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THE DESIGN OF COGNITIVE SOCIAL SIMULATION FRAMEWORK USING STATISTICAL METHODOLOGY IN THE DOMAIN OF ACADEMIC SCIENCE

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Abstract: *Modeling the behavior of the cognitive architecture in the context of social simulation using statistical methodologies is currently a growing research area. Normally, a cognitive architecture for an intelligent agent involves artificial computational process which exemplifies theories of cognition in computer algorithms under the consideration of state space. More specifically, for such cognitive system with large state space the problem like large tables and data sparsity are faced. Hence in this paper, we have proposed a method using a value iterative approach based on Q-learning algorithm, with function approximation technique to handle the cognitive systems with large state space. From the experimental results in the application domain of academic science it has been verified that the proposed approach has better performance compared to its existing approaches.*

Keywords: *Cognitive architecture, Social Simulation, Reinforcement learning, Function approximation.*

I. INTRODUCTION

A cognitive architecture specifies the underlying infrastructure for an intelligent system. Briefly, architecture includes those aspects of a cognitive agent that are constant over time and across different application domains. These typically include:

1. The short-term and long-term memories that store content about the agent's beliefs, goals, and knowledge;
2. The representation of elements that are contained in these memories and their organization into larger-scale mental structures;
3. The functional processes that operate on these structures, including the performance mechanisms that utilize them and the learning mechanisms that alter them.

Because the contents of an agent's memories can change over time, one would not consider the knowledge and beliefs encoded therein to be part of that agent's architecture. As different programs can run on the same computer architecture, so the different knowledge bases and beliefs can be interpreted by the same cognitive architecture. There is also a direct analogy with a building's architecture, which consists of permanent features like its foundation, roof, and rooms, rather than its furniture and appliances, which one can move or replace.

II. EXAMPLES OF COGNITIVE ARCHITECTURES

A. ACT -R

ACT-R [7][8] is the latest in a family of cognitive architectures, concerned primarily with modeling human behavior, that has seen continuous development since the late 1970s. ACT-R is organized into a set of modules, each of which processes a different type of information. These include sensory modules for visual processing, motor modules for action, an intentional module for goals, and a declarative module for long-term declarative knowledge. Each module has an associated buffer that holds a relational declarative structure (often called 'chunks', but different from those in Soar). Taken together, these buffers comprise ACT-R's short-term memory.

B. SOAR

Soar [4][5][1] is a cognitive architecture that has been under continuous development since the early 1980s. Procedural long-term knowledge in Soar takes the form of production rules, which are in turn organized in terms of operators associated with problem spaces. Some operators describe simple, primitive actions that modify the agent's internal state or generate primitive external actions, whereas others describe more abstract activities. For many years, Soar represented all long-term knowledge in this form, but recently separate episodic and semantic memories have been added. The episodic memory [2] holds a history of previous states, while semantic memory contains previously known facts.

C. ICARUS

ICARUS is a more recent architecture [14] that stores two distinct forms of knowledge. Concepts describe classes of environmental situations in terms of other concepts and percepts, whereas skills specify how to achieve goals by decomposing them into ordered sub goals. Both concept and skills involve relations among objects, and both impose a hierarchical organization on long-term memory, with the former grounded in perceptions and the latter in executable actions. Moreover, skills refer to concepts in their heads, their initiation conditions, and their continuation conditions.

D. PRODIGY

PRODIGY [6] is another cognitive architecture that saw extensive development from the middle 1980s to the late 1990s. This framework incorporates two main kinds of knowledge. Domain rules encode the conditions under which actions have certain effects, where the latter are described as the addition or deletion of first-order expressions. These refer both to physical actions that affect the environment and to inference rules, which are purely cognitive. In contrast, control rules specify the conditions under which the architecture should select, reject, or prefer a given operator, set of operator bindings, problem state, or goal during the search process.

