Forgotten AI? Advancing agent reasoning in models

Nanda Wijermans and Harko Verhagen

Understanding human intelligence has been the core driver of the field of AI/cognitive science and the accumulated knowledge, tools and algorithms are used in many ways. One of the oldest branches of AI concerns the development of agents that aim to reproduce human reasoning to learn more about human decision making and behaviours it leads to. Until this day these architectures, models and theories influence many scientific disciplines that operationalise them for advancing their field as well as informing policies. The rational actor model utilised in and deployed by economics (thus also called homo economicus) is a prominent example of this. The renewed interest in machine learning makes one almost forget the diversity that the label AI also encompasses and thus fail to make use of the complementary power of these diverse approaches and abilities in addressing real world problems. In this abstract, we illuminate a way for advancing human reasoning realism in models by describing the use of analytical tools can support agent reasoning to be context sensitive. We argue this supports the understanding of human reasoning as well as increases the awareness of advantages and dangers of using context sensitive (policy) models compared to the use of agents applying one reasoning mechanism.

Where context sensitive reasoning agents should live

One of the application areas of agents is agent-based modelling (ABM) for simulation. A special variety of simulation is social simulation (Gilbert, 2008; Gilbert & Troitzsch, 2005), which allows for the development, formalisation and testing of novel theories/explanations of social phenomena (Conte & Paolucci, 2014). ABM for social simulation is a rapidly growing area that contributes to a wide variety of scientific and real-world domains (Macal, 2016). Typically addressing the problems studied are characterised by a high degree of complexity, i.e. the system's behaviour cannot be explained by solely looking at the behaviour of its constituents. While agent models in agent research may or may not be related to models of human behaviour, in agent-based social simulation the correspondence between agents and humans is a necessity with respect to the behaviour of the individuals and the resulting system-level behaviour (Gilbert, 2008). For validity of the simulation model as a valid representation of the phenomenon the simulation tries to emulate, the realism in the representation of human behaviour is key. This is particularly true when addressing real world challenges, such as (response or adaptation to) climate change, avoiding over-consumption, overuse of resources, social conflict, mass migration etc. Behavioural realism in real world problems often implies a diversity of behaviours and responses that change over time. Where humans differ in how a situation is perceived, how they respond to it, and how these perceptions and ways of dealing may differ over time. Behavioural realism thus often involves a variety of actors, entities, interactions and events etc.

This correspondence between agent reasoning and human reasoning based on insights of human decision-making and human behaviour from the social and behavioural sciences lies in the forefront of understanding the underlying mechanisms of human behaviour. Where the extremes of traditional good old fashion AI (GOFAI) - symbolism - and embodied cognition - sub symbolism - marked a transformation in thinking where the importance of placing cognition in a bodily, social and biophysical context. The operationalisation of agent reasoning sensitive to different social context remains a tremendous challenge.

The number of models that reflect (social) human behaviour and decision-making is growing rapidly in (Carley, 2008), almost as much as the recognition of the need to model human behaviour, e.g. (Fulton, Smith, Smith, & van Putten, 2011; Rounsevell, Robinson, & Murray-Rust, 2011; van Putten et al., 2012). See the Journal of Artificial Societies and Social Simulation (*jasss.soc.surrey.ac.uk*, n.d.) for a representative impression. However, the majority of the models focus on representing one type of behaviour in a specific, stable context. Unfortunately, many models have rather simplistic decision makers, not sensitive to context, not able to perceive a situation in different ways, or even change their own responses/perceptions over time. The representations of decision made by agents are often ad hoc or following the default rational actor reasoning without any particular reason.
The many voices of (self)critique (led to) increasingly calls for behavioural realism, sometimes in the form of advocating in using more theory (Carley, 2008; Jager, 2017), use of (qualitative) empirical insights (Hall-Arber, Pomeroy, & Conway, 2009), the inclusion of emotions (Bourgais, Taillandier, Vercouter, & Adam, 2018), role of context (Edmonds, 2014) and moving beyond homo economicus type of models (Jager, Janssen, de Vries, De Greef J, & Vlek, 2000; Levine, Chan, & Satterfield, 2015). As a consequence some researchers have started to pave the road aiming to make implementing alternatives easier by comparing/reviewing the different decision models, e.g. (An, 2011; Balke & Gilbert, 2014; Groeneveld et al., 2017), developing frameworks to enable the communication and ability to find relevant theories (Schlüter et al., 2017). However, guidance for the different contexts and situations are still rare and the adoption or use is sporadic. Frameworks such as, the Model Social Agent (Carley & Newell, 1994) and the Contextual Action Framework for Computational Agents (CAFCA) (Elsenbroich & Verhagen, 2016) are the exceptions and have much potential in guiding the challenging journey of increasing realism without necessarily increasing the often-dreaded complexity of models itself.

How context-sensitive reasoning agents come to be

To enable the increase the realism of behaviour in models, we here focus stimulating the consideration of the potential different decision-making contexts when (further) developing an agent-based model. In particular, we advocate for the use of generic frameworks combining different theories and models from a variety of the social and behavioural sciences to help designers ensure relevant aspects are considered. We illustrate the advantages by showing how the application of Contextual Action Framework for Computational Agents (CAFCA) to an agent-based simulation model FIsher Behaviour diversity in fisheries (FIBE) (Wijermans, Schlüter, Orach, Boonstra, & Hentati-Sundberg, n.d.). The use of CAFCA enables the addition of situational-behavioural realism to the model by specifying the relations between different social context apprehensions and agent reasoning models. Such frameworks may also be useful for agent modelling in general, especially when social concepts such as norms and team reasoning are at play.

