Contextual Cognition In Social Simulation

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***Abstract*—The role of context is crucial when modeling human for social simulation. This paper investigates the use of contextual cognition in social simulation. A lightweight cognitive model with regard to the implementation of context-dependent cognition within social simulation models is explored. The main finding is that less "smooth" learning and inference algorithms in the agents which mimic some aspects of context-dependency might well result in a simulation that matches the observed outcomes better. In other words, what matters is the cognitive model encoded in the agent.**

Introduction

Models of human agents in social simulation range from very simple cellular automata where mostly there is no cognition represented at all, through to simulations embedding detailed cognitive models. Although it would not be feasible to include all the features of a rich cognitive model, there should be enough number of agents including hundreds if not thousands of individuals if one wants to develop a meaningful society. On the other hand, in order to reflect the interplay among the social and individual actors, at least some aspects of cognition should be entailed within the models of human. In other words, both cognitive (what individuals believe) and social dimension (most common patterns of) are important. So, as a result of the interplay of the beliefs of individuals process from the "bottom up", with the dominant norms restricting individual from the "top-down", a new process emerges (Conte et al., 2013). Given the complexity of this interaction, the term 'contextual cognition' refers to the idea that cognitive processes of the agents in a simulation are, mostly context-dependent. Due to the nature of the context-dependency of these cognitive processes, a different set of social outcomes emerge in comparison to the assumption of context-free cognitive processes.

While the next section explores the nature of this context-dependency in more detail, following sections will explain the use of this contextual cognition in a social simulation.

Main Definitions of Context and Context-Dependency

Although context is a crucial aspect of the human-beings' social and cognitive aspects, it often goes unnoticed. Due to its implicit nature, the use of the word "context'" may be "over-loaded" as it may mean a variety of related, yet distinct, concept. Most of the time, when a theory does not work, "context" might be cited as a reason. This term is also related to other concepts such as tacit knowledge (Polanyi, 1966), or other cases such as the framing problem in the field of AI (Artificial Intelligence) (McCarthy and Hayes 1969), or in the field of psychology (Goffman, 1974), and the "situation" (Barwise and Perry, 1983).

Situational Context

The situational context refers to particular factors of a situation (e.g. such as time, location, persons involved and their knowledge level) in which described phenomena occurs. In general, what is relevant about that particular context, is left implicit. Therefore, the phrase "the context" may refer to those aspects which may help one to understand the particular occurrence even though it may refer to the situational context in general.

Linguistic Context

The linguistic context entails the words surrounding an utterance or phrase which may include common knowledge to be reasonably expected to be known by the listener/reader, e.g. aspects of the relevant culture. Needless to say, as the linguistic context could refer to almost any of the language or culture surrounding an utterance, it cannot be captured in its entirety.

Cognitive Context and Framing

While some knowledge may be acquired in a particular situation it may be made available in similar situations. This recognition of a situation with regard to its relevancy to pieces of information – is sometimes called the "cognitive context" (Hayes, 1995). Such cognitive contexts could be identified by the set of all the knowledge, norms, expectations, habits etc. that are immediately accessible once recognized.

The idea of cognitive context relates to the idea of psychological framing in psychology as introduced by Goffman (1974), where frames refer to schemata of interpretation in order to locate, perceive, identify, and label" experiences. According to Elliott & Hayward (1998), frames are associated with, various social and cultural contexts which define the relevancy of particular norms of behavior. (p.234)

In a similar vein, Shafir, Simonson and Tversky (1993) assert that different frames and contexts highlight different reasons and considerations that influence decision-making process (p.34) Thus the action of framing can be seen as the outcome of the cognitive context with regard to one's opinion and choice.

Social Context

The context of an event is usually described in social terms. So, there is a close relationship between this context and the synchronised cognitive context which is crucial for communication and understanding.

Due to the context-dependency of human cognition norms, habits, terms, etc. are associated with the social context which helps one organize one's relevant behavior in a social setting. Therefore, as a result of the context-dependency of our cognitive capabilities, social context plays an important role in terms of our understanding of the world.

