A Human-Inspired Cognitive Architecture Supporting Self-Regulated Learning in Problem Solving

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Abstract

Many approaches were explored in recent years to introduce principles of metacognition and meta-learning into cognitive architectures, yet none of them resulted in a scalable human-like learner. This work presents an approach intended to fill the gap between human self-regulated learners and artificial learners by introducing a new spin of the familiar core cognitive architecture paradigm, taking it to a meta-level. The resultant architecture enables in artifacts exclusively human higher cognitive and learning abilities: specifically, deliberative new knowledge construction. Model predictions agree with results of a pilot study with human subjects.

Traditional Cognitive Architecture Paradigm and Its Limitation

A *cognitive architecture* is a computational model that describes functional components of a complete intelligent agent and their interactions (Newell, 1990; SIGArt, 1991; Pew and Mavor, 1998; Ritter et al., 2003; Gluck and Pew, 2005; Gray, 2007). Traditionally, cognitive architectures emerge as blueprints of agents capable of intelligent behavior when embedded in a proper environment that may include other artificial and/or human agents. For this and other reasons, cognitive architectures are frequently human-inspired. E.g., their main structural components include the basic memory systems found in humans: procedural, working, semantic, episodic (e.g., Laird, 2008, cf. Cohen and Eichenbaum, 1993). Cognitive architectures are usually characterized and compared to each other based on these components plus general functional capabilities (e.g., http://members.cox.net/bica2009/cogarch/).

Another, equqlly important characteristic of a cognitive architecture is its top-level dynamic cycle. It is less used for comparison or characterization, because most cognitive architectures are based on one and the same standard template – essentially, a cycle of three fast-alternating phases of information processing:

(i) sensory perception,
(ii) cognition and decision making,
(iii) behavioral action.

For example, the execution cycle in Soar consists of (i) Input, (ii) Proposal and Decision, and (iii) Application and Output (Laird and Congdon, 2009, p. 21).

This general paradigm has a limitation: not all examples of human intelligent activity are well-captured by the above template (i)-(iii). For example, imagine a student working on a complex mathematical problem using her mind only, without paper or computer. She already understood the given data and is exploring various approaches. She comes to a solution plan and at the same time learns how to solve similar problems, doing all this without utilizing phases (i) and (iii). What are we missing?

A Metacognitive Architecture Paradigm

The essence of the concept of metacognition (or metareasoning, which is understood more narrowly: Cox and Raja, 2007) is captured by Figure 1. It involves at least two levels of cognitive representations in the system: "object" and "meta" levels. Figure 1 clarifies the similarity between cognitive and metacognitive levels: the two cycles of information processing are organizationally equivalent.

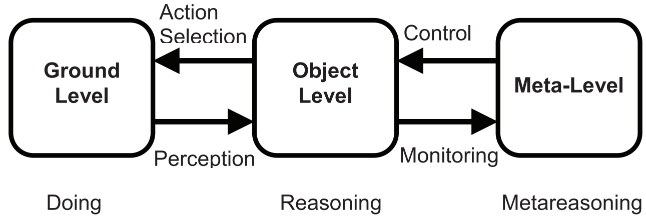

Figure 1. The general framework for metacognition in a cognitive agent architecture (from Cox and Raja 2007).

Indeed, introspective monitoring at the meta-level appears to be analogous to perception at the object level, and metacognitive control appears to be a counterpart of behavioral action selection. Both cycles are consistent with the template (i)-(iii), which at the meta-level becomes:

(iv) introspective monitoring,

(v) metacognition and self-instruction,

(vi) metacognitive self-control.

The detailed interpretation of Figure 1 may vary (Russel and Welfad 1991, Cox and Ram 1999, Raja and Lesser 2007), yet the question remains: does this scheme explain the above example with the student?

It seems that an explanation of this sort would suffer from the same problem: the functioning of the object level, which is necessarily involved in problem solving, according to Figure 1 depends on continuous perception and action in the physical environment, contrary to the example. In addition, Figure 1 does not capture the process of learning (while in principle it has room for it).

Self-Regulated Learning Paradigm

Could it be that the key to understanding what happens in student's mind in the above and similar examples is the notion of *self-regulated learning* (SRL)?

