Cynefin, Statistics and Decision Analysis

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Abstract

David Snowden's Cynefin framework, introduced to articulate discussions of sense-making, knowledge management and organisational learning, also has much to offer discussion of statistical inference and decision analysis. I explore its value, particularly in its ability to help recognise which analytic and modelling methodologies are most likely to offer appropriate support in a given context. The framework also offers a further perspective on the relationship between scenario thinking and decision analysis in supporting decision makers.

Keywords: Cynefin; Bayesian statistics; decision analysis; decision support systems; knowledge management; scenarios; scientific induction; sense-making; statistical inference.

1 Introduction

Several years I attended a seminar on knowledge management given by David Snowden. At this he described the *Cynefin* conceptual framework, which, *inter alia*, offers a categorisation of decision contexts (Snowden, 2002). Initially I saw little advantage over other categorisations of decisions, such as the strategy pyramid: *viz*. strategic, tactical and operational (see Figure 2 below). However, Carmen Niculae had more insight and working with her and others, I have appreciated Cynefin's power to articulate discussions of inference and decision making. Below, I explore Cynefin and its import for thinking about statistics and decision analysis. There is nothing dramatic in anything I shall say. Many will have reached similar conclusions. Perhaps also David Snowden will take this as a small apology for my initial dismissal of his ideas.

I hope it becomes clear that Cynefin offers benefits to several types of user: analysts can use it to help identify what methodologies might be suitable for the problem faced by their clients; their clients themselves can use it to gain insight into the qualities of the issues that they face; and academic researchers may use it in exploring and categorising methodologies within statistics, decision analysis and operational research. In this paper, my discussion leans much towards the last of these three, though there are many elements that speak to all three audiences. Thus this paper adds to many discussions of operational research (OR) methodology and the OR process that may be found in the literature, recasting parts of them into the Cynefin framework and drawing, I believe, some new insights, particularly in relation to the interplay between decision makers' knowledge of the external world, themselves and the types of statistical, decision and OR analysis that may be most suited to their current context (see, e.g., White, 1975; 1985; Mingers and Brocklesby, 1997; Mingers, 2003; Ormerod, 2008; Luoma *et al.*, 2011).

In the next section I describe Cynefin, before turning in Section 3 to some specific applications that I have found helpful in articulating discussion across range of statistical and decision analytic contexts. In Section 4, I explore the relationship between knowledge management and decision making. Knowledge and the process of inference are intimately related; in Section 5, I explore some relationships between Cynefin, the Scientific Method and statistical methodology; and in Section 6 I build on this to discuss decision analysis in the knowable and complex domains. There I discuss how uncertainties might be addressed, exploring a relationship between scenario thinking and formal decision analysis. Section 7 offers some brief conclusions.

2 Cynefin

So what is Cynefin? The name comes from the Welsh for 'habitat', at least in a narrow translation. But Snowden (2002) suggests there are also connotations of acquaintance and familiarity, quoting Kyffin Williams, a Welsh artist:

> "(Cynefin) describes that relationship – the place of your birth and of your upbringing, the environment in which you live and to which you are naturally acclimatised."

The embodiment of such ideas as familiarity makes Cynefin clearly relevant to knowledge management. Nonaka's concept of *Ba* serves similarly: a place for interactions around knowledge creation, management and use (Nonaka, 1991; 1999; Nonaka and Toyama, 2003). Snowden distinguishes Cynefin from Ba through the Welsh word's association with community and shared history: for further discussion, see Nordberg (2006). Our concern will be with how Cynefin

- characterises various forms of uncertainty,
- helps structure our thinking about statistical inference and the design of research studies,
- relates to decision making, decision analysis and decision support, and
- relates to our self-knowledge of our values – and values, it should be remembered, should be "the driving force of our decision making" (Keeney, 1992).

Snowden's Cynefin model roughly divides decision contexts into four spaces: see Figure 1. In the *known space,* also called *simple order* or *the Realm of Scientific Knowledge,* the relationships between cause and effect are well understood. The known space contains those contexts with which we are most familiar because they occur repeatedly; and because we have repeated experience of them, we have learnt underlying relationships and behaviours sufficiently well that all systems can be fully modelled. The consequences of any course of action can be predicted with near certainty, and decision making tends to take the form of recognising patterns and responding to them with well-rehearsed actions. Snowden describes decision making in these cases as SENSE, CATEGORISE AND RESPOND (Kurtz and Snowden, 2003). Klein (1993) terms this *recognition-primed* decision making; French, Maule and Papamichail (2009) term such decision making *instinctive.*

In the *knowable space*, also called *complicated order* or *the Realm of Scientific Inquiry*, cause and effect relationships are generally understood, but for any specific decision there is a need to gather and analyse further data to predict the consequences of a course of action with any certainty. Snowden characterises decision making in this space as SENSE, ANALYSE AND RESPOND. Decision analysis and support require the fitting and use of models to forecast the consequences of actions with appropriate levels of uncertainty. In this realm standard methods of operational research and decision analysis apply (see, e.g., Clemen and Reilly, 2004; Taha, 2006).

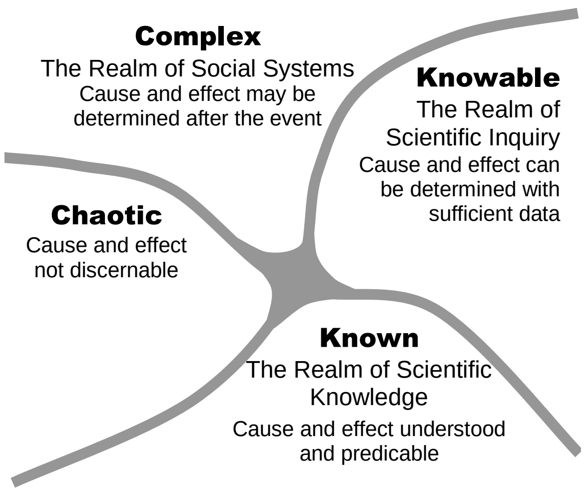


Figure 1: Cynefin

In the *complex space*, also called *complex unorder* or *the Realm of Social Systems*, decision making situations involve many interacting causes and effects. Knowledge in this space is at best qualitative: there are too many potential interactions to disentangle particular causes and effects. Every situation has unique elements: some unfamiliarity. There are no precise quantitative models to predict system behaviours such as in the known and knowable spaces. Decision analysis is still possible, but its style will be broader, with less emphasis on details. Decision support will be more focused on exploring judgement and issues, and on developing broad strategies that are sufficiently flexible to accommodate evolving situations. Snowden suggests that in these circumstances decision making will be more of the form: PROBE, SENSE, AND RESPOND. Analysis begins, and perhaps ends, with informal qualitative models, known as soft modelling, soft OR or problem structuring methods (Rosenhead and Mingers, 2001; Mingers and Rosenhead, 2004; Pidd, 2004; Franco *et al.*, 2006; Shaw *et al.*, 2007). If quantitative models are used, then they are simple, perhaps linear multi-attribute value models (Belton and Stewart, 2002). One point of terminology should be noted: namely, this difficulty of understanding cause and effect can occur in environmental, biological and other contexts as much as in social systems.