Identifying and Talking about Context

One of the difficulties in discussing cognitive context is that they may well not;

(a) be within our reach

(b) be specified even though they may be within our reach and

(c) be exactly defined although we can specify them.

In other words, despite the process of abstraction in terms of some properties of that particular state for the purpose of retrieval in similar situational contexts, one should not assume that these properties corresponding to the cognitive context can be correctly retrieved.

The cognitive context for any situation is often not made explicit due to the assumptions held by the individuals participating within that context. Yet, although the cognitive context may not be directly within the reach of our consciousness it might be partially covered or become only partially inferable.

Approaches to Cognitive Contextuality in Social Simulation

Despite the importance of context-dependency for human cognition and social behavior, most of the social or cognitive simulations do not take context-dependency into consideration. In other words, the cognitive processes of the agents in social simulations do not have the tendency to recognize context. This seems to be reasonable as the agents are considered to being exposed to a single and fairly simple set of situational contexts, yet many simulations have a context-free representation. The underlying assumption is that either the simulation is to be considered as an analogy or that individual behavior, norms etc. are not taken into account by the simulator.

Among a few number of simulations that take into account the context-dependency of their agents into account, the following can be cited:

- A cognitive learning model that entails some aspects of context-dependency (Edmonds, 1998);
- The difference that context-dependent learning and reasoning can contribute to an artificial stock market (Edmonds & Norling, 2007)
- Andrighetto et al. (2008)'s use of an approach based on social norms as some part of knowledge of agents are dependent upon the social context of the group they belonged to.
- Alam et al. (2010)'s use of context-sensitive learning/decision-making mechanism for agents in a simulation involving power structures within Afghanistan. The authors relate this to folk psychological accounts abut dynamics of reasoning based on available observational and participant evidence.
- Knoeri et al. (2011)'s analysis about Gidden's structuration theory and structural agents, in which the authors implement a context-dependent agent-based model using an analytical hierarchy process within the context of mineral construction in Switzerland.
- Dignum et al. (2004a, 2004b)'s use of a multi-layered system for specifying agents in simulations entailinhg the context-specific interpretation of social norms.
- Antunes et al. (2000) & Nunes et al. (2013)'s research about context specificity in terms of different social networks and their related social influence.

According to these studies, context-sensitive cognition can make a difference.

A Model of Contextual Cognition

The cognitive model outlined in this section enables the implementation of a context-dependent cognition within social simulation models. Within this model, there is a blend of both machine-learning and AI (Artificial Intelligence)-based reasoning via a context-embedded memory. When the scope of learning is limited to a particular context, learning and reasoning are in general more feasible as in this case one needs only to deal with the relevant knowledge. Yet, some internal correlate of the external context should be present to enable agent to identify which set of beliefs apply (McCarthy 1987). This is mentioned as the internal correlate the cognitive context – or the "internal" approach as specified by Hayes (1997). Two tasks are required for this purpose:

• the specification of the appropriate cognitive context based on the perceptions of the environment;

• the access of the appropriate beliefs within the specified cognitive context.

Based on the underlying pattern of commonalities within a problem domain, the "pragmatic roots" of context, i.e. why context works, can be understood more in detail (Edmonds, 1999). As the cognitive context specifies the boundaries of what might be relevant in any particular situation it serves at a more fundamental level, as a way of developing a feasible model of the world. When learning to deal with the complex world around us, we take into account the stability of the possible causes of events (Zadrozky 1997). It would be infeasible to take into account all of the possible causes in our models. So, once we learn a simple model in one circumstance we can use it in another similar circumstance (i.e. in the same "context"). This possibility of the transference of knowledge through means of simple models from the circumstances in which they have been learnt to the circumstances in which they are being applied lead to the emergence of context.

In order for such transference to occur, the following conditions need to be fulfilled:

• Some of the possible factors in relationship to important events can be easily recognized;

• The foreground features can be distinguished from the others (the constant, background features);

• Similar background factors can easily be recognized later on as the same "context";

• The world provides enough stability for such models to be learned;

• The world provides enough stability for such learnt models to be useful where such a context can be recognized.

