigogine's initial interest was in non-equilibrium thermodynamics and led to considerations of how patterns in certain chemical and hydrodynamic systems open to the environment came to emerge. He was inspired by the work of Bénard (Jantsch, 1980), a French physicist who discovered patterns of convection cells in a liquid layer when heat is applied from below, and through the experiments of two fellow Russians, Belousov and Zhabotinsky (Jantsch, 1980), who discovered, in a particular mix of chemicals, that the colour of the mix oscillated between yellow and clear. Alan Turing (1950) was also making similar discoveries.

Prigogine (1947, 1996) is perhaps best remembered for these explorations of non-equilibrium thermodynamics. His subsequent work (Prigogine, 1978), showed that the emergence of patterns (later called self-organization) came from the inter-relationship of the *function* of the underlying process together with *fluctuations*. Monod (1970) explores a similar theme in his book, *Chance and Necessity* though he assumes that the chance of creative events is small whereas Prigogine took such events to be inevitable and frequent. By *function*, Prigogine was referring to the underlying internal dynamics; in an ecology, for example, this would define what drove the 'rules' of interactions; who can eat whom, what food intakes are typical, how long it takes for mature fish to grow and so on. He also underlined the fact that the particular history of a particular ecology or market or chemical system depends on the particularity of chance events or variations. This complex, systemic view introduces 'history' into science (Prigogine, 1978). It implies that most situations cannot entirely be understood through mathematical equations defining universal laws.

As an example, if we consider a pond, and consider the density of pondweed, the temperature of the water, the size, age and type of fish, the size of the ripples on the water, such factors will not be uniform over the pond or with time. Furthermore, if we ignore these variations, we run the risk of throwing out the very information that determines future states. It is this fine-graining, which Allen (1997) termed micro-diversity, that is fundamental to the potential for self-organization, self-regulation, the potential for emergence of radically new qualities and forms and for the fact that the future *is under perpetual construction* (Prigogine, 1997: 1). Prigogine emphasized that fluctuations *play an essential role* (1978: 781) and affect the direction the system subsequently follows. As Jantsch (1980: 6) states:

> a system now appears as a set of coherent, evolving, interactive processes which *temporarily* manifest in globally stable structures.

This combination of coherent behaviour and yet random variation gives the tension between 'chance and necessity', between 'uncertainty and prediction'. Chance fluctuations give the system its unique history and yet the movements take place in the context of coherent dynamics which are stable, at least for a time. As Allen (1997: 16) explains:

> [this] begins to throw light on the basic difference thought to exist between 'science' and 'history'. In the former, explanation was believed to be traceable to the working of eternal, natural laws, while the latter provided explanation on the basis of 'events'. In this perspective of self-organising systems we see that both aspects are present and that such systems are not described adequately by either laws (their internal dynamics) or events (fluctuations) but by their interplay.

THE DEVELOPMENT OF COMPLEXITY SCIENCE

Hiding complexity

Following the early insights into complexity and the importance of non-average events and non-average types, we can situate the many different ways that the real complexity of the world is hidden in contingent, closed and simplified representations. This is shown in Figure 10.1 which illustrates the different types of representation and mathematical models that arise from successive assumptions about stability within and outside the system.

Figure 10.1 represents, starting from 'reality' on the left, which is full of uncertainty and doubt, and, making successive assumptions about the piece of 'reality' under study, one passes from complete uncertainty, through various intermediate views to one of complete deterministic certainty when prediction is believed possible. We will look at these in turn to see how the actual complexity and uncertainty of 'reality' is hidden from view and tools and models are developed that appear to offer control and knowledge to those that possess them. In essence the things that make prediction 'possible' are closure to outside influences and fixity within.

