A Preliminary Research on Modeling Cognitive Agents for Social Environments in Multi-Agent Systems

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Abstract

Cognitive agents for social environments are one of the most prevalent ideas in multi-agent design today. A vast majority of existing research either takes a centralist, static approach to organizational design or takes an emergent view which makes the behavior of the system as a whole is unpredictable. This paper elucidates our ideas on a general theory of collective behavior and structural formation. Our system is designed to achieve two goals. First, it aims to model the meso-level multi-agent interaction by capturing both the organizational view and the emergent view. Our second goal is to provide a computational descriptive decision model of the highly cognitive process wherein decision-making. The architecture is intended to be as generic as possible, in which different decision heuristics and social structures can be implemented.

Keywords

Agent modeling, cognitive agent, society, decision making, multi-agent systems.

Introduction

Recent works on cognitive agents [7, 11] for social environments generally focus on two levels: the *micro-agent* level where people are essentially interested in the interactions between individual agents [15, 45, 46], and the level of *macro societies* (or organizations or groups) where interest is mainly concentrated on the centralist, static approach to organizational design and specification of social structures [38, 17]. The first one is the experimental approach in which an attempt is being made to obtain emergent properties. The second is a top-down approach, and is characteristic of the approach of an engineer attempting to obtain a system that responds to a need [43]. In spite of this, either approach takes singly a point of view of economics or sociology; while classical economics is under-socialized, i.e. it grants zero agency to social structure, as the selfish actions of individuals are carried by an invisible hand to a plateau of overall organization; sociology, on the other hand, is over-socialized, i.e. it is ascribed little agency when compared to the group or social structure [18]. There is little methodology suitable for the design of complex multi-agent systems where both the agent view and the societal view can be modeled.

In the case of decision-making, there are three basic models: prescriptive, normative and descriptive models [25]. A prescriptive model is one which can and should be used by a real decision maker [40]. A normative model requires the decision maker to have perfect rationality [33], for example, the classical utility function belongs to this category. Many normative theories have been refined over time to better "describe" how humans make decisions. Kahneman and Tversky's Prospect Theory [21, 37] and von Neuman and Morgenstein's Subjective Utility Theory [39] are noted examples of normative theories that have taken on a more descriptive guise. One of the central themes of the descriptive model is the idea of Bounded Rationality [31], i.e., humans don't calculate the utility value for every outcome; instead we use heuristics to determine if one situation is better than another. However, existing descriptive methods are mostly informal, therefore there is a growing need to study them in a systematic way and provide a qualitative framework in which to compare various possible underlying mechanisms.

Motivated by these observations, we propose an agent architecture for cognitive agents for social environment. We aim the *meso-level* of the micro-macro relationship in multi-agent systems and use the *descriptive* decision model to simulate human decision makers. Our long term goal is a general theory of collective behavior and structural formation with a resulting architecture that can be broadly applied. The work described in this paper is the first step in a larger effort directed toward the goal.

There are several existing works sharing the same scope with our system. COGENT (COGnitive agENT) [9] is a cognitive agent architecture based on the RPD (Recognition Primed Decision) model [26]. However, it focuses on providing decision-aiding at multiple levels of information processing, such as information filtering and situation assessment, while our model is a "white box" that processes real human social behaviors.

CODAGE (COgnitive Decision AGEnt) [25] is an agent architecture that derived its decision model from cognitive psychological theories to take bounded rationality into account. However, CODAGE does not address three major issues regarding agent interaction: 1) it does not consider the level of macro societies; 2) there is no communication between CODAGE agents, while we consider communication as an important approach for forming societies; 3) CODAGE is a centralized system where only one decision maker makes decisions for each agent, while ours is a distributed system where each agent makes their own decisions.

The structure of this paper is as follows. Section 2 introduces the system architecture. Section 3 discusses our two-phase decision-making models. Section 4 describes the micro-macro relationship in our system. Section 5 explains what has been done in experiments and what to do next. Section 6 concludes the paper.

