Chapter 9
Modelling Human Behaviour in Agent-Based Models

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Abstract The modelling of human behaviour is not at all obvious. First, humans are not random. Second, humans are diverse in their knowledge and abilities. Third, besides being controlled by rational decision-making, human behaviour is also emotional. This chapter attempts to present principles driving human behaviour and reviews current approaches to modelling human behaviour.

9.1 Introduction

The behaviour of humans as individuals, in small groups, and in societies is the subject of several fields of research because it has such an important role in many aspects of daily life. However, incorporating human behaviour into Agent-Based Models (ABMs) is a real challenge, primarily because of the short history of our scientific observation of human behaviour, but there is hope. This chapter discusses the challenges of modelling human behaviour, presents and critiques the major approaches available along with some basic principles of human behaviour before providing information on how to integrate human behaviour into ABMs. The chapter starts with how not to model human behaviour.

9.2 How Not to Model Human Behaviour

To start, humans are not random. They (we) are strange and wonderful. Their behaviour may be unexpected or inconsistent (i.e., noisy), but it is not random. As an example, here is a simple demonstration. An easy question will be presented below

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and you may take hundreds of milliseconds to answer, but do answer. The question is: "Pick a number between one and four." Have an answer?

The most common response is "three" and there is a secondary effect of this task: people feel a need to explain why they chose whatever answer they did. The second most common answer is "two". Very few people decide to respond with either "one" or "four". Sadly, there is not a serious study of this behaviour but undocumented sources suggest that the response statistics are close to 50% for "three", 30% for "two" and about 10% for the other two answers.

The common explanation for the selection of "three" is that it was the most "interesting" number in the range. There is also a small number of people who are compelled to answer outside of the range, with fractions, or irrational numbers. These are rare occurrences. Similar results are obtained when the task is to pick a number between 1 and 20. The similarity is that people pick their most interesting number. For this range, the most common response is 17, occurring about 40% of the time, well above a "rationally", "logically" expected 5%. Other primes are also favored as answers because they too are interesting.

This behaviour is interesting. The decision-making process should be simple, but it certainly does not appear to be a simple random selection among equally likely options. What this shows us is that people cannot even be random when they want to be. Further, if this task had been modeled as a uniform random distribution among equally likely choices, it would have been very different from actual behaviour.

Modeling human choices as uniform random distributions is making a very serious claim about human behaviour. It is saying that all choices are equally likely even when we know nothing about how people actually decide. It also assumes people have no preferences, do not consider the consequences of their actions, have no memory of previous choices, and can be more consistent than the data shows. Modeling human behaviour requires some data or some experience. Luckily, modelers are human and should know better.

9.3 Levels of Modelling Human Behaviour

The first question in an effort to model human behaviour is at what level the behaviour is to be modelled. The choices are basically at the individual level, at some small grouping of individuals, such as a household, and as a society. Modelling of a society can be done statistically, i.e., without dealing with individuals within the society. They could be inanimate particles because there is no effort to represent their decision-making process, only to describe what they have done. Small groups are typically modelled as if they were individuals and the science behind modelling individuals applies to small groups as well. This chapter addresses the modelling of individuals.

9.4 The Science Behind Modelling Human Behaviour

There appears to be at least two levels of sophistication in social organisms, "sociobiology" as E.O. Wilson termed it (Wilson 1975/2000). Social organisms such as slime moulds and social insects seem to be totally driven by inherited instincts that fully define their reactions to environmental stimuli. Social mammals, on the other hand, appear to have some degree of general problem-solving capabilities, such as a Theory of Mind, or in other words, their own model of other agents. This general capability results in the social behaviour of at least mammals being far more complicated than seems possible from a fixed set of inherited instincts. Humans and a majority of the great apes have many traits and resulting behaviours in common – see Wilson (1978/2004).

