The Effects of Personality in a Social Context

Kirsty Kitto (kirsty.kitto@qut.edu.au)
School of Information Systems, Queensland University of Technology
2 George Street, Brisbane, 4000, Australia.

Fabio Boschetti (fabio.boschetti@csiro.au)
Marine Research, Commonwealth Scientific and Industrial Research Organisation (CSIRO)
School of Earth and Geographical Sciences, The University of Western Australia
Private Bag 5, Wembley, 6913, Australia

Abstract

What is the purpose of a model? We consider the need for models that can explore the effects of contextual factors upon underlying cognitive primitives. Taking the problem of modelling attitude change in a social context, we consider the difference between epistemological and ontological uncertainty in cognitive models. While uncertainty frequently arises from a genuinely undecided agent, existing models do not appear to capture this effect, however, the recent quantum inspired geometrical models can. A proof of concept agent based computational model of attitude change is discussed, as well as some of its recently obtained results. **Keywords:** cognitive models; quantum decision theory; attitude change; agent based modelling

What is the Role of a Cognitive Model?

What is the role of a cognitive model? Should it be expected to reproduce empirical results? Perhaps we can ask that it contribute to our dynamical understanding of a cognitive process (be that computational, analytical, physiological etc.). Maybe it should propose mechanisms that will aid us in generating this understanding? While we agree that a model should take the simplest possible set of elements required in order to reproduce some behaviour of interest, such a program frequently falls into difficulties when those primitive elements display *contextual* dependencies.

For exmple, consider the problem of modelling attitude change. Attitudes are highly contextual, and this makes them extremely difficult to model formally, even once a primitive representation of an attitude is agreed upon. People's attitudes are not static immutable objects, but change in response to persuasion (Seiter & Gass, 2010), and the attempt to maintain cognitive consistency (Cooper, 2007). We often express different attitudes and opinions in accordance with the social scenario we find ourselves in (Asch, 1956; Bond & Smith, 1996), and it is frequently the case that an explicitly expressed attitude is quite different from an internally held one (Greenwald & Banaji, 1995).

The Elaboration Likelihood Model (ELM) (Petty & Cacioppo, 1986); and the Heuristic-Systematic Model (HSM) (Chaiken, 1987) are the two traditional models of attitude change, but both depend upon a number of poorly defined variables, which led Mosler, Schwarz, Ammann, and Gutscher (2001) to create a computational model of attitude change in order force a more accurate specification of the largely heuristic ELM. In essence, both models posit that some processes of attitude change require relatively high amounts of mental effort, resulting from situations where individuals are motivated to pay attention to a message, or have the cognitive capacities to consider it carefully. In these *high effort* or *high elaboration* processes, people's attitudes will be determined by an effortful examination of all relevant information, and so changing them will expend high amounts of cognitive energy. In contrast, other *low effort* or *low elaboration* processes of persuasion require relatively little mental consideration by the persuadee, resulting in attitudes determined by factors like emotions, 'gut feeling', liking, and reference to authority.

There are few analytical models capable of describing the dynamics of low elaboration attitude change. While high elaboration processes are more logical and considered, hence frequently following processes similar to first order logic, and so equivalent to a computational process, low elaboration processes are wilder and more open to subtle social influences. These are the contextually dependent processes, where a person is often genuinely undecided as to what their attitude towards a given issue actually is.

This raises an interesting question as to what kind of uncertainty is appropriate in a social simulation; does it arise from a lack of knowledge on the part of the modeller, or does it result from an undecided agent? We shall illustrate this question with an example of an individual agent's decision, driven by attitude change in a political context.

Decision Making and the Framing of a Problem

Imagine next month a referendum is called to decide the future of nuclear energy in Australia. I need to vote. My initial attitude towards nuclear power is one of discomfort: the images of Fukushima's reactor and the memory of the Chernobyl radioactive cloud moving over Europe instinctively prime images of nuclear holocaust. However, my knowledge of the issue is superficial and I am willing to consider other views.