System Overview

Our system is designed to achieve two goals. First, it aims to model the meso-level multi-agent interaction by capturing both the level of micro agents and the level of macro societies. We keep an individual perspective on the system assumed by the traditional multi-agent models, i.e. agent is an autonomous entity and has its own goals and beliefs to the environment. On the other hand, we take into account how agent's decisions are influenced by the choices made by others. Concepts as social identity, social proof and social approval are external to individual agent and independent from its goals. However, they constrain the individual's commitment to goals and choices and contribute to the stability, predictability and manageability of the system as a whole [38].

Our second goal is to provide a computational descriptive decision model of the highly cognitive process wherein decision-making. The descriptive theory assumes agents undergo two fundamental stages when reaching a final decision: an early phase of *editing* and a subsequent phase of *evaluation* [21]. In the editing phase, the agent sets up priorities for how the information will be handled in subsequent decision-making phase and forms heuristics which will be used during the decision-making process, i.e. the agent only acts with bounded rationality. In the evaluation phase, there exist two generic modes of cognitive function: an *intuitive* mode in which decisions are made automatically and rapidly, and a controlled mode, which is *deliberate* and slower [22, 32]. When making decisions, the agent uses *satisfying* theory [31, 34], i.e. it takes "good enough" options rather than a single "best" option. Section 3 provides our thoughts in detail to the two-phase decision model.

To provide a finer distinction which could be used for setting up priorities for information and form heuristics in the editing phase, we follow experimental studies performed by cognitive psychologists. They suggested the existence of some variables that accounted for a large amount of the ability of agents to perform attentional, behavioral and memory tasks [3]. These variables are arousal, attention and expectation. *Arousal* was conceptualized as a form of "energization" of behavior. Low and high levels of arousal result in similar low performance states. *Attention*, here we mean both environmentally driven and voluntary attention. The high level state results in attention focused on a particular task while the low level results in a disengaged state suitable for monitoring or scanning the environment. *Expectation* predicts what will occur in the near future. Depending on the success of the predictive state, the expectation function shows different levels: high if there is an unpredicted reward, mid if the reward occurs as predicted, and low if the predicted reward does not occur. We use these three variables to separate relevant information from less relevant information which can be discarded in decision-making.

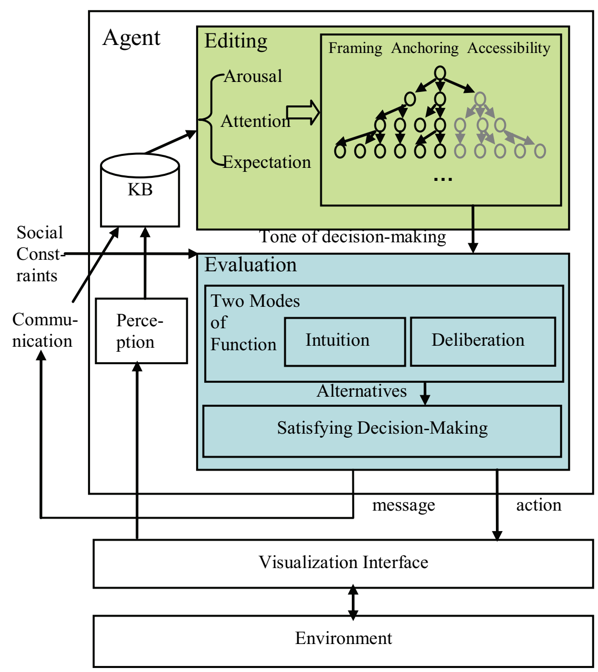

Figure 1 System Architecture

Fig. 1 is the system architecture. Our system uses discretized time. At each time step, every agent has an execution cycle, shown in Fig. 2.

```
/* The function is executed independently by
   each agent, denoted self below.
*/
function execute(KB_self, env, messageQueue, t)
   inputs: KB_self, the knowledge base for agent self
           env, the environment
           messageQueue, the message queue for self
           t, the current step

   //editing phase
           observation(env);
           check(messageQueue);
           editing(KB_self);
   //evaluation phase
           action = evaluate(KB_self);
           message = evaluate(KB_self);
   //perform the outputs of decision-making
           do(action);
           resource-sych(env);
           update(env);
           add(message, messageQueue);
           masterserver-sych;
   // move to next step
           t++;
```