PRODIGY's explanation-based learning module constructs control rules based on its problem-solving experience [20]. Successful achievement of a goal after search leads to creation of selection or preference rules related to that goal and to the operators whose application achieved it. In addition, PRODIGY includes separate modules for controlling search by analogy with earlier solutions [11] learning operator descriptions from observed solutions or experimentation [21], and improving the quality of solutions [12]. Although most research in this framework has dealt exclusively with planning and problem solving, PRODIGY also formed the basis for an impressive system that interleaved planning and execution for a mobile robot that accepted asynchronous requests from users [10].

E. THE CLARION

CLARION is an integrative cognitive architecture consisting of several distinct sub systems [16][18][15]. These include the action-centred subsystem (ACS), the non-action-centred subsystem (NACS), the motivational subsystem (MS), and the metacognitive subsystem (MCS). The ACS controls actions, whether for external physical movements or internal mental operation. The NACS maintains general knowledge, either implicit or explicit. The MS provides under-lying motivations for perception, action, and cognition in terms of impetus and feedback (for example, indicating whether outcomes are satisfactory or not). The MCS monitors, directs, and modifies the operations of the ACS dynamically, as well as the operations of all the other subsystems.

Modeling the behavior of the cognitive architecture in the context of social simulation using statistical methodologies is currently a growing research area. Normally, a cognitive architecture for an intelligent agent involves artificial computational process which exemplifies theories of cognition in computer algorithms under the consideration of state space. More specifically, for such cognitive system with large state space the problem like large tables and data sparsity are faced. Hence in this paper we have proposed a method using a value iterative approach based on Q-learning method with function approximation to handle the cognitive systems with huge state space. From the experimental results in the domain of academic science it has been proceeded that to proposed approach results better performance compared to its existing approach.

III. CAPABILITIES OF COGNITIVE ARCHITECTURES

Any intelligent system is designed to engage in certain activities that, taken, together, constitute its functional capabilities. This section, discusses the varied capabilities that a cognitive architecture can support. Although only a few abilities, such as recognition and decision making, are strictly required to support a well-defined architecture, the entire set seems required to cover the full range of human-level intelligent activities.

- Recognition and Categorization
- Decision Making and Choice
- Perception and Situation Assessment
- Prediction and Monitoring
- Reasoning and Belief Maintenance
- Execution and Action
- Interaction and Communication
- Remembering, Reflection and Learning
- Problem solving and Planning

IV. COGNITIVE MODELS

Cognitive models attempt to represent the users as they interact with a system, modeling aspects of their understanding, knowledge, intentions or processing. Cognitive models are divided into three categories.

- The first described the hierarchical structuring of the user's task and goal structure. Eg. GOMS (Goals, Operators, Method, Selection) CCT (Cognitive Complexity Theory).
- The second model concerned with Linguistic and grammatical models, which emphasized the user's understanding of the user system – dialog. Eg. BNF (Backus Naur Form), TAG (Task Action Grammar).

- Third model based on the more solid understanding of the Human Motor System. Eg. KLM (Keystroke – Level Model).

V. EXISTING A COGNITIVE ARCHITECTURE IN SOCIAL SIMULATION

One application of CLARION to social simulation is in understanding organizational decision making and the interaction between organizational structures and cognitive factors in affecting organizational decision making [Sun, 04].

In terms of organizational structures, there are two major types: (1) teams, in which agents act autonomously, individual decisions are treated as votes, and the organizational decision is the majority decision; and (2) hierarchies, which are characterized by agents organized in a chain of command, such that information is passed from subordinates to superiors, and the decision of a superior is based solely on the recommendations of his/her subordinates. In addition, organizations are distinguished by the structure of information accessible by each agent. Two varieties of information access are: (1) distributed access, in which each agent see a different subset of attributes (no two agents see the same sub-set of attributes), and (2) blocked access, in which several agents see exactly the same subset of attributes.

Several simulation models were considered in [9]. The experiments by [9] were done in a 2 x 2 fashion (organization x information access). In addition, human data for the experiment were compared to the results of the four models [9].

