A Computational Cognitive-Based Approach to Represent Knowledge within Intelligent Tutoring Systems

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Abstract

In this paper we present some characteristics of a new computational model to represent knowledge within intelligent tutoring systems. This model is inspired (1) by research in artificial intelligence on modelling, structuring and organising knowledge and (2) by theories of cognitive psychology which explain the human cognitive activity in terms of memory subsystems and their processes. Here, we describe one originality of our novel approach : the parsimonious use of cognitive structures suggested by psychology to encode the knowledge to be taught. Primitive units of semantic and procedural knowledge, chosen with a small level of granularity, are used to build complex knowledge entities which are dynamically combined in order to represent the learner cognitive activity. Traces of this activity are used as episodic knowledge which is specific to each learner. Episodic knowledge analysis allows to retrieve semantic and procedural knowledge and to establish their acquisition level in function of their context of usage.

1. Introduction

History of intelligent tutoring systems (ITS) can be written in different ways, but all those who tried to do it (see, for example [11,19]) noted that although their continuous evolution, much progress remains to be made in various axes such as knowledge representation within these systems. Moreover, recent models (see, for example, [6,13]) attempt to fill in this gap and showed that their elaborate structures, inspired from psychological and cognitive based approaches, can offer more realistic representations. That leads us to deduce that AI researchers in the field of knowledge representation within ITS may find it very beneficial to make a serious attempt to integrate the knowledge psychological research have accumulated on understanding the cognitive mechanisms of human learning and all the positive results obtained in computational modelling theories.

This paper presents some characteristics of our computational cognitive-based approach for representing knowledge within ITS. Here, we discuss – according to an AI opinion – the advantages of a parsimonious use of knowledge types, connected to various human memory subsystems, as knowledge representation structures. This leads us, before, to describe the distinction – made by psychological theories – between various types of knowledge. The remainder of the paper is organised as follows. First, In order to introduce our proposed knowledge representation structures which are inspired from those of the human memory, we briefly describe the latter – deeply studied and interpreted in psychology and neurology – as a knowledge aid. Next, we present three types of knowledge, embodied in our model, which refer to particular memory subsystems according to the way in which their contents in knowledge are handled; followed by some argumentations and originalities on their utilities to be implemented. Finally, other interesting aspects of our work are announced.

2. The human memory

If we are interested in education and teaching, and have the ambition to endow an artificial system with competence in those fields, it is not possible to be unaware of all that concerns training, cognition and memory. The latter is one of the most enthralling properties of the human brain. If it is quite true that it governs the essence of our daily activities, it also builds the identity, the knowledge, the intelligence and the affectivity of human being [14,7]. Rather than being a simple hardware device of data storage (as in the computer's case), the principal characteristic of this memory is carrying out categorisation, generalisation and abstraction processes [8]. However, if the human memory has its extraordinary faculties of conservation, it sometimes happens to us to forget. This failure intervenes when information did not undergo suitable treatment.

Indeed, the organisation process is essential in the success of the mechanism of recall. In other words, chances to find a recollection (a fact in the memory) depend on the specificity of elements with which it has been linked. Those facts and recollections can be acquired explicitly (for example, we can acquire them by speech). They correspond to an explicit memory called *declarative memory* (whose contents in knowledge are declarative, according to the AI paradigm). Moreover, our practice and savoir-faire are largely implicit, they are acquired by repetitive exercises rather than consciously. They correspond to an implicit memory called *procedural memory*. Whereas the latter is mainly made up of procedures acquired by practice, declarative memory can be subdivided in several types such as, semantic memory and episodic memory. Russell [15] affirmed that despite the difficulty in distinguishing those two forms of memory in practice, there can be no doubt that both forms exist. But, the episodic/semantic distinction debate is still in hand. Sophisticated experiments [9,12,17,18] tried to prove that the two memory subsystems are functionally separate. Other surveys were against the distinction between them [1]. However, the overall results seem to be mixed : evidence has been found both for and against the episodic/semantic distinction. It seems that at least there is significant overlap between the two memories, even if they are functionally different. Basically, it has been argued that knowledge is encoded in various memory subsystems according to the way in which their contents are handled and used. In our model, we take into account three main subsystems (mentioned above) presenting, each one of them, a particular type of knowledge.