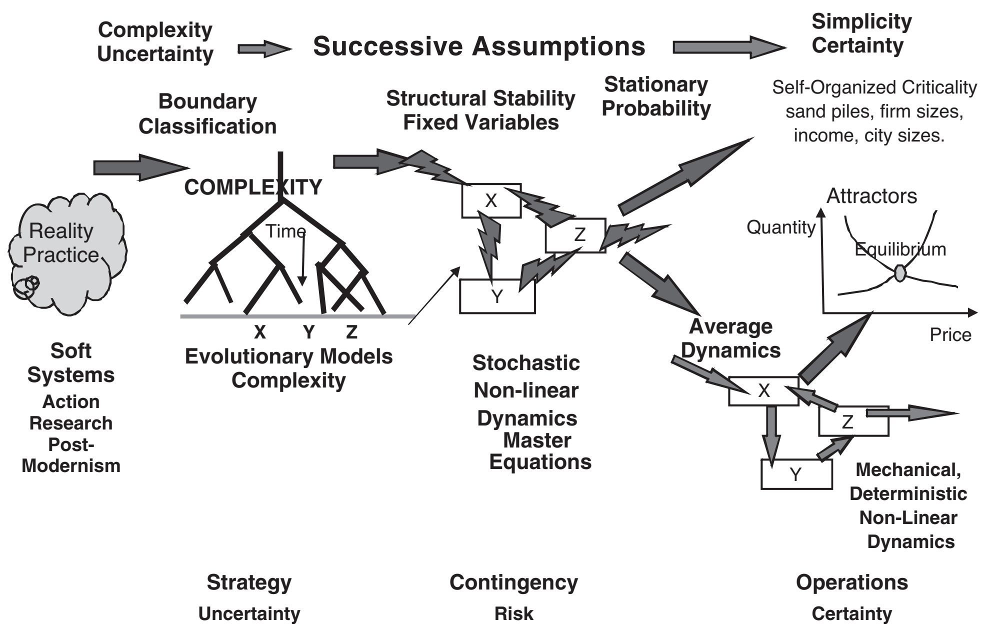

Figure 10.1 The different kinds of models and understanding attained by making successive assumptions about uncertainty in moving from the left to the right of the figure

'Reality'

One can argue that we need make no assumptions and should just engage with 'reality'. Whilst we can interact with particular situations and contexts in 'real life', it is impossible, in general, to work in this way as the amount of information required to look at every detail, every nuance, is prohibitive. Lyotard (1984), in *The Postmodern Condition* gives the example of an emperor wishing to make a perfectly accurate map of his empire; the project leads the country to ruin as the entire population is needed to devote all its energy to cartography.

But, on the other hand, neither can we argue that problems have stable outcomes and are open to abstraction. Quoting Lyotard (1984) again: *the continuous differentiable function is losing its pre-eminence as a paradigm of knowledge and prediction.* So what is to be done? Figure 10.1 shows us how, in scientific models, understanding and prediction are achieved in practice by making successive assumptions concerning the situation under study. On the left-hand side, where no assumptions have been made, there are no established types, variables or equations. We are in the realm of literary and historical endeavour, where we are describing and perhaps responding to what is happening, but are limited in our ability to learn or generalize or predict. It is the realm of postmodernism, of action research and of many anthropological methods where we are reminded that any generalizations are likely to be misleading. Emphasis is placed on staying with the actual experience of what is, on focusing on the particularity of an actual, living situation and working with all the variation and all the uncertainty that is present.

Such heuristic methods are indeed very important and stop us from blindly applying, and indeed uncritically accepting, models and theories. However, we would argue that modelling plays its part as an aid to exploring complex problems and we are interested here in critiquing differing approaches to modelling and understanding their differing assumptions.

Evolutionary complex models

The first assumption, in moving away from 'raw reality', is to say that there is a 'boundary' and that some things will be considered to be inside and others will be outside, in the environment; even this assumption must be handled carefully as boundaries may shift or may be permeable and any assertions or selections regarding boundaries will typically be open to the criticism that they are assumed or constructed. However, modelling allows us to explore and test such assumptions and understand the sensitivity to such choices.

The second assumption concerns that of 'classification' in which we decide to label the different types of thing that populate our system. This might be biological species and perhaps their age cohorts, or, in social systems, people classified according to their ethnicity or philosophical beliefs, or their skills or professional activities; so in this way we specify the variables of the system.

What happens if we make only these two simplifying assumptions but still work with nonlinear interactions and feedback and allow 'noise' or variation in the system? We are in the realm of evolutionary complex models. In Figure 10.2 we see the results of a computer run in a 200 × 200 character space in which we study the populations over time where we have reproduction, exploration (mutation) into neighbouring character cells, and both synergy and competition for resources for any particular type. What we find is the creation over time (time is downwards) of a simple ecology of populations (Corliss et al., 1990).

In this approach, we find that over time the constituent types may change. New types and activities emerge and others leave. Over time qualitative evolution occurs and the system is not structurally stable in that the variables and therefore the equations describing the mechanisms and processes at

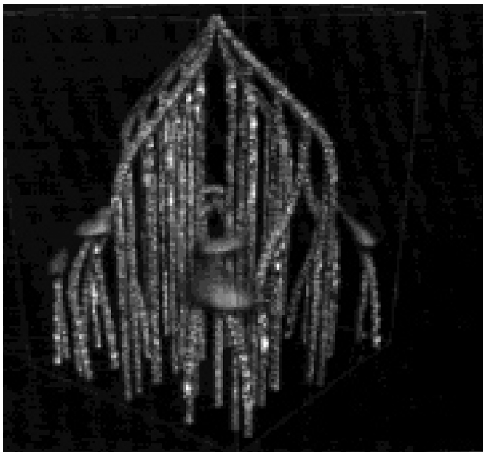

Figure 10.2 The emergence of a simple ecology over time for a population diffusing in a 200 × 200 character space. Each population has synergy and competition for resources

work within it can change; there are a series of instabilities as new things emerge and others disappear.

Variations both determine which possible outcomes emerge and furthermore they shape the future possible dynamics. In other words, the microscopic variability and randomness in the system drive evolution, confer on the system the ability to learn and hence to adapt and in so doing impact on the environment which co-evolves with it. There is no way that we can exclude ‘luck’ from the evolution and changes that occur in the system, and there is no way that we can banish uncertainty from our considerations.

