Cognitive Constructor:
A Biologically-Inspired Self-Regulated Learning Partner

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Abstract

Limitations of modern artificial intelligence are most evident in comparison with the human ability to self-regulate cognitive and learning processes. Is it possible to model the human self-regulation ability in artifacts? And vice versa, can a computer model of this sort help students to develop self-regulation skills? This work describes a blueprint of an innovative intelligent tutoring system called Cognitive Constructor, to be used as a self-regulated-learning assistant to students in mathematical problem solving paradigms. Cognitive Constructor will enable parallel acquisition of domain-specific mathematical skills and general self-regulated problem solving skills. At the core of Cognitive Constructor is our recently developed cognitive architecture GMU BICA that provides a suitable basis for modeling self-regulated problem solving.

Introduction

Probably, the most exciting challenge of our time is to build a general-purpose artifact capable of human-level cognition. Modern supercomputer resources measured in total numbers of memory bits / bits processed per second approach those of the higher cognitive areas of the human brain (Samsonovich & Ascoli 2002). Nevertheless, modern supercomputers do not grow up into human-like "artificial persons". Software agents forever remain clueless outside domains and paradigms for which they were designed. The gap separating artificial and natural intelligence appears today almost as deep as it was 50 years ago, showing that the bottleneck is probably not in the hardware limitations.

Which particular property of the human brain-mind allows it to grow cognitively from a baby to an adult level of intelligence? What allows it to develop new domains of knowledge, create dreams beyond imagination of previous generations, and in some cases fulfill those dreams? Is it possible to replicate these capabilities and phenomena in a computational model, and if yes, then what would it take?

One possible (if not obvious) answer is that it takes human-level learning abilities. The challenge is then to identify and create a *critical mass* of intelligence that will be able to start the process of self-sustainable cognitive growth, plus to design the *ladder* (curriculum) that artifacts will follow in their cognitive development. The metrics and criteria for success, which constitute the real Hard Problem in artificial intelligence, should be based on practical realizations of the desired growth characteristics. Here the approach is to replicate human learning abilities, starting from the easiest point in development, and if no easy point exists in natural cognitive development, then creating one. One of the best ways to learn how to do this is probably by computational modeling of human learning.

If we now compare human learning to modern machine learning, then we can notice one very big difference: a complex of features labeled in the educational literature *self-regulated learning* (SRL: Figure 1). SRL involves deliberative construction of knowledge by using goals, strategies, self-reflection and self-control (Zimmerman & Schunk, 2001). SRL, either naïve or professional, is always a hallmark of human cognition and learning. The power of SRL is in the interplay among metacognitive, motivational and behavioral processes that enables their rational control.

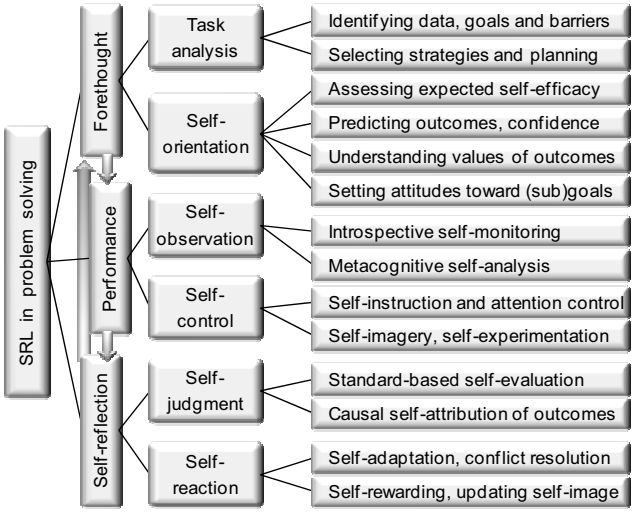

Figure 1. The cycle of three phases and the hierarchy of SRL components in problem solving (based on Zimmerman 2002, Zimmerman and Kitsantas 2006, Samsonovich et al. 2008).