Depending on the complexity or difficulty of the cases, the underlying recognition mechanism may not always be apparent. This has been referred to as the "frame problem" within the existing body of literature (McCarthy and Hayes 1969). It should be taken into account that although the frame problem may appear to be unsolvable in general, it can be learnt in particular contingent cases. Also, the identification of appropriate contexts may not always be a precise and reliable process. Therefore, knowing B within the context of A, cannot be translated into statements such as A→B, because the A is not a reified entity that can be reasoned about.

The power of context seems to come from this combination of "fuzzy" and fluid context identity and crisp, relatively simple context "contents". Thus, context straddles the fields of Machine Learning and Artificial Intelligence. Machine learning seems to have developed appropriate methods for complex and uncertain pattern recognition suitable for the identification of context. Artificial Intelligence has developed techniques for the manipulation of crisp formal expressions. Context (as conceived here) allows both to be used for different functions in a coherent way.

Context in Learning

Within the field of machine learning, the use of context is based on a goal, the application of knowledge acquired in one field to a different context; and the utilization of existing information about contexts to improve learning.

Among the few research studies that investigate the issue of learning within relevant contexts, Widmer (1997)'s work is crucial as in his study a meta-learning process is implemented to a basic incremental learning neural net; the meta-algorithm changes itself based on the dynamics of the basic learning process. Similarly, in one of his studies, Harries et al. (1998) implemented a batch learner as a meta-algorithm to specify constant contexts and the authors suggested that the contexts are contiguous in the "environmental variables" and the technique can only be done off-line. Furthermore, an incremental instance-based learning technique is implemented by Aha (1989) along with a clustering algorithm to specify the importance of features (Aha, 1989).

Combining Context-Dependent Learning and Reasoning

The difficulties of implementing a context-dependent approach for both reasoning and learning can be summarized as follows:

• It would not be feasible to determine explicitly the information required for a set of potential contexts. Therefore, apart from some exceptional studies (e.g. CYC (Lenat 1995)), only a few contexts exist for trial when it comes to context-dependent learning or reasoning. A possible solution (also the one applied in this study) is to acquire as much knowledge as possible about the contexts.

• This acquisition of knowledge of how to recognize when certain beliefs held in a previous situation can again apply to another context) requires a kind of meta-learning.

This ability to learn about the context enables one to move beyond the traditional 'loose' loop of:

repeat

learn/update beliefs

deduce intentions, plans and actions

until finished

to a more integrated loop of:

repeat

repeat

recognise/learn/choose context

induce/adapt/update beliefs in that context

deduce predictions/conclusions in that context

until predictions are consistent

and actions/plans can be determined

plan & act

until finished.

Such a collaborative design of cognitive contexts along with the related "contents" leads to a new issue when the knowledge in these contexts is used to infer predictions. Therefore, the next arising issue can be summarized as follows:

• In case of some mistaken contents, how would it be possible to find out which of the context and the content were wrong?

Although this will depend on the nature of the domain and related domain contexts, the following heuristic can be stated: in case of a disapproval of a few of the context related knowledge elements, it is likely that these are wrong (update the set); in case of a disapproval of many of the context related knowledge elements it is likely that the context is wrong (change it and learn from this).

Within this context, there are four modules within the suggested architecture:

(1) the context identification system;

(2) the context-dependent memory;

(3) the local learning/induction algorithm; and

(4) the inference system, as shown in Figure 1.

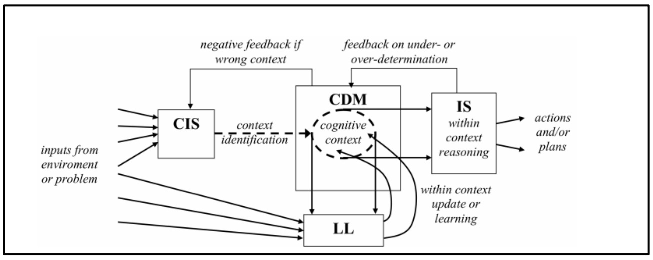

Figure 1. The dynamics of the context-identification system (CIS), the context-dependent memory (CDM), the local learning algorithm (LL), and Inference system (IS)