Probabilistic dynamics; The Master Equation

With only two assumptions (boundary and classification) we see that the general evolutionary model shows us that qualitative change will occur, that new qualities will emerge and others disappear; but cannot say exactly in what way or when. What happens if we make a further assumption that the dynamics, the basic interaction mechanisms that govern the situation cannot change, but we still allow fluctuations and non-linearities?

Prigogine had established the central and creative role of variation and fluctuations in creating the future. Prigogine (Nicolis and Prigogine, 1977; Prigogine et al., 1977) and also Haken (1978) wanted to understand *the way* in which fluctuations play their part. Traditionally there were two distinct methods of exploring how a number of elements interacted. If there were a small number of elements, then it was possible (at least in principle) to track the movement and interaction of each element. In contrast to this *dynamical, mechanical method*, if there were large numbers of elements, then *statistical mechanics* was used and the behaviour of the system was treated essentially as if it were a fluid and average qualities such as density or temperature, were tracked; elements were classified into categories and were assumed to be identical and unchanging and, most importantly, only the most probable events were assumed to occur. In both cases, generally, only first-order effects were calculated; so the interaction of any two elements in the dynamical case were assumed not to be affected by the presence of other elements; and in both cases interactions were assumed not to be influenced by previous interactions. These two methods, basic mechanics and statistical mechanics, sit off to the right of the processes shown in Figure 10.1; they are ‘off the map’ in terms of their simplicity and their inability to deal with complex interactions and change.

Dynamical systems are deterministic but are sometimes very sensitive to initial conditions (when the parameters correspond to a ‘chaotic’ attractor); probabilistic systems are also deterministic but are largely *independent* of initial conditions and move towards equilibrium. How then do these two methods relate to each other and how can either method make sense of the role of fluctuations and the propensity for self-organization and multiple possible outcomes?

Progress was made to resolve this dilemma through the use of the so-called 'Master Equation' that governs the dynamics of a probability distribution (Allen, 1988). This method allows one to work with *all possible sequences of events,* taking into account their relative probability, rather than just assume the most probable events occur, as would happen using 'normal' statistics. The collection of all possible dynamical paths is taken into account in a probabilistic way. But for any single system this allows into our scientific understanding the vital notion of 'freedom' or 'luck' or 'uncertainty' in the behaviour of the system. Although, a system that is initially not at the peak of probability will *more probably* move towards the peak, it can perfectly well move the other way; it just happens to be *less probable* that it will. A large burst of good or bad luck can therefore take any one system far from the most probable average, and it is precisely this constant movement that probes the stability of the most probable state. It also points us towards the very important idea that the 'average' for a system should be calculated from the distribution of its *actual* possible behaviour, not that the distribution of its behaviour should be calculated assuming the average is fixed.

Allen (1988), in the first instance, investigated a simple grazing predator–prey system of two species; both species can reproduce and die. Traditional statistical mechanics would assume equilibrium and give an average outcome corresponding to a balance of numbers between the two species, depending on the food resources available. However, working with less simplification through using the Master Equation, Allen shows that for some conditions the probability distribution moves from whatever its initial condition is towards a distribution with two distinct peaks of probability. The first corresponds to the extinction of both species and the second to a stable balance between them. In other words, when the individual events that underlie the mechanisms are treated probabilistically, allowing for different possible sequences of events according to their probability, the state of the system demonstrates path-dependence, moving to one or other of the possible stable configurations. We see also that the word 'outcome', which seems so innocuous, really hides an assumption of equilibrium, of having got to where it must go. But with non-linearities in the interactions the system may have several different possible configurations to which it could 'go'.

This simple example was very important. It shows how, if qualities are averaged as in 'normal' statistical methods, the very detail that determines the path of the system is lost; that is to say a bifurcation occurs. It shows that working only with the most likely 'outcomes', as with statistical mechanics, can be *qualitatively* misleading. So, the use of the Master Equation shows us the importance of the actual history of a particular real situation. Can we know which outcome would have happened in practice in the 'real' world? What would have tipped the system into one direction rather than the other? Or could both outcomes occur simultaneously in different places?

Stationary probability; solving the dynamic equations

The dynamic equations of probability that we have described in the last section are quite difficult to handle, involving correlated probabilities of interacting variables and so further assumptions are often used to make the problem simpler. There is a choice; either we can adopt a traditional scientific approach and try to 'solve' the dynamic equations to find their stationary solution; or we can decide to retain only the dynamics that results from the most probable events and follow the path that unfolds. This second approach, the dynamical systems approach, we will explore in the next section.