The study of human behaviour is as old as social primates themselves. A large part of social behaviour is the internal modelling of others for the purpose of knowing how to get along with them successfully. Prehistoric oral traditions have taught us how people supposedly behaved and the consequences of that behaviour (Stone 2011). The scientific study of how humans behave began less than 150 years ago with the advent of psychology as a modern scientific field – see James (1892/2001). The work is progressing, but due to the nature and complexity of the human mind, progress could be said to be slow.

In the mid-1950s, a cognitive revolution resulted in the research in behaviour changing from explaining all behaviour as simple stimulus-response associations to applying a new theory. The new theory was that behaviour could be explained in computational terms, but not simply via a "computer metaphor", i.e., literally like a computer, but a "computational theory of mind". This meant that the mind could be explained "using some of the same principles" as computers (Pinker 2002, p. 32).

One of the early concepts that has been both useful and distracting, is the metaphor of the brain as a computer (Newell and Simon 1972). It has been useful in providing a framework to understand the mind in terms of inputs, processes, and outputs. This reductionist approach has led to advances in understanding the modular organization of the mind and the brain (Anderson 2007). However, our focus on the von Neumann computer architecture, i.e., a separate memory and processor, which operate serially, has resulted in a symbol vs. connections debate (Anderson 2007). Neural network approaches to modelling cognition is an ongoing research area, but such systems are difficult to build and it has been difficult to make steady, incremental progress.

The pursuit of modelling or replicating human behaviour has developed two camps: Artificial Intelligence and Cognitive Science. The work in AI is aimed at replicating the intelligent behaviour of humans and surpassing human intelligence when possible, as in mathematics from arithmetic to calculus. However, most AI researchers have little interest in replicating the all too human errors or unintelligent behaviour observed in nature. On the more psychological side, researchers in

Cognitive Science seek to understand human cognition in all of its forms, rational as well as emotional, intuitive, and erroneous. Both approaches have developed methods and techniques that can be useful in modelling human behaviour.

Focusing on the rational and analytic side of human cognition has generated the largest amount of research in this area and significant progress had been made, e.g. see Kahneman (2003). There has been far less research on other behavioural drivers such as intuition or emotions, but research is growing in this area – see Damasio (1994).

9.5 Basic Principles

In this section, a set of basic principles of human behaviour is provided. These principles are focused on the causes of human social behaviour, not the behaviour of individuals alone or over very short periods.

9.5.1 Humans as Information Processors

Humans process sensory information about the environment, their own current status, and their remembered history to decide what actions to take. However, their environmental sensors are limited in type to the traditional five senses (touch, sight, hearing, taste, and smell). Humans can also sense temperature, internals (kinesthetic or proprioception), pain, balance, and acceleration. Each has a range and a minimum sensitivity and duration threshold.

Humans also have diverse personality traits. These are characteristics that effect the thoughts, behaviour and emotions that they are born with, which seem to be relatively constant over a life span, and that are a large part of individual differences. Traits are intended to be relatively independent and seem to have normal distributions with large populations. There are two taxonomies of personality traits known as a three-factor model (Eysenck 1967/2006) and a five-factor model (McCrae and Costa 1987). Both share two traits: extraversion (sociability) and neuroticism (tendency toward emotional behaviour). Other potentially important traits associated with social behaviour include agreeableness, risk avoidance, and impulsivity.

Taken together, humans as information processing systems have a limited informational input bandwidth, limited memory, and limited processing capability. However, because humans have language, their information sources can be very wide, and with written language, they can have memories spanning centuries.

9.5.2 Human Motivations

A very highly cited 1943 paper on human motivation provided an organization of human motivations into a "Hierarchy of Needs" (Maslow 1943). This ordering is not rigid but has survived intact over the years. Maslow proposed that humans' first need is to meet their basic physiological requirements. After these are adequately met, the next priority is for safety and security. When these are adequately addressed, the next priority is the social needs of friendship, family, and sexual intimacy. The last two layers deal with external esteem and self-actualization. This hierarchy is useful in ordering potentially competing priorities of agents representing humans in ABMs.

