Teaching for Long-Term Memory

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Abstract A major goal of education is to help students store information in long-term memory and use that information on later occasions, in the most efficient manner. This chapter investigates the use of analogy as a strategy for encoding information in long-term memory. The results of a study concerning the ability of students to use analogy when learning computer science are presented.

1 Introduction

There are plenty of metaphors and models for memory. Starting from Aristotle, who had an integrated view on memory and thinking, human mind and its processes have been observed and studied. Nowadays, there is a huge amount of knowledge on brain, mind, and reasoning: these complex objects have been approached from different perspectives in various fields of science.

From issues addressing the evolution of the brain [21] to abstract models of the cortex [16], scientists provided insights into the mechanisms of the brain. The study of the energetics of the brain's computations is currently done, among others, by a group at the Interdisciplinary Center for Scientific Computing in Heidelberg, Germany, lead by Bert Sakmann, Nobel Prize laureate in Physiology and Medicine. With tools like algorithm-based reconstructions and annotated graphs, the scientists managed to picture the link between brain anatomy and function at the scale of tens of nanometers [7].

While biologists and neuroscientists use the modern instruments that science developed to understand the brain from the biophysics of the neuron to the biophysical basis of consciousness, from the executive functions of the human brain

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to which sections process various types of information [5], computer scientists look at the brain in a specific manner. Namely, like a computer system who stores a great amount of information, system that we query in order to generate a desired output [17]. Using the available understanding, at a certain moment, of computers, brains and mind, we can try to understand brain by analogy, building a “cognitive computer” [18]. Even if this approach is not new, answers are still waited—can we find out more on the brain, not by using computers to study it, but modeling it as a computer system? If an end-user is not interested in *how* a computational system retrieves the information required, and looks only at *what* was returned, teachers are among those who search for answers: how can they organize “the input” such as to help students find the desired “output” as accurate as possible, in various contexts that might require their knowledge or abilities?

2 Investigation

The aim of this chapter is to point out some findings concerning the degree to which analogy can help students to have a better, long-lasting understanding of the content they are taught, and what kind of supportive elements (visual, lexical or semantic) allow them to formulate analogies. The participants of the study where 50 students (aged between 20 and 24, 86 % males, 42 % already employed) in the second year of the undergraduate programme Informatics at the Faculty of Sciences, University “Vasile Alecsandri” of Bacau, Romania. During a semester, their regular activities included the following tasks:

1. To map a real-life situation on a given totally connected graph.
2. To formulate two suggestive analogies for the database concept: one in lexical form and one in graphical form (a drawing).
3. To define (in any modality they consider appropriate) the concept of “complex system” and to give two significant examples.
4. To imagine a system analogous to the human immune system and to offer significant representations of it, in any form they find that the analogy is relevant.
5. To formulate an application of the Generalized Assignment Problem.
6. To complete phrases with analogies.
7. To integrate the same word in various lexical contexts, in order to produce different semantics.
8. To specify what elements support them for an efficient learning.
9. To describe in what way the literature they approached helped them to understand the concepts they are currently studying in computer science.
10. To present a classification type of analogy and an association type of analogy, from any topic they choose.
11. To formulate three analogies, each involving content from: literature, fine arts, and social sciences.

12. To find an analogy that includes concepts from geometry.
13. To solve a probabilities problem, given an analogous problem and its solution with Bernoulli scheme.
14. To design and implement a simulation program for the above solved problem.

The results of the students' activities have been recorded and analyzed. Moreover, discussions took place in an informal manner, aiming to reveal the needs and the perspective that the students have on the use of analogy in their future work. Students were observed during their classes (courses, seminars, laboratories) in order to register other significant aspects (such as the involvement and attention).

In what follows, findings of the study will be connected to the topics discussed.

2.1 Structure of Memory. Points at Which Information can be Lost in Learning

The understanding of such complex system as the mind clearly needs to go beyond brain structure–function correlations [26]. The way that information is organized and represented in memory has been intensively studied, but the findings remain speculative. However, according to memory researchers, the components of the Memory System are: sensory information storage (SIS), short-term memory (STM), and long-term memory (LTM). Each systems has its own characteristics with respect to function, the form of the information which can be retained, the amount of time the information is stored, and the capacity of the information that can be processed. Focusing on long-term memory, three aspects can be emphasized: episodic memory deals with the ability to recall experiences deployed in the past, stored as images; semantic memory contains verbal information, organized either as particular pieces of information (known as facts) or as generalized information (concepts, rules); procedural memory deals with the information that allows tasks performing (conditioned reflexes, emotional associations, and skills and habits).

Cognitive psychologists use an important concept related to memory organization: that of "schema". A schema denotes any pattern of relationships among data stored in memory [14]. Of course, any piece of information in memory may be connected to different, overlapping schemata. Definitional, assertional or implicational networks [25] are simple computational models of such schemata. Unlike in these semantic networks, which use a straightforward declarative representational mechanism that allows the automated reasoning, the way the output appears in the human mind is much more complex. However, like in semantic networks, the information returned as response to a query essentially depends on how previous knowledge is connected in memory and on how the pieces are used to build this output. Accordingly, the content that already exists in students' minds and the understanding that they got on that content have a major influence on what students integrate or experience as new content. They can retrieve only their interpretation on what they stored in long-term memory, as far as mental models cannot be avoided.