In discussing the complex space, one should be careful to avoid confusion with complexity science. While some complexity science does relate to Snowden's complex space, it is more concerned with computational issues relating to very complicated models. Such models and computational issues belong more to Snowden's knowable and known spaces rather than the complex one. Models, however complicated, seek to encode known understandings of cause and effect. The difficulty is that, though causes and effects, correlations and non-linearities are understood, their great number makes it difficult, if not intractable to compute the predicted effects of a set of causes.

In the *chaotic space*, also called *chaotic unorder*, situations involve events and behaviours beyond current experience with no obvious candidates for cause and effect. Decision making cannot be based upon analysis because there are no concepts of how to separate entities and predict their interactions. Decision makers will need to take probing actions and see what happens, until they can make some sort of sense of the situation, gradually drawing the context back into one of the other spaces. Snowden characterises such decision making as ACT, SENSE AND RESPOND: more prosaically, 'trial and error' or even 'poke it and see what happens!'

Donald Rumsfeld famously said:

“There are known knowns; there are things we know we know. We also know there are known unknowns; that is to say we know there are some things we do not know. But there are also unknown unknowns - the ones we don't know we don't know.”

He missed a category: ‘unknown knowns’. ‘Known knowns’ corresponds to knowledge in the known space; ‘known unknowns’ to that in the knowable space; and ‘unknown unknowns’ to that in the chaotic space. ‘Unknown knowns’ would correspond to our knowledge in the complex space, in which we know candidates for causes and effects, but not their full relationships.

Cynefin has parallels with the strategy pyramid: see Figure 2. In this the strategy pyramid has been extended from its more common trichotomy of operational, tactical and strategic decisions by including a fourth category of instinctive or recognition-primed decisions (French *et al.*, 2009). Strategic decisions set a broad direction, a framework in which more detailed tactical and operational decisions may be taken. In delivering operational decisions, many much smaller decisions have to be taken. These are the instinctive, recognition-primed ones. Simon (1960) noted that strategic decisions tend to be associated with unstructured, unfamiliar problems. Indeed, strategic decisions often have to be taken in the face of such a myriad of ill-perceived issues, uncertainties and ill-defined objectives that Ackoff (1974) dubbed such situations *messes*. There is a clear alignment of the context of strategic decision making and the complex and even chaotic spaces of Cynefin. Tactical, operational and instinctive decision contexts have increasing familiarity and structure, and occur with increasing frequency. Again the alignment with Cynefin is clear. Jacques (1989) distinguished four domains of activity, and hence decision making, within organisations: the *corporate strategic, general, operational* and *hands-on work*. French *et al*. (2009) relate these directly to the strategic, tactical, operational and instinctive categories in the extended

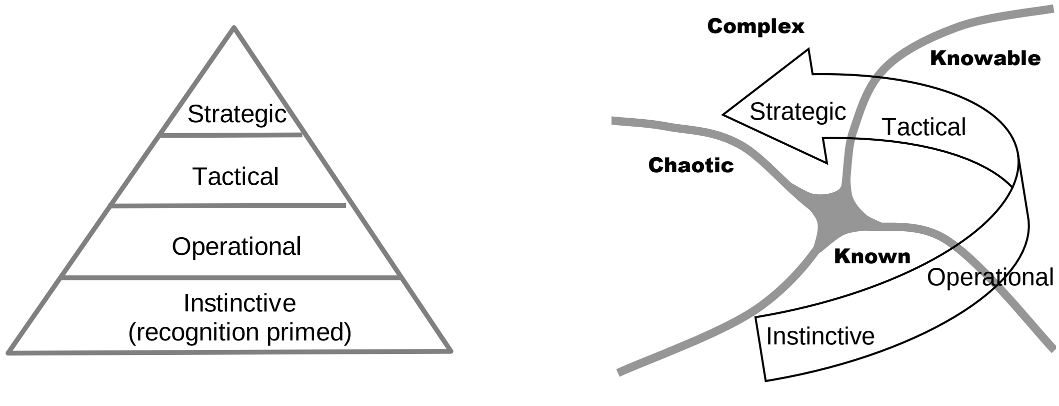


Figure 2: Relationship between the perspectives offered by the strategy pyramid and Cynefin

strategy pyramid, and hence they also relate to Cynefin as in the curved arrow in Figure 2. Note, however, that I do not claim precise identification of the chaotic, complex, knowable and known spaces with strategic, tactical, operational and instinctive decision making contexts. While the appropriate domain for instinctive decision making may lie entirely within the known space, operational, tactical and strategic decision making do not align quite so neatly, overlapping adjacent spaces. Indeed, the boundaries between the four spaces in Cynefin should not be taken as hard. The interpretation is much softer with recognition that there are no clear cut boundaries and, say, some contexts in the knowable space may have a minority of characteristics more appropriate to the complex.

Snowden uses Cynefin to discuss issues such as organisational culture and leadership, and knowledge management (Snowden, 2002; Snowden and Boone, 2007). Within knowledge management there is distinction between *explicit knowledge* – i.e., knowledge with can be encoded – and *tacit knowledge* – the skills, expertise, values and so that we cannot articulate, at least currently, other than by showing them in our behaviours (Polyani, 1962; French *et al.*, 2009). Nonaka's SECI cycle (Figure 3) suggested four mechanisms by which knowledge is created, explored and shared (Nonaka, 1991; 1999):

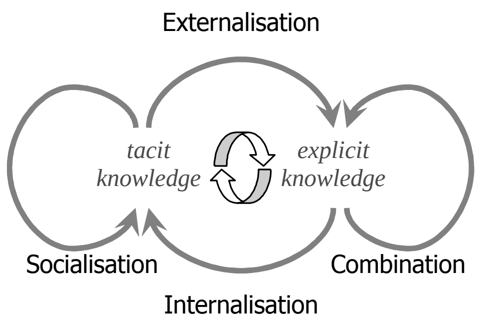


Figure 3: Nonaka's SECI cycle

- *Socialisation* – sharing tacit knowledge in communities through mentoring, discussion, collaboration etc.;
- *Externalisation* – articulating tacit knowledge explicitly in words, tables, charts, diagrams, models, expert systems and so on;
- *Combination* – drawing together and systematising explicit knowledge into more generic, simpler, and more widely applicable forms;
- *Internalisation* – intuitively understanding the implications of generic explicit knowledge and deploying this tacit understanding in our behaviour and decision making.