9.5.3 Humans Behaving Rationally

Human behaviour is commonly thought of as being rational. Rational Choice Theory (Coleman 1990) is based on the presumption that humans behave in ways to maximize their benefits or minimize their costs, and in either case, follow logical processes. This approach typically assumes all possible actions are known, all agents have perfect knowledge of the environment, and that the preferences of agents are well behaved, i.e., have necessary ordering and transitivity properties. Tempering this approach is the idea that agents have "bounded rationality", i.e., have limited information, limited cognitive abilities, and limited time to make decisions (Simon 1996). In addition, there may be limitations as to how many variables humans can process and how mathematically sophisticated the evaluation of those variables are in order to determine their rational behaviour. Although many forms of knowledge representation are possible, the representation of human knowledge is generally accepted to be in two basic forms: declarative knowledge of facts and procedural knowledge typically represented in IF-THEN rules (Newell 1990; Anderson 2007). Rational behaviour also includes learning of declarative knowledge, and new procedural knowledge in some cases. How long knowledge is retained varies from systems that never forget knowledge to systems that have very little memory for either form of knowledge. Clearly, systems of human behaviour need to have some memory, but how much and how formally it is modelled depends on the purpose of the system. Therefore, a rationally behaving model needs to be able to represent knowledge, learn, remember new knowledge, and apply that knowledge to determining the behaviour of the agent.

9.5.4 Humans Behaving Emotionally/Intuitively/Unconsciously

In addition to being rational beings, humans have other factors that affect their behaviour. These include emotional, intuitive, or unconscious decision making processes. The representation of human behaviour in ABMs may need to include these other decision-making processes. Research in emotions and the effect of emotions on decision-making is taken in this discussion as the leading representative of the non-traditionally rational decision-making processes.

There is evidence of a common set of basic emotions: interest, joy, happiness, sadness, anger, disgust, and fear (Izard 2007). These emotions are considered evolutionarily very old and have neurobiological bases. They are generally infrequent, short lived, and do not directly affect cognition. However, emotions can lead to longer-term moods and result in complex behaviour.

There have been many studies of emotions but the relation of emotion to cognition, and therefore to behaviour is a highly debated topic in psychology (e.g., LeDoux 1995). Whether emotions are modifiers of the rational decision-making process or a separate mental process is not yet settled. Kahnemann (2003) discusses a System 1 and System 2 approach to dual cognitive processes. The predominant theory of emotion is Appraisal Theory (Scherer 1999).

The appraisal theory poses that there are a fixed set of dimensions of factors needed to determine the emotional status of an individual. However, there is wide variance of thought on what the dimensions are. Progress is being made and repeatable results are starting to produce interesting results (Scherer 1999).

Although it may seem natural to presume humans behave to maximize their expected emotions, the effect of emotions on decision-making can be more richly discussed (Loewenstein and Lerner 2003). Emotions can alter rational decision-making by distorting the agent's perceptions of the environment and the likelihood of future evaluations. Loewenstein and Lerner (2003) offer two limitations concerning the impact of emotions on decision-making. First, some behaviour is not the result of decision-making and can be the result of emotional drivers directly. Second, the impact of emotions on decision-making cannot be easily classified as improving or degrading the rational decision-making process.

9.5.5 Humans Behaving Socially

As social beings, the behaviour of individuals is shaped by input from others in two basic ways. First, humans have a Theory of Mind by which they imagine what others have as their goals and what they are thinking and feeling (Dunbar 2004). Second, human behaviour is influenced by and combines with the behaviour of others (Latané 1981; Friedkin and Johnsen 1999; Surowiecki 2005; Kennedy and Eberhart 2001).

A Theory of Mind supports the transference of information based on establishing and sharing common concepts among agents, i.e., language. The exchange of information and goods and services among groups of agents then provides for the development of culture and economies within and among societies.