In the intervening weeks the main political parties make their position public. The yellow party, concerned mostly about addressing climate change, believes nuclear power provides the most viable alternative to fossil fuel and thus supports its introduction; for its representatives, compared to the impact of fossil fuel on climate change, nuclear energy is the least of the environmental evils. The purple party, concerned mostly of economic imperatives and less about climate change, believes that nuclear power is less cost-effective than current fossil fuels and should not be pursued. The orange party, focussed mainly on environmental concerns, finds the risks and waste production resulting from nuclear power generation unjustifiable. Each party's view is coherent and well argued, given the assumptions and priorities of the world-views the parties represent.

Now that I am familiar with the parties' view, my decision is considerably more complex. First I need to decide whether to follow my instinctive perception of the problem or whether to carefully analyse the parties' lines. If I choose the latter, my decision will most likely not be about the party lines themselves, since they are all equally well argued, rather about the parties' framing of the problem; in other words, I will need to decide whether, for me, this is i) an issue of economic choice, ii) of relative environmental risk or iii) of absolute environmental risk. Once the frame is chosen, the reasoning will follow rationally.

I struggle on this issue for a few weeks, but slowly I converge to a choice: on referendum day I vote against nuclear power. Whether I did so by following my initial instinctive attitude, or whether I liked the orange party's argument, or whether I supported orange party's argument because it rationalised my initial attitudes, I will probably never know.

A few weeks after the referendum I find myself discussing the referendum with colleagues. It is now much easier to recognise and articulate my position on the issue. Whether this is the result of my careful consideration of the problem as imposed by the need to vote, or my striving for coherence and consistency, it is now far more likely than before that I declare myself against nuclear power. Thus, I am now quite decided, but at the beginning of this process my attitudes were not so well formed.

What Uncertainty?

This example illustrates the manner in which agents are *commonly* undecided. Opinions and attitudes are malleable and subject to change, and yet our models treat them as ontological, with well defined states and values. For example, Mosler and Martens (2008) treat the contextuality of low elaboration processes in a deterministic manner. While there are many variables working together in their model, leading to nonlinear effects and indeterminacies that are hard to predict, there is no uncertainty in the model itself; an agent will always respond in the same manner to a situation that is identical, which leaves uncertainty in the mind of the modeller, not the agent. Although Mosler & Martens do propose an implementation of random generators that drive individual behaviour with a well defined variance (Mosler & Martens, 2008), this step would still keep uncertainty in the epistemological realm, as modellers we do not know how the agent will react, but they have a well defined attitude.

Other current modelling approaches tend to assume the same thing, that agents have a well defined but epistemologically unknowable state; as modellers we "know too little" (Brugnach, Dewulf, Pahl-Wostl, & Taillieu, 2008) about that state, and this is the cause of the uncertainty most commonly incorporated into our models of cognitive systems. However, people are frequently *genuinely undecided* about issues and courses of action to follow; they have yet to make up their minds and so their cognitive state is in some sense undefined. Philosophically, this difference is quite profound. An agent who has already formed an attitude towards a social issue (which we admittedly might not know about) may exhibit very different behaviour from one who has not considered their response to that same issue. Indeed, the second agent may, from a given initial state, respond very differently to a question, survey, piece of information etc. depending upon how it is framed (Tversky & Kahneman, 1981; Brugnach et al., 2008). This *contextuality* of a social agent is not something that is well treated by current analytical approaches to social modelling, and it seems likely that this lack will have a large impact upon models of low elaboration attitude change.

In this paper, we shall introduce a dynamical model of low elaboration attitude change, showing how it is possible to mathematically represent the manner in which the social context of an agent can affect their expressed attitudes. The model uses a cognitive state to represent an attitude, but is non-deterministic, which allows for us to represent the notion of an agent who is genuinely undecided about how they will act. Thus, the model has both dynamical and probabilistic characteristics, which we suggest allows for a bridge to be built between two very different philosophies about what role a cognitive model should fulfil. A simple computational implementation will be discussed, and a key effect of agent personality upon their attitude changes, and upon the society as a whole will be explored.