Implicit in the socialisation loop is the possibility that some tacit knowledge will never be rendered explicit. Within Cynefin one would expect tacit knowledge to dominate in the complex and chaotic spaces, while explicit knowledge dominates in the known and knowable spaces. This, in turn, suggests that knowledge management relies more on socialisation in the complex and chaotic spaces and on combination in the known and knowable spaces. Indeed, behaviour in the known and knowable space builds on scientific knowledge, the archetypal example of *combined* explicit knowledge, i.e. scientific models and theories.

What does Cynefin bring to discussions of decision making? I do not claim that any of the following could not be – indeed, has not been – discussed without the structure of Cynefin: e.g., see Brundtland (1987). However, Cynefin does seem to facilitate such discussions well, perhaps because it simultaneously addresses knowledge and decision making. In the next section I illustrate this point with a number of applications.

3 Illustrations of how Cynefin can articulate issues and concerns in a variety of applications.

[For many further examples and discussions of applications of Cynefin, see http://www.cognitive-edge.com/.]

An interpretation of some of the issues in emergency management

Emergency management provided the first example to convince me of the power of Cynefin to articulate and communicate issues. Looking at many past instances of the handling of large scale emergencies, it was apparent to Carmen Niculae and me that the authorities, despite addressing the physical aspects of the emergency well, often lost the confidence of the public. We found that we could articulate the dynamics of an emergency intuitively using Cynefin. Essentially, the authorities think that they are handing an event in the known or knowable spaces, whereas associated socio-political-economic issues may pull the emergency into the complex space. There is a dislocation between the authorities' perception of the situation and reality (French and Niculae, 2005). In the heat of a crisis the imperative is to do all one *physically* can to save and protect life and to remove the source of the danger. But many are affected in different, non-physical ways. Justifiable concerns and stresses build: individuals fear for or mourn loved ones, and as do communities; ways of life are changed temporally, perhaps permanently; economic effects occur and can quickly impact some groups disproportionately; etc. Stresses and concerns grow rapidly (Barnett and Breakwell, 2003; Kasperson *et al.*, 2003), outstripping the resources devoted to community care.

In the early phase of the Chernobyl Accident, the decision context could be placed in the knowable space: causes and effects were understood, although there were gross uncertainties about the source term and the distribution of the contamination. Successive post-accident strategies, which continued to be based upon assumptions belonging to the known and knowable spaces, focused on technical issues of radiation protection and neglected the enormous social and cultural harm that the accident was causing (International Atomic Energy Agency, 1991; Karaoglou *et al.*, 1996; French *et al.*, 2009). Thus, the context passed into the complex space, but for a period was managed as if it were in the known or knowable domains. This dislocation led to affected communities questioning and essentially rejecting all the authorities' protective and recovery measures. Eventually socio-economic issues were addressed. For instance, the ETHOS project applied an approach which explored social and cultural understandings along with more technical perspectives through multi-disciplinary teams and strong involvement of the local population to rebuild a good overall quality of life (Heriard Dubreuil *et al.*, 1999).

The same issues can be discerned in the handling of many crises: e.g. Three Mile Island, Mad-Cow Disease, and Hurricane Katrina (Niculae, 2005). Indeed, as I write this, BP is being pilloried for its mismanagement of the Gulf Oil Spill and, admittedly before all the evidence is published, I cannot help reflect that they may have myopically concentrated on the technical issues of sealing the well-head, issues largely in the known and knowable spaces, and missed the socio-economic and cultural impact, both actual and feared, that the spill was creating, issues that clearly lie in the complex space. Such issues have led many to argue for a more coherent socio-technical approach to emergencies in which the authorities embrace and address all the public's concerns throughout the response and not just recovery phase (Fischhoff, 1995; Mumford, 2003; French *et al.*, 2005; French and Niculae, 2005).

Categorisation of decision support process and systems

To understand the appropriate use of decision analysis and support, one needs to categorise decision support processes and systems according to the level of support provided and the decision context (2009). French (2010) categorises the level of support as in Table 1 and uses Cynefin for decision contexts: see Figure 4. This suggests, for instance, that simulation methods have a role to play in offering Level 2 support in the known and known spaces, but are not relevant to the complex or chaotic spaces because in those cause and effect are not understood sufficiently for simulation. Many similar points become apparent on mapping other decision support processes and systems into this categorisation: e.g.

- Databases and data mining provide Level 0 support over all the spaces, but are often called management information systems (MIS) or executive information systems (EIS)

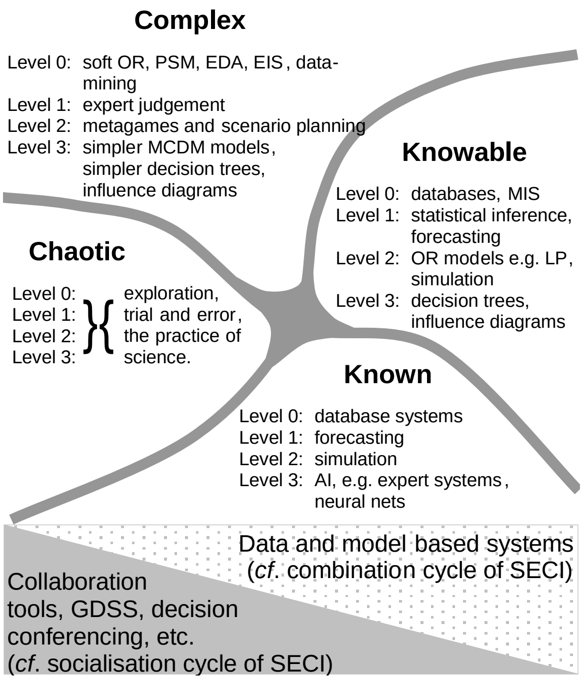
• **Level 0**	Acquisition, checking and presentation of data, directly or with minimal analysis, to decision makers.
Level 1	Analysis and forecasting of the current and future environment.
Level 2	Simulation and analysis of the consequences of potential strategies; determination of their feasibility and quantification of their benefits and disadvantages.
Level 3	Evaluation and ranking of alternative strategies in the face of uncertainty by balancing their respective benefits and disadvantages.
Table 1:	**Levels of support that may be offered by decision support processes and systems (French *et al.*, 2009).** Note that levels 0 – 2 relate mainly to supporting the evolution of decision makers' perceptions of the external world; whereas level 3 relates to their understanding of their preferences and evaluation of the options before them, i.e. their understanding of themselves.

in the knowable and complex spaces, respectively (Alter, 2002; Laudon and Laudon, 2009).

- Expert systems (ES), neural nets, and other artificial intelligence (AI) techniques provide level 2 and 3 support. Some authors suggest that AI-based systems have much wider application, but such systems are only really suited to the highly structured, repetitive situations in the known and knowable spaces because of their need for large training sets (see also Edwards *et al.*, 2000).