Latané proposed a formulation of social influence based on experiments where a group attempts to influence a human subject (Latané 1981). The relationship he found was of the form:

$$I = s\,N^{t} \tag{9.1}$$

where I is the influence in terms of the percentage conforming or imitating behaviour in the subject, s is a constant associated with the circumstances, N is the number of others involved, and t is a factor less than one and often near one half. However, this influence also inhibits action by, in a sense, distributing the social responsibility to act such that a social inhabitation to act by bystanders has been found (Latané 1981). Extending the study of influence, Friedkin and Johnsen (1999) reported on the influence of a group's members on each other and the result can be that the group settles on the group's mean, a compromise different from the mean, on the position of an influential member of the group, or may not form a consensus.

Groups can also develop results greater than those of any of the individuals. Groups of diverse people independently making evaluations with an appropriate method of bringing their results together can have this kind of result (Surowiecki 2005). He explored conditions that resulted in good collective results and found that they result from the differences in the evaluations among group members, not compromises or achieving consensus. This appears to be another outgrowth of social influences, which can lead to conformity, a lack of independence, and then poor results. For example, he reports that in a crowd, due to diversity, there will be some willing to riot, some who would never riot, and many that will decide based on social influences.

This section has attempted to identify the basic principles of human behaviour. They are intended to be the causes of human social behaviour, not the behaviour of individuals. Of course, this is incomplete, possibly wrong, and the subject of much research. The next section addresses current approaches in applying this knowledge to modelling human behaviour.

9.6 Current Approaches

Although this book is about ABMs, within an ABM, the representation of the cognition driving a modelled human's behaviour can have its own internal architecture. A cognitive architecture (Newell 1990) is the structure and functionality that is unchanging throughout the simulation and supports the cognitive model that drives behaviour. There are several cognitive approaches to consider. For presentation here they are grouped as: (1) *ad hoc* direct and custom coding of behaviours mathematically in the simulation's programming language; (2) conceptual frameworks to be implemented within the target system; and (3) research-quality tools for modelling the cognitive functioning of an individual at the millisecond scale.

9.6.1 Mathematical Approaches

Mathematical approaches to modelling human behaviour are methods that produce agent behaviour through the use of mathematical simplifications. First among these, and the most severe simplification, is the use of random number generators to select between predefined possible choices. The fallacies of this approach were addressed at the beginning of this chapter, and includes that people are not random, that random number generation is not a replacement for unknown quantities, and that using a random number generator is making very strong and very wrong claims about human behaviour.

Better than relying on random number generators would be to directly code threshold-based rules. These are of the form that when an environmental parameter passes a threshold, a specific human behaviour would result. This would provide simple behaviour, but they would be explainable and could approximate human behaviour. The parameter could be transformed so that the action is taken when the transformation of the parameter is above, below, or between thresholds.

Using a threshold is equivalent to comparing two values in that the difference in the two values can be compared to a threshold. For example, if the intent is to compare function1 with function2, this is the same as comparing (function1 – function2) and a threshold value of 0. For instructional purposes, all sample rules presented here are in the form of a function compared to a threshold. Variables and functions are descriptively named between "<>" and actions are in italics.

As an example:

IF <hunger> is below <hungerThreshold1> THEN *agent-dies*.
IF <hunger> is above <hungerThreshold2> THEN *address-another-goal*.
IF <hunger> is between <hungerThreshold1> and <hungerThreshold2> THEN *search-for-food*.

Another mathematical approach is the use of multi-dimensional functions of parameters rather than comparing a single environmental parameter to a threshold. Here, several parameters are combined to define a modelled human's behaviour. The major weakness in this approach is that available data does not validate humans as pure optimizing agents.

IF <evaluation of <hunger> & <thirst>> is above thresholdHT THEN *focus-on-safety-issues*.

Finally, Dynamic Modeling (Hannon and Ruth 1994) represents human decision-making as "stocks and flows" or, in a sense, as a hydraulic system with pipes, tanks, valves, and pumps. The representational sophistication of this modelling approach is that the rate of change of a variable can be a function of its own magnitude. Such a model uses differential equations to describe relationships in the model. The hydraulic theory of emotion can be traced back to René Decartes (1596–1650) (Evans 2001). An example is:

IF <anger> is above <ventThreshold> THEN *act-to-vent-anger*.

