Multi Agent Machinery in Construction of Cognitive Systems

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Abstract

Construction of cognitive systems equipped with self-organized and collaborative computing agents is presented. The methodology for building agents specifies how deductive entities can be decomposed into a set of distinct modules and how these modules should be made to interact in order to achieve information accumulation, deduction and exchange. Models for agent machinery and the system abstract architecture are given by relevant mathematical structures, meanwhile, deductive logic is constructed on strict logical arguments reinforced with the specified rules of inferences. Deductive reasoning agents are implemented based on ideas of symbolic representation of the underlying intelligence, where the classified entities are specified using formulae of first-order predicate logic. Integration of discrete information is achieved through formation and dynamic changes of attitudes and mainly specifies the assimilation of information with existing cognitions or thoughts, each relevant piece of information having two qualities: value and weight. Cellular automata predefined by a 4-tuple over a finite lattice, finite set of cell values, finite neighborhood, and local transition function underlies the cognitive system and activation network based on weights.

IndexTermscellular automaton, computing agent, self-organization, predicate logic

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Introduction

Enormous quantity of structured and unstructured information accumulated during centuries of human civilization creates and permanently promotes the global knowledgebase reflecting theoretical and empirical discoveries in almost every area of human thinking and intelligence. Digitalization of human intellectual heritage made it possible to load knowledge into computers and to transform machine readable raw data into meaningful output, where accuracy of the derived information mainly depends on the decisions made, as well as on acquired data veracity and trustworthiness. While sensitivity, range, precision and resolution of sensor devices are restricted in production technologies, anyway, the upper bound of the sensors' theoretical capabilities are limited in our perception of the Universe, which, obviously, is richer than the methods that are introduced to describe and to model phenomena under consideration. Human understanding of the Nature is bounded philosophy of science, and, obviously, cannot encompass the Universe solely by approaches such as: rationalism; empiricism; pragmatism and their Kantian synthesis. Henri Poincare formulated the selection of mathematical theories to describe natural phenomena as *conventionalism*, and he justified the approach by assuming coexistence of different types of geometries (Euclidean and non-Euclidean) and physics (Newtonian mechanics and Einstein's theory of general gravity being applicable solely in definite models and considerations).

Nowadays, intensive evolution of semantic networks to support reasoning is observed. Designed for representing knowledge in patterns of interconnected nodes, semantic networks become more and more appealing in Artificial intelligence (AI) and Natural language programming (NLP). This state of the art points out to the need for newer science of mind in terms of cognitive systems promoted on cybernetic viewpoint, where the developed cognitive models try to reveal and reflect human perception, knowledge and experience. Scrupulous representation of natural objects or scenes through revelation of their most important characteristics will mostly condition the accuracy of the implementation. With the help of cognitive technologies, computers learn to feel the world around them through sensors. Combining the two types of solutions implementing: a) strict mathematical logic with traditional computing of structured data, and b) cognitive technologies capable to manage enormous quantity of unstructured inputs, opens a new horizon in the development of modern intelligent systems.

Background and Related Works

A cognitive system can be viewed as a resource-constraint physical device designed over a set of equations implementing human-level cognition and reasoning. While embedded systems are a whole or a part of a larger assembly of a specific functionality, intelligence is the capability of a computer-controlled system to perform human-specific tasks and achieve self-awareness. Development of methods and software tools enabling real-time decision making based on collective intelligence in ad-hoc substructures is another possibility to codify and stimulate consciousness.

Among other concerns, and given the wide spectrum of intellectual tasks, information integrity and security in data collection, storage and exchange are other major issues. Similar to human blood-brain-barrier (BBB) which is a highly selective border of endothelial cells that prevent solutes into the central nervous system where neurons reside, hardware and software based cognitive systems' architecture should involve cyber defense firewalls in order to maintain and test the business continuity, fault-tolerance and disaster recovery.

In his work [1], Max Tegmark explored physics implications of the so-called External Reality Hypothesis (ERH) and Mathematical Universe Hypothesis (MUH). He stated that there exists an external physical reality completely independent of humans. While discussing various implications of the ERH and MUH, ranging from standard physics topics like symmetries, irreducible representations, units, free parameters, randomness and initial conditions, the author focused on broader issues like consciousness, parallel universes and Gödel incompleteness. He hypothesized that only computable and decidable (in Gödel's sense) structures exist pointing to a definite relation between physical systems, mathematical structures and simulation.