- Quantitative OR modelling, e.g. linear programming, inventory and maintenance models (Denardo, 2002; Taha, 2006), underpins many of the systems used in the knowable space at levels 2 and 3, but most quantitative OR techniques assume too much structure to be appropriate for the complex space.

- Problem and issue structuring tools (PSM), often called soft OR or soft modelling tools, can provide Level 0 support in the complex space (Rosenhead and Mingers, 2001; Mingers and Rosenhead, 2004; Franco *et al.*, 2006; Shaw *et al.*, 2007; French *et al.*, 2009). So can exploratory data analysis (EDA)



- **Figure 4: Categorisation of decision support processes and systems (French, 2010).** *Key*: AI – artificial intelligence; EDA – exploratory data analysis; EIS – executive information system; LP – linear programming; MCDM – multi-criteria decision making; MIS – management information system; OR – operational research; PSM – problem structuring methods.

(Tukey, 1977), which is often incorporated into EIS. Modern data mining techniques may also be appropriate here (Hand *et al.*, 2001; Korb and Nicholson, 2004). However, automated though these procedures seem, they inevitably require judgement to separate interesting and useful patterns from spurious ones; there is insufficient repetitivity for more 'objective' techniques such as confirmatory significance testing.

- For level 1 or level 2 support in the complex space one may use methodologies such as scenario planning (Schoemaker, 1995; van der Heijden, 1996; Montibeller *et al.*, 2006) or metagames (Howard, 1971), methodologies that stimulate decision makers to anticipate contingencies, and perhaps provide some simple qualitative consequence modelling.
- Level 3 support in the complex space may be provided by some simpler multi-criteria decision making models (Belton and Stewart, 2002), such as multi-attribute value analysis (Keeney and Raiffa, 1976), multi-criteria decision aids (Roy, 1996) or the analytic hierarchy process (Saaty, 1980), which help decision makers explore their values. Simple decision trees and influence diagrams may also be used to understand some of the broad uncertainties facing decision makers. Further discussion is offered in Section 6.

Finally remembering our discussion of Nonaka's SECI cycle, decision making in the complex and chaotic spaces on the left hand side of Cynefin will be based more on judgement, tacit knowledge and exploration. Thus the primary activity in deliberating on possible strategies will be the socialisation and sharing of tacit knowledge. Whereas in the known or knowable spaces, decision making will be based more on explicit knowledge and the use of decision models and data will be more common (Niculae *et al.*, 2004). This suggests that in the complex or chaotic spaces effective decision support needs to focus on facilitating collaboration, whereas in the known or knowable spaces decision support systems will be data- or model-based: see Figure 4.

Human behaviour, risk analysis and high reliability organisations

Recently, I was part of a research project to survey and critique human reliability analysis (HRA) methodologies and consider their role in summative risk and reliability analyses (Adhikari *et al.*, 2008; French *et al.*, 2010a). Our findings were not comforting. The empirical evidence is that human behaviour, not necessarily erroneous behaviour, is involved in something like 75% of all systemic failures. Yet current HRA methodologies lack the sophistication to model current understandings of human behaviour, particularly in relation to the correlations and dependencies that it can introduce into systems. Modelling approaches used in HRA tend to be focussed on easily describable sequential, low-level tasks, i.e. ones in the known space in which the operators tend to use recognition-primed decision making. But such tasks are seldom the initiators of systemic failures, which almost invariably involve the occurrence of and higher-level responses to unexpected, infrequent events in the complex space, for which operators need problem solving and decision making skills. Moreover, such high level responses can affect many parts of the system, correlating events. In other words, the empirical base of HRA is inappropriate to many of the behaviours in systemic failures.

Our research found that Cynefin was an effective in articulating such issues, providing a framework to discuss the applicability of different HRA methodologies (see also Deloitte, 2009). Further, we also suggested that risk and reliability studies should use Cynefin to categorise the various contexts of human activity within a system before beginning any HRA.

We also considered high reliability organisation (HRO) theory as part of our studies. Again Cynefin offered an effective way of articulating a concern. Early HRO theory drew on examples such as carrier flight deck operations to provide its empirical base and then extrapolated its thinking to risk and crisis management in contexts such as Bhopal and Chernobyl (see, e.g, Weick, 1987). Yet this moves from repetitive contexts in Cynefin's known space to unique contexts in the complex or chaotic spaces. High reliability in known contexts is likely to be based upon agreed single perspective science – a single shared mental model; whereas in complex contexts high reliability organisations need to manage multiple perspectives and families of shared mental models.

Cynefin, sense-making and problem structuring

At its simplest the decision analysis cycle involves three phases (French *et al.*, 2009):

- *Formulation* or *Sense-making Phase*, during which the problem, issues, objectives uncertainties and options are identified and formulated. This phase is much more visible in the knowable and complex spaces. In the known space, the problems repeat so often that they were formulated long ago and sense-making becomes a matter of recognition, as acknowledged in term 'recognition-primed decision making'.
- *Analysis Phase*, during which the issues, objectives, uncertainties and options are modelled and analysed. This involves predicting the consequences of each possible option in terms of their success in achieving the decision makers' objectives, taking

account of the uncertainties in the prediction. Thus the analysis offers guidance towards options which promise to achieve their objectives. The analysis itself may be formalised as in the quantitative techniques of finance, decision analysis and OR; or it may be much more informal and qualitative, perhaps a few diagrams and lists. Moreover, there may be more than one strand of analysis, each representing a different perspective on the problem, perhaps those of different stakeholders or, as discussed below in Section 6, different future scenarios (French, 2003; French *et al.*, 2009).

- *Appraisal and Decision Phase*, during which the decision makers decide which option to implement or whether more analysis is needed. Since any model is a simplification of the real world, there will be a need to reflect on the recommendation and see if it makes sense once the complexity of reality re-enters the discussion. Has the analysis brought enough understanding to make the decision? Is it requisite (Phillips, 1984; French *et al.*, 2009)? If so, decide and implement; if not, introduce further issues into the formulation and reanalyse.

During the formulation or sense-making phase, an analyst seeks to explore, evolve and challenge the perspectives of the decision makers to build a shared understanding of the issues and problem(s). The PSMs, referred to above, provide tools to help in this. As Snowden and his colleagues have emphasised (Kurtz and Snowden, 2003), Cynefin is an excellent PSM for challenging decision makers to explore the context of the problem. In decision workshops I have outlined the Cynefin framework to participants, sketched it on a flipchart and then invited them to discuss where the issues that concern them lay, perhaps locating them on the chart using post-its. The ensuing discussion has always been enlightening. Participants seem to find the Cynefin framework intuitive and catalytic. Not only does it help them set the issues that they face within a broader context, it has proved useful in helping them understand why their favourite problem solving tools may be inappropriate in this case: *cf.* Figure 4. For case studies of the use of Cynefin in problem structuring, see Deloitte (2009) and www.cognitive-edge.com.