These mathematical approaches to modelling human behaviour rely on a simplification of the perception, reasoning, and actions important to the purpose of the model. For many models, the vast majority of the human behaviour is not of interest to the model and the behaviour of interest can be reasonably well specified. If more general behaviour is important to the modelling effort, a more general approach may be appropriate.

9.6.2 Conceptual Frameworks

Conceptual frameworks are approaches to modelling human decision-making using more abstract concepts than mathematical transformations of environmental parameters. They involve concepts such as beliefs, desires, and intentions (BDI), emotional state and social status (PECS), and "fast and frugal" decision hierarchies. Three conceptual frameworks will be addressed.

The first approach is based on beliefs, desires, and intentions (BDI) (Rao and Georgeff 1995). The BDI approach is a theoretical framework based on the idea that human behaviour can be modelled by representing an individual's beliefs, desires, and intentions. Beliefs are the individual's knowledge about the world, i.e., the world as they perceive it to be. Desires are the individual's motivation, i.e., its goals. Intentions are the agent's deliberative states. A BDI implementation develops a decision tree and this complete decision tree is transformed into a possible worlds model from which a deliberation process decides the best course of action. The BDI framework is very general and can be realized in many ways. Its weakness is that it is so general that it provides little more than a conceptual framework for thinking about how to model the human cognition behind behaviour. The next framework is more specific and provides more guidance for implementing a model of human behaviour within an agent-based system.

The second framework involves physical, emotional, cognitive, and social factors (PECS) affecting behavioural decisions (Schmidt 2002). This framework includes a representation of the human mind, specifically perception and behaviours, and mathematical representations of physiology, emotion, cognition, and social status. Within cognition are mathematical transformations for a self-model, an environmental model, memory for behaviour protocols, planning, and reflection. The declared purpose of the PECS framework is to replace the BDI framework, and it is more specific and implemented. The PECS framework can represent simple stimulus-response behaviours and more complex behaviours that involve the determination of drives, needs, and desires and their transformation into motives. Motives, depending on their intensity, are state variables that indirectly determine behaviour. Advantages of this framework are that behaviours can be explained in terms of their causes in a reasonably plausible manner. Two challenges for this framework are the internal parameters for the mathematical transformations of environmental parameters into the internal state variables and the combination, prioritization, and integration of the various motives into the selected behaviour.

The third framework is called "fast and frugal" and was developed by analyzing data on human decisions. Gigerenzer (2007) reported on the analysis of how intensive care units make decisions about whether a patient is having a heart attack and how two judges evaluate court cases and make decisions on whether to grant bail for defendants. The analysis in both cases identified three sequential questions that could be answered by environmental variables, and the use of these "fast and frugal" trees performed very well compared to human decision-making. In the medical case, the decision tree developed for a U.S. hospital performed better than the heart disease predictive instrument or physicians, and the decision trees explained 92% of the two UK magistrates' decisions (Gigerenzer 2007). The design of these rules in these trees is not aimed at identifying all the variables to justify implementation of a particular behaviour, but an attractive characteristic of this framework important to ABMs is that these decision trees are inexpensive computationally and should scale up well to large numbers of agents.

These three frameworks are different approaches to modelling human behaviour at a level of rigor between the pure mathematical representations and full, research quality models of human cognition. The third level, research-quality models are tools intended for use usually in representing the cognitive decision-making of individuals.

9.6.3 Cognitive Architectures

A third approach is to use research tools developed for a purpose different from agent-based modelling for social simulation. Their purpose is research into abstract or theoretical cognition on the one hand and understanding human cognition on the other. This section discusses Soar, ACT-R, and other architectures. These are architectures in the sense that the basic system is unchanging throughout the use of the system. Cognitive models of specific tasks are implemented within these cognitive architectures. Such a cognitive model can be used to drive the human behaviour of an ABM.