In their work, the agent models used were very simple, and the “intelligence” level in these models was low. Moreover, learning in these simulations was rudimentary: there was no complex learning process as one might observe in humans. With these shortcomings in mind, it is worthwhile to undertake a simulation that involves more complex agent models that more accurately capture human performance. Moreover, with the use of more cognitively realistic agent models, one may investigate individually the importance of different cognitive capacities and process details in affecting organizational performance [19].

Hence, a simulation with CLARION used for modelling individual agents in an organization was conducted [19]. The results closely accord with the patterns of the human data, with teams outperforming hierarchical structures, and distributed access proving superior to blocked access.

Also, as in humans, performance is not grossly skewed towards one condition or the other, but is roughly comparable across all conditions, unlike some of the simulation results from [9]. The match with the human data is far better than in the simulations conducted in [9]. The better match is due, at least in part, to a higher degree of cognitive realism in this simulation. See [19] for further details, including the interesting effects of varying cognitive parameters.

Another application of CLARION to social simulation is in capturing and explaining the essential process of publication in academic science and its relation to cognitive processes [3]. Science develops in certain ways. In particular, it has been observed that the number of authors contributing a certain number of articles to a scientific journal follows a highly skewed distribution, corresponding to an inverse power law. In the case of scientific publication, the tendency of authorship to follow such a distribution was known as Lotka’s law.

Herbert Simon developed a simple stochastic process for approximating Lotka’s law. One of the assumptions underlying this process is that the probability that a paper will be published by an author who has published i articles is equal to a/i^k, where a is the constant of proportionality. Using Simon’s work as a starting point, [13] attempted to model Lotka’s law. He obtains his simulation data based on some very simplified assumptions and a set of mathematical equations. To a significant extent, Gilbert’s model is not cognitively realistic. The model assumes that authors are non-cognitive and interchangeable; it therefore neglects a host of cognitive phenomena that characterize scientific inquiry (e.g., learning, creativity, evolution of field expertise, etc.).

Using a more cognitively realistic model, one can address some of these omissions, as well as exploring other emergent properties of a cognitively based model and their correspondence to real-world phenomena. The results of the simulation based on CLARION [3] are shown along with results (reported by [13]) for Chemical Abstracts and Econometrica, and estimates obtained from previous simulations by [3]. The tables indicate number of authors contributing to each journal, by number of papers each has published. More specifically, for such cognitive system with large state space the problem like large tables and data sparsity are faced. Hence in this paper we have proposed a method using a value iterative approach based on Q-learning algorithm with function approximation technique to handle the cognitive systems with large state space.

VI. PROPOSED WORK

Function approximation and feature based method

A. *Problem Specification*

We consider the following form of RL task for the learning agent.

What is given?

- Set S of possible states.
- Set A of possible actions.
- Unknown transition function δ: $S \times A \rightarrow S$
- Reward function R, which is 1 in goal state and o else where goal states are terminal.

What to find?

An optimal policy $\prod * = S \rightarrow A$ for selecting the next action a_i based on current observed states.

It may be generally very difficult to learn a Q-Function perfectly. We often expect learning algorithms to set only some approximation to the target function.

