A Conceptual Framework for Human Decision Making within Agent Based Models

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Agent based models of human systems, such as those found in behavioural economics, implement their agents intelligence through the use of simple rules. These models have proved to be worthwhile research tools. However, improving the outputs of these models will require a greater emphasis on the development of intelligence within the model agents. A deeper understanding of the cognitive process of human decision making is also needed. In this paper a conceptual framework for the cognitive process of human decision making is put forward. This conceptual framework is developed around the work of Lonergan and Polanyi. Further, the conceptual framework utilises the fuzzy logic of Zadeh for its implementation. The resulting conceptual framework can be embedded within agents that model human systems.

1 Introduction

Agent based models have been utilised to provide insights into the emergent behaviours and properties of complex systems. While there has been initial excitement about the potential for these models to provide appropriate outputs and consequent insights, the reality is that these models have little resemblance to the systems that are being modelled [4]. This *model reality gap* is substantially due to the difficulty in modelling agent intelligence. It is anticipated that improved intelligence within the agents will yield more meaningful insights into the behaviour of complex systems [1, 4].

Within the agent based human system modelling domain the issue of modelling intelligence is akin to the issue of modelling cognitive processes. Cognition is itself a complex phenomena consisting of many parts that are themselves complex systems. For example, speech, vision and decision making are complex systems that contribute to the complex phenomena of cognition. The fact that cognition is itself a complex system is often overlooked by modellers who often use reductionist techniques borrowed from the Artificial Intelligence (AI) community [4]. The reason for the use of these reductionist techniques is that they are simple to implement and have low computational complexity which is important when simulating millions of agents.

There is an identified need for the development of a meta-theory for the implementation of cognitive processes within agent based human system modelling. This meta-theory should aim to develop rules that encompass the human behavioural aspects of needs, decision making and learning [2]. This paper presents a conceptual framework for the modelling of an agents cognitive processes. This conceptual framework will address the behavioural aspects of the meta-theory suggested by Jager and Janssen. Further, this framework will be grounded in the philosophies of Polanyi [6] and Lonergan [3] and the fuzzy logic of Zadeh [8].

This paper will proceed in three sections. In section §2 a hierarchy for human decision making will be presented. This hierarchy will provide the basic structure for the conceptual framework. In section §3 a model of perceptions will be put forward. The model for perceptions will be overlayed on the hierarchy of decision making thus yielding the conceptual framework. In section §4 conclusions and further work will be discussed.

2 The Hierarchy of Human Decision Making

While the properties of complex systems are still the topic of debate there is a single agreed property that a complex system must exhibit. This property is that the *emergent* property of the complex system cannot be accounted for by any of its parts alone. Within the realm of cognitive processes this writer also puts forward that a complex system must be hierarchal and exhibit causal emergence.

Polanyi [7] uses the cognitive process of speech to describe emergence. Polanyi's example of speech is represented as a hierarchy. The hierarchy has five layers and consists of voice at the bottom followed by words, sentences, literary style and finally literary composition. Voice is shaped into words, which are shaped into sentences, which are shaped into style that is finally shaped into literary composition. At each of these levels there are applied two sets of rules. The first set of rules are the rules governing the layer itself. For example, voice is shaped by the laws of phonetics, words by the rules of lexicography, sentences by the rules of grammar, style by the rules of stylistics and literary composition by the rules of literary criticism. The second set of rules that guide the formation of speech are the rules that are applied from a layer to that layer immediately beneath it.

Like speech, the cognitive process of human decision making is also hierarchal. Lonergan [3] describes the cognitive process of human decision making as a hierarchy consisting five levels of consciousness. These five levels are illustrated in Fig. 1:

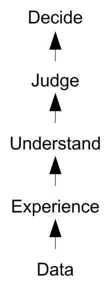

Figure 1: Lonergans hierarchy of the human decision making process.

The five levels of Lonergan's hierarchy of the human decision making process are data, experience, understanding, judgment and finally the decision itself. The first four levels within the hierarchy represent the reflective process of what Lonergan terms insight while the level of decision making is an action that maybe taken as a result of the insight. The fact that this hierarchy is a conscious act implies that there is an awareness within the *self* during the decision making process. That is there is an awareness of the activity that occurs within each layer and an awareness of the ascent from one layer to the next within the hierarchy.

The impetus for the human decision making process is a question and it is from the question that the conscious act of inquiry follows. The act of inquiry first begins with the conscious act of attending to data. This data may take many different forms and can emanate from many different sources. Such data can include both data observed through our senses and also data that is of internal nature such as feelings.

