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COGNITIVE RESPONSIVE E-ASSESSMENT OF CONSTRUCTIVE E-LEARNING

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Semantic networks from 900 higher education students from different knowledge domains were obtained by using a computer system. Using computer simulated schemata behavior and/or analysis of semantic networks, relevant course schemata-related words were selected to implement semantic priming studies. The aim was testing for students´ word recognition latencies of schemata word pairs before and after course attendance. A trained neural net successfully differentiated students who integrated course schemata-related concepts in their lexicon from those who did not by analyzing recognition times after a course. Thus, an innovative e-assessment was implemented by developing a software system that integrates cognitive reports of mental representation due to learning (constructive assessment) with cognitive reports of automatic recognition processing of course content (reactive assessment). It is argued that this combined cognitive assessment leads to innovative advanced forms of

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e-learning evaluation.

1 Introduction

For a long time, the standard approach to systematic evaluation of student learning in education was norm-referenced assessment, where each student is ranked with respect to the achievement of others through different knowledge domains to discriminate between high and low achievers (e.g., summative assessment; Black & Wiliam, 1998). Heated debates on adequacy of this standardized way to evaluate student learning (Sanders & Horn, 1995) have led to a negative perception of standardized measurement and to the development of alternative (non-standardized) ways of assessing learning. For instance, criterion-referenced testing proposes a more personalized assessment of learning, where the performance of other examinees is irrelevant to the evaluation of a specific student. Rather, the assessment goal is to determine whether each student has attained specific skills or knowledge. An instance of this approach to assessment regarding computer instructional technology can be found in Computerized Adaptive Testing (CAT), where computer-based testing is adapted to the examinee's ability level (for a review see Lindem & Glass, 2010). Thus, alternative assessment of learning is frequently described as strategies aimed at ascertaining what a person knows, as opposed to finding out what a student does not know, as is the case in classical assessment and testing (e.g., Ifenthaler, Dummer. & Seel, 2010).

Evaluating student knowledge acquisition by using mental representation analysis, such as semantic networks (Clariana, 2010a; 2010b; Holley & Danserau, 1984) and comparable tools (concept mapping, tree diagrams, causal diagrams, etc.; Hyerle, 2009) subscribes to alternative approaches to establishing what a student knows after learning. This approach has inspired computer-based testing for the assessment of knowledge (e.g. Rainer, 2005), which empowers students with conscious and controlled externalization of their knowledge in long-term memory by means of specific representational formats. In contrast to a cognitive measurement of conscious manifestation of students´ mental representations (e.g., constructive methods of knowledge diagnosis; Seel, 2010), this approach allows for measuring unconscious and automatic organization of the mind by using reaction times (a core premise of cognitive psychology; Lachman, Lachman & Butterfly, 1987). With regard to using reaction times as a measure of student learning, a limited range of applied technology has been developed, since it is argued that this approach to assessing learning is difficult, prone to terror and has no strong validity (e.g., responsive methods of knowledge diagnosis; Seel, 2010).

Contrary to this last argument, this work is based on the premise that by combining recent advances in responsive and constructive methods of knowledge diagnosis, insightful tools for personalized assessment of learning can be developed and would lead to innovative e-assessment. For instance, in a set of computer studies, Lopez and colleagues (2014) have shown that a neural network can be implemented to determine if students have integrated in their lexicon schemata-related concepts introduced through a school course. In these studies, the net was trained to discriminate between successful and unsuccessful students´ semantic priming latencies of schemata-related words obtained through a semantic priming study conducted at the beginning and the end of a course. This classification capacity is based on the idea that, once a student has integrated knew knowledge into his/her long term memory, a semantic priming effect is obtained from schemata-related words (single-word schemata priming; e.g., Gonzalez, Lopez & Morales, 2013), which in turn empowers