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Abstract— The purpose of this paper is to compare between a set of cognitive architecture where we conduct a detailed functional comparison by looking at a wide range of cognitive components, including perception, goal representation, memory types, learning mechanism and problem-solving method. This comparison aims to determine the most appropriate architecture for our e-learning system.

Keywords— Cognitive architecture, Cognitive science, Hybrid approach, Multi-Agent Systems (MAS), e-Learning, systems.

I. INTRODUCTION

Early in the development of semantic web, Multi-agent systems (MAS) come to show their relevance for design and modeling of complex systems. Actually, the concept of an agent is the technology that is more efficient; it represents a new paradigm for the development of intelligent systems that are characterized by the ability to represent adaptive behavior, rational, and the ability to communicate and to act autonomously to achieve their own goals [1].

In this perspective, we try to build a multi-agent system in e-learning environments, that can create an intelligent system aims to minimize the intervention of a human expert in the performance of a task, to facilitate localization and customization of appropriate e-learning resources, thus to foster collaboration in e-learning environments. After determining our main goal, we must think now how can we build this system? Moreover, what are the most flexible components that must be previously considered?

Consequently, the objective of this paper is to provide some rational, structured access to an analysis of cognitive and agent architectures. Six architectures have been used for this preliminary analysis representing a wide range of current architectures in artificial intelligence. This study is based to determine the cognitive architecture that has been designed to be consistent with what is known from cognitive science and neuroscience. It must represent a working model of human cognition more than being just a computational architecture. The cognitive architecture should be similar that the human architecture in terms of its capacity to have various forms of learning, memorization, making decisions and reasoning.

This paper is divided into four main parts. In Section 2 deals with general principles of cognitive architecture concepts and the classification of these different approaches, specifying the advantages and given the limitations of each. Section 3 compares a kind of cognitive architectures with reference to a multitude of criteria covering perception, goal representation, memory types, learning mechanism and problem-solving method. And Section 4 represents an analysis that determines the most suitable architectures to our system.

II. COGNITIVE ARCHITECTURE

A. Definition

Cognitive architecture is a term used with some frequency in modern cognitive science [2]. It was brought by Newell through an analogy to computer architecture [3]. The cognitive architecture is a set of mechanisms of human cognition, which is through the use human knowledge process, specifically it is based on the simulation of human behavior to create a model capable of understanding, reasoning, and problems solving.

The cognitive architecture defines the manner in which a cognitive agent manages the primitive resources at its disposal [4]. It can be defined as is the overall essential structure and process of a domain-generic computational cognitive model, used for a broad, multiple-level, multiple-domain analysis of cognition and behavior. The premise of Anderson's theory is that the human mind can be characterized, like a computer, as a mechanism (hardware) that executes programs [5]. According to Anderson cognitive architecture is defined as “A cognitive architecture is a specification of the structure of the brain at a level of abstraction that explains how it achieves the function of the mind.” [2]. The development of cognitive architecture is based on memory and learning. As shown in the figure below, the combination of these two elements forms a taxonomy of three main categories of cognitive agent architecture: symbolic, emergent, and hybrid models [5].

B. Cognitives Architectures Models

Cognitive architecture is a term used with some frequency in modern cognitive science [2]. It was brought by Newell through an analogy to computer architecture [3]. The cognitive architecture is a set of mechanisms of human cognition, which is through the use human knowledge process, specifically it is based on the simulation of human behavior to create a model capable of understanding, reasoning, and problems solving.

1) *Symbolic Architecture:*Symbolic model is one of the three main approaches to model cognitive architectures. It is based on two key concepts that are representation and computation [6].

2) In this traditional approach, human cognition can be thought of in much the same way, as a symbolic manipulation process [7], for this it's interested in the mind that compared to a computer.

Symbolic cognitive architectures are the classical representation theory that considers the mental operations on knowledge pass through symbolic representations and which information processing is executed in a serial and hierarchical way. Generally, symbolic approach focus on "working memory" that draws on long-term memory as needed, and utilize a centralized control over perception, cognition and action [8].

However, the cognitive approach known practical and theoretical limits; as regards the first include the difficulty of access to human knowledge and complexity of such processes, and with regard to the theoretical limits, equally difficult problems arise [6].