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Implementing principles of human SRL in a computer will require a sort of biologically inspired cognitive architecture (BICA) that allows for self-awareness and metacognition. Incidentally, while a major goal of the DARPA IPTO BICA program (2005-2006) was to develop a biologically inspired embodied cognitive agent that could be taught like a human, there is a growing demand in school education for artificial intelligent agents that can dynamically model SRL processes and use this modeling to assist students in acquisition of SRL skills (e.g. Winne & Nesbit, 2009).

The SRL assistant that we call *Cognitive Constructor* (CC) is based on the cognitive architecture GMU BICA developed under the DARPA IPTO BICA program (Samsonovich & De Jong 2005, Samsonovich et al. 2006). Unlike other BICA, GMU BICA is self-aware, therefore, capable of modeling mental states and cognitive processes underlying self-reflection, self-monitoring, self-imagery, self-evaluation, self-guidance, self-judgment, self-experimentation, self-analysis, self-instruction, self-control etc., all of which are elements of SRL (Figure 1). This unique complex of features of GMU BICA defines the level of cognitive modeling that is new compared to existing state-of-the-art intelligent tutoring systems (ITS) and has only several examples explored so far in artificial intelligence in general (e.g., Kim & Gil 2008).

Designing CC-Based Interventions

Architecture and General Settings

Experimental setup for the study of CC-based interventions (Figure 2) includes five interacting agents: CC, the student, the teacher, and the designer of CC. CC in turn consists of two overlapping components: a computer-based learning environment (CBLE) and a pedagogical agent Bica based on GMU BICA. Here CBLE includes Semantic Memory (a database representing the curriculum), Procedural Memory (useful scripts and primitives), and a graphical-textual Interface. Bica shares with CBLE its Input-Output buffer used for interactions with CBLE, as well as Procedural and Semantic memories. Other components of Bica include Working Memory, Episodic Memory (both populated by mental states, current or past), Cognitive Map providing spatial representations of semantics, Reward System used for reinforcement learning, and the Engine that runs all components. The key building blocks of Bica (and therefore of CC) are (1) schemas[1] that are stored in Semantic Memory and populate mental states, (2) mental states that represent mental perspectives taken by the subject, and (3) Self axioms: organizational and dynamical principles and constraints that together implement the concept of Self and self-awareness (Samsonovich & Nadel 2005), thereby enabling metacognition and self-control. Finally, our Interface is also an innovative tool that uses the "magic wand" controlled by the mouse and free-style text messaging to manipulate objects on the screen, in addition to a traditional GUI (a demo of its rapid prototype is available at http://binf.gmu.edu/~asamsono/hpsi.wmv).

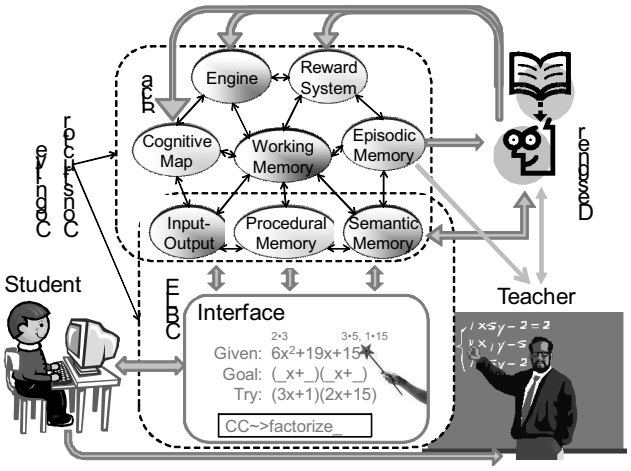

Figure 2. Experimental setup for study of interventions in math problem solving based on Cognitive Constructor.

The two concepts described above – SRL and Bica – can be mapped onto each other. Indeed, each box in the right column of Figure 1 can be viewed as a separate functional component of a cognitive architecture, with information flowing from one box to another. There are, however, too many boxes – elements of SRL that are not shown in Figure 1. Implementing them all as separate architectural components could be a difficult task. The solution is suggested by the fact that GMU BICA is a dynamical architecture: mental states in its Working Memory are continuously created, altered, moved from one mental perspective to another, deactivated, etc., and only several mental states are simultaneously active at any given moment of time. This feature suggests the following mapping principle: each (meta)cognitive perspective represented by a box in Figure 1 can be taken, when necessary, by a separate mental state in Bica's Working Memory (Figure 3).