Once the data is sensed it is translated into an experience that our cognitive processes can process. From the experience our attention then turns to the understanding of the experience. In the understanding of the experience our background knowledge and the drawing of correlations between the sensory experiences comes into play.

On having an understanding of the data a judgment can then be passed. The judgment is similar in nature to the decision but it is orientated to the self. That is the judgment is an answering of the questions "Is it true?" or "Is it right". That is judgement is an affirmation of understanding. Lonergan calls a judgement a reflective insight. From the judgment we can then move to making a decision. However, unlike a judgment which is oriented to the self, a decision is an action which Lonergan calls a practical insight.

Further, at any point in the hierarchy the individual can elect not to ascend to the next level of the hierarchy. For example, the understanding of data does not necessarily mean that one needs to pass judgment and likewise judgment does not necessarily imply a decision.

Also, progression through the hierarchy during the decision making process can be recursive. That is, at any point in the hierarchy of decision making other questions may arise resulting in a branching to answer these new questions before continuing with the initial inquiry.

3 Perceptions

While Lonergan's hierarchy of human decision making provides the different stages within the process of human decision making it gives no assistance with the underlying mechanics of the process.

It is asserted that the underlying entity required to implement the process of human decision making is perception and it is the interaction of perceptions that supply the underlying mechanics for the process of human decision making.

Perceptions are our interpretation of reality. Tradition, culture, expectation, need and experience all affect our perspective of the world and its underlying realities [6]. Plato in his narrative of the cave also makes the point that our reality is but our perception and is only a shadow of the truth [5].

Consequently, Lonergan's hierarchy of decision making must utilise perceptions at each level. For example, there is the perception of data which we know as an experience. The perception of understanding is achieved through the development of correlations between perceptions of experiences and the formation of higher level concepts. From the perception of understanding a perception of certainty is attained. This perception of certainty is the judgment and from the judgment the decision is made.

Perceptions are complicated entities and grow in complexity as one ascends through the hierarchy of human decision making. Therefore, the simplest perceptions to model are the perceptions within the layer of experience. A perception within the layer of experience p_t^s is related to data source s and occurs at some time t. This perception p_t^s consists of three parts. These three parts are the inquirers background knowledge k_t^s, a need/expectation of the data n_t^s and the current experience e_t^s. The creation of a perception p_t^s within the layer of experience can be considered as a contraction of a trigraph as shown in Fig. 2:

Each of the nodes in the trigraph of perception, the background knowledge k_t^s, the need n_t^s, the experience e_t^s and the perception itself p_t^s are fuzzy variables. The concept of a fuzzy variable was first offered by Zadeh [8] in his work on fuzzy logic. A fuzzy variable is a variable whose values can be defined by words. For example, temperature is a fuzzy variable that may have fuzzy values of *cold*, *warm* and *hot*. The actual value of temperature would have a degree of membership μ to each of these fuzzy values where the degree of membership $\mu \in [0, 1]$. Fuzzy variables are useful for the development of a model of perceptions as they tend to represent the way humans think. That is, humans tend to think in terms of words rather than numbers.

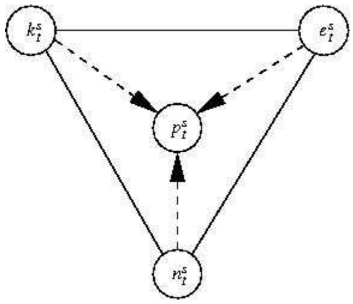

Figure 2: The trigraph of a perception.

In this paper a general fuzzy variable F is defined for nodes within the trigraph of perception. The fuzzy variable F is illustrated in Fig. 3:

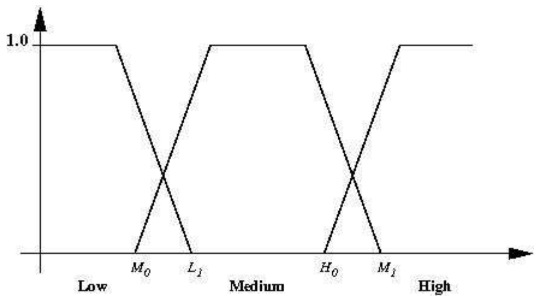

Figure 3: Fuzzy variable.

The values M_0 and M_1 are the left and right upper-bounds respectively of the fuzzy value of $Medium$ while L_1 is the upper bound of the fuzzy value Low and H_0 is the lower bound of the fuzzy value $High$.