The first of these methods, 'solving' the dynamic equations to find their stationary solution, leads to particular probability distribution functions shaped by the mechanisms contained in the Master Equation and gives a view of the final probability distribution to which, it is assumed, the problem has settled. For particularly simple mechanisms such as a 'sand pile' to which grains are continually being added (Bak, 1997) the probability of an avalanche of a given size can be calculated. These ideas have been applied to many different systems such as the probability of earthquakes, city sizes and firm sizes. The distribution of probability is often that of a 'power-law' that describes the probability of different-sized events. For instance, it might suggest that the probability of finding a city or firm twice the size of another is only one quarter, i.e. it follows an inverse square law. If this pattern holds for cities or firms of all sizes, then the distribution is said to be 'scale free' (Bak, 1997).

We would question this approach on two counts. First, how often, in practice, do we find data that corresponds to this kind of stationary, stable, scale-invariant distribution? For city and firm sizes the data over time tells us that there is still a great deal of dynamic change occurring, as cities and firms grow and decline (Batty, 2008). We may wish to assume stationarity, but even within a stationary probability distribution, there can still be considerable underlying changes occurring. In the spectrum of automobile manufacturers for example, Toyota recently replaced GM as the largest company, but recent problems may lead to further re-ordering in the distribution. And how can we decide whether the variations occurring at any given moment are simply fluctuations within the stationary probability distribution or instead reveal a changing distribution? For example, in considering climate change it is very difficult to tell whether some 'freak weather' event is simply an extreme event within the pre-existing distribution or is in fact an indicator of a change in the distribution. It is very difficult from the data to decide whether the assumption of stationarity is justified.

Second, when nonlinear terms are present in the interactions between elements we know that different possible 'attractors' can exist and the corresponding probability functions will be multi-modal (have different peaks corresponding to different possible solutions) and not tend to a single peak, a single stable outcome. Clearly, where there are multiple equilibria, the shape of the probability distribution will be described by much more complex mathematical functions than a power law, x^{-a}, since it will have to describe several different peaks of probability. This is the situation we considered in the previous section as exemplified by the grazing predator–prey model.

Dynamical systems

If instead of asking 'what will actually happen to *this* system?', that requires us to deal with all possible system trajectories according to their probability, we ask 'what will *most probably* happen?' then we have a much simpler approach. We proceed by assuming that only the most probable events occur; that things happen at their average rates. This leads us into 'system dynamics' which is in general a nonlinear set of dynamical equations that appear to be predictive and deterministic. In other words, they seem to allow the future trajectory of the system to be calculated. Such an approach would seem to provide a basis for policy and strategy analysis by comparing the differences made over time by investigating the impact of one intervention as opposed to another, that is, by running the model several times using different assumptions. This is a very tempting picture for any decision or policy maker. It appears to offer a way to test different decisions and allow their advantages and disadvantages to be compared.

In situations where not much is changing in the broader environment or indeed within the system itself, then system dynamics models may well provide a good representation of system behaviour. They can show the probable effects of a particular intervention, assuming that no structural changes are provoked. They can also show the factors to which the system is potentially very sensitive or insensitive, and this can provide useful information. But systems dynamics models are still deterministic; they still only allow for one solution or path from a particular starting point. It is the path into the future traced by average elements interacting through average events, and is only reasonable if non-average elements and non-average events have no systemic effect; that is to say there is no self-organization or learning for example. Such systems can function but not evolve.

Risk, uncertainty and prediction

The important point that we need to reflect on is that such apparent powers of prediction, as implicit in deterministic models, is only real if, and only if the assumptions made in achieving it are in fact true. In other words the real uncertainty that may characterize the long-term evolution of an ecology, economy, market or firm is only banished by assumption. In this light therefore, we must admit that understanding and predictions will only hold until things change and our expectations are confounded. Our methods therefore do not scientifically eradicate the uncertainty of an evolving world, but instead mask it and tell us that providing the system doesn't change then we can predict what it will do. But clearly the uncertainty is now as to whether the system will change or not.

While it may be reasonable to believe that the system may hold its structure for short times, this becomes increasingly unlikely for longer times, since history has shown us that over longer time periods everything of interest seems to change as new entities and types appear in the system and others become extinct.

What indeed is uncertainty? We would argue, along with Knight (1921), that uncertainty is defined as that which cannot be known, as an 'unknown unknown'; it is associated with the underlying structures and constructs themselves shifting, or disappearing and new ones appearing.

This is something more than risk. Risk refers to situations in which the variables and mechanisms are known as well as the dimensions of the model and its environment, and signifies the case where these do not change. So stochastic nonlinear dynamics allow us to investigate risk, or known unknowns, but only evolutionary models allow us to consider true uncertainty.

COMPLEXITY AND UNCERTAINTY IN HUMAN SYSTEMS

The evolution of complex, resilient natural systems is linked to the retention of mechanisms of adaptability within them and reflects an underlying lack of specific purpose. Human beings, on the other hand, want to improve, direct or control systems for some particular end and because of this tend to eliminate any apparently unnecessary parts and to streamline operations. This leads to vulnerability, however, because though the system may operate better for a particular purpose it lacks alternative mechanisms that may be needed if circumstances changed. For example, the potential for growth and diversity of any society or city depends to an extent on the imagination of its people. But ideas cannot be produced by dictat, according to some rational plan. They depend on a population's diversity and originality of thought; on its individual freedom and ability to experiment; and on the finer details of its history, culture and social interactions. Generally speaking, microscopic diversity resulting from the mixing of cultures and diverse doctrines will be an important ingredient for a population's survival, although nearly all rational planning aims at minimizing such 'inefficient' eclecticism.