3. Semantic knowledge modelling

Semantic knowledge is located in a particular memory subsystem. This latter is the memory of facts, symbols, of their relations, their functions and their genesis. In our approach, we see semantic knowledge as concepts taken in a broad sense. Thus, they can be any category of objects, relations or functions. Moreover, we subdivide concepts in two principal types : primitive concepts and described concepts. The first is defined as a syntactically non-split representation. More precisely, a primitive concept representation can not be divided into parts. However, this type of concept is not semantically non-split. For example, the symbol "9" is a non-split representation of the corresponding integer number, but number 9 can be semantically seen as a sum of 2 and 7. On the other hand, we define described concept as a syntactically decomposable representation. For example, the symbol "3+6" is a decomposable representation of number 9. It can represent an addition relation between numbers 3 and 6, two primitive concepts. The symbol "+" represents a sum function (which is a primitive concept). In this way, the semantic of a described concept is given by the semantics of its components and their relations or functions (which take those components as arguments to create the described concept). For example, as shown in the diagram depicted by Figure 1, in the expression "3+6 = 9", symbols "3", "6" and "9" are associated to primitive objects (integer numbers), the symbol "+" is associated to primitive function (the sum) and the symbol "=" is associated to primitive relation (the equality). Finally, "3+6 = 9" is a described object having three components: "3+6", "=" and "9" and it represents an equation.

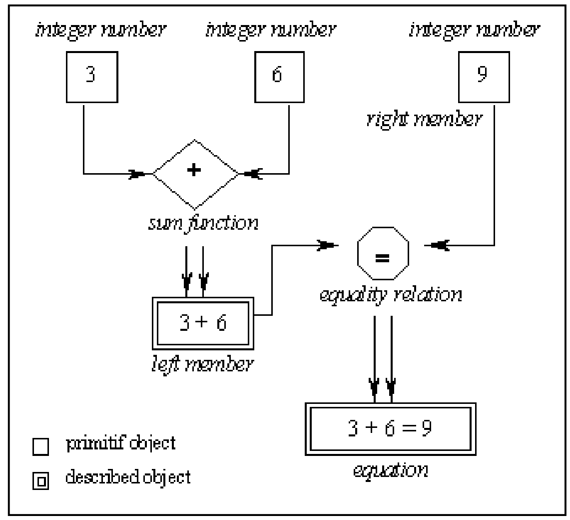

Figure 1. Semantic components of an equation.

Note that – in our model – a function can be seen as a particular case of relation. For example, the function "+" is a relation of addition between two or several numbers. What distinguishes a function from a relation is that the latter does not create directly a new concept representation. On the other hand, the former does it. For example, the function "+" associated to numbers "2" and "7" (which we note by "+(2,7)") has an image ("9"), the sum of both. Therefore, "+(2,7)" is a new representation of the concept "9" (the image).

4. Procedural knowledge modelling

Procedural memory supports the realisation of cognitive and motor tasks. This memory subsystem serves to automate problem solving processes by decreasing the quantity of handled information and the during time of resolution. In opposition to semantic knowledge which can be expressed explicitly, procedures are inferred by a succession of actions achieved automatically – following internal and/or external stimuli perception – to reach desirable states. For example, procedural knowledge allow us to add mechanically "42 + 11" without using the attention resources (without being obliged to recall the algorithm explicitly). This automation, via the use of procedures, reduces the necessary cognitive complexity of problem resolution [16]. Note that a procedure can be transformed into semantic knowledge by means of reification. For example, the tutor who explains the sequence of actions applied to produce a solution to a problem reify the corresponding procedure. Nevertheless, the two types of knowledge (semantics and procedural) can coexist, since automation is not made instantaneously. It is done, rather, in the course of time and with the frequency of use [3].

In our approach, we subdivide procedures in two main categories : primitive procedure and complex procedure. Executions of the first are seen as atomic actions. Those of the last can be done by sequences of actions, satisfying scripts of goals. Each one of those actions results from a primitive procedure execution; and each one of those goals is perceived as an intention of the cognitive system. For example, when the learner objective is adding mentally "42 + 11", satisfying this goal amounts (1) to make the sum of the units "2 + 1", (2) the one of tens "40 + 10" and (3) to twin the two preceding sums "50 + 3". Each one of these three actions represents a primitive procedure, applied to satisfy a subgoal. Thus, knowledge allowing to add mentally "42 + 11" is a complex procedure giving rise to three subgoals and made up of three sub-procedures (see Figure 2). As there can be various ways to do this addition, number and order of applied sub-procedures depend on the selected complex procedure. This last constraint implies that number and order of subgoals are not determined statically in advance.

5. Episodic knowledge modelling

Our experiences are remembered in terms of situations that record who did what to whom where and when, or describe states of affairs wherein multiple entities occur in particular configurations. This form of memory, the episodic memory [17], retains details about our experiences and preserves temporal relations allowing reconstruction of previously experienced events as well as the time and context in which they took place.