Self-regulation refers to the degree to which a learner is a metacognitively, motivationally, and behaviorally active participant of his or her learning process (Zimmerman, 2002). SRL is a critical strategic thinking process for supporting students' abilities to learn and solve problems. The concept of SRL plays the central role in modern educational science. In general, SRL involves a complex set of techniques and strategies employed by learners for deliberate regulation of their learning processes (Winne and Perry, 2000; Winne and Nesbit, 2009).

According to Zimmerman (1990, 2000, 2008), SRL includes 3 phases that appear to be analogous to the aforementioned phases (i)-(iii). They are known as

(a) *Forethought*: understanding the task, setting goals and attitudes, selecting strategies, planning steps…

(b) *Performance*: executing the plan, trying out strategies under self-monitoring and self-control…

(c) *Reflection*: self-evaluation, causal attribution of outcomes, conflict resolution, adaptation, etc.

The essential difference between (i)-(iii) and (a)-(c) is in their targets: the environment in the case of (i)-(iii) and the knowledge of how to solve problems in the case of (a)-(c). This knowledge is being actively constructed by the agent in working, semantic and episodic memory systems, possibly without interaction with the environment. The difference between (a)-(c) and (iv)-(vi), in addition to the targets, is in the level of cognition at which the main information processing occurs. The similarities between all 3 examples are in the functional organization of the cycles.

A Unifying Architecture

Based on the intuitive analogy between the cycles (i)-(iii), (iv)-(vi) and (a)-(c), it is possible to construct an architecture that unifies them. The idea is to introduce a new spin of the familiar core cognitive cycle template. The blueprint of a metacognitive architecture proposed in the previous work (Samsonovich, 2009) is used here as a prototype. The result is shown in Figure 2.

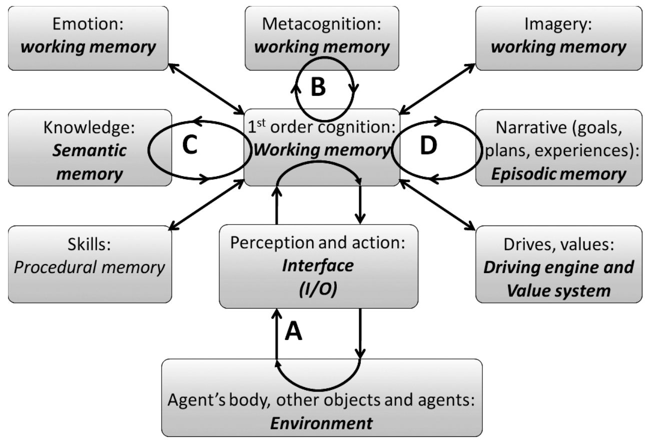

Figure 2. Generic cognitive architecture design consistent with the SRL paradigm. The design allows for support of metacognition, imagery, emotional and social intelligence. **A:** The main cycle of information processing, (i)-(iii). **B:** the metacognition cycle (iv)-(vi). The loops **B, C,** and **D** together implement the SRL cycle (1)-(3) that implements (a)-(c). **A** may not be involved in self-regulated problem solving. Some of the remaining arrows are potentially replaceable with similar cycles.

In order to implement the SRL cycle (a)-(c), it is necessary to understand that the main target of (a)-(c) viewed as a learning process belongs to the declarative long-term memory systems: episodic and semantic, and not to the environment or working memory. Therefore, the template (a)-(c) should be modified for implementation in a cognitive architecture as follows:

(1) retrieval and selection of relevant semantic knowledge and episodic memories,

(2) metacognitive construction of new goals, strategies, schemas and self-instructions, and

(3) the updating of episodic memories, semantic knowledge, meta-knowledge, self-image, the personal system of values, goals and attitudes, and conflict resolution.

It is interesting to note the analogy between memory retrieval / formation in (1)-(3) and perception / action in (i)-(iii). If this analogy applies to human cognition and learning, then human SRL in problem solving should resemble cognitive models of active perception, deliberative cognition and controlled voluntary action.