Figure 2 Agent Execution Function

Two-Phase Decision-Making Process

Kahneman and Tversky suggest a two-phase decision model for descriptive decision-making: an early phase of editing and a subsequent phase of evaluation. In the editing phase, the decision-maker constructs a representation of the acts, contingencies and outcomes that are relevant to the decision. In the evaluation phase, the agent assesses the value of each alternative and chooses the alternative of highest value. Our decision model incorporates their idea and specifies it by five mechanisms:

- Editing
  - *Framing*: the agent frames an outcome or transaction in its mind and the utility it expects to receive.
  - *Anchoring*: the agent's tendency to overly or heavily rely on one trait or piece of information when making decisions.
  - *Accessibility*: the importance of a fact within the selective attention.
- Evaluation
  - *Two modes of function*: intuition and deliberation.
  - *Satisfying theory*: being good enough.

Next we discuss each phase in a sub-section.

Editing

One important feature of the descriptive model is that it is reference based [40]. This notion grew out of another central notion called **framing** where agents subjectively frame an outcome or transaction in their minds and the utility they expect to receive it thus affected [21]. This closely patterns the manner in which humans make rational decisions under conditions of uncertainty.

Framing can lead to another phenomenon referred to as **anchoring** [21]. Anchoring or focalism is a psychological term used to describe the human tendency to overly or heavily rely, *anchor* on one trait or piece of information when making decisions. A classic example would be a man purchasing an automobile, the client tends to "anchor" his decision on the odometer reading and year of car rather than the condition of the engine or transmission.

Accessibility is the ease with which particular information come to mind [20]. The concept of accessibility is applied more broadly in this research than in common usage. The different aspects and elements of a situation, the different objects in a scene, and the different attributes of an object – all can be described as more or less accessible, for an individual agent exposed to a certain decision situation. As it is used here, the concept of accessibility subsumes the notions of stimulus salience, selective attention, and response activation or priming.

For our purposes, the descriptive decision model provides three main results that are to be incorporated both theoretically and practically into this approach. First, an agent should utilize prior knowledge of previous states to frame potential outcomes for its current state. In framing these potential outcomes, an agent can ascribe for reference based expected utility functions to them. Here, information anchoring or bias becomes a positive force as it leads to the agents ability to make reference based utilities for each potential outcome. Second, when an agent makes decisions, it does not have to search all information it has. In stead, it will concentrates on the relevant and important information and can prunes less relevant and important one. Third, a decision which was chosen before will receive more attention (or high accessibility) than other alternatives and tend to be more positively evaluated before it is chosen again.

Evaluation

In the evaluation phase, there exist **two modes of cognitive function**: an intuitive mode in which decisions are made automatically and rapidly, and a controlled mode, which is deliberate and slower [22, 32]. The operations of the intuition function are fast, automatic, effortless, associative, and difficult to control or modify, while the operations of the deliberation function are slower, serial, effortful, and deliberately controlled; they are also relatively flexible and potentially rule governed [32]. Intuitive decisions occupy a position between the automatic operations of perception and the deliberate operations of reasoning [23, 24].

Intuitions are thoughts and preferences that come to mind quickly and without much reflection [21]. In psychology, intuition can encompass the ability to know valid solutions to problems and decision making. For example, the RPD model aimed to explain how people can make relatively fast decisions without having to compare options [26]. Klein found that under time pressure, high stakes, and changing parameters, experts used their base of experience to identify similar situations and intuitively choose feasible solutions. Thus, the RPD model is a blend of intuition and deliberation. The intuition is the pattern-matching process that quickly suggests feasible courses of action. The deliberation is a conscious reasoning of the courses of action.

We adopted a different approach from the RPD model to handle the intuitive and deliberative decision-making. For our purpose, what becomes accessible in the current situation is a key issue determining the tone of decision-making, i.e. intuitive or deliberative. Accessibility is determined in the editing phase by several factors. First, motivationally relevant and emotionally arousing information spontaneously attract attention and becomes easily accessible. This includes all the features of that information including those that are not linked to its motivational or emotional significance [27]. Second, physical salience also determines accessibility: if a large green letter and a small blue letter are shown at the same time, 'green' will come to mind first. However, salience can be overcome by deliberation: an instruction to look for the smaller letter will enhance the accessibility of all its features [21]. Third, accessibility also reflects people's social approval from others. For example, people from the same group are more willing to share information than doing it with the people from different group [20].