In this chapter we cannot look at the way complexity and uncertainty are handled over the whole breadth of social systems. We will, however, look at one example, that of economics.

Limits to knowledge in economics

Introduction

Complexity thinking has influenced the emergence of evolutionary economics (Nelson and Winter, 1982; Metcalfe, 2007), ecological economics (Boulding, 1950, 1981; Georgescu-Roegen, 1971; Daly, 1999; Costanza et al., 2007), behavioural economics (Simon, 1955) and complexity economics itself (Beinhocker, 2007). However, it is a self-evident truth and perhaps never more self-evident than in current times that there is a huge uncertainty in how any particular economic policy will play out in practice. For example, the neo-liberal policies of the last several years have been predicated on the view that market forces, if left largely free, give the 'best' chance of 'success' and that regulation should be kept to a minimum; but 'best' in what respect, and success for whom? It appears that, whilst growth has been substantial, the divide between the incomes of the rich and the poor with this reliance on market forces has significantly increased (Harvey, 2005) and there has been a general tendency for diversity and consumer choice to reduce with markets increasingly dominated by decreasing numbers of increasingly large players.

Equally, the deregulation of the money markets has led to a sort of pyramid selling, with a consequent collapse. And of course we are now, more than ever before, facing the question as to whether some natural resources are running out, whether population growth will overtake the ability of the land to feed it, whether climate change will rend many parts of the globe too hot or too dry or too drowned for human use. How can economics deal with these factors?

Perhaps what is most concerning about economic policies is that the system in question, the global economic system, is hugely complex and full of uncertainties; we cannot assume the rationality and consistency of actors, nor that they act with all the information they need; we cannot assume that the past is a good predictor of the future; we cannot assume stability; we cannot assume simple cause-and-effect relationships and be certain what causes what. This is hardly a surprise, yet the methods and assumptions of neo-classical economics still largely prevail. And on top of this, we cannot really isolate economic decisions from issues of social justice, the environment, security and the longer-term.

Equilibrium

How is uncertainty viewed within economics? Traditional neo-classical economics parallels and indeed borrows the assumptions embedded within the physics of equilibrium thermodynamics and implicitly assumes the economy is not far from equilibrium and that the mechanisms that influence it can be described as simple, linear, causal relationships. Any uncertainty or variety or learning or historicity or the possibility of multiple and reflexive inter-relationships are largely ignored within the models. Change is largely treated as an optimizing move towards equilibrium. If such a statistical approach were positioned on the diagram in Figure 10.1, such an approach in fact sits to the right of the models described due to the restrictiveness of its assumptions.

Why *should* things find balance or move towards equilibrium? Economists have borrowed equilibrium theory from the natural sciences. But in physics this is based on the behaviour of certain types of closed systems and reflects the conservation of mass, energy and momentum at the microscopic level of molecular collisions. Is the transfer of this mathematical framework valid when modelling the economy, and is there evidence to support this approach? This attribution of science is very compelling. The economist Leon Walras, in 'Elements of Pure Economics' written in 1874 is unequivocal in asserting its validity. He says: *this pure theory of* *economics is a science which resembles the physico-mathematical sciences in every respect.*

Social theorist Thorstein Veblen, as early as 1898, challenged these assumptions in his paper, *Why is Economics* not *an Evolutionary Science?* In this he points out that assuming the economy moves towards equilibrium or balance is a teleological argument; that is to say, it is assuming a pre-ordained end point to which things naturally move. Why should there be such an end point?

Veblen in fact, argued that to see the economy as evolutionary, constantly shifting as variations and new things challenge the status quo, is a much more rational perspective. Complexity economist Brian Arthur (1994) recognized that, to assume a move towards equilibrium, one had to assume that negative feedback loops prevail in economic relationships, leading to the notion of perfect competition based on supply and demand balanced by price; but there is no reason to suppose that this always prevails. Arthur points out that in many circumstances, positive feedback or increasing returns is the norm, and competition can be affected by small events and choices which 'lock-in' certain solutions and where successful firms keep growing at the expense of the competition.

Arrow (1994), points out that this insight was not new, but has surfaced every decade or two, throughout the history of economics, starting with Cournot in 1838. The idea that there are in practice multiple potential and temporary points of stability has been well-aired in economic literature.

Economic Man

As well as assumptions about the underlying dynamics of the economy, neo-classical economic approaches need to assume, for ease of calculation, that consumers act rationally, in the sense that Economic Man makes consistent, rational, easily analysable choices typical of his 'type'; furthermore, competition is deemed to drive the economic process; competition is regarded as 'perfect' in the sense that it is undertaken with full and perfect information available to all the players and that it plays itself out to completion.