An important aspect related to the schemata is the fact that these are resistant to change. Meanwhile, new mind-sets tend to form quickly—that is why teachers need to facilitate for their students a meaningful context that includes at least: examples, analogies, and alternative interpretations. In the rapidly changing environment that we all face today, this should not be a difficult task. Previous, well-organized pieces of knowledge, past experiences, cultural values, as well as the stimuli perceived by the students in the learning space have a major influence on their new acquisitions.

For the study group, it appears that the transfer of the information in the short-term memory (first point where problems may appear) suffers from lack of attention and, when attention is given to the current activity, from a superficial level of attending it. From the questionnaires and from our direct observations, this attitude comes from a weak motivation or even from its absence. There are multiple sources of such an attitude, the top two being: a bad understanding of what a computer scientists should learn (for example, students share the opinion that the mathematical instruments are not important, or that the weight of the theoretical lessons is too big), and a perspective that they do not appreciate as favorable (due to the actual economical context; some of the graduates happen to work in other fields of activity). However, those who are interested in the topics approached (and who have no deficits in sensory systems such as visual, auditory or kinesthetic) mentioned a friendly, informal, quiet environment, music, and breaks as factors that allow them to elaborate on the incoming information. Some of them also mentioned personal good will as crucial in their implication.

In this stage, the teacher needs to pay attention to the following aspects: to present the information clearly (so that it reaches the sensory register and is correctly perceived by the students) and ensure that students attend the information, focusing on relevant aspects and not on collateral ones.

A second point where problems can arise is working memory, where the information must be held long enough to work with it. When approaching a problem in computer science, several components must be referred in order to solve it: data structures, algorithms, heuristics, strategies, programming languages, complexity issues, etc. First of all, the teacher must help the students to identify these pieces of knowledge. Activating them, as has been proven in physiology [11], facilitates the transfer to long-term memory, as well as bringing it back for future use. Another role of the teacher is to provide support for prior information that is needed. Considering this aspect, the study group pointed out that students appreciate that written information (on paper) is preferred when working on a problem, as well as the process of rewriting it. Also, this is the point where mastering the basic skills appears to be critical, because their use must not occupy space in the working memory.

The third point at which students may not properly deal with information is the bridge from working memory to long-term storage. The success of this transfer is related to the following important aspects: development of associations between the new input and the schemata already existing in the memory, the work with the information in more than a single context, and the complexity level of these processes. Categorization (which is the capacity to place new information in several categories, in order to create multiple pathways to access it) appeared to be one of the problems faced by the students in the study group. In the applied questionnaires, the 10 items dealing with categorization (each item appreciated with 0 up to 5 points, according to the correctness of the answer) scored a minimum of 3 and a maximum of 38 points, the average score being only 21.4. Meanwhile, the 10 items measuring the amount of effort and cognitive capacity used to process information (the complexity level of processing; each item also appreciated from 0 to 5, according to the complexity and the completeness of the answer) scored a minimum of 2 and a maximum of 40 points, the average score being only 18.75.

As a conclusion with important consequences in education, it appears that memory storage is an ongoing process resulting from continuous changes and parallel processing in the brain [10]. Therefore, increasing the number of examples, the variability of examples, and the use of those that minimize the cognitive load [27] can improve schemata acquisition.

In the matter of memory retrieval (the fourth critical point where problems can appear in memory processing), medical studies [19] proved that, in accordance with the tasks to be solved, a selection between competing representations is carried out, in interaction with domain-general cognitive control. The following section considers analogy as a system of representation and its role in memory retrieval, problem solving and understanding, in general.

2.2 Use of Analogy in Learning and Retrieval of Information

At humans, learning is a process indistinguishable from evolution itself [3]. Learning through analogy is a superior form of learning. In fact, analogy has a major role in our lives: starting with basic things that we learn by imitation in childhood, going through the use of language to the completion of skills and competencies in our professional development, most of the learning acts use various forms of analogy.

According to Cambridge Advanced Learner's Dictionary and Thesaurus, analogy denotes "a comparison between things which have similar features, often used to explain a principle or idea". Collins English Dictionary (11th edition) explains analogy as "agreement or similarity, especially in a certain limited number of features or details" for two relational systems. Human mind, as well as human intelligence and language proved to be fundamentally analogical and figurative [28]. The history of science counts numerous discoveries that are due to analogies. Creative scientists' statements prove that new theories appeared when they applied, in their field of expertise, an analogy to a phenomenon observed in another domain, sometimes very disparate [6, 29].

The use of analogy in science has been widely investigated. Philosophy [1], rhetoric [20], linguistics [2], cognitive psychology [12], pedagogy [4] expressed their perspectives on analogy and its uses. During the last three decades, new insights into the role of analogy have also been provided by numerous computational models (see [8] for a comprehensive list, also [9]).