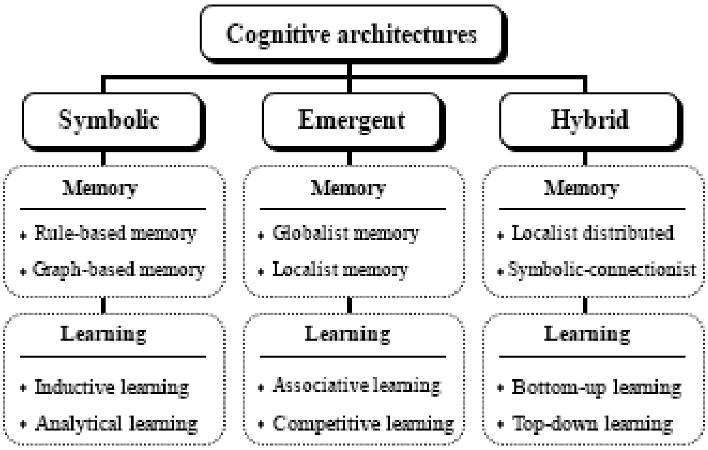

Figure 1: Simplified taxonomy of cognitive architectures

3) Emergent Architecture:

Another kind of cognitive architecture is interested in the brain and trying to understand cognition with neural networks, this approach assumes that there is no mental representation. In Emergent approach, cognition is the process of adapting to the environment through maintaining its own autonomy, it considers that perception is represented in the acquisition of sensor data and assert that the primary model for cognitive learning is the anticipative skill construction rather than knowledge acquisition [9]. The emerging approach includes together connectionist, dynamical and enactive systems [10]. The big difference from cognitivism, so that neural networks are not programmed, but they are driven.

4) Hybrid Architecture:

Hybrid approaches which combine aspects of the emergent systems and cognitivist systems. In practice, they combine the advantages of symbolic architectures to represent its world and rule based reasoning to reason about its knowledge. And lower level, sub-symbolic architectures by performing emergent actions to explore the world and construct its knowledge base [9]. Their objects should be represented as invariant combinations of precepts and responses, where the object properties need to be learned through object manipulation.

The aim of developing such systems is that they learn tasks that they were not explicitly designed for. It tries to find a kind of focal point with recent models of multi-agent systems.

III. COMPARATIVE CRITERIA

In this section, we try to compare a various cognitive architecture according to several criteria that are Underlying Architectures Models, Goal representations, Components, Perception, Memory types, Learning mechanisms and Problems solving methods.

A. Underlying Architectures Models

As previously informed, cognitive architecture can be symbolic, emergent or hybrid. In Soar, clustering is subsymbolic, where non-symbolic perceptual structures are combined together to create symbols [11]. ACT-R is a hybrid cognitive architecture where the subsymbolic equations control many of the symbolic processes [12]. A 4CAPS model consists of a set of centers; each center is a hybrid symbolic/connectionist system with a resource supply of fixed capacity [13]. CLARION a fundamentally hybrid architecture [14]. The LIDA architecture is partly symbolic and partly connectionist with all symbols being grounded in the physical world in the sense of Brooks [15]. DUAL is hybrid (symbolic/connectionist) cognitive architecture, it is hybrid at the micro level (i.e. it consists of hybrid agents) rather than at the macro level (i.e. it does not consist of separate symbolic and connectionist modules) [16].

TABLE I - UNDERLYING ARCHITECTURES CRITERIA

Cognitives Architectures	Underlying Architectures
SOAR 9	Hybrid
ACT-R 7	Hybrid
4CAPS	Hybrid

CLARION	Hybrid
LIDA	Hybrid
DUAL	Hybrid

B. Goal Representation

Goal setting is a cognitive process of the brain at the perception layer that is represented by a target state that an agent wants to achieve for a motivation or an action. In ACT-R, a goal can be decomposed into subgoals and the new goals are added into the goal stack in ACT-R. A goal is subsequently removed from the goal stack once it is accomplished [17]. In CLARION, a motivational subsystem creates and stores goals using a goal structure, which can be a goal stack or a goal list [18]. Whereas the goal stack works in a similar way as other architectures, the goals in a goal list can be accessed randomly and they compete with each other to be the current goal [19].

TABLE II - GOAL REPRESENTATION CRITERIA

Cognitives Architectures	Goal Representation
SOAR 9	SOAR supports automatic impasse-driven subgoals [11].
ACT-R 7	Goals are stored in the intentional module and are available to the central production system via the goal buffer [20].
4CAPS	It adds the task-goal class of declarative memory element.
CLARION	A motivational subsystem creates and stores goals using a goal structure.
LIDA	In the LIDA model, drives and goals are not built-in [21].
DUAL	The goals will be represented by active agents in the semantic memory [22].