4 Knowledge Management, Inference and Decisions

Snowden introduced Cynefin as a framework to discuss knowledge management. Since the main focus of this paper relates to statistical inference and decision analysis, it may be helpful to discuss the relationship between the three topics briefly (for further discussion of decision making and knowledge management, see Nicolas, 2004). Let me begin by making distinction between data, information and knowledge (for references and further discussion of this distinction, see French *et al.*, 2009). *Data* are facts about things, events, activities, transactions, etc. Data do not relate for any specific context. *Information*, on the other hand, does relate to a specific context. Information is formed by selecting, organising, summarising data to be meaningful and useful within a specific context. *Knowledge* is more generic, relevant to many contexts, and longer lasting. Knowledge includes, among other things, the understandings – Boisot (1998) terms these *perceptual and conceptual filters* – that enable us to make inferences, forecasts and decisions. As we have noted, some knowledge is tacit; data and information, however, can always be made explicit and codified.

Philosophers have distinguished kinds of knowledge in many ways: e.g. *procedural knowledge* or ‘knowing how’, which refers to a person’s skills; *propositional knowledge* or ‘knowing that’, which refers to general theories, models and understandings; and *personal knowledge* or ‘knowing things through acquaintance’, which refers to an individual’s knowledge of objects, people and systems. For me, personal knowledge also contains a person’s understanding of his or her internal self, including his or her beliefs and values.

Figure 5 outlines one view of how knowledge is used in decision making; the related tasks of inferring and forecasting are discussed shortly. Firstly, one needs to recognise that information can take many forms. Information is data selected and organised for a purpose in the formulation phase. In the complex or the chaotic spaces that may require an exploration of a range of nebulous, partially perceived issues and feelings to bound the context and identify the need for a decision: sense-making in the broadest of senses. Decision makers and their analysts need to draw on much judgement, experience and creativity to make sense of the situation, using tacit as well as explicit knowledge, leading into much clearer processes, the use of PSMs, EDA and so forth. In the known and knowable spaces, the formulation phase will be well-rehearsed, maybe completely so, drawing on much explicit knowledge learnt from past experience. Arrow A in Figure 5 indicates these uses of knowledge in the formulation phase. More detailed organisation of data in the analysis phase of decision making is also indicated by arrow A. In the known and knowable spaces, the analysis may be

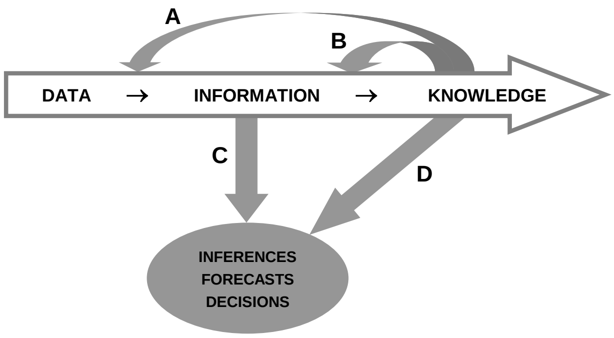


Figure 5: The relationship between data, information and knowledge and the making of inferences, forecasts and decisions (French *et al.*, 2009)

quantitative involving statistical, mathematical, or operational research models; in the complex and certainly the chaotic spaces, it will be much less formal.

Arrow C indicates that the decision makers are informed by the outputs of the formulation and analysis phases. Arrow D indicates that to understand the information and accord it appropriate weight in their thinking, they need to draw on their knowledge of the analytic methods used and how these have helped them in the past. Kuhn (1961) makes a similar remark relating to scientific inference. They need to use further judgement, i.e. tacit knowledge, to recognise when the analysis is requisite, providing them with sufficient understanding to proceed to decide and implement a course of action.

Over time, decision makers, or their analysts, may recognise certain new common patterns in several of the contexts in which they have formulated, analysed and made decisions. This in turn may suggest new generic insights, i.e. new knowledge, which may be applied in the future. This ability to recognise such patterns and form new knowledge requires insight and higher level knowledge, indicated by arrow B in Figure 5, of how one learns; some of this will be explicit, but much may be tacit. For a recent review on this aspect of learning and how it might occur, see Dorfer (2010). This ability underpins the practice of scientific induction to be discussed in the next section.

5 Cynefin, Sense-making and Statistical Inference

Much of my early career was spent in the then nascent school of modern Bayesian statistics. Back in the 1970s and 1980s there were many vibrant, some might say bitter, discussions of scientific induction, the role of statistical inferential methods, objectivity versus subjectivity, the need for repeatability, and where EDA fitted in (for a broad discussion of these issues, see Barnett, 1999; Nakicenovic and Swart, 2000). Looking at Cynefin, I wonder if we might have articulated those discussions better within its framework.

One can sketch the growth of human knowledge – *science*, in its generic meaning – on Cynefin very easily. We begin ignorant, facing events and behaviours in the chaotic space. Causes and effects are unclear. Things are 'random' to us. Gradually through our interactions with our environment: by 'environment' I mean anything that we observe and which affects our lives. By acting, sensing and responding, we begin to make sense of some parts of it, seeing patterns or some such. Slowly our perception of those parts of the environment move into the complex space as we perceive some causes and their effects, but we still do not have enough understanding to model and predict the precise effects of a set of causes. Through continued interactions with the environment – probing, sensing and responding – we make more sense of some of the behaviours and build a much tighter understanding of cause and effects, building models and laws. While we still cannot predict perfectly, needing parameters or similar to complete the models; our understanding moves into the knowable space. Next we seek data to determine parameters and so on, which will allow our models to predict more detailed effects from a particular set of causes. Through more interactions – sensing, analysing and responding – we determine the parameters, finding that some are very widely applicable, e.g. physical constants, and these aspects of our understanding move into the known space, where we can predict effects from a set of causes without further data simply by categorising and responding.

Of course, this is a very naive description of the process of science, though perhaps not as naive a description as I have heard in some research methodology courses! While this description lacks subtlety and sophistication, particularly in the later stages of the process as models and laws are inferred, it has the virtue of beginning with sense-making in the chaotic and complex spaces. Too often thinking on scientific induction and statistical inference begin with the assumption that we have made enough progress to have some understanding of cause and effect, perhaps even a hypothesis or putative model. Sense-making has not received the attention it should have in the Philosophy of Science; and it still has to achieve an equal status with statistical inference within descriptions of scientific induction. Rather the methodology of science has focused much more on the testing and validation of models and theories and the estimation of parameters, i.e. those processes that fall in the known and knowable spaces. Such contexts are necessarily repeatable or commonly occurring.