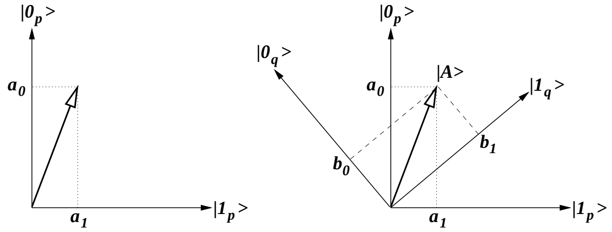
Modelling Decisions in a Social Context

Our model takes *Quantum Decision Theory* (QDT) (J. R. Busemeyer, Pothos, Franco, & Trueblood, 2011; J. Busemeyer & Bruza, 2012) as its starting point, due to its implicit capacity to represent the effect of context upon a decision. This theory is has been shown capable of providing a unified explanation for many of the so called 'violations' of rational decision theory that are exhibited by individual humans. A recent work (Kitto & Boschetti, 2013) introduces an extension of the basic QDT model, which considers the process by which a society of agents self-organises into a set of ideologies representing their combined, and often contradictory, attitudes towards a social issue. This section will briefly introduce that model, but full details can be found in the longer paper.

The Basic QDT

We shall begin with a consideration of an agent A, called Alice, who is deciding whether or not to 'act' in response to a given social issue. Recognising that A's decision is likely to depend upon their social context, we shall represent her cognitive state as a vector $|A\rangle$ in a vector space,[1] the structure of

[1] Dirac notation being used here. It was invented as a shorthand for quantum physics (Isham, 1995). It explicitly allows us to repre-



(a) (b)

Figure 1: An agent attempts to decide whether or not to act. (a) Their probability of action is proportional to the length squared of the projection of their state onto the axes labelled $|0_p\rangle$ (no action) and $|1_p\rangle$ (action); (b) The changing context of a decision. The probability of the agent acting changes between the two depicted contexts, which can immediately be seen by the different lengths of the projections from the state $|A\rangle$ onto the two different 'act' axes $|1_p\rangle$ and $|1_q\rangle$.

which will depend upon the nature of the issue under consideration. If A has decided to act on this issue, then we shall denote this state of action as the vector $|1\rangle$, to represent a situation where it is *true* that she has *chosen to act* (in contrast to a state of inaction which we denote as $|0\rangle$).

These decisions only make sense with respect to a particular social context, and the probability of A acting could change with a new social setting. However, the quantum formalism can easily incorporate this contextuality due to its vectorial representation of the state $|A\rangle$. Thus, QDT represents the cognitive state of Alice, defined with respect to the context p as

$$|A\rangle = a_0|0_p\rangle + a_1|1_p\rangle, \text{ where } |a_0|^2 + |a_1|^2 = 1, \qquad (1)$$

a situation that is illustrated in Figure 1(a). Pythagoras theorem is used to extract the probabilities of A acting (or not) in this context, with the probability of action given by $|a_1|^2$ and that of inaction similarly given by $|a_0|^2$. Thus, the *projection* of the state $|A\rangle$ onto the current context decides the probabilities of action for this model (Isham, 1995).

With reference to Figure 1(a), we see that in the context p Alice is genuinely undecided. The cognitive state $|A\rangle$ represents an agent who has *yet to decide how to act* within some context, in contrast to the more standard modelling scenario where the agent has decided how to act, but we as modellers *do not know what that decision is*. Thus, the probabilities that arise in this model are fundamentally different from those of the more standard Kolmogorovian approaches (both Bayesian and frequentist), and this difference can have a profound effect with a change in context.

This can be seen with a consideration of figure 1(b), which is an elaboration of figure 1(a), and represents the changing probabilities of action that arise in the case of two different contexts, p and q. With reference to figure 1(b) we can quickly see that while our agent is highly likely to act in context q, this is not the case in context p, where A is much less likely to act (since by examination of the figure we can see that while $|a_0| > |a_1|$ in context p, $|b_1| > |b_0|$ in context q).

Social Framings of an Issue

This simple model can be naturally extended across a set of multiple agents which we shall call a *society* $\{|A\rangle, |B\rangle, |C\rangle \ldots\}$, all of whom are considering an issue, where each individual agent X is described with a cognitive state $|X\rangle$ which is expected to change in time.