Because most of the projects in computer science relate to complex problem-solving tasks, our investigation also focused on: the ability of the students to recognize similarities between problems belonging to separate domains, their capacity to transfer solutions from one problem to another, how they represent analogy, and the predominant modality they use to represent analogical relationships (through text or visual image).

The process of problem solving has been magnificently analyzed by Polya in "How to Solve It. A new aspect of mathematical method" [22], for the world of mathematics. But the main idea of this book, which can be generalized to all fields, idea that is important for students and teachers as well, is that learning must be active.

Basically, the process of analogical problem solving involves three steps [13]: a representation of the original and of the target problem (1), mapping of the two representations (2), and use of the mapping to generate the solution to the target problem (3). What can a teacher do in order to constantly improve the ability of its students to operate successfully on all three steps?

The first stage-representation—is crucial. Basically, it decides how difficult the solution is to be found. Students in Informatics are presented several strategies to build representations in the Artificial Intelligence course, where analogy is intensively used. The students in the sample group did not attend this course at the moment of the study; therefore, their knowledge on representations comes from the background. The items designed to reflect their capacity to build representations invoked previous knowledge, acquired in fundamental courses and programming practice. But, most of all, those items intended to make students use their creativity, to rethink objects and situations, to find new ideas that might work on the indicated topics, hence avoiding "functional fixedness" [24]. The results, however, denoted that imagination is not one of the students' strong points: only standard, common representations have been indicated. The average score of the items dealing with representation ability was 20.35 (on a scale from 0 to 50). Descriptive representations (although imperfect and suffering from lack of details) predominated over the visual ones (very few students chose to give graphic representations: 6 for task 2 and 8 for task 4; the solutions provided by students used mainly graphs and data flow graphs). The interface designed for the simulation program required for task 14 was a graphical one in only 7 cases (representing 38.8 % from a total of 18 functional applications and only 14 % of all 50 expected cases). On task 12, only 16 correct answers (32 %) were recorded. Interviews revealed that experience and intuitive, specific examples are considered by students as elements that can improve their capacity to frame good representations.

The second stage in analogical problem solving—mapping of the representations of two similar systems—is fundamental in applications and in several superior courses (such as Multiagent Systems and Natural Computing, for example). Analogical mapping is the process of determining the best correspondence between the objects and relations of an original and of a novel, target problem. If the students are given the two systems, their corresponding elements are easily recognized, in general. On the same scale (0–50), the average score of the items dealing with mapping of representations was 28.7. But path-mapping theory [23] pointed out on the integration of analogical mapping in the process of problem solving. As the following paragraph shows, this integration has not been achieved by the students in the study group.

The third step (use of the mapping to find a solution for the target problem) was not as successful as the previous one. The average score for this step was 22.4 (of a possible maximum of 50, corresponding to task 13). The explanations that we have found for this result is that, in general, our students tend to develop a lack of persistency in working for a goal. Also, the concepts and results required by this particular analogy were not sufficiently familiar to the students.

The items dealing with lexical contexts and semantics attained to an average score of 20.5 (out of 50). Corresponding to task 11, relevant analogies have been formulated as follows: 25 in social sciences, 32 in literature, and only 14 in fine arts (representing, accordingly: 50, 64, and 28 % of the expected answers). Students described that some pieces of literature they have read helped them to understand a few concepts in computer science, also that examples coming from real life situations and projections in specific application areas remain for a long time in their memory. For example, an application in medicine that they have been presented [15] has been mentioned by students related to task 3, in 5 cases.

3 Conclusions

The study allowed us to extract some practices which might help students to perform better when they need to access information acquired long ago. The following are to be experienced by the students: over-learn new material—in order to imprint the information; read actively—to improve short-term memory registration; explain and communicate on the problem to be solved—this could activate some mind maps; do research on the problem (reading, thinking)—some analogous problems may appear, previous experiences may come in mind; approach a holistic perspective—do not limit the problem, search for as many applications as possible; make connections to other domains—even if only weak, on the surface links with the problem are seen; keep in mind the goal—the solution of the problem; summarize information from various sources—this could offer new perspectives or details; when solving the problem, have initiatives—take decisions and evaluate them; put everything on paper—this will help working memory; be creative, have the courage to do things—there is an inherent uncertainty in problem solving; have a positive attitude and perseverance.

Teachers can help their students to enhance long-term memory and to develop a more effective memory with various strategies: encourage and demonstrate the construction of mental images that store the important aspects of the problem; avoid teaching algorithmically; compare a few analogies during teaching; facilitate retrieval practice (reviewing information, tests) and learning from feedback; give the students opportunity and space to reflect on what is presented; create them various scenarios to recall and apply the newly-formed memories; ensure that students store accurate information; when designing lessons, pay attention to the time needed for consolidation; assign a meaning for the educational process.

All these attitudes might improve students' subsequent retrieval of information. Some have been particularly experienced on problem solving in computer science, but most of them are consistent with every instruction field. The use of "brain-friendly" techniques, examples, simulations, role playing [30] can significantly improve students' learning.

In terms of an overall assessment of the conducted experiment, we consider that the students in the study group have to improve their skills in working with analogy, as well as in other general aspects: reading, building vocabulary, time management, up to developing a personal learning style.

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