B. Proposed Architecture

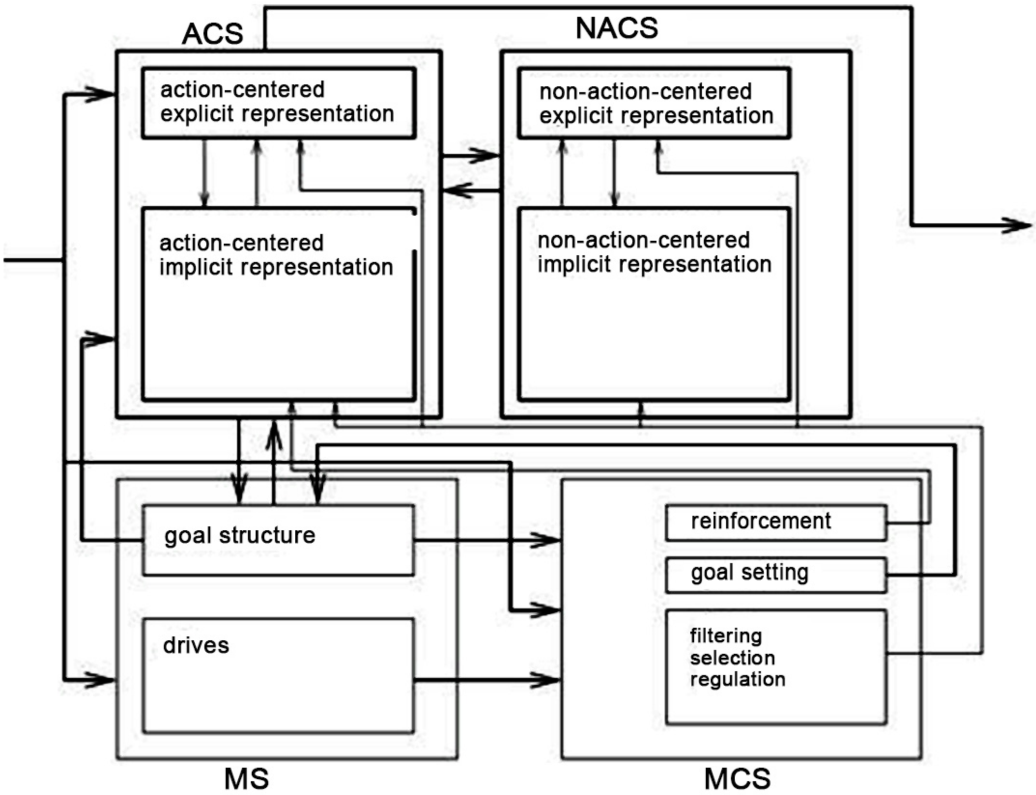

Figure 1: Clarion Architecture with Function Approximation

We will use function approximation here and learn a representation of the Q-Function as a linear function of combinations of features, where the features describe a state. In other words, we will translate a state S into the set of features $f1, f2,\ldots fn$. Where n is the number of features.

We have set of Q- functions:

$$Q^a(s,a) = \theta_1\, af_1 + \cdots + \theta_n\, af_n$$

The update rule is

$$\theta^a_k = \theta^a_k + \alpha[r + \gamma \max_{a'} Q^a(s', a') - Q^a(s,a)] \frac{dQ^a(s,a)}{d\theta^a_k} \quad (1)$$

Algorithm The RL Algorithm with Function Algorithm
initialize all thetas to 0
repeat
Generate a starting state s_0
$i = 0$
repeat
Choose an action a_i, using the policy obtained from The current values of thetas
Execute action a_i, observe R and s_{i+1}
$i=i+1$
until s_i is terminal(i.e., a goal state)
for $j = i - 1$ to 0 do
Update the value of θ^a_k for all taken actions using (1)
end for
until no more episodes

VII. EVALUATION AND RESULTS

Science develops itself in particular ways. In particular the number of authors contributing a certain number of articles to scientific journals tends to follow a highly skewed distribution, corresponding to an inverse power law. In the case of scientific publications, the tendency of authorship to follow such a distribution is known as Lotka's law. Herbert Simon developed a simple stochastic process for approximating Lotka's Law. One of the assumptions underlying this process is that the probability that a paper will be published by an author who has published i articles is ali^k, where a is a constant of proportionality. Using Simon's work as a starting point, Gilbert attempted to model Lotka's Law. He obtained his simulation data on the basis of some simplified assumptions and a set of mathematical equations. To a significant extent, Gilbert's model was not cognitively realistic. The model assumed that authors were non-cognitive and interchangeable; it therefore neglected a host of cognitive phenomena that characterized scientific inquiry.

In clarion simulation they have introduced a cognitive approach by comparing the previous results. In our model the number of articles per author reflected the cognitive ability of an author, as opposed to being based on auxiliary assumptions such as those made by Gilbert.