The nature of Economic Man's rationality is taken to mean that his decisions are about satisfying his own, and largely immediate, needs in a cost-effective manner. As Frank Knight (1921) points out:

> economic man … is postulated as knowing definitely and accurately all the facts and magnitudes, knowledge of which would influence his behaviour. … The economic subject would in many cases have to have perfect foreknowledge as well as perfect knowledge.

In reality, Alan Greenspan (2008), reminds us that: *the innate human responses that result in swings between euphoria and fear repeat themselves generation after generation with little evidence of a learning curve.*

Risk and uncertainty in economics

The fact that the economic landscape is uncertain and risky is not a new thought. Frank Knight (1921) made his famous distinction between 'risk' (randomness with knowable probabilities) and 'uncertainty' (randomness with unknowable probabilities). Keynes (1937) reflected similarly:

> By 'uncertain' knowledge …, I do not mean merely to distinguish what is known for certain from what is only probable. The game of roulette is not subject, in this sense, to uncertainty … The sense in which I am using the term is that in which the prospect of a European war is uncertain, or the price of copper and the rate of interest twenty years hence … About these matters there is no scientific basis on which to form any calculable probability whatever. We simply do not know.

The sociologist Zygmunt Bauman, reflecting on what he calls the current 'liquid times' (2007) postulates that uncertainty and fast change are defining features of our age. He says that:

> social forms (structures that limit individual choices, institutions that guard repetition of routines, patterns of acceptable standards) can no longer

> (and are not expected) to keep their shape for long, because they decompose and melt faster than the time it takes to cast them, and, once they are cast, for them to set.

Uncertainty, in economics, has, perhaps, generally been considered a limitation; something to aim to diminish through risk assessments or standardisation. In contrast evolutionary and complexity thinking suggest that a level of variation and messiness is *necessary* for adaptability and development as we have already discussed. Nowotny et al. (2001), for example, say:

> The inherent generation of uncertainties in both science and society is one of the crucial elements in their co-evolution.

And, indeed Shackle (1958) also recognized the generative quality of uncertainty. He said:

> the word uncertainty suggests an objectively-existing future about which we lack knowledge rather than [more positively] a void to fill with new creation.

So uncertainty is not a new thought to economists; the difficulty is, of course, that if the economist accepts uncertainty in its entirety then he is limited in what he can do to try and advise on how to predict or to control the future. So the economist makes do, perhaps, with deterministic models because, otherwise, he is limited in what he can achieve.

This is not to say that economists have not developed approaches which, in terms of the range of models shown within Figure 10.1 do not move us towards the left of the diagram, more towards uncertainty and the messiness of the real world. The field of evolutionary and complexity economics is increasingly well-developed (e.g. Foster and Metcalfe, 2001; Witt, 2008).

Alan Greenspan (2003) states: *Uncertainty is not just an important feature of the monetary policy landscape; it is* the defining characteristic *of that landscape*, and (Greenspan, 2003) states: *Our problem is not the complexity of our models but the far greater complexity of a world economy whose underlying linkages appear to be in a continual state of flux.*

Modelling market evolution

Instead of simply assuming that a market is populated with decision makers having perfect information and knowledge the complexity view leads us to consider the more realistic situation in which investors, managers and consumers have very incomplete and imperfect knowledge about what will happen and in which we do not imagine that there is only one possible outcome. They are trying to learn and to adapt according to outcomes, in line with the notions of exploration and exploitation described in March's (1991) classic paper.

Allen et al. (2007) have developed models that explore the likely probabilities of success where firms adopt not just different particular strategies (price/quality) but different *meta*-strategies. For example, these may be: (a) a strategy of incremental learning, (b) a strategy of imitating the strongest competitor, and (c) an intuitive, entrepreneurial strategy represented in the simulations by choosing 'randomly'. These meta-strategies are related to those discussed by March (2006) in his paper entitled 'Rationality, Foolishness and Adaptive Intelligence'. In the case of Allen et al. (2007) the meta-strategies of incremental learning and of imitation of the current winner represent different forms of rationality, while the entrepreneurs are 'foolish'. The paper explores the relative effectiveness of these different approaches, as well as their interdependences.

Allen et al.'s (2007) model tests the benefits or otherwise of 'learning' as a meta-strategy, which is important because if 'random strategies' were found to work better, there would be no point in studying, or in obtaining and analysing sales and market data; we could simply rely on our intuitive powers, or flip a coin, to decide what strategy to adopt. This relates to Schumpeter's (1939) important ideas about creative destruction; Schumpeter makes no real comment on whether firms can actually improve their survival rates as a result of internal processes. Instead, it is really the introduction of new firms that will have randomly better or worse technologies and internal structures that shapes the evolution of the market. Ormerod (2005), similarly, shows how it appears from the data that firms do not in fact learn.