Nevertheless, the goal in designing a cognitive machine as a new kind of consciousness should not be to imitate human behavior: some of these structural characteristics are different from those displayed by the neurons of the human brain. With this regard, natural action selection, as a task of deciding “what to do next”, is a general problem facing all autonomous entities, such as animals and artificial agents. Based on clear understanding of the inherit bases of behavior, two major areas of focus are: what constitutes an action, and how actions are selected.

Similar to human brain that is composed of the cerebrum, cerebellum, and brainstem, each of which having own lobs, computational cognitive systems comprise multiple self-organized agents with distributed intelligence.

C. Zhang and A. Hammad proposed collaborative multi-agent systems for real-time monitoring and planning [2]. The potential advantages of the proposed approach are: more awareness of dynamic construction site conditions, a safer and more efficient work site, and a more reliable decision support based on good communications.

In case the cognitive system simulates a collective behavior, like swarms or fish forest, information full exchange between the agents promote another vital characteristic to the model such as: *collective intelligence*, where intelligence of a group of nodes is greater than the sum intelligence of the individual members [3].

D. Novick described a rule-based shell for multi-agent problems involving actions, beliefs, and communication [4]. Conventions for clear representation of actions, beliefs, and goals are introduced and applied in cooperative problem solving and in developing robust, naturalistic coordination of autonomous agents.

G. Weib introduced a methodology in learning in reactive multi-agent systems [5]. The central problem addressed was how several agents can collectively learn to coordinate their actions such that they solve a given environmental task together. In approaching this problem, the author took two important constraints into consideration: the incompatibility constraint, that is, the fact that different actions may be mutually exclusive; and the local information constraint, that is, the fact that each agent typically knows only a fraction of its environment.

Terminology used to describe and promote cognitive systems comprises the following concepts: *agents* (event-driven entities which are trained to learn and make relevant decisions), *environment* (with which agents interact without capability to change), *agent state* (parameters and property values), *actions* (decisions that are predefined and hardcoded in advance), and *policy* (probability distribution assigned to the set of actions).

Mathematical framework used to model and solve decision-making problems with partly random and partly controllable outcomes involves reinforcement learning equipped with well-known Markov Decision Process (MDP) utilizing Markov Property. Markov property holds in models where the values in any state are influenced only by the values of preceding states, as follows:

$$p(x_1 x_2 \cdots x_n) \approx \prod_{i=1}^{n} p(x_i \mid x_{i-k} x_{(i-k)+1} x_{(i-k)+2} \cdots x_{i-1}),$$
$$1 \le k < i \qquad (1)$$

In case the parameter $k=1$, the current state properties will depend on the immediately preceding state reflecting the behavior of the first-*order* Markov process. Higher order Markov processes are modeled with higher values of the parameter.

Representation of the Machine Consciousness as a Multi-Agent System

When speaking about creating machine intelligence and consciousness, one should not induce copying every detail of human thinking, behavior or performance: we are free to consider human intelligence like a pattern to follow meanwhile being encouraged by rather the likelihood or the possibility to touch the goal in creating machine intelligence. Note: achievements in this area are remarkable. There are many different kinds of activities that human-created devices or microprocessors do in an obviously better way: *remembering* or *forgetting* as many items as needed; working tirelessly; making labor-intensive calculations days and nights; classifying input parameters according to their quality and relevance; dominating human opponents in chess, etc.

Anyway, if we look at the achievements and solutions in AI, we will notice that all the great projects are mainly constrained in their specific tasks performance: computer program winning the chess champions cannot detect and identify a parrot! Especially from this point of view, machine consciousness should be viewed and promoted rather as a heterogeneous multi agent simulation system, where each agent presents a specific awareness, skill and intelligence. Meanwhile, the simulation effects back and impacts the agent self-awareness by information and experience analysis rather than commanding or waiting for outside instructions. Each awareness is autonomous, embodied and pro-reactive, also learning is non supervised. Traditionally, agents continuously observe the environment (that is the consciousness, the simulation) where they are situated in, and permanently react to environmental changes. Thus, an agent acting behavior is a best guess about the most likely state of the environment. This is the way the system perceives, learns, decides, predicts, and produces relevant actions, whereas the cognition (the mind) of the system is evolved gradually through perception of the entourage by combining experimental knowledge and the trained wisdom (thoughts).