C. Components

Each of the architectures has its own set of components where some are similar to each other while others are different. In SOAR the new components influence decision making indirectly by retrieving or creating structures in symbolic working memory that cause rules to match and fire [11]. ACT-R's main components are modules (perceptual-motor modules, declarative memory modules and procedural memory modules), buffers and pattern matcher. 4CAPS is based on a number of centers corresponding to particular brain areas [5]. In particular, CLARION is made up of subsystems: memory retrieval and inference, motivational processes, decision making, and metacognition [23]. Each DUAL agent consists of two parts: L-Brain and R-Brain, designed according to the symbolic and connectionist paradigm, respectively [16].

TABLE III - COMPONENTS CRITERIA

Cognitives Architectures	Components
SOAR 9	Working memory activation, Reinforcement learning, the appraisal detector, Semantic memory, Episodic memory, A set of processes and memories to support visual imagery and Clustering.
ACT-R 7	Perceptual-motor modules, Goal module, Declarative module, and Procedural system [20].
4CAPS	Centers; Declarative elements; Procedural Memory.
CLARION	It distinguishes itself by addressing the fusion of symbolic and sub-symbolic information and metacognition [14].
LIDA	Learning, memory and decision making [14].
DUAL	L-Brain and R-Brain.

D. Perception

Perception is the first step in social cognition, it involves the cognitive processes required for organization, identification, and interpretation of sensory information in order to represent and understand the environment. In this step, an agent may sense the world through different modalities, just as a human has access to sight, hearing, and touch [24]. The perception is essentially the interface between the outer (environment) and inner worlds of the system. The perceptual process combine of a set of senses involving the ability to detect changes in the environment.

In Soar, clustering is subsymbolic, where non-symbolic perceptual structures are combined together to create symbols [11]. ACT-R in its original form did not say much about perceptual and motor operations, but recent versions have incorporated them. The input into CLARION is a series of dimenion/value pairs describing the state of the world. It consists of the objects in the environment, as well as the items in the working memory and the current goal(s) [19].

TABLE IV - PERCEPTION CRITERIA

Cognitives Architectures	Perception
SOAR 9	Perceptual information is submitted to the clustering module then they are stored

	in short-term memory [11].
ACT-R 7	There are modules for perception (visual and aural) [25].
4CAPS	4CAPS provides a planning framework. It can represent beliefs independent of perception [9].
CLARION	Perceptual input represented as dimension/value pairs
LIDA	Perception: The process of assigning meaning to incoming sensory data [21].
DUAL	DUAL have a lot of other features like the perceptual mechanisms of Copycat.

E. Memory Types

Several researchers have proposed that memory is not a unitary process, but rather, consists of multiple interacting systems, which differentially contribute to is our ability to encode, store, retain and subsequently recall information and past experiences in the human brain [26]. All architectures mainly consist of a memory that is either short-term memory or long-term memory.

Soar Cognitive Architecture has consisted of a single long term memory, which is encoded as production rules, Symbolic short-term memory holds the agent's assessment of the current situation derived from perception and via retrieval of knowledge from its Long-term memory [11]. In ACT-R a declarative memory module that stores episodic and semantic information, and a number of sensory and motor modules [27]. CLARION has a variety of memories: general "semantic" memory in both implicit and explicit forms, episodic memory, procedural memory in both implicit and explicit forms, working memory [28].

TABLE V - MEMORY TYPES CRITERIA

Cognitives Architectures	**Memory types**	
	Short term memory	**Long term memory**
SOAR 9	Symbolic short-term memory.	Semantic memory, Episodic memory and a set of memories to support visual imagery.
ACT-R 7	Contains goal, perception, relevant knowledge, and motor action in the various buffers [19].	Declarative memory and Procedural memory [2].
4CAPS	Working memory contains storage and processing aspects.	Declarative memory and Procedural memory [13].
CLARION	Working memory.	Semantic memory, Episodic memory, Procedural memory.
LIDA	Working Memory buffers [15].	Procedural Memory and Episodic Memory.
DUAL	The Working Memory consists of the currently active agents [16].	The Long-Term Memory of the cognitive system includes all the DUAL agents.

F. Learning mechanism

Ohlsson decides that there are nine different modes of learning and insist that the interoperation of such modes is the key to human success in this world [29].