Paradigms

Now we are ready to describe the general paradigm of an intervention based on CC (we assume that a student subject is engaged in CC-assisted problem solving over a prolonged period of time). The paradigm has three phases.

1. During initial sessions of interactive problem solving using the CC environment, Bica is used to build a model of the individual student mind.

2. This model is used by Bica to recognize mental states of the student from student's behavior, determine what kind of a difficulty the student experiences at a given moment, and provide the necessary SRL scaffolding.

3. Based on dynamics of the adaptive Bica model, as well as on more traditional SRL measures (Winne et al. 2002), the improvement of student SRL skills is measured over time, complementing the standard performance metrics.

[1] The notion of a *schema* is understood uniquely in this context: see Samsonovich & De Jong (2005), Samsonovich et al. (2006).

The intervention can be considered "working as expected", if (a) Bica adequately detects student mental states, as determined by the analysis of student-filled evaluation forms; (b) a systematic improvement of student's SRL abilities over time is observed; and (c) a significantly positive correlation is detected between student's SRL abilities and student's performance at the task level. This criterion naturally leads to quantitative measures of the outcome to be used for optimization of the CC malleable parameters, examples of which are described below.

An SRL assistant cannot teach 'pure SRL', and therefore needs to serve as a problem solving tutor as well. The main malleable parameter of CC is *metacognitivity*: the relative weight of SRL in all tutoring processes, including scaffolding provided by Bica to the student and Bica own internal representations. Metacognitivity is the degree to which metacognition and SRL are encouraged and supported by CC. Another malleable parameter of CC is *abstractness*: the level of detail in representation of knowledge in CC. Abstractness of CC determines the level of lower details in represented cognitive processes, including internal representations and interactions with the student: for example, the student may be relieved of the necessity to do routine arithmetic calculations manually (can get them done automatically with a correct button click) and focus attention on higher cognitive aspects of the problem. Alternatively, the student may be asked to perform every step manually in order to stimulate awareness and learning.

There are many other important features of CC that can be manipulated independently. The paradigm of iterative design of CC includes manipulating those parameters and selecting best combinations in a sequence of iterations, each consisting of a number of parallel laboratory or classroom experiments. The task is to find an optimal configuration of the intervention and also see how results depend on other factors (the domain, the level of difficulty, the level of student preparedness, etc.).

Illustrative Example

The three phases of a CC-based intervention can be implemented using a sequence of problems in high school algebra (which includes elements of probability theory). The illustrative example presented below demonstrates the possibility of making improvement in student SRL skills resulting in an improved problem solving ability over a period of time that is sufficient for a sequence of individual CC sessions. In this example we consider solution of the following three seemingly trivial word problems (modified from Michalewicz & Michalewicz, 2008).

- **Problem 1.** Parents have two children (not twins), one of which is a boy. What is the probability that the other child is a boy?
- **Problem 2.** In families with two kids, are boys on average more likely to have a sister, compared to girls?
- **Problem N.** According to a statistical report, the number of boys in classroom A is equal to the number of girls in classroom B plus five. What is greater: the size of classroom A or the number of girls in both classrooms?

Session 1

Suppose that after constructing (or retrieving) a representation of Problem 1 in CC, the student selects the following facts from the available knowledge base to be used in her solution (Figure 3):

- Each child is equally likely to be born as a boy or as a girl.
- The sex of each child is determined independently of other children.