We suggest presenting the abstract architecture of cognitive systems in terms of relevant mathematical structures, as follows:

$$MS = \langle E,\ S,\ Node,\ KBp,\ Wu,\ Ac,\ Ag,\ Fb \rangle \quad , (2)$$

where

- E is the set of states of the environment,
- S is the set of states of the agent,
- $Node$ is a vertex on the semantic graph. The nodes assume accumulating knowledge, history and evolving operational capabilities of the agents.
- KBp is the knowledge base pool which collects and assimilates the derived information,
- Wu is the unit of so-called *Wisdom* which can be implemented combined with an embedded expert system. The unit decides on the best strategy to utilize the knowledge and to interact with other agents relevant to the scope of interaction.
- Ac is the set of actions which are selected in accordance with the current decisions made,
- Ag is the agent which in its strict mathematical formulation is a chain of mappings, as follows:

$$E^* \to S \to Node \to Kb^* \to Wu \to AC \, . \qquad (3)$$

- Fb is the feedback which is activated upon completion of every execution of actions, and presents the mapping shown below:

$$Fb \rightarrow Node \rightarrow Kb^{*} \rightarrow Wu \rightarrow Node^{*}. \quad (4)$$

Feedback semantics may involve quality and quantity criteria in order to best evaluate the agent performance. A current mission achieved, the feedback will contribute to the reinforcement learning by assigning a computed weight aimed at the evaluation of the consistency of actions.

Below is a brief overview of the concepts which outline the proposed model.

In this closed system of self-organized agents,

- The classified nodes are specified using formulae of first-order predicate logic,
- The integration of discrete data (limited travers path of the graph) is performed on the analysis of how attitudes are formed and changed (the current state of the agent vs the momentum state of agent that is generated after processing 2 nodes at minimum),
- The corresponding candidates of existing cognitions or thoughts are selected from the knowledge base pool and are inferred through assimilation of the derived information and skills.
- Through evaluation of generated candidate knowledge against the current state and the environment, the Wu selects the best strategy to react to stimuli. Wu can also negotiate other agents to decide on the best expert knowledge in case of uncertainty and/or concurrency of strategies.
- The best strategy (of a higher probability) selected, the prescribed Ac will be executed.

Semantic Graph for a Cognitive System: Mathematical Preliminaries and Construction

By a non-strict definition, a semantic graph is a directed or undirected network, where nodes represent concepts, and arrows represent logical (semantic) relationships between those concepts. Semantic graphs allow developers to directly use a natural language constructs and vocabulary to label the nodes and edges, and this is a convenient way to allocate concepts/entities/nouns on the graph vertices, meanwhile, the logical relations combining those concepts will label the edges of the graph.

The proposed construction embeds an <Entity-Responsibility-Semantic Link> triad, where Entities possess knowledge, skills and competencies and are responsible to perform the prescribed actions, whereas, the semantic links enable information exchange, deliberation and collaboration. For the purpose, a *value/weight* type of a cellular automaton defined as a 4-tuple is introduced, as follows:

$$CA = \langle Z, S, N, f \rangle$$

Where,

- Z is a finite lattice,
- S is finite set of cell values,
- N is the finite neighborhood,
- f is the transition function.

Specifically, nodes get connected by a certain wisdom.

Allocation of the knowledge and activation of actions to train the model involves the following steps.

1. Travers paths get selected according to input data and state. This can be achieved by using algorithms of Breadth-First or Depth-First traversal of graphs.
2. Connections get validated applied a relevant predicate calculus which filters available logical links through reinforcement learning,
3. Training of the current cell achieved, connections are assigned numerical values,

4. Current state and the volume of the assimilated knowledge reconfigures the activation networks based on weights which are assigned using Greedy algorithms suggesting selection of the best strategy to react.

Definition: A finite state cellular automaton is said to recognize the subset $W \subseteq A^*$ over an alphabet A, and implements a deductive logic, when

- the machine is started in a specific initial state s_0,
- the machine produces a 1 output for each sequence in W, and otherwise produces a 0 output. This can be achieved by applying algorithms for tracing decision trees in the random forest, here, in the semantic graph.

The mind of conscious agents is constructed with an assumption that the entourage contains:

- *objects*, like: entities; theories; knowledge; skills; experiments, etc.,
- *relations*, like*:* partial orders; chains; comparisons; control structures, etc.;
- *functions,* like: regression; classification; clusterization; calculus, etc.