Chunking is Soar's learning mechanism that converts the results of problem solving in subgoals into rules – compiling knowledge and behavior from deliberate to reactive [11]. 4CAPS suggests a new mechanism for strategy innovation—namely, the dynamic formation of novel and noncanonical large-scale networks [13]. Clarion : Both top-down and bottom-up learning are supported in such a way that low-level procedural knowledge develops first followed by higher-level declarative knowledge at later stages [14]. LIDA (Learning IDA) adds three modes of learning to the IDA model: perceptual, episodic, and procedural learning [21].

TABLE VI - LEARNING MECHANISM CRITERIA

Cognitives Architectures	**Learning Mechanism**
SOAR 9	Reinforcement Learning, Semantic learning, Episodic learning and Chunking learning mechanism.
ACT-R 7	Declarative Learning, Procedural Learning [2].
4CAPS	New strategies result from organizations of existing brain areas into non-canonical large-scale networks.
CLARION	Both top-down and bottom-up learning [14].
LIDA	Perceptual, Episodic, and Procedural learning [21].
DUAL	DUAL have a lot of other features like the learning mechanisms of ACT*.

G. Problem-Solving method

Problem solving is one of the fundamental cognitive process of the natural intelligence of the brain that searches a solution for a given problem or finds a path to reach a given goal through an integration with many other cognitive processes such as abstraction, research, learning, decision making [30].

In SOAR, problems are solved by decomposing the goal into hierarchical subproblems. Problem solving in ACT-R occurs via the activation of chunks in the declarative memory and the retrieval of knowledge from the procedural memory [19]. The problem solving mechanism for CLARION has not been explicitly outlined in the literatures reviewed. However, CLARION combines recommendations from the top and bottom levels to decide on appropriate reactions. The process of searching for appropriate actions may be considered as a form of problem solving [19].

TABLE VII - PROBLEM-SOLVING METHOD CRITERIA

Cognitives Architectures	Problem-Solving Method
SOAR 9	Soar incorporates a wide range of problem solving methods and learns all aspects of the tasks to perform them [31].
ACT-R 7	Activation of chunks and the retrieval of knowledge.
4CAPS	The general model inherits its problem-solving mechanisms from Soar.
CLARION	Combination of Q-values calculated in the bottom level and rules in the top level to choose the course of actions [19].
LIDA	Non-routine problem solving algorithm.
DUAL	Symbolic processing and activation function in node and link manner.

IV. A SURVEY ANALYSIS

In our context, which in summary is the construction of a multi-agent e-learning system, there seems to be more of a trend toward the integration components from symbolic architectures in hybrid architectures, rather than taking a purely symbolic approach. The thing that makes us stand facing a multitude cognitive architecture that can be useful. These cognitive architectures can share many characteristics of artificial intelligence, including symbolic representation, production rule based inference, and problem solving methods. This requires us to specify the most suitable architecture for our system.

From Section 3, we can see that for each cognitive architecture there is a tension between functional and theory goals. From the functional perspective, there is pressure to add features and mechanisms to capture several phenomena. From the theory perspective, there is pressure to simplify the representations and eliminate features that are not strictly necessary architecture.

In ACT-R learning processes have to attempt several different ways to represent knowledge, so that the optimal one can be selected. It can distinct between declarative and procedural knowledge. ACT-R has a separate procedural and declarative memory, each of which has their own representation and learning mechanisms. In addition to that, ACT-R has a modular structure, which cannot arbitrarily access any information it wants, but has to communicate with other systems through a buffer interface [32].

ACT-R is notably different from Soar by its strong emphasis of producing a psychologically motivated cognitive model [19].

CLARION is made up of subsystems: memory retrieval and inference, motivational processes, decision making, and metacognition, but a great deal is still missing such as learning, episodic knowledge and creativity [14].

LIDA features several types of specialized memory, however its drives and goals are not built-in, and in addition it have the flaw of relying on overly simplistic learning algorithms, which drastically limit their scalability. Moreover, it does not address time in an explicit fashion [14].

The Dual approach seems promising and innovative, but it is difficult to know how the approach will scale to high-dimensional data or complex reasoning problems due to the lack of a more structured high-level cognitive architecture.

Finally, we choose between ACT-R 7 and Soar 9 as our examples to review here in detail, because these are the symbolic architectures that have been most closely tied in with the human brain structure and function.

V. CONCLUSIONS

In this paper, we have presented a research in the field of cognitive architectures by providing a comparative survey between several of cognitive architecture. That may allow us to identify the most appropriate architecture for our system.

In the next research, we will try to stabilize the architecture to conducting a functional and detailed comparative study between the two cognitive architectures Soar and ACT-R.

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