Consequently, each data source s has associated with it a fuzzy variable F^s with the mid point of $Medium$ constantly adjusting as new data d_t^s presents itself. That is $\bar{M}^s = \sum_{i=1}^{t} \frac{d_i^s}{t}$. Similarly, the values of the upper bound of Low, L_1 and the lower bound of $High$, H_0 can also be expressed as percentages of the mid point of $Medium$, $\bar{M}^s$. This process of updating the parameters of the fuzzy variable F^s is akin to unsupervised learning. Further, the background knowledge k_t^s within the experience layer is a history of the fuzzy values over t while the need n_t^s can be assigned from a data source d_t^k or from another perception.

A perception within the experience layer p_t^s can then be computed by counting the number of occurrences of the fuzzy values for each of the nodes background knowledge k_t^s, experience of the data e_t^s and the need n_t^s within the trigraph of perception. This results in p_t^s having two values $n : f$ where n is the count of the fuzzy value that occurs the maximum number of times within the trigraph of perception and f is the associated fuzzy value.

For example, if the background knowledge $k_t^s = High$ and the experience of the data $e_t^s = High$ and the need $n_t^s = High$ then the perception of the experience is $p_t^s = 3 : High$. That is there is a strong perception that the experience is $High$. Now consider a second example where the background knowledge $k_t^s = Low$, the experience of the data $e_t^s = High$, and the need $n_t^s = Medium$. In this case there is a tie so the fuzzy value would default to $p_t^s = 1 : Medium$ which is akin to an indifference.

Following the computation of the perceptions within the layer of experience is the computation of the perceptions within the layer of understanding u_t^k. This proceeds in two parts. Firstly, correlations between perceptions within the layer of experience are computed. Traditionally the correlation r between two variables X and Y is given by:

$$r_{XY} = \frac{\sum_{i=1}^{n}(x_i - \bar{X})(y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{X})^2 \sum_{i=1}^{n}(y_i - \bar{Y})^2}} \tag{1}$$

For the purposes of this work equation 1 could be rewritten as:

$$r_{p^x p^y} = \frac{\sum_{i=1}^{t}(|p_i^x| - \hat{p}^x)(|p_i^y| - \hat{p}^y)}{\sqrt{\sum_{i=1}^{t}(|p_i^x| - \hat{p}^x)^2 \sum_{i=1}^{t}(|p_i^y| - \hat{p}^y)^2}} \tag{2}$$

In equation 2 the variable $\hat{p}^x$ is the mode of the perception p^x and remembering that $p_i^x = n : f$ then $|p_i^x| = n \times v(f)$ where:

$$v(f) = \begin{cases} -1 & \text{if } f = Low \\ 0 & \text{if } f = Medium \\ 1 & \text{if } f = High \end{cases} \tag{3}$$

The second part of the computation of the perceptions of understanding is the identification of perceptions within the layer of experience with a high correlation $r_{p^x p^y}$. New perceptions u_t^k are now constructed by contracting these highly correlated perceptions p^x and p^y. If there are a group of perceptions that form a complete graph all of these perceptions can be contracted to the one perception of understanding u_t^k. Again, a value $n : f$ is computed in a similar manner for the new perception u_t^k. The value of n is the frequency of the highest occurring fuzzy value within the perceptions that are correlated and f is the fuzzy value that represents the highest frequency.

These new perceptions u_t^k in the understanding layer could be considered concepts. The process of creating higher level concepts then continues using a similar technique of finding correlations and then creating new concepts through contractions. The process continues until no more new correlations between concepts exist. At this point the highest level concepts are moved to the judgment layer and the judgment becomes implicit. The concepts that are moved from the layer of understanding to the layer of judgment are relabeled j_t^k.

The decision is then made by determining the concept within the judgment layer j_t^k with the highest strength n. The decision $D(f)$ is then:

$$D(f) = \begin{cases} \text{Negative} & \text{if } f = Low \\ \text{Undecided} & \text{if } f = Medium \\ \text{Affirmative} & \text{if } f = High \end{cases} \quad (4)$$

For this approach to be functional there are some caveats. Firstly, the question underpinning the decision making process must be framed as a *yes/no* question. Secondly, careful consideration must be given to the formulation of the fuzzy variables used in the experience layer F^s. That is, the assignment of the values Low, $Medium$ and $High$ may not be intuitive.

4 Conclusions and Further Work

In this paper a conceptual framework for the consideration of the cognitive process of human decision making has been put forward. This framework is built on the hierarchy of human decision making as put forward by Lonergan and this writers model of perceptions which utilises Zadeh's fuzzy logic. This framework is currently being implemented in an agent based model of human systems.

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