In building a model such as Allen et al. describe, the modeller is confronted with the problem of what knowledge and uncertainty an agent can sensibly be assumed to have concerning the sales and revenue generation that will result from a given strategy. If no firm ever went bankrupt then we might make the mistake of thinking that considerable knowledge was present. However, an examination of the statistics concerning firm failures (Foster and Kaplan, 2001; Ormerod, 2005) shows that, whatever it is that entrepreneurs or firms believe, they are clearly, often completely wrong. The bankruptcies, failure rates and life expectancies of firms all attest to the fact that the beliefs of the founders, managers or investors are often not correct. Clearly, what really happens is that agents adopt, and probably believe in, particular initial strategies relating to product, quality and price, and the marketplace is then the theatre of learning in which some of them discover that their meta-strategy *does* take them on a successful trajectory, and others discover that it does not.

For the mathematics of such a model, see Allen et al. (2007).

The model generates a market evolution as goods or services are produced and consumed. The revenues from the sales of a firm are used to pay the fixed and variable costs of production, and any profit can be used either to increase production or to decrease the bank debt if there is any (see Figure 10.3).

All bankrupt firms are 're-launched' into the simulation with a randomly chosen strategy, but they retain their identity as learner, imitator or entrepreneur, so that there are always six of each kind competing in the system. The program runs a simulation with random initial strategies (quality and choice of mark-up), and replacements dependent on a random sequence of numbers; 'seeds' are used so that particular random starting points can be reproduced.

Results

Summarizing the results of multiple simulations for different random sequences (seeds 1 to 10) then we find the overall results of Figure 10.4. The message from this is clear. Learning by experiment is the best meta-strategy. Adopting entrepreneurial randomness is good, and imitating winners is the least successful meta-strategy.

It is indeed interesting that entrepreneurs really do better than might be expected; in addition provide exploratory behaviour of use to the rest of the system. This finding rather supports the remark made by March (2006): *Survival may also be served by the heroism of fools and the blindness of true believers. Their imperviousness to feedback is both the despair of adaptive intelligence and conceivably its salvation*.

Allen et al. (2007) also studied the spread of results obtained by all the different 'learning' curves and this showed that the results are robust.

Allen et al. (2007) concluded that, although in general 'learning' is better than 'not learning' the spread of the results shows that in any particular case this may turn out not to be true. This suggests that, even if a player owned the simulation model, it would still not be possible to use it to predict the exact strategy and meta-strategy to use in order to be sure of 'winning', because the strategy choices that will be made by other firms, represented in the simulation by the particular random sequence selected, cannot be known at any particular moment (Allen et al., 2006).

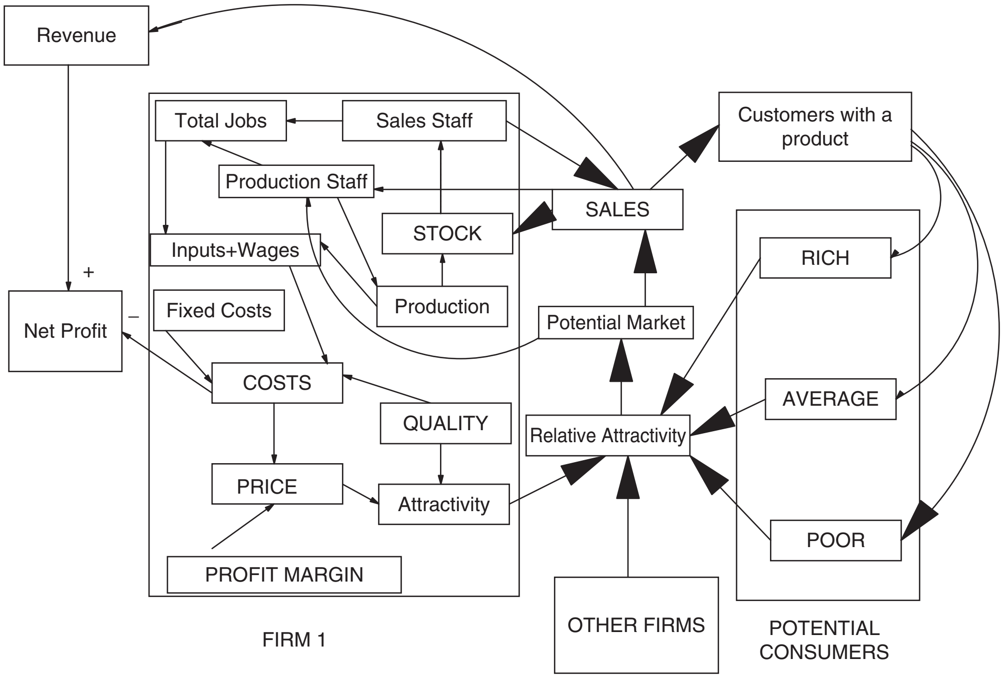

Figure 10.3 The evolutionary market model

Of course, over time, evolution will occur and new technologies, innovations, organizational changes would change the parameters, the mechanisms and the behaviours of the agents involved, as with full-blown evolutionary models. Over longer times, it is necessary to widen the perspective of the exploration and try to discern whether or not the dynamical system is evolving qualitatively.