Based on above analyses, we compile an information list. In addition to physical properties such as size and distance, the list includes more abstract properties such as relevance, similarity and importance. At the beginning, this fact is known to the designers. The list will be dynamically updated along with the system processing. For example, the physical properties may be changed if the object moves; the deliberation process may change the salience; people's social identity may make him easily access the information of others who are in the same group. Finally, the more relevant, highly similar and important information can be easily accessed than other ones. The accessibility of all information will be normalized and compared with a threshold for triggering the intuitive function for decision-making.

When making decisions, agents use the **satisfying theory**: First introduced by Simon, the satisfying theory presents an alternative notion of individual optimization in multi-agent settings to the classic utility theory [30]. The idea is to reconstruct utility around preferences, rather than actions. It basically states that the only information we can draw from are the preferences of individuals [2, 19]. This concept is an important one, since it reminds us not to ascribe spurious qualities to the individuals studied and abstracted by a utility function; such a function is a mere representation and may contain aspects that do not actually reflect the individual's nature. Stirling's satisfying game theory also shows that people do not judge the utility based off analysis of desired results, but based off other agents' preferences [35, 36]. We model the decision-making as a multiattribute decision-making problem [1], which includes a finite discrete set of alternatives which is valued by a finite discrete set of attributes I. A classical evaluation of alternatives leads to the aggregation of all criteria into a unique criterion called value function V of the form:

$$V(a) = w \cdot v(a) = f_{i \in I}(w_i v_i(a)) \tag{1}$$

where a is an agent, $V(a)$ is the overall value for agent a, w_i is a scaling factor to represent the relative importance of the ith attribute, $v_i(a)$ is a single attribute value with respect to attribute index $i \in I$ and f is the aggregation function. Function f normally is domain dependent, for example, it can be additive value functions for preference independence [8, 44], discounted value functions when there is reward for different preferences [30], or Constant Absolute Risk Aversion functions for risk-averse decision-making [25, 5].

Emergent Agents and Societies

Agent/Society Duality

We take up the classification proposed by Ferber [14], that multi-agent systems are an agent/society duality. There are two levels of organization in multi-agent systems, which are illustrated in Fig. 3:

(1) The *micro-agent* level, which is in essence represented by the interactions between agents. There are three common types of interaction: cooperation, competition and negotiation [41]. Agents interact with each other through two ways: its sphere of influence in the environment and direct communication to other agents [41].

(2) The *macro-society* level, which is represented by the dynamics of agents together with the general structure of the system and its evolution.

Our work focuses at the meso-level of the agent/society duality. Any society is the result of an interaction between agents, and the behavior of the agents is constrained by the assembly of societal structures. For this reason, a society is not necessarily a static structure, that is, an entity with a predefined characteristics and actions. If societies such as public institutions or companies possess an individuality of their own which distinguishes them from the assembly created by the individualities of their members, it is not necessarily the same for simpler collective structures such as working groups or herds of animals [14]. Even societies considered as being complex, such as colonies of bees or ants, should not necessarily be considered as individuals in their own right if we wish to understand their organization and the regulation and evolution phenomena prevailing there [4, 10]. Therefore in our view, a society is the emergence of properties of individual interactions, without its being necessary to define a specific objective which represents such an outcome [1].