Soar (Lehman et al. 2006) is an Artificial Intelligence system originally based on matching human performance in problem-solving tasks at a symbolic level of granularity and is the basis of Newell's proposal for Unified Theories of Cognition (Newell 1990). As an AI system, its purpose is to meet or exceed human performance on a wide variety of tasks. The Soar system could be considered to be an implementation of a BDI architecture in that it maintains an internal representation of the world, is always working to solve a goal, and has available internal state variables. Soar has a long history of modelling human behaviour framed as problem solving in research settings and for commercial customers. Although a stand-alone system, Soar has been connected to several other environments including games. A Soar model consists of a collection of rules written as text that uses environmental or internal variables and either changed internal variables or takes an action that changes the environment. The system, which includes demonstration models, is available at no cost from the Soar website, http://sitemaker.umich.edu/soar/home. There is also a Java based version being developed at http://code.google.com/p/jsoar/. There is an active Soar community, it offers training on using Soar, and 40–60 members meet annually.

ACT-R (Anderson and Lebiere 1998; Anderson et al. 2004), which most recently stands for Atomic Components of Thought-Rational, has been used in basic research in cognition for many years. ACT-R provides architecture assumptions based on both symbolic and sub-symbolic representations of knowledge. Over the years, ACT-R has evolved into a comprehensive cognitive architecture demonstrating successful models of many cognitive phenomena and it has been linked to the functional regions of the brain (Anderson 2007). Successful here means closely matching human performance data. However, ACT-R is focused on relatively low-level cognitive phenomena operating over very short time periods. It does not support higher-level concepts such as beliefs, desires, or intentions explicitly. An ACT-R model consists of a collection of declarative facts and rules written as text that uses environmental or internal variables and either changed internal variables or initiates actions in the environment. ACT-R is also available at no cost and has an active community supporting it. Courses on using ACT-R are offered in Europe and the United States annually and the community meetings of 40–60 people also occur approximately annually. Their home page is: http://act-r.psy.cmu.edu/. There is also a Java version of ACT-R in development and use: http://jactr.org/, which has been connected to and operates a mobile robot – see http://www.nrl.navy.mil/aic/iss/.

There are other cognitive architectures used in research. Several are reviewed in the National Research Council report (Zacharias et al. 2008). However, none of these other symbolic architectures have the wide acceptance and active community that Soar and ACT-R have.

9.7 Challenges in Modelling Human Behaviour

There are at least three challenges in the efforts to model human behaviour in agent-based systems: understanding humans, data, and validation & verification. As should be obvious, although human behaviour has been noticed for thousands of years and scientifically studied for a couple of hundreds of years, there is still much unknown. The genetic, historical, and current environmental factors affecting the behaviour of such diverse agents as humans may appear incomprehensible, but progress is being made and will continue. Research continues to develop data on how people behave under certain circumstances and this is replacing the poor default of assuming that human behaviour is random and unknowable. However, data for many or most behaviours of interest to the ABM community may not yet exist. The lack of data makes validation and verification of models of human behaviour difficult, at best. However, as humans are the ones constructing ABMs of human behaviour, hopefully, some knowledge, some generally accepted practices, and a good dose of common sense will result in good models of human behaviour.

Additional Resources

While research and the practice of modelling human behaviour continues, there are sources supporting this effort. The U.S. Air Force asked the U.S. National Research Council to provide “advice on planning for future organizational modelling research”

(Zacharias et al. 2008, p. 1). The resulting report provides an excellent review of the state of the art, although a criticism is that it does not adequately address work outside the U.S.

Current research and results in agent-based modelling is presented in scientific conferences held regularly. In the United States, the Behaviour Representation in Modeling and Simulation Society meets annually to present and discuss current work. Their website is: http://brimsconference.org/. In Europe, the European Council for Modelling and Simulation meets annually and their web site is: http://www.scs-europe.net/.

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