Our model is using learning and function approximation is able to give a good match to the results of clarion simulation. Using function approximation we have got better output than the previous results. That is, we put more distance between mechanisms and outcomes which made it more difficult to obtain a match with the human data. Even though, being able to match the human data reasonably well shows the power of our approach.

The proposed method data for the two journals could be fit to the power curve $f(i) = a/i^k$, resulting in an excellent match. *Table 1* and *Table 2* clearly show the good results achieved from the proposed method.

Table 1: Number of Authors Contributing to Chemical Abstracts.

No. of Papers	Actual	Simon's Estimate	Gilbert's simulation	CLARION simulation	Proposed Method
1	3991	4050	4066	3803	3850
2	1059	1160	1175	1228	1238
3	493	522	526	637	646
4	287	288	302	436	444
5	184	179	176	245	252
6	131	120	122	200	206
7	113	86	93	154	160
8	85	64	63	163	168
9	64	49	50	55	60
10	65	38	45	18	20
11 or more	419	335	273	145	150

Table 2: Number of authors contributing to Econometrica

No. of Papers	Actual	Simon's Estimate	Gilbert's simulation	CLARION simulation	Proposed approach
1	436	453	458	418	430
2	107	119	120	135	138
3	61	51	51	70	72
4	40	27	27	48	50
5	14	16	17	27	28
6	23	11	9	22	23
7	6	7	7	17	19
8	11	5	6	18	19
9	1	4	4	6	9
10	0	3	2	2	4
11 or more	22	25	18	16	20