Governianceof the Thoughts of the Agents: First Order Logic Synthesis

In the proposed model, the self-awareness of the agents assumes involving the following concepts and constituents:

- *Variables*, such as: $x; y; z$, etc.,
- *Coefficients*, such as: $a; b; c$, etc.,
- *Constants*, such as: π; Virus Name; Shapes (diamond; spade); pieces (King; Bishop), etc.,
- *Predicates,* such as: is Visited; is Even; is Connected, is Activated, etc.,
- *Mapping,* such as: injection; association; self-association; bijection, etc.,
- *Logical Connectives*, such as: $\wedge; \vee; \neg;$
- *Quantifiers,* such as: $\exists; \exists!; \forall$, etc.

Note, that here, the theory of quantification is built over classical propositional logic formalized by Hilbert and Ackermann. They suggested to put propositions in conjunctive, or disjunctive, normal form, and have shown how one can use those forms to describe all the consequences of a finite set of propositions. Later on, by following the principles of axiomatization, Hilbert and Ackermann stated that the most important questions which arise, are of *consistency, independence* and *completeness*.

Accuracy of the proposed model implies application of the Gödel principal proof of completeness of the derived semantical consequences.

Description and implementation of quantification and the proof of completeness are solution-specific and are out of the scope of this paper.

In the proposed model, first-order sentences are made equivalent to Boolean combinations of distinguishability sentences. The approach allows to decompose deductive thoughts of the agent into a set of distinct statements and make them to interact in order to achieve information accumulation, deduction and exchange. 2450

For a given semantic graph, first order logic fully reflects the binary relations over dynamically selected vertices which get connected logically and ad-hoc. For example, for a given semantic graph $G(V,E)$ with the set of vertices V and the set of edges E, the following first-order logic implements predecessors: $E(a,b) \wedge \neg E(b,a)$, $a,b \in V$.

The cellular automata recognizing words over W of the form $W = \langle \forall^*, E, E!, E^* \rangle$ will be capable to process phrases *for every x* (called a *universal quantifier*)combined with the phrase "there exists an x such that'' (an *existential quantifier)*. Accordingly, a formula that contains variables gets evaluated provided each of these variables is bound by a quantifier.

Besides the core (initial geometric) construction of semantic graphs, provision of logical connectedness becomes vital. In order to meet intellectual requirements, dynamic linkage of the nodes will implement current wisdom and required actions: agent attitudes toward intuition and action selection.

It is well known that in order to promote some theory, underlying axioms are required. As stated by mathematicians, axioms should be true without any proof due to their obviosity. Among the axioms for semantic graphs, perhaps the most important is the development of the *axiom of choice*.

We suggest using lattice-valued predicate logic in order to promote axioms for semantic graphs by introducing lattice-valued closure and separation operators (at minimum). Good examples are axioms reflecting closures under group operations, or partial belonging and total nonbelonging relations between nodes of the sematic graph which get activated in order to meet some strategy. This inevitably implies involvement of semantics, formulas and consequence relations.

Besides, computational theory of mind assumes to model learning and behavior based on processes such as prediction error and surprise represented in neural net modeling in cognitive science, AI and machine learning, known as error-driven learning and reinforcement learning. These concepts are mainly implemented by inference algorithms using Markov chain Monte Carlo and belief propagation. Bayesian approach in cognitive science, where judgments and decisions are interpreted by conditional probabilistic inference combining prior knowledge and current evidence, is another supporting mechanism and technology in the area.

The proposed solution also suggest a series of lattice operations supported, as follows.

Given S be the set of entities which present environmental symbols or discrete pieces of information,

- S^* will be the free monoid generated by S, i.e. contains all of the finite sequences of elements of S for a finite cellular automaton, and S is a partially ordered set,
- $+$ is a composition on S such that $x+y$ is the least upper bound for x and y, and presents the information additive integration
- $\times$ is a composition on S such that $x \times y$ is the greatest lower bound for $\boldsymbol{x}$ and $\boldsymbol{y}$, and presents the information distributive integration, both $+$ and $\times$ being associative.

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We require the least upper and greatest lower bounds to be compositions defined for each pair of entities and are unique for each pair of elements in the lattice.

Thus, for every area of application, a suitable cognitive system may be introduced, evolved and optimized based on permanent observation, feedback and reinforcement.

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