The Bica agent is monitoring student behavior. In principle, this behavior could be viewed as indicative of an intention to implement a correct plan of solution; however,

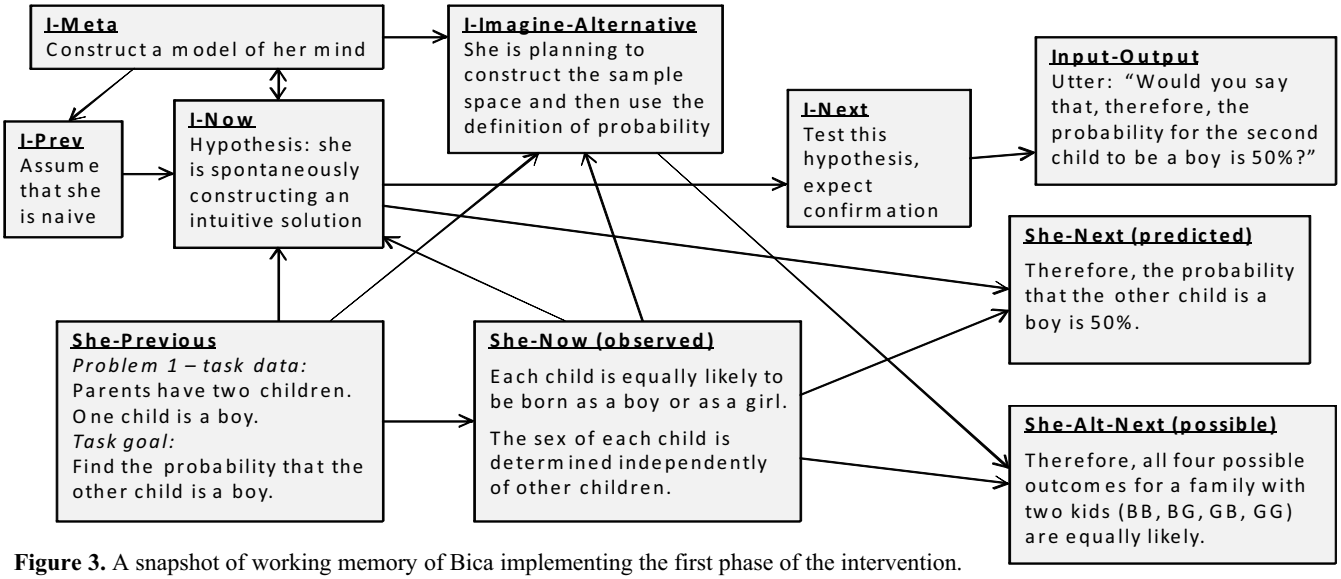

Figure 3. A snapshot of working memory of Bica implementing the first phase of the intervention.

Bica initially assumes that the student is SRL-naïve and is trying to fit available facts spontaneously until they bridge the given data with the goal. This assumption appears to be consistent so far with the observed student activity, as detected by mapping a corresponding metacognitive hypothesis from the Bica own mental perspective I-Now (Figure 3). Based on the perceived scenario, Bica predicts a possible next step of the student (which does not have to be the most likely next student's step):

- Therefore, the probability that the other child is a boy is 50%.

In order to check the hypothesis, i.e., whether this step would be consistent with the current student strategy and the state of mind, Bica asks a question: "Would you say that, therefore, the probability for the other child to be a boy is 50%?" (this particular prediction and the question will not be preprogrammed). If the student answers "yes", then Bica will suggest taking an alternative approach based on the notions of a sample space and probability.

Most importantly, based on the student answer Bica will learn about the SRL skill level of this student, and next time may avoid similar test questions.

Session 2

When the student is working on Problem 2, the scenario may develop as shown in Figure 4. Now, instead of pointing to a wrong conclusion (She-Now, second statement) drawn by the student from her past experience, Bica suggests to make a change at a higher SRL level.

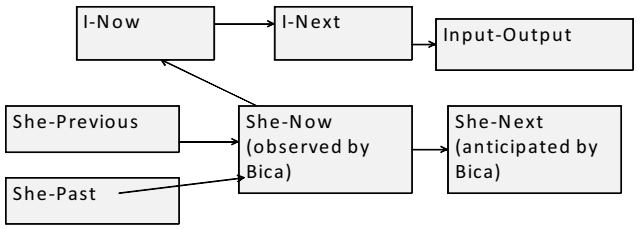

Figure 4. Bica performs model-based SRL teaching. Only labels of mental states are shown. Corresponding contents are:

I-Now: She is constructing an intuitive solution, using the known solution of Problem 1.