Traditionally, in cognitive architectures such as Soar and ACT-R (Anderson and Lebiere, 1998; Anderson et al., 2004) memory retrieval is done automatically at a lower cognitive level and without an explicit involvement of deliberation. Similarly, traditional forms of machine learning such as reinforcement learning or chunking do not involve the top cognitive level in the process of memory storage. In this context, the above analogy hypothesis may seem counterintuitive. It predicts that SRL processes that occur during problem solving in the human brain should not be similar to stochastic rule matching, but should resemble organized goal-directed behavior of an agent.

Example: A Pilot Study

In order to test the analogy hypothesis, the following study was conducted with 19 undergraduate student subjects who took the college course in linear algebra Math 203 at George Mason University. An idea of the study was to extract from the student mind the process of creation of a schema of solving a given kind of a problem. Example of a problem: determine whether a given set of 5 matrices spans the space of 2x2 matrices. Students worked in a computer-based learning setup designed based on the paradigm (1)-(3) that allowed them to use any of 24 given elements (general facts and steps) to construct "a plan" (schema) of a solution. This was done before the problem was attempted, as follows. First, the working window was populated by the student with selected relevant elements. Then, the student connected elements by arrows indicating their logical dependence and at the same time representing the skeleton of a solution. Student actions were recorded by the software. All new arrow additions were divided into 4 categories, depending on how the new arrow was adjacent to the previously added arrow: chaining (the new arrow starts from the end of the previous arrow), abduction (ends at the origin of the previous one), fan-out (starts at the origin), convergence (ends at the end) and not adjacent.

Results show significant predominance of forward chaining (34% of 448 arrow additions performed by all students together) compared to abduction (1.8%), fan-out (3.9%), and convergence (9.6%). In other words, students tend to construct the new schema by sequentially connecting given facts and steps into linear chains. Students were not instructed to do this, and the correct solution corresponds to a converging tree rather than to a linear chain.

This observation indicates that student SRL is based on imaginary perception of relevant knowledge and deliberate imagery of the sequence of actions rather than on random recognition of relevance and usefulness of selected facts.

Discussion: Connection to Social Systems

Social intelligence and social learning are key capabilities of social agents, that are also critical for the cognitive growth (individual development) of an agent. These capabilities rely on the key concepts of the self: the proto-self, the core, or minimal self, and the narrative, or self-conscious self (Damasio, 1999; Gallagher, 2000; Samsonovich and Nadel, 2005). The latter, narrative or self-conscious self, essentially amounts to the changing mental perspective of the subject and can be implemented in a cognitive architecture using structures called *mental states* (Samsonovich & Nadel, 2005; Samsonovich & De Jong, 2005) that populate working and episodic memory systems and play the key role in metacognition and SRL (Samsonovich, De Jong and Kitsantas, 2009).

The key difference between episodic and semantic memory systems from the cognitive architecture point of view is that episodic memory stores mental states, while semantic memory stores schemas (Samsonovich & De Jong, 2005). The notion of episodic memory in psychology also depends on the notion of a mental state and on the self concept (Tulving, 1983), and is much broader than the notion of memory of past events. Episodic memory stores personal experiences of all kinds and includes prospective and retrospective memories, goals, plans, dreams and imagination, etc.

Therefore, social capabilities critically depend on episodic memory and on the ability of the agent to construct episodic memories deliberately – in the manner outlined here. The limited volume of this paper does not allow discussing further details. The bottom line is that principles illustrated in Figure 2 appear to be critical for the development and expression of human-level social capabilities in intelligent agents – those capabilities that today are known to exist in humans only.

Conclusions

This work presented an approach that fills the gap between natural and artificial learners by introducing a new spin of the familiar core cognitive architecture paradigm. The three phases (1)-(3) described above and illustrated in Figure 2 are analogous to the traditional three phases of cognitive architecture dynamics (i)-(iii): *perception*, *cognition* and *action*, only now they work at a meta-level, with a different target, and critically depend on the concept of self as it is known in the human psychology (Gallagher, 2000; Samsonovich and Nadel, 2005). The outcome is a form of learning available for artifacts that currently is known to exist in humans only.

In conclusion, the challenge of creating a real-life computational equivalent of the human mind can be solved by designing a cognitive architecture that supports higher forms of human learning (Samsonovich, 2007). The present work makes a step toward this overarching goal.

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