We assume that agents can make decisions to act within one of two contexts, which we denote as *local*, and *global*. This is taken to represent the manner in which, while we frequently make internal or private decisions (as represented by a local frame), we must sometimes cast our choices within a societal domain (as represented by a global frame) when for example, we are required to vote in a general election. The local frames of the individuals in a society might be similar to a global understanding, or they might differ substantially, depending upon the agent and how they think about the world. Local frames might arise from a wide range of both external and internal factors, such as the socioeconomic status of an agent, their educational background, race etc. and so are likely to be highly complex, and multidependent variables, however, as a first approximation, we shall model them as another basis in the two dimensional vector space already introduced for the states and global frame. This allows us to anticipate that global frames will result from an aggregation function[2] applied to the local frames of every agent who somehow identifies with that ideology.

Kitto and Boschetti (2013) claimed that this framework provides an opportunity to model low elaboration processes of attitude change nontrivially, due to its explicit recognition of the context in which an agent makes a decision. The QDT approach allows for the probability of an agent acting to vary over the full range $(0,1)$ in response to the range of angles that can be taken by the cognitive state of the agent within the Hilbert space that represents the issue currently under consideration. Thus, in order to evaluate Alice's probability of acting, we must take both her current cognitive state $|A\rangle$, *and* her current social context p of the agent A (as represented by a global or local frame) into account.

We postulate that an agent who has made a decision is likely to feel a certain amount of *cognitive dissonance* (Cooper, 2007) as their internal cognitive state will not be aligned with their decision (unless their cognitive state was

sent a vector a using a *ket*, $|a\rangle$, with the transpose given as a *bra* $\langle a|$. This allows for an immediate recognition of the inner product between two vectors $\langle a|b\rangle$ (a *bra-ket*) and of the outer product $|a\rangle\langle b|$. We use it here to make explicit the difference between our agent A and her cognitive state $|A\rangle$, a distinction that will become important when the effects of social context are discussed. The vector space being used is a Hilbert space, which is a real or complex inner product space that is also a complete metric space with respect to the distance function induced by the inner product (Isham, 1995).

[2] In what follows we shall use clustering, however, we anticipate that there are many potential aggregation functions, and that different ones will prove necessary for different issues (List, 2012).

already aligned with the relevant frame from which they are currently considering an issue). This means that they will feel a certain amount of psychological discomfort, which will drive them to alter their view of the world to fit with their decision within the context that it was made. They can do this in the current model by adjusting either their cognitive state, or their local framing of the issue, to more accurately reflect their decision. However, the literature suggests that some people are more comfortable with cognitive dissonance than others; their *personalities* will therefore play a key role in how this adjustment occurs. For example, some agents will feel far less comfortable with uncertainty than others, and so be more affected by dissonance (R. Sorrentino & Roney, 2000; R. M. Sorrentino & Hewitt, 1984). In order to model these intuitions, we note that an agent whose cognitive state lies close to the axes representing their current frame will be more certain about their likely future actions than one whose cognitive state lies between those axes (i.e. has the cognitive state forms a 45° angle between choosing to act and choosing not to act in the frame p). This leads us to introduce a measure of the *uncertainty* that an agent experiences about their likely future decisions, using binary entropy, which is defined as the entropy of a Bernoulli trial (e.g. a two-outcome random variable such as a coin toss), with a probability of success given by P, and is specified as:

$$H_b(P) \equiv -P\log_2 P - (1-P)\log_2(1-P), \tag{2}$$

which is a function taking its minimum values at $P = 0$ and $P = 1$, and its maximum at $P = 1/2$.

This entropy measure allows us to model two different drives for cognitive consistency that we hypothesise are experienced by an agent making a decision in a social context:

1. A desire for internal cognitive consistency. This results in a drive to align their cognitive state with the local frame within which they are currently considering an issue.

2. A desire to 'fit in' with the society and its current norms. This desire is expressed by a pull of their local frame towards the current global frame (or ideology) to which they belong, which serves to reframe the agent's understanding of the issue.

These drives will affect the agent's future actions, and this is reflected in the model. Thus, agents who make a decision in their local context update their cognitive state towards that decision, with the amount of pull towards that decision weighted by their desire for cognitive consistency, while agents who make a decision in the global context update both their cognitive state towards that global decision (weighted by their cognitive consistency) and their local frame towards that same decision (weighted by their social conformity).