Repeatability has come to lie at the heart of the scientific induction (Chalmers, 1999). Scientific models and theories can only be validated if they can be tested again and again in identical circumstances and shown to explain and predict system behaviours. It is not surprising, therefore, that *Frequentist* approaches dominated as statistical methodologies developed during the late 19th and most of the 20th century: i.e. approaches based upon conceptions of probability which have repeatability at their heart. Moreover, the primary goal of such statistical methods was to formalise the processes of estimation of parameters and confirmation or refutation of hypotheses. Such statistical inference comes at the end of a long process of sense-making, discovery, creation and refinement of scientific knowledge.

The underpinning philosophy and methodology of statistical inference are controversial topics, surprisingly so for what is often perceived as a dry subject (Barnett, 1999). There are many schools of thought, often gathered together into the *Bayesian* and *Frequentist*. But that dichotomy is a gross categorisation that misses many subtle differences. Below I identify four general schools, and even that rides roughshod over many issues deserving more careful exploration. But four will be sufficient to locate and explain my position.

Broadly, the categories relate to two related factors: whether a school takes an objective or subjective stance and how it interprets probability.

- *Subjective Subjectivist Schools*. Essentially these approaches lie at the extreme of the subjective-objective dimension. The statistician or scientist lies at the heart of the approach and the role of scientific induction is to make sense of and ultimately predict the sensory stimuli that he or she receives. Often one feels that the existence of an external world may be moot, though whether it exists is immaterial to the theories of inference that are developed. An external world may explain the correlations between the sensory stimuli, but such explanations are strictly irrelevant to the process of inference which aims simply to model the correlations between stimuli to predict further stimuli. Sense-making becomes a matter of perceiving exchangeability relations between series of stimuli and developing previsions, DeFinneti's term for what are essentially probabilities of future stimuli. From these probability models follow, along with prior beliefs. Inference based upon Bayesian updating naturally follows. Prior probability distributions are updated through a likelihood function in the light of new evidence to give posterior probability distributions. Any parameters that arise within the probability models are artefacts which characterise the exchangeability assumptions and do not necessarily represent 'states of the world', i.e. measurements of external entities: for key references see DeFinetti (1974; 1975) and Lad (1996).
- *Subjective Objectivist Schools*. These approaches do begin by postulating an external world and the process of sense-making is, first, one of identifying a state space that has the capacity to describe the statistician's or scientist's perception of this world and, second, of building sufficient understanding of the world that his or her beliefs about it may be articulated through probability distributions over the state space. Again inference based upon Bayesian updating follows naturally. In this case, however, at least some the parameters in the models may be identified with measurements of external entities. Moreover, in addition to representing his or her beliefs about entities, the probability distribution may also represent randomness that he or she believes to be present in the

world. Key references in this area are Lindley (1965), DeGroot (1970), Box and Tiao (2008), Forster and O'Hagan (2004), French and Rios Insua (2000) and Savage (1972).

- *Logical Objectivist Schools*. In this case the focus is on the language in which the external world is described. This language is independent of the scientist or statistician: a public language. These approaches suggest that objective knowledge can be embedded in an objective language. Probability is defined by through assessments of how much the truth of one proposition is entailed through the truth or falsity of other propositions. Sense-making becomes a matter of exploring potential descriptions of the world and identifying their prior probability from the relationship between their expression in propositions and propositional knowledge already encoded probabilistically. Since both prior knowledge and evidence are both encoded through probability distributions, Bayesian updating again becomes the mechanism of inference. Key references in this area are Carnap (2009), Jeffreys (1961) and Keynes (2004).
- *Empirical Objectivist Schools*. Here the focus is on repeatability. Probability is interpreted as the long run frequency of outcomes of an infinitely repeated experiment or infinitely repeated sampling of a population. Probability thus relates to external randomness and not to beliefs or knowledge. Frequentist statistical inference cannot use Bayesian updating as a model of inference because it has no probabilistic way of representing prior beliefs or knowledge. In this case sense-making relates, as in subjective objectivist schools, to identifying a state space that has the capacity to describe the statistician's or scientist's perception of this world, but unlike the subjectivist objectivist schools it does not extend to building sufficient understanding that beliefs or knowledge about this space may be expressed probabilistically. Inference becomes a case of defining functions of the data, e.g. estimators or test statistics, which are sensitive in some sense to the region of the state space which best describes the external world. There are a host of references in this area since frequentist statistics was the dominant methodology for so long and so many statisticians contributed to its foundations; so I cite only the encyclopaedic work of Stuart (2009).

The first three schools use the same methods to guide inference and are often perceived as simply providing different justifications of the Bayesian approach. But it need be recognised that sense-making needs to be explored and interpreted in different ways according which philosophical perspective one takes. Thus exploratory data analysis will have a different interpretation in each school. I have always found myself most comfortable in the subjective objectivist school. For me the world exists: I can model those parts of it that I understand with mathematical models replete with parameters that have cognitive meaning. In other words, the state space has existence – in a sense that I shall qualify below – before I ascribe probabilities to represent my beliefs. My view of scientific induction is that one cannot avoid the prejudices and influence of prior knowledge so I include it *explicitly* in my statistical modelling, rather than *implicitly* as frequentists inevitably do.

I am making these points because I need to be clear that this perspective shapes my discussion of statistical inference and subsequently decision analysis. If you adopt another perspective, you will need your own explanations.

I interpret Bayesian statistics as a *model* of rational inference not a *prescription* of it (French, 1986; French, 2011). I believe that Bayesian analyses *guide* our inferences. They do this by providing a model of rational inference in a model world. The model of inference reflects my real beliefs about behaviours in the real world through the use of prior probability distributions and likelihoods relating parameters and observations in the model world. Note that these are never going to be perfect reflections of my beliefs in the real world. I doubt that I am ever as perfectly rational as demanded by the Bayesian paradigm, and I certainly do not have the infinitely fine levels of discrimination demanded of my judgements. But subject to constraints of rationality embodied in the probability calculus, they are as close to my beliefs as possible. Moreover, the process of elicitation helps my actual beliefs evolve towards rationality (Phillips, 1984; French, 1986; French, 1988; French and Smith, 1997; French *et al.*, 2009). By exploring that model of rational inference, investigating its behaviour as the prior and likelihood are varied a little, i.e. by using sensitivity and robustness analyses (Rios Insua and Ruggeri, 2000; French, 2003), I gain further insight into the real world and my beliefs about it. The Bayesian model of inference is no more than a close metaphor for the cognitive process that I should like to follow; as with all metaphors, it helps my understanding and communication.

It should be clear from my move to the first person active that I see the process of inference as a personal one. Wider scientific knowledge reflects consensus among statisticians and scientists which forms as more and more data accumulate and the likelihood dominates individual priors leading to a common posterior (Box and Taio, 1973; Smith, 1984; Rios Insua and Ruggeri, 2000; French, 2003).   But I shall not discuss that here.