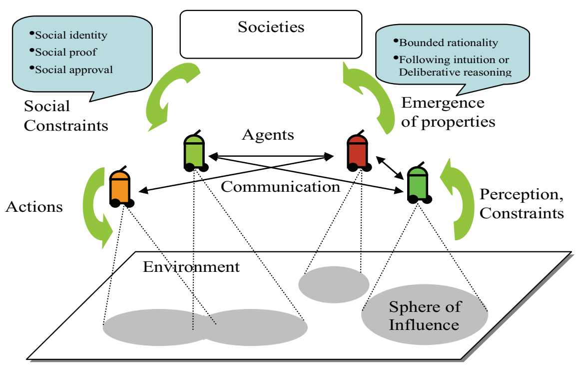

Figure 3 Agent/Society Duality

The agent/society duality characterizes the processes that take place between the agents and the societies which result from them. We are dealing with dynamic interaction, the logic of which depends simultaneously on the capabilities of the agents and the constraints of the system as a whole. In our system, agents have their own goals and are capable of performing various actions. On the other hand, their behaviors must satisfy two types of constraints from the system. The first is the environmental constraints imposed by the spatial geometries, such as physical distance between two agents or obstacles on the way of finding food. The second is social constrains which represent rules associated with social structures that shape an individual's behaviors. We will focus on the social constraints in the next section.

[1] Conversely, this does not mean that it is impossible or useless to represent societies as entities in their own right. We can of course design a society in the form of an agent, and thus consider MASs as packages of agents and societies, like what has been done in [38].

Social Constraints

It is a generally accepted observation that people in the same society may behave similarly. From the perspective of sociology, this is because people's behaviors are constrained by social structures through social identity, social proof and social approval [29].

- Social identity. As noted by March [28], social identities include an individual's age, gender, social positions and religions. Agent's decisions are constrained by the rules associated with these identities.
- Social proof. Social proof is a phenomenon that when people encounter a new situation with insufficient information, they are more likely to follow the decisions made by others, special the people from the same society as him [16]. People are adept at adopting others' innovations because early decisions by group members change the environment and hence, the attractiveness of choices for subsequent group members, i.e., early group members reduce the costs for followers.
- Social approval. People desire to obtain social approval from others. Others may know something that they don't. Therefore, getting social approvals can help one share the information that others know.

In summary, initially, societies are formed by agents similar to each other. Along the system processing, agents pursuit their own goals but their behaviors are constrained by the rules associated with their social identities, social proof and social approval. These rules are normally known by the designer and will be encoded into the system in the design phase. Agents' decision-making is the combination of their goals, capabilities and social rules. The result is that some agents may join the society from outside but some may leave. Finally, the system as a whole will reach a point of stability where we hope to see the formation of the societies.

Experiments

At an early phase of developing this architecture, we have tested the intuitive attitudes toward risk [12] in an extended prisoner's dilemma problem [8, 44]. We extended the classical prisoner's dilemma in two ways. First, outcomes are cumulated so the outcomes of a previous game have effect on an agent's decision in subsequent games. Second, while in the classical prisoner's dilemma the four outcomes are fixed, here we allow them to be uncertain. Each test includes a total number of 2000 agents and is allowed to operate a fixed number of 500 iterations. At each iteration, we randomly pair agents to play a dilemma game. This "pairing" approach has been used as a way to investigate social interactions in multi-agent systems [6, 42]. The results show that agents were able to manage risk by balancing risk-seeking and risk-averse behaviors based off their initial asset position and the structure of their society. Also, our method can quickly lead the whole system to a point of stability where the agents are able to safely maintain their asset position and manage risk over the long term.

Our next test will move to Sugarscape, a classical experiment for growing agent-based artificial societies [13]. Sugarscape is a suitable domain for the initial testing of our model, because it simulates the process of how social structures and group behaviors, such as group formation, cultural transmission and trade, arise from the interaction of individuals following simple social rules [13]. This later work is still in progress and will be described in a subsequent paper.

Summary

From a human cognitive psychological perspective, an agent's behaviors can be viewed as the outcomes of its decision-making process. We conjecture that an agent's decision-making process follows the combination of three conventions: intuition, bounded rationality and social constraints. We have developed a general model of cognitive agents for social environments. This model captures both the organizational view and the emergent view of multi-agent systems. We also provide a computational descriptive decision model of the highly cognitive process wherein decision-making.

The work described in this paper is the first step in a multidisciplinary research involving computer science, sociology, economics and neuroscience at Trinity University. The project is funded by ACS Task Force on Undergraduate Research and Engagement in summer 2007.

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