DISCUSSION

One important error that we need to expose is that after recognizing the shortcomings of 'classical science' in dealing with highly-connected real-world situations, we can simply turn to 'complexity science' to provide a set of 'tools' that can be applied to obtain prediction, control and the knowledge necessary to make decisions and policies. We have to recognize that prediction, control and complete understanding are always an illusion, except for exceptional, controlled, closed and fixed situations, usually in laboratories.

However, this does not mean that 'modelling' has no role to play in complex situations. On the contrary, the alternative to 'trying to build a model' is 'not trying to build one', which can require us to rely on the use of intuition and plain pragmatism instead. And, as Einstein said: *Intuition is the summation of prejudices acquired up to age eighteen.* Thinking itself is a form of modelling.

Faith and hope would mark such an 'intuitive' approach and the bankruptcy data tells us that, except for the very lucky, this is not an effective strategy. Pointing out the nature of the assumptions that need to hold for a particular type of model to be correct can help us to explore the behaviour of domains of linkage which, for some time, may be useful. In other words, complexity tells us that ultimately we are involved in pragmatism; but instead of simple intuitive pragmatism we can adopt a pragmatic approach to models and see them as experiments in

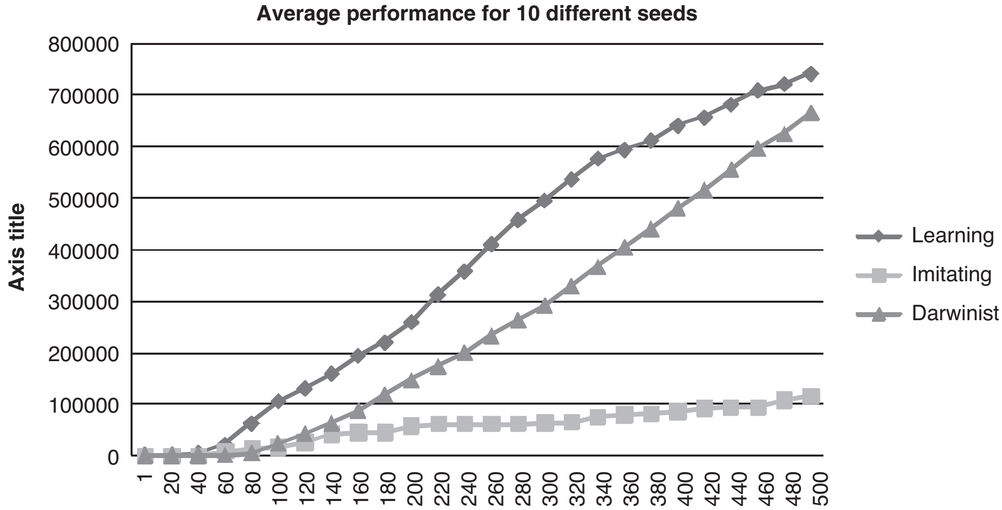

Figure 10.4 The average results for 10 random sequences, each with six firms of each type

representation, where we retain those that seem useful and continue to modify those that fail and treat all as an adjunct to thinking, not as defining 'the answer'.

We would argue that information about many technical systems cannot be obtained in any way other than by simulation. Where such simulation and modelling methods fail is often where human reactions and responses are included, and some simple rationality has been assumed. Humans are more complicated, more confused and more heterogeneous than that, and also they get bored, change, learn and imitate, often incorrectly. However, in dealing with many management issues there are production systems, logistical supply and distribution systems, collaboration, competition and changing market conditions. In order to 'manage to survive' it seems clear that trying to understand and perhaps 'model' the situation is advantageous, providing that any outcomes are not taken as the incontrovertible truth. As shown in the example in the section 'Complexity and uncertainty in human systems' it is on the whole better to try to 'learn' from experiments than not. Learning beats intuition or imitation on the whole. The learning that is possible is limited and needs to be constantly tested and re-worked on a constant basis. We can never sit back and say, 'that's it, I know how the system works and can simply continue like this'. The world, other agents, and technological possibilities will move on and whatever assumptions are contained in a particular representation will be found inadequate at some point.

This implies that we are destined and indeed evolved to live always with uncertainty. Certainty only arises for closed systems and correspondingly closed minds. But the real world, outside the laboratory, is not closed from outside connections or from internal heterogeneity and micro-diversity. Without uncertainty, we would argue that life would not be worth living, since all would be pre-determined. But evolution has fashioned us to face it and even enjoy it, while working all the time to try to reduce it through our actions of organizing, constructing and protecting. Uncertainty is one face of evolution and complexity, and our game is to try to counter it with actions and innovations that actually, whether we mean to or not, create new uncertainties as we go. This is a never-ending (we hope), multi-level game of creation and response that is far more appealing and interesting than the closed, controlled and predictable world that we may have believed was where science had led us. Uncertainty and complexity are therefore part of a modern, deeper, scientific understanding of the evolutionary processes in the universe.

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