I-Next: Make sure the student learns the correct general approach.

She-Previous: Problem 2: In families with two kids, are boys more likely to have a sister, compared to girls?

She-Past: Problem 1 solution experience.

She-Now (observed by Bica): If a family has a boy and a girl, then the boy has a sister, but the girl does not. If one child in a family with two kids is a boy, then the other child is more likely to be a girl.

She-Next (anticipated by Bica): Therefore, a boy is more likely to have a sister than a brother.

Input-Output: - Try to select an approach that corresponds to the task instead of intuitive guessing. For example, imagine doing a survey of kids, and construct a representative sample.

Suppose that this practice continues through a sequence of similar probability problems, during which the student guided by Bica gradually develops the ability to follow a standard SRL scheme (Figure 1) that includes recognition of the kind of problem, identification of the given data and the goal, selection of the appropriate strategy of solving the task and planning the solution, building confidence that the plan will work, carrying out the plan while doing metacognitive self-monitoring and self-control, looking back: validating the steps and the result, self-attributing outcomes and, if necessary, seeking help (cf. Polya 1945). Initially, this should be done by the student explicitly, by including available graphical representations of SRL elements as a part of the constructed solution.

Session N

Suppose that at some point during phase 3 of this example intervention, Bica knows that the student has mastered the ability to use the SRL scheme, and the student has stopped using explicit representations of SRL elements. Suppose that at this point Problem N is given to the student. What should Bica do if the student tries to construct a "solution" as follows?

- Let X be the number of boys in classroom A, and let Y be the number of girls in classroom B.
- It is given that X = Y + 5.
- Each child is equally likely to be born as a boy or as a girl.
- Therefore, each classroom has approximately equal numbers of boys and girls.
- Therefore, the size of classroom A is approximately 2X, and the size of classroom B is approximately 2Y.
- Therefore, the number of girls in both classrooms is approximately X+Y.
- Because X = Y + 5, it follows that 2X = (X+Y) + 5.
- Because 2X is substantially greater than X+Y, the size of classroom A is greater than the total number of girls.

The straightforward automatic feedback would be to point to the flaw in logic (or, even simpler than that, to accept the correct final answer). However, this may not be very helpful to the student in mastering general SRL skills. A metacognitive analysis should tell that the student failed to recognize the domain to which the problem belongs as the domain of linear inequalities rather than statistics or probability theory. Because all previous student experience in this example intervention was limited to probability theory, the student had limited opportunity to learn the step of problem domain identification, and apparently is missing this skill. Therefore, the student needs to return back to using explicit representations of SRL elements on the screen in her second attempt to solve the same problem. Bica will be able to find the correct diagnosis by modeling student's mental states underlying the observed "solution" and then analyzing them metacognitively.

Discussion

Self-regulated learners are metacognitively, motivationally and behaviorally active participants of their own learning. Metacognitively, learners plan, set goals, self-organize, self-monitor, and self-evaluate during SRL. Behaviorally, they develop personal SRL environments. Motivation is necessary, e.g., for causal attribution of outcomes and is vital for success in SRL specifically (Zimmerman 2008). Therefore, CC will enhance student motivation in learning.

Having Bica at the core of CC implementing adaptive dynamical cognitive modeling of the student mind will allow CC, among other things, to select the right level of SRL feedback in each given case. To the best of our knowledge, no existing SRL-enabled ITS can offer this degree of flexibility. In many of existing systems, SRL processes occur sequentially, with discrete transitions between states. For example, the Betty Brain tutoring system (Biswas et al. 2005, Leelawong et al. 2008, Jeong et al. 2008) employs a hidden Markov model to describe transitions between various cognitive and SRL phases. In most other implementations, statistical measures of student behavior and a simple Markov decision tree (if not a fixed decision rule) is used to diagnose SRL problems and to provide SRL scaffolding. Arguably, these approaches are not sufficient for building a faithful model of human SRL that can be transferred to students in a variety of domains and scenarios (they may work well as statistical models fitting human data, but without providing a useful insight). A unique feature of CC with Bica inside is its flexibility and expected robustness in unforeseen situations.