Defining Θ as the angle between the agent's current state $|A\rangle$ and the decision to act in the global frame to which they currently belong (defined as the closest global axis to their current state), and taking θ to perform a similar function in their local frame, we introduce function which measures the uncertainty of the agent A with respect to both frames:

$$H(|A\rangle, \theta, \Theta) = w_i(A)H_b(P(\theta)) + w_s(A)H_b(P(\Theta)) \tag{3}$$

where the weights $w_i(A)$ and $w_s(A)$ refer to agent A's need for internal consistency and social conformity respectively. These weights can be set to range over a population of agents, indicating a rough parameterisation of a society's social make-up. This measure can naturally be extended to consider the uncertainty of the whole society of N agents:

$$H_{b_{Tot}} = \sum_{i=1}^{N} H(|i\rangle, \theta_i, \Theta_i) \tag{4}$$

$$= \sum_{i=1}^{N} [w_i(i)H_b(P(|i\rangle, \theta)) + w_s(i)H_b(P(|i\rangle, \Theta))] \tag{5}$$

which should become smaller as the agents settle into a set of stable *ideologies*, or global attitudes about the world.

Implementation

A proof of concept model has been implemented in MATLAB, which allows for an investigation of the timewise behaviour of this new agent based modelling paradigm. Space does not permit a full explanation of this implementation, however, we direct the interested reader towards the actual MATLAB script[3] which implements the basic pseudocode shown in Figure 2.

```
Number of global frames = G
Number of agents = N
For i=1..N
 Assign coherence & consistency variables
 If RandomPersonality = 0 then
  conformity = 0.5 and consistency = 0.5
 If RandomPersonality = 1 then
  consistency & conformity range over [0-1]
 Assign cognitive states & local frames randomly
For each timestep
 Find the position of the global frames (use k-means)
 For each agent
  Calculate which global frame the agent belongs to
  Probabilistically choose to act or not in one frame
  If acting in local frame then update cognitive state
  If acting in global frame then update cognitive state
   and local frame
  Calculate entropy of the agent
  Calculate total entropy of system
```

Figure 2: Basic pseudocode for the computational implementation.

Modelling Attitude Change in a Social Context

While the model described above is admittedly very simple, it does exhibit a number of key features which one could reasonably expect should be found in an agent based model of

[3] Available at http://www.per.marine.csiro.au/staff/Fabio.Boschetti/quantumPeople.html .

attitude change. For example, Kitto and Boschetti (2013) describes the manner in which a population self-organises into a set of ideologies, which evolve and update in time. As predicted, the entropy (4) has a tendency to decrease in time. It is also possible to guide the behaviour of the population, through shifting a global frame, and to then watch the system reorganise into a new semi-stable configuration. In this paper we shall instead focus upon one key feature that has not yet been described, namely, the importance of personality in driving the attitude changes of a society of individuals.

The Importance of a Personality Spread

Two different seeding strategies have been utilised to initialise the consistency and conformity parameters ($w_i(A)$ and $w_s(A)$) for each agent within the computational model. A random distribution is possible, where each agent is seeded with parameters that randomly range from 0 to 1, or alternatively all agents can be seeded with a fixed personality distribution. This allows for an investigation of the effect that varying personality spreads can have upon a population.

Random Personality When agents are seeded with a random personality mix the time evolution of the system is predictably at its most erratic. While the entropy of the system has a tendency to decrease throughout a run, the agents tend not to find a stable configuration, and the system remains in a state of flux and change; states, local, and global frames can all move throughout a run.

Figure 3 shows a set of shots from a typical run for this scenario, along with the entropy plot as it gradually decreases through time, although subject to some stochastic variance as agents realign their local frames. Two global frames were specified, and their location at each timestep found using a k-means style algorithm. Agent's cognitive states are represented using black lines, global frames by the large dots above the cognitive states, and local $|1\rangle$ frames as small black spots.

Figure 4 shows a collection of entropy plots for two, three, and four global frames, all initialised with a random mix of personality parameters. Note that in all cases the entropy decreases, but that the system shows more erratic behaviour when more global points of view are available for the agents to align with. The limited nature of the current computational implementation (which has only been performed for two dimensions) means that arbitrarily adding more frames to what is a very small space does not result in realistic behaviour, however, work is currently in progress to extend this model to a higher dimensional state space, and this would allow for the interaction of far more social contexts to be investigated.