Back to Cynefin and sense-making: since I see Bayesian analysis as a model of an idealised statistician making inferences in a model world, the process of sense-making is one of model building; but model building *both* of the real world *and* of me. At least, it is clearly so in the knowable and known spaces; in the complex space things are, well, more complex. Since my understanding of cause and effect in behaviours there is poor, any model of the real world there will at best be simplistic, if possible at all. Moreover, the lack of repeatability means I will seldom have experienced the same events and behaviours before, so I will be unclear on both my judgements on what might be happening and on my values in how much I care if it does. Thus building subjective probability, value and utility models will be challenging, and will certainly require much introspection and thought, if possible at all.

The lack of clarity on cause and effect will mean that situations will have an element of novelty to them. As a statistician/scientist I will need to explore what observations I have and see if I can begin to discern patterns. This is the motivation for using EDA. Tukey (1977) suggested methods that were often pen and paper based and hence two-dimensional; but the advent of easily accessible, powerful computer graphics and scientific visualisation brought more sophisticated ways of exploring data (Chambers *et al.*, 1983; Cleveland, 1994; Zhang *et al.*, 2010). Multivariate statistical methods, e.g. factor analysis, cluster analysis and multi-dimensional scaling (Krzanowski and Marriot, 1994; 1995; Everitt and Dunn, 2001), offer ways of transforming or representing data differently so that patterns might be more visible; and data-mining, knowledge discovery and innovization techniques provide potentially interesting and semi-automated ways of identifying patterns (Hand *et al.*, 2001; Klosgen and Zytkow, 2002; Deb and Srinivasan, 2006). Problem structuring methods offer ways of exploring less quantitative data and perceptions (Rosenhead and Mingers, 2001; Mingers and Rosenhead, 2004; Franco *et al.*, 2006; Shaw *et al.*, 2007; French *et al.*, 2009). However, whether one uses pencil and paper or the latest computer visualisation techniques, initially sense-making involves looking at past experiences and seeking patterns in them. As Gelman (2003) emphasises, even this requires some modelling, some understanding in order to identify appropriate data. The first step of sense-making is necessarily an intuitive, creative one involving recognition of putative cause and effect mechanisms; intuition is something that generally cannot be proceduralised. Exploratory methods offer tools to help me form my perceptions of behaviours sufficiently that I can construct models and hypotheses to be evaluated against data in subsequent confirmatory analyses.

The distinction between exploratory and confirmatory analyses is important, though hardly a clear one. Sometimes confirmatory analyses can be used as 'quick and dirty' methods for exploration: e.g., analysis of variance may be used to identify potential cause and effect relations for more detailed investigations, taking significance levels with a 'pinch of salt', indicative but not conclusive. Equally, an exploratory plot sometimes so clearly indicates a relation that confirmatory statistical analysis is barely necessary. The point is that in the complex space exploratory approaches must dominate. When and only when some regularity in behaviour becomes apparent, can confirmatory techniques be applied. When such regularity does become apparent, then the behaviour is close to being classified within the knowable rather than the complex domain.

Looking back several decades, there was much discussion of whether Bayesians could adopt exploratory analyses without compromising their ability subsequently to construct appropriate prior distributions. A prior distribution represents knowledge before looking at the data, but an exploratory analysis means that one does precisely that: look at the data. An immediate response is that once I have sufficient understanding to build a putative hypothesis or model, I should express my growing understanding within a prior distribution, design a new experiment or survey, collect new data and analyse those to form the posterior. A more subtle response, however, is to remember that I see Bayesian analysis as providing an idealised model of inference. I learn from the analysis as one learns from a metaphor. It brings insight, but that process of gaining insight is a tacit one, one that we can acknowledge but not articulate explicitly. How I learn from the analysis will be moderated by how closely I feel the idealised model of inference reflects the actual situation. When the prior is truly independent of the data, I may feel a little more confident in my learning; when there is no such independence, I should be less confident, but surely I should not entirely reject the relevance of the analysis (see also Good, 1983; Gelman, 2003).

I have focused on sense-making as my understanding grows taking behaviours from the complex to the knowable spaces. For the chaotic region, my understanding is so meagre that even designing an exploratory analysis may be beyond me; even the simplest exploratory analysis needs some prior understanding (Gelman, 2003). Thus any move from the chaotic to the complex spaces is likely to be driven by more intuitive, tacit processes. Conversely in the known space, my understanding is so substantial that exploratory analyses are usually unnecessary. Indeed, confirmatory analyses are seldom needed; perhaps only to drive the recognition stage of recognition primed decision making.

These remarks cause me some concern when I look at some of the literature today. While I have explained my position from a Bayesian perspective, many of the issues also need to be addressed by those of other persuasions. In particular, it is only in the known and knowable spaces that one has sufficient understanding to undertake confirmatory analyses fully. In the complex and chaotic spaces exploratory methods are needed: see Figure 6. I agree that one may use confirmatory methods as exploratory tools so long as significance levels are taken as informative, but imprecise indications. Bayesians may even use frequentist methods in EDA. In the complex space and certainly in the chaotic space, one has too little knowledge to build probability models with any confidence; and any results from estimation, confidence intervals and hypothesis testing are at best suggestive (Roberts, 1979; French, 1986). So I am continually concerned by the prevalence of confirmatory statistical analyses, especially hypothesis testing, in articles in many management and social science journals, including such stalwarts as *Management Science* and the *Academy of Management Journal*. In most cases the complexity of the issues in the Cynefin sense is beyond question. Yet precise statistical analyses are conducted using complicated methods such as analysis of covariance or structural equation methods, and the superficial implications of quantitative indicators such as *p*-values followed mechanically. I repeat that I am not saying that *all* such analyses are inappropriate; but, for me, many are.

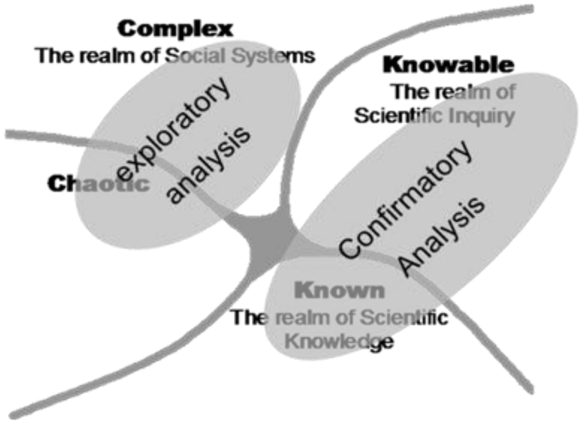


Figure 6: Cynefin, exploratory and confirmatory analyses

To close this section, let me turn briefly to experimental design. Formal quantitative experimental design methods should be used to design data collection, be it from experiments or surveys, for confirmatory analyses. What concerns me comes prior to that. Before beginning any investigation, I would use the Cynefin framework to locate the situation and issues that I wish to investigate. If I conclude that my present understanding is such that they lie in the complex space, I will lean to using exploratory methods to gain a handle on what is going on, sufficient, I would hope, to bring them into the knowable space and allow me then to conduct more confirmatory analyses. If, on the other hand, I already have sufficient understanding to form a statistical model, i.e. if I perceive the situation and issues to lie in the knowable space, then I may begin with a confirmatory analysis. Cynefin thus provides a formalism in which to frame what we might call ‘qualitative experimental design’.