In our model, the episode representation is based on instantiation of generic statements retrieved from semantic memory. This contains information about classes of instances (concepts); while, episodic memory contains information about instances, stored in episodes. In some cases, requests assumed to be directed at the semantic memory could be answered in terms of knowledge retrieved from the episodic memory. This is due to the semantic content of episodes [18] which we call : *cognitions*. We consider semantic knowledge used during any procedure usage as a cognition. This is a mentally handled instance of a concept and describes the perception that the learner has of an abstract or concrete object as it was at a given moment. The recall of cognition allows to the learner to distinguish various occurrences of a concept according to the episode where they occur. For example, the expressions "1+ ¾" and "2-¾" call two distinct occurrences from the same concept, the quotient "¾".

Executions of procedures are encoded in episodic memory. More precisely, each goal realisation is encoded in an episode (in this manner, the learner episodic memory stores all facts during training). Thus, episodic knowledge is organised according to goals. Each episode specifies a goal which gives a sense to the applied actions. These actions are specified by procedures and are realisation of subgoals. Arguments of the goal, which are concepts in the goal definition, become cognitions. As mentioned above, we can not determine systematically, in a static way, subgoals starting from the main goal. Generally, the complex procedure "P", which achieves a given goal "G", determines number and order of "G" subgoals whose each one can be achieved, in turn, by a procedure (called, in this case, a "P" sub-procedure) . Goal realisation can be made in various ways (by various executions of procedure sequences). Number and chronological order of "G" subgoals depend on the actual teaching context, on the degree of concepts and abilities mastery, and on the learner preferences during task achievement. Those preferences can be retrieved from the learner episodic knowledge analysis.

Episodic knowledge results from the learner cognitive activity. Each episode represents an action (which can be a complex one) applied by the learner to achieve a goal. Since this one is done by means of procedures, the episode is generally composed of sub-episodes which describe the realisation of sub-procedures achieving subgoals. Thus, there are as many sub-episodes as sub-procedures and each sub-episode which is reached using a complex sub-procedure implies that other sub-sub-episodes will be created to describe sub-sub-procedures realisation. The process stops when, during a given episode, a primitive procedure is selected. The episode, currently in construction in the working memory (WM), is the current episode. If the selected procedure is a complex procedure then the WM creates a sub-episode for the episode in progress. The new episode becomes the current episode. Let's return to our mental addition example of "42+11". To calculate the sum of the units, the one of tens and to twin the two preceding sums are three sub-procedures whose the realisation of each one (which satisfy a subgoal) is stored in a sub-episode. Figure 2 illustrates the corresponding diagram. The complex procedure of the mental addition is encoded in a main episode calling upon these three sub-episodes. Since those latter are primitive, they will not generate other sub-sub-episodes.