Fixed Personality In contrast, when the personality mix of the agents is fixed at $w_i(A) = 0.5$, $w_s(A) = 0.5$ the system exhibits a far more stable time evolution pattern, and becomes fixed in a static configuration around timestep twenty-five. Figure 5 shows a typical run for this scenario, note that the entropy minimises very early during a run, as the agents settle into a stable scenario that does not need to re-adjust.

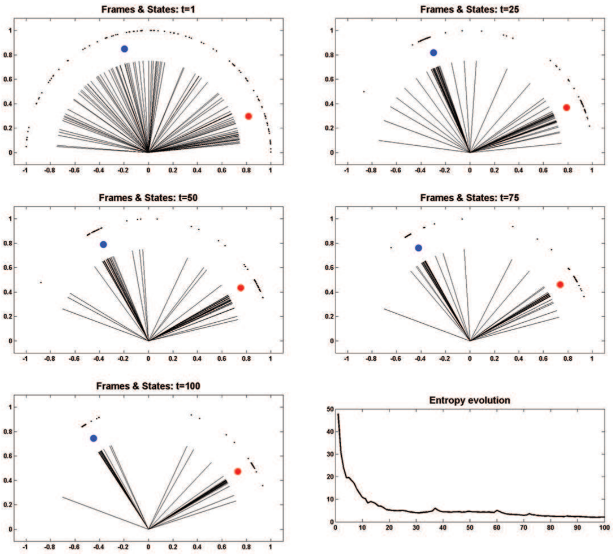


Figure 3: A typical run of a system initialised with agents of random personality spread. Note that the entropy of the system has a tendency to decrease in time, but that it never fully minimises or stablises.

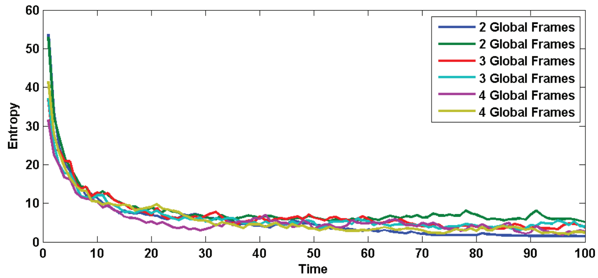


Figure 4: A collection of entropy plots for two, three, and four global frames, initialised with a random mix of personality.

All agents can find a state and local frame that minimises (3), and the system rapidly settles down. This dynamics is also evident for for higher numbers of global frames.

Evolution Requires Consistency and Cohesion

This brief discussion highlights the need for a society to contain a range of personality types. A society of individuals who all have the same personality mix quickly becomes static in this model, it settles down into a scenario where the attitudes of the agents, and their framing of those attitudes, do not change in time. This situation becomes even more dramatic when the society is seeded with individuals who have nonzero values *only* for conformity *or* for consistency. In both of these scenarios the model does not evolve at all, it stays in the same condition as the one that it initialised in.

This behaviour plausibly reflects the behaviour of societies in general. Difference of opinion and a varying response to

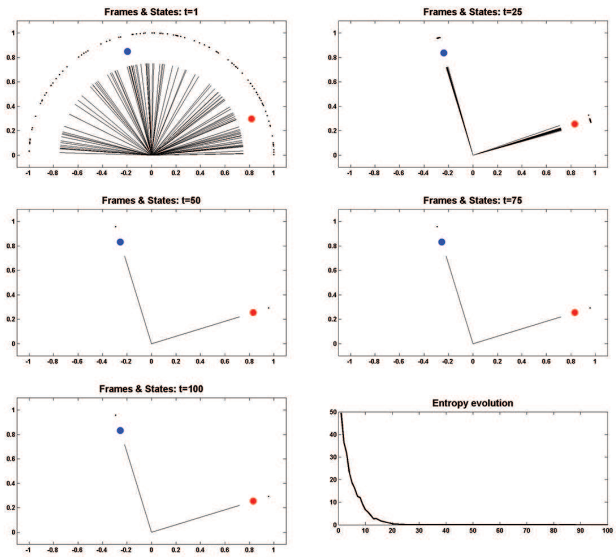


Figure 5: A typical run of a system seeded with a population of fixed personality type. (In this case $w_i(A) = 0.5$ and $w_s(A) = 0.5$.) The system quickly stabilises into a configuration where all agents are of one, or the other, state of mind. This behaviour is observed for all fixed personality profiles.

the social context are both key and essential features of a society, and yet such behaviour does not tend to be well captured by current modelling technology. Thus, the contextualised apparatus of QDT offers an interesting new perspective on the modelling of social behaviour that we feel holds promise as it is expanded in the future.