6 Decision analysis in the Knowable and Complex Spaces

I have always seen decision analysis and statistical inference as inexorably connected (French and Rios Insua, 2000). As indicated in Figure 5, knowledge management is closely linked to both: consider decision analysis in the context of Cynefin. We shall build on the discussion of Figure 4 in Section 3.

To make a decision I need to form, draw together and balance two sets of judgements: what I believe might happen and how much it matters to me if it does. In saying this, I realise that I am not emphasising sufficiently the entire process from an initial, possibly ill-defined feeling that I do need to take a decision, through formulation, analysis and appraisal to an ultimate choice and implementation: see French *et al*. (2009). Here I simply want to focus on:

- forming and representing my uncertainties, i.e. what I believe might happen; and
- forming and representing my preferences, i.e. how much it matters to me if it does.

In doing so, I will concentrate again on situations in the complex and knowable spaces. In the chaotic space decision making is, inevitably perhaps, intuitive and perhaps relies not a little on luck until I have acquired enough understanding to move the issues into the complex space. In the known space, decision making is mainly recognition primed, choosing automatically along rehearsed lines without recourse to much analysis.

Following Bayesian prescriptions of decision making based on the subjective expected utility model (French and Rios Insua, 2000; French *et al.*, 2009), the analysis requires that I construct subjective probabilities to represent my uncertainties and similarly construct (multi-attribute) utilities to represent my preferences. In some cases, uncertainty may not be a driving issue and I might represent and explore conflicting objectives in my preferences through a multi-attribute value function (Belton and Stewart, 2002; French *et al.*, 2009). Whatever the case, I can only follow either of these routes in the knowable space, since they require that I have sufficient understanding both of myself and the external world to build a model, in which I have some trust. In the complex space, I might be able to use simple multi-attribute models and perhaps very simple decision trees or influence diagrams in exploratory ways, much as confirmatory methods of statistical inference can be used in exploratory ways. But it is important that in doing both that I interpret the analysis informally and do not myopically follow its prescription. Thus strategic decision making in complex situations may be guided by multi-attribute value analysis to set a broad framework for a way forward. There are many examples of this. For instance, my work on long term decision making after Chernobyl (French *et al.*, 1992; French *et al.*, 2009) involved only six attributes and no modelling of uncertainty. I make no claims that it faithfully modelled either the world as it was or the preferences of many decision makers and stakeholders. But it did serve to articulate discussion and build a shared understanding among the decision makers of their broad objectives in adopting long term remedial strategies. Often decision analysis within the complex space may involve no quantification but relies on problem structuring methods and soft OR (see, e.g., Friend and Hickling, 1997; Eden and Ackermann, 1998; Checkland, 2001).

Recently Theo Stewart, Jesus Rios and I have been exploring the interface between scenario planning and decision analysis to explore issues in the complex space (French *et al.*, 2010b; Stewart *et al.*, 2010). The approach seems to have potential to extend the application of quantitative modelling. Essentially the idea is to recognise that while one may not have sufficient understanding of the way that the world is working to build a single model on which to base the analysis, one may construct a few scenarios, each embodying sufficient assumptions to enable a decision model to be built *within* the scenario. If the scenarios are chosen in an interesting way, then conducting decision analyses within each may be helpful in bringing understanding and informing the decision. What might be interesting ways is a moot point. Some methods have been suggested in the scenario planning literature (van der Heijden, 1996), to which we have added some further suggestions. As in the scenario planning literature, we would seldom make any claim that the scenarios 'span' or 'partition' the future; nor that they be equally likely in any sense. Rather they are a backdrop for strategic conversations in which one may investigate the relative merits of alternative strategies. For instance, one might choose one of the scenarios to represent a highly unlikely, but totally catastrophic future to explore the robustness of different strategies.

Cynefin can also provide a general indicator of whether we might expect the decision makers to be clear on their preferences *a priori*. Repeatability does not just lie at the heart of Science: it has helped us think through and form many of our values – but far from all. It has always concerned me that some decision analysts have sought to *measure* preferences, whereas I have always sought to help decision makers *think through*, *evolve* and *articulate* their preferences. I have always seen value and utility elicitation as a constructive, reflective process not simply measurement. Cynefin has given me new insights into this distinction.

In the known and knowable spaces, familiarity with similar circumstances means that I will have explored and thought through my preferences: my judgements will be well rehearsed. I will know what I want to achieve in any particular decision simply because I 'have been there before'. The same will be true of other decision makers. For analysts whose work relates to contexts in these spaces, perhaps because they have tended to work with artificial intelligence techniques, expert systems, recognition primed decision making and some of the more operational areas of OR, it is perhaps not surprising that they think of preferences as predetermined, waiting to be measured. Such is not the case in the complex or chaotic spaces. Novel issues require decision makers to reflect upon what they want to achieve (Slovic, 1995). The methods of value focused thinking and the exploration, evolution and elicitation of values, weights and utilities (Keeney and Raiffa, 1976; Keeney, 1992; French *et al.*, 2008) lie at the heart of decision analyses in the complex space. As decision analysts we need to work with our clients to help them deliberate on what their values are or, perhaps it would be better to say, to help them contextualise their fundamental values to the circumstances that they face.

Scenarios can be helpful in exploring preferences in the complex space, just as they can support the exploration of gross uncertainties (Stewart *et al.*, 2010). Firstly, their use can help individuals address questions such as: "How will I feel about this in the event that that happens?" But they can also help structure deliberations between different stakeholder groups who may hold very different fundamental values. Cultural theory (Douglas, 1992) suggests that in a society facing a complex issue, several distinct sets of fundamental social, political, economic and ethical values may be observed: e.g.

- entrepreneurial values favouring appropriate risks if there are sufficient potential benefits;
- hierarchical values seeking to control and regulate behaviours and risk;
- egalitarian values seeking to conserve the environment for future generations;
- fatalist values which tend to accept what the future brings.

By constructing scenarios, each reflecting one such set of fundamental values, analysts can help stakeholder groups explore and debate how different strategies might play out against worlds consistent with their own ideals and against other worlds consistent with other sets of ideals. Such explorations may be carried out entirely qualitatively as in scenario planning or with some simple quantitative decision analytics support.

7 Conclusion

It is necessary to explore context much more than sometimes we do if we are to adopt an appropriate form of statistical or decision analysis. Cynefin seems to offer a very catalytic and supportive framework for achieving this. It encourages us to seek an appropriate balance between qualitative sense-making and quantitative analysis. I hope that this paper stimulates further discussion on this.

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