The first two problems in the example of a possible CC-based mini-intervention are interesting in the sense that they require an ITS capable of metacognitive tutoring. E.g., merely cognitive (task level) tutoring appears to be insufficient in this case and may actually produce a negative effect, as illustrated by a possible student mistake (Figure 2, She-Next). This mistake could be induced by previous experience with Problem 1. Moreover, switching the order of the first two problems does not change the situation. It would be probably a mistake to start tutoring in this case by explaining low-level fallacies, when the student is clueless at a general level. In contrast, teaching SRL at a high level in this case can produce a significant improvement in student learning over time, and is feasible based on CC with Bica as its core. On the contrary, during phase 3, explaining a low-level failure to the student becomes more necessary than explaining a general SRL scheme (which the student has presumably mastered); however, even in this case precautions should be taken and decisions should be made based on metacognitive analysis of perceived student mental states, as illustrated by the example of Problem N. In order to be able to do this automatically, one needs an SRL simulator based on a biologically inspired cognitive architecture.

The purpose of the above analysis was to demonstrate the key advantage of having Bica, a cognitive architecture implementing an adaptive dynamical model of SRL, as the core of CC. The key value of having Bica in CC should be clear now, based on the Bica inherent ability to self-monitor, self-diagnose, self-correct, self-instruct, self-reward (producing reinforcement learning), self-predict, etc., in other words, to implement the basic elements of SRL (Figure 1) dynamically as an adaptive cognitive system, and apply the same capabilities to representations of other minds. This is a unique feature of CC based on Bica, which separates it from all existing ITS. To the best of our knowledge, no existing ITS implement SRL dynamics internally based on a cognitive architecture at the level that Bica can offer. While CC and interventions based on it exist only at a level of a blueprint, GMU BICA was previously implemented, tested and mapped onto the brain (Samsonovich & De Jong 2005, Samsonovich et al. 2006).

Concluding Remarks

Self Regulated Learning (SRL) has been identified as a critical strategic thinking process for supporting and promoting students' abilities to learn and solve problems. In most cases, the failure of a student to make normally expected progress in learning can be attributed to a lack of efficient self-regulation skills (Pashler et al., 2007; Zimmerman, 2008). Currently, transfer of SRL skills to students occurs in informal 1-1 interactions with an instructor, or with Computer Based Learning Environments (CBLEs) that provide limited and mostly passive or reflexive SRL support. As a consequence, the effective transfer of SRL skills to students continues to be an open problem (Winne & Nesbit, 2009).

Based on the concept described in the present work, a new and easily scalable intervention can be created in the form of an ITS called Cognitive Constructor that can be used as personal student assistant to facilitate the acquisition of SRL skills without disruption of the learning process. CC is based on the cognitive architecture, the key feature of which is its built-in support for meta-cognitive activities consistent with SRL. As such, the CC architecture is curriculum neutral. However, there is clear evidence that new and innovative interventions are needed in the area of high school mathematics, particularly with student populations involving women and minorities (Grigg et al., 2007; Hoang 2008).

We end our presentation by making an analogy with a magic trick. Every magic trick has three parts: the *pledge*, during which something that seems ordinary is presented, the *turn*, during which the ordinary situation becomes extraordinary (e.g., an object disappears), and the *prestige*, during which things 'magically' become ordinary again. The pledge is that perhaps the most exciting challenge of our time is to build a general-purpose artifact capable of human-level cognition. The turn is that under closer examination the challenge disappears as a sensible goal: we do not know what to build or what for, forget how! The prestige is that it is nevertheless possible to return a rational practical sense to the challenge, take it seriously and solve it in the near future. We are proudly looking forward to demystifying the 'magic' of human cognition and learning.

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