Conclusions

The modelling technology of cognitive science must expand to incorporate contextual effects. In such scenarios, uncertainty frequently arises within the mind of the agents themselves, not in that of the modeller, and yet much of our apparatus tends to assume the opposite. We have shown one viable approach towards this expansion, based upon QDT, and illustrated its key features using the example of attitude change in a social context. A proof of concept computational model was discussed, and a set of varying personalities was shown to be essential for the dynamical evolution of the model. Thus, a way forwards presents, and future work will seek to develop this exciting new approach.

Acknowledgments

KK was supported by an Australian Research Council Post Doctoral Fellowship (DP1094974) during her completion of this work. The authors would like to acknowledge many helpful discussions with Peter Bruza and Iain Walker.

References

Asch, S. E. (1956). Studies of independence and conformity: A minority of one against a unanimous majority. *Psychological Monographs*, *70*(9), 1-70.

Bond, R., & Smith, P. B. (1996). Culture and Conformity: A Meta-Analysis of Studies Using Asch's (1952b, 1956) Line Judgment Task. *Psychological Bulletin*, *119*, 111-137.

Brugnach, M., Dewulf, A., Pahl-Wostl, C., & Taillieu, T. (2008). Toward a relational concept of uncertainty: about knowing too little, knowing too differently, and accepting not to know. *Ecology and Society*, *13*(2), 30.

Busemeyer, J., & Bruza, P. (2012). *Quantum models of cognition and decision*. Cambridge University Press.

Busemeyer, J. R., Pothos, E., Franco, R., & Trueblood, J. (2011). A Quantum Theoretical Explanation for Probability Judgment Errors. *Psychological Review*, *118*(2), 193-218.

Chaiken, S. M. (1987). The heuristic model of persuasion. In P. Zanna, J. M. Olson, & C. P. Herman (Eds.), *Social influence: The Ontario symposium* (Vol. 5, p. 3-39). Hillsdale, NJ: Erlbaum.

Cooper, J. (2007). *Cognitive dissonance: 50 years of a classic theory*. Sage.

Greenwald, A. G., & Banaji, M. R. (1995). Implicit social cognition: Attitudes, self-esteem, and stereotypes. *Psychological Review*, *102*, 4-27.

Isham, C. J. (1995). *Lectures on Quantum Theory*. London: Imperial College Press.

Kitto, K., & Boschetti, F. (2013). Attitudes, ideologies and self-organisation: Information load minimisation in multi-agent decision making. (Under Review)

List, C. (2012). The theory of judgment aggregation: An introductory review. *Synthese*, *187*(1), 179-207.

Mosler, H.-J., & Martens, T. (2008). Designing environmental campaigns by using agent-based simulations: Strategies for changing environmental attitudes. *Journal of Environmental Management*, *88*(4), 805 - 816.

Mosler, H.-J., Schwarz, K., Ammann, F., & Gutscher, H. (2001). Computer Simulation as a Method of Further Developing a Theory: Simulating the Elaboration Likelihood Model. *Personality and Social Psychology Review*, *5*, 201-215.

Petty, R. E., & Cacioppo, J. T. (1986). *Communication and Persuasion: Central and Peripheral Routes to Attitude Change*. New York: Springer-Verlag.

Seiter, R. H., & Gass, J. S. (2010). *Persuasion, social influence, and compliance gaining* (4th ed.). Boston: Allyn & Bacon.

Sorrentino, R., & Roney, C. (2000). *Uncertain mind: Individual differences in facing the unknown*. Psychology Press.

Sorrentino, R. M., & Hewitt, E. C. (1984). The uncertainty-reducing properties of achievement tasks revisited. *Journal of Personality and Social Psychology*, *47*(4), 884-899.

Tversky, A., & Kahneman, D. (1981). The framing of decisions and the psychology of choice. *Science*, *211*(4481), 453-458.