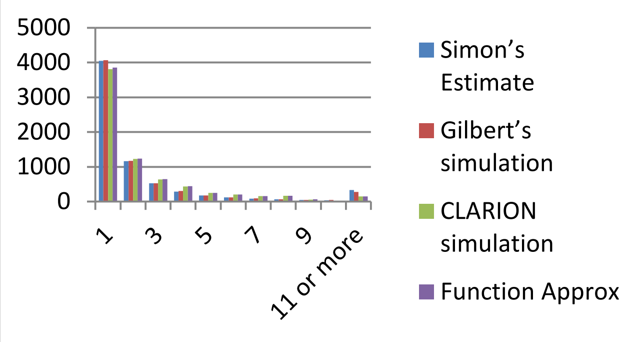

Figure 2: Proposed method result for different setting

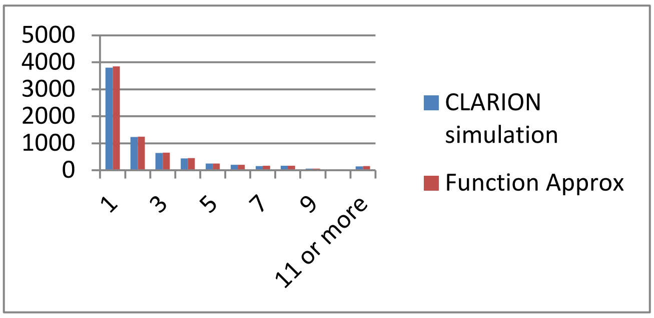

Figure 3: Proposed method with CLARION

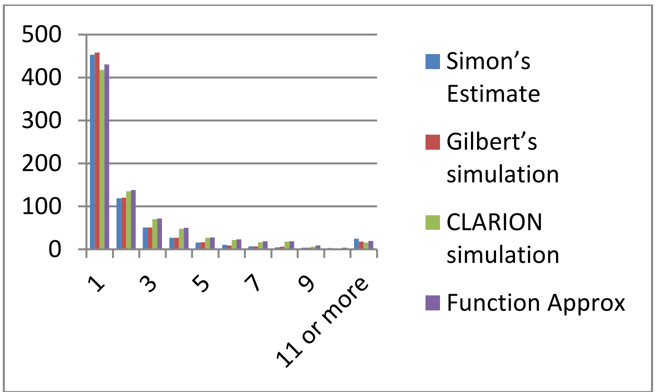

Figure 4: Proposed method result for different setting

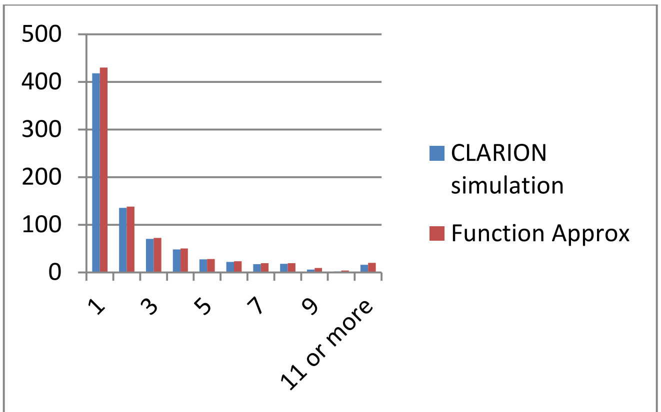

Figure 5: Proposed method with clarion.

Note that, in this simulation, the number of papers per author reflected the cognitive ability of an author, as opposed to methods based on auxiliary assumptions such as those made by [13]. This explains, in part, the greater divergence of these results from the human data: whereas Gilbert's simulation consists of equations selected to match the human data. This approach relies on much more detailed and lower-level mechanisms namely, a cognitive agent model that is generic rather than being task-specific. The result of the CLARION based simulation is therefore emergent, and not a result of specific and direct attempts to match the human data. That is, one put more distance between mechanisms and outcomes, which makes it harder to obtain a match with the human data. Thus, the fact that it was able to match the human data reasonably well shows the power of this cognitive architecture based approach.

VIII. CHALLENGES FACING COGNITIVE SOCIAL SIMULATION

An important development in the social science has been that of agent-based social simulation (ABSS). This approach consists of instantiating a population of agents, allowing the agents to run, and observing the interactions between them. The use of agent-based social simulation as a means for computational study of societies mirrors the development of cognitive architectures in cognitive science.

The two fields of social simulation and cognitive architectures can be profitably integrated. This is an important challenge. As it has been argued before, social processes ultimately rest on the choices and decisions of individuals, and thus understanding the mechanisms of individual cognition can lead to better theories describing the behavior of aggregates of individuals.

At the same time, by integrating social simulation and cognitive modeling, one can arrive at a better understanding of individual cognition. Traditional approaches to cognitive modeling have largely ignored the potentially decisive effects of socially acquired and disseminated knowledge (including language, norms, and so on). By modeling cognitive agents in a social context, one can learn more about the socio cultural processes that influence individual cognition.

The most fundamental challenge in this regard is to develop better ways of conducting detailed social simulation based on cognitive architectures as basics. Although some cognitive details may ultimately prove to be irrelevant, this cannot be determined a priori, and thus simulations are useful in determining which aspects of cognition can be safely abstracted away building blocks. This is not an easy task. Although some initial work has been done (e.g., [17][19] much more work is needed.

There is also the challenge of computational complexity. Social simulation could involve a large number of agents, up to thousands. Computational complexity is thus already high, even without involving cognitive architectures as agent models. To incorporate cognitive architectures into social simulation, one has to deal with a great deal of added complexity.

IX. CONCLUSION

We have proposed here a method using a value iterative approach based on Q-learning algorithm with function approximation to handle the cognitive systems with large state space. From the experimental results in the domain of academic science it has been proved that the results of proposed approach are better as compared to its existing approach. These results and algorithms can be very useful to the researchers those who are in academic science and cognitive architecture.

X. FUTURE WORK

Emotions play a central role in human behavior, yet few systems offer any account of their purpose or mechanisms. There is a need of new architectures that exhibit emotion in ways that link directly to other cognitive processes and that modulate an intelligent behavior. Most architecture incorporate some form of learning, but none have shown the richness of improvement that humans demonstrate. There is a need of more robust and flexible learning mechanisms that are designed for extended operation in complex, unfamiliar domains.

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