The Contextual Action Framework for Computational Agents (CAFCA)

The CAFCA framework (Elsenbroich & Verhagen, 2016) aims to aid modelling by highlighting all aspects and processes that can play a role in agent decision making on two dimensions: the sociality and reasoning dimension. These dimensions together constitute the agent's interpretation of the situation (context) in which the decision is to be made. Both dimensions have three modes: the sociality dimension consists of the individual, social and collective mode and the reasoning dimension consists of the automatic, strategic and normative mode. In total the framework encompasses nine contexts (see figure 1a). In essence, the modes of the sociality dimension can be described as follows:

- individual mode: the agent interprets the decision as independent of others
- social mode: the agent recognises other agents in the situation, but see themselves as distinct from or in competition with them
- collective mode: the agent not only recognises others, but perceives itself as belonging to the others, as a member of a collective or team

The reasoning modes and the resulting contexts are described as follows

- *Automatic reasoning* results in non-reasoned action, a behavioural reaction to a stimulus just as a regular reactive agent. For the individual mode, this implies to simply repeat previous actions. In the social mode an automatic reaction is to perceive and imitate the actions of other agents. A collective automatic reaction entails also to perceive the actions of other agents considered part of the same collective, but rather than simply imitating their behaviours, an agent will understand others' intentions and participate in the activity.
- *Strategic reasoning* is goal-directed reasoning where the goal is utility maximisation. The social dimension in strategic reasoning determines who is considered in the decision making. In the individual mode the situation is judged from the agent's own and choosing the action that produces the optimal outcome. In the social mode the payoffs of different agents are interdependent as modelled in for instance game theory and related approaches. In the collective mode the agent applies the strategic considerations not to its own utility but to the utility of a group, team or collective.
- *Normative reasoning* is rule following rather than goal directed, where the sociality dimension determines the origin of the rules. In the individual case the rules are seen as given, e.g., a set of laws. An agent needs to be able to recognise the correct rule for the situation and resolve conflict in case of inconsistent rules. In the social mode the rules are generated by the agent observing the behaviour of other agents and inferring a social norm of how to behave. In the collective mode rules are extrapolated by taking the collective into account, thus the rule needs group wide or universal applicability, like moral principles.

		SOCIALITY DIMENSION		
		INDIVIDUAL	SOCIAL	COLLECTIVE
REASONING DIMENSION	AUTOMATIC	Repetition	Imitation	Joining-in
	STRATEGIC	Rational choice	Game theory	Team reasoning
	NORMATIVE	(institutional) rules	(social) norms	(moral) values

		SOCIALITY DIMENSION		
		INDIVIDUAL	SOCIAL	COLLECTIVE
REASONING DIMENSION	AUTOMATIC	FIBE	FIBE	
	STRATEGIC	FIBE		
	NORMATIVE			

Figure 1a. The different context of the CAFCA framework	Figure 1b. The contexts that a model (FIBE) reflects using the CAFCA framework

Using a framework to determine a model's context-sensitive reasoning

To illustrate the use of a framework and how this may advance context-sensitive agent reasoning in models, we will look at an agent-based model of FIsher BEhaviour diversity (FIBE) through the eyes of the CAFCA framework. FIBE is a simple, dynamic, spatial ABM of a single species fishery that includes a multitude of heterogeneous individual fishers with fishing as their main income source. The model simulates daily decisions of individual fishers on *whether* and *where* to fish and their effect on fish stock levels, fishers' income, and their level of satisfaction in pursuing their goal(s).

Figure 1b summarises that FIBE incorporates three of the nine sociality-reasoning contexts of CAFCA. In particular, the individual and social modes of the sociality dimension and the automatic and strategic levels of the reasoning dimension are addressed. The absence of FIBE in the remaining 6 cells triggers questions and ideas about future research for FIBE. One option would be to occupy each of these cells. However, they might not be important for the scenario FIBE is trying to simulate. Of course, the absence of FIBE could be that the modeller has a blind spot and it is meaningful to extend FIBE. Thus, the analysis exercise not only has questions for the empirical and theoretical input we as modellers should look for and also to evaluate ourselves, did we really take everything of importance into account?

Since FIBE is a model that strives to include more behavioural realism (Wijermans, Boonstra, Orach, Hentati-Sundberg, & Schlüter, in press.), there is a need to thus revisit the literature, experts, and empirical data to see whether there are for instance normative or collective considerations in the decision-making context that may lay bare an important aspect of fisher behaviours. Another direction of future research is to compare FIBE with other fishery models to compliment and substantiate the claim that FIBE is rather unique in the inclusion of behavioural diversity by comparing models based on their decision-making contexts and analyse what sets of models exists that may enrich the behavioural diversity on the sociality-reasoning dimensions. All these triggers allow for directed and relevant (further) development of agent-based models of fishery.

Even if CAFCA was developed from the viewpoint of use during the design phase of simulation models, it also enables an analytical lens to critically deconstruct agent-based models to detail the decision-making contexts they comprise of. It enables a reflection on a different level that ties in with the realism and usefulness of a model, which is in this case heavily relying on the realism of agent reasoning.

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