There are various inputs within the context identification system (CIS) so that it gets informed about the indicators of the context in a flexible way (which it outputs to the memory). In case of the disapproval of too many context related knowledge elements, CIS learns based on negative feedback. Based on the input provided by the CIS, the context-dependent memory (CDM) specifies all those memory items stored within that context. Based on an evaluation of their correctness, it returns a negative (in case of many incorrect elements) or positive feedback to the CIS so that another context can be identified. In case the necessary number of truly indicated contents are sufficient, then within that context the items are updated locally. So, knowledge in the memory is updated by the local learning algorithm (LL). This may entail both the propagation of successful items and the deletion/correction of incorrect items which are replaced by newly induced ones. Finally, based on the actions to be executed, the planning/inference system (IS) aims to deduce some decisions by trying to predict the future states of the world given possible actions and comparing the predictions using its goals.

Learning Context

The context-dependent information needs to be acquired so that context-dependent reasoning can happen. The underpinning idea is to get informed about the ideal models and the circumstances. In case of sufficient stability in the environment some clusters of similar circumstances can be specified and the related models can be induced. Yet, as the clustering and induction parts of the algorithm cannot function independently; clusters of similar circumstances need to be specified so that models for these clusters can be induced. This is due to the fact that the contexts are influenced by those circumstances where particular models work best. Contexts may be inextricably intertwined or overlapping.

Within this regard, the set of candidate models can be summarized as follows:

- a crisp model in a formal language (the content) and
- some information that specifies the model's domain of application (the domain).

Below is the basic learning algorithm:

Randomly generate candidate models and place them randomly about the domain, D

for each generation

repeat

randomly select a point in D, P

pick n models, C, tending towards those near P

assess all in C over a neighborhood of P

select random number x from (0,1)

if x < propagation probability

then propagate the fittest in C to new generation

else cross two fittest in C, put result into new

generation

until new population is completed

next generation

The general heuristics for learning context can be summarized as follows:

• *Formation:* As long as a cluster consisting of models with similar domains can be developed these domains can be abstracted to a relevant context.

• *Abstraction:* If there are shared models among two (or more) contexts with the same domain, these may be abstracted to another context. So, a super-context with a wider domain of application can be developed.

• *Specialisation:* In case of the development of much more specific domain context, many more models (and hence useful inferences) can be included to create a sub-context.

• *Content Correction:* In case of the existence of one (or a few) models erroneous models within the same context, then these models should either be removed from this context or their contents be revised.

• *Content Addition:* If a model's domain is the same as an existing one, then this can be added to that context.

• *Context Restriction:* If all or most the models in a context seem to be erroneous at the same time, then the conditions under which the errors occurred should be eliminated from the context.

• *Context Expansion:* If all or most of the models in a context continue to function under some new conditions, then the context can be enlarged so that it involves these conditions.

• *Context Removal:* If a context has only a few models left or is no longer applicable to a domain, then it should be forgotten.

Conclusions

A lack of recognition of the social context may lead to a change in the degree of social complexity when agents with cognitive ability interact among each other. This is particularly true, especially when new and specific habits, norms etc. are developed as the social context becomes more recognizable. As a result of this co-development of social context, some aspects of social phenomena may not be captured by simulations.

Within the light of this information the following suggestions can be made:

• If a simulation entails agents with mostly non-context cognitive models it might be deceptive, especially in cases where learning of the agents occur based on different situations.

• In some cases where via means of less “smooth” learning and inference algorithms the agents can mimic some aspects of context-dependency, results might be more similar to the observed outcomes. Therefore, the cognitive model encoded in the agent plays a crucial role.

One cannot merely assume that an “off-the-shelf” model based on features of another context, like AI or machine learning, will be good enough. Context-dependency is a crucial aspect of social phenomena, as a feasible modeling is limited to some specific variables of context. It may have forgotten that long ago Max Weber- the father of sociology- mentioned the inherent context-dependency of social phenomena (Coser 1977). Although this study could not fill the whole gap within this field it purports to make a reminder for the importance of this field.

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