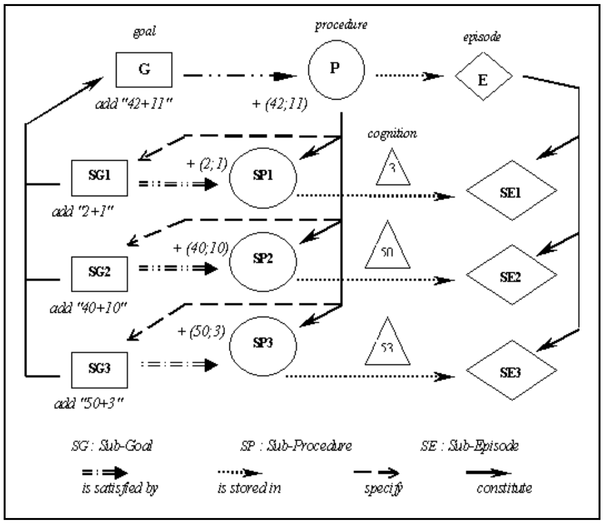

Figure 2. Goals, procedures and episodes relationships

6. Originalities

Cognitive approaches attempt to model the human process of knowledge acquisition during training. For example, in MIACE [10], a human cognitive architecture which try to model the learner cognitive activity, knowledge has been structured according to the three categories described earlier (semantic, procedural and episodic). We think that it would be advantageous and practical, to be inspired by a psychological model, to represent knowledge within ITS as follows : we use these knowledge representation structures to encode the knowledge to be taught and we divide these structures into two parts : on one hand, semantic and procedural knowledge which are common to all learners and, on the other hand, episodic knowledge which is specific for each learner. That is similar to what occurs in classes during courses : semantic and procedural knowledge are taught to all learners, are potentially accessible and are shared – in various degrees – by all of them. While, episodic knowledge is a knowledge whose contents depend on the way with which the common knowledge (semantic and procedural) is perceived and handled. We believe that these subsystems and processes (once implemented) – because they are similar to those used by the learner – facilitate the identification of correct and/or erroneous acquired knowledge and suggest the planning of a suitable sequence of pedagogical activities to improve significantly the cognitive level of the learner. In this mind, we also take up, basically, the overall idea of Anderson [2] which gave rise to the successful tutorial series of ACT-R [3,4,5], but, we add elements which make the representation structures more adapted to e-learning, such as the integration of pedagogic and didactic knowledge in our structuring and the transformation of these structures into reusable knowledge objects (both, briefly presented in last sections) . Our hope is to build knowledge representation structures and to encode the processes treating these structures in order to optimise the use of the knowledge to be taught, to make easier its acquisition, and to improve diagnosis and prediction of the learner behaviour.

One of the originalities – described here – of our novel approach lies in the parsimonious and dynamic use of cognitive structures suggested by psychology to encode knowledge of the domain and the user knowledge. The dynamic aspect is seen in the non-predefined combinations between occurrences of concepts and applied procedures which handle them and which translate the learner interests (goals). Primitive units of semantic and procedural knowledge, chosen with a small level of granularity, are used to build complex knowledge entities which are dynamically combined – to create a new knowledge – in order to represent the learner cognitive activity. The encoded traces of this cognitive activity represent a memory subsystem content formed by episodic knowledge which is specific to each learner. Thus, semantic and procedural common knowledge are combined to form a new specific episodic knowledge. In this way, episodic knowledge analysis allows to retrieve semantic and procedural knowledge and to establish their level of acquisition (for each learner) in function of their context of usage. In other words, if we encode the episodes lived by a learner, then no information about this last is lost. Thus, it is possible to go further with this user model. For example, it is possible to simulate and analyse, step by step, a problem which s/he solved before, or, part of this one. The tutor can exploit this to build suggestions and examples well adapted to the learner because they are built with specific and quite detailed cognitive elements that the learner has. Moreover, our structuring of episodic knowledge places the episode in a hierarchical context thanks to the concept of sub-episode. Thus, the episode becomes easily accessible and manageable in an object oriented model, for example.

Another original aspect of our approach is the explicit introduction of goals into the knowledge representation. Although they are treated by means of procedures, we are convinced that goals are a special case of semantic knowledge that represents intentions behind the cognitive system actions. i.e., a goal is seen as a semantic knowledge which describes a state to be reached. We think that there exists a particular form of energy employed to acquire goals. That distinguishes them from any simple form of semantic knowledge. This distinction involves a different treatment for goals in the human cognitive architecture. We propose to treat goals explicitly to reify them as particular semantic knowledge which is totally distinct from those which represent objects, relations and functions.

Besides the explicit treatment of goals, other interesting aspects of our work remain to be presented, described and discussed. Due to space limitation and as they are not the object of this paper, we briefly speak about them below. We note that Java implementation is actually under development to validate our global approach

6.1. Pedagogic/didactic knowledge distinction

Another area of ongoing research that is direct relevance to the work described here concerns the organisation of the didactic and pedagogic knowledge. The latter is independent of the subject matter content. For example, it allows to professors to build teaching activities which support learning. This knowledge, being of general nature, could be encoded independently of the contents. On the other side, didactic knowledge highlights the interaction between the content and the training processes. This knowledge, because it is specific to the content, could be encoded with concepts and procedures of the domain. It makes us confident that this distinction provides an added value to our knowledge representation structures which approaches, even more, that of the human cognitive architecture.

6.2. Reusable learning objects

We will also show that if didactic knowledge were encoded with the contents, the latter would be composed of learning objects which contain all necessary information which allows them to be taught. Moreover, if these contents are organised in classes (according to an object oriented model), then it should be possible for each learning object to inherit knowledge from its super-class. This way of proceeding has the advantage to transform knowledge in reusable learning objects in various teaching situations. Inheritance will make it possible to design these objects in an incremental way to facilitate their usage in similar contexts.

7. Conclusion

The idea described in this paper is a part of a larger approach whose purpose is to profit from (1) computational research on modelling and organising knowledge and (2) cognitive theories which explain and structure the human cognitive activity in terms of memory subsystems and their processes. We have described three types of knowledge which refer to particular memory subsystems in term of their contents of knowledge, we have discussed their utilities to be implemented as knowledge representation structures within ITS and we have briefly presented other aspects of our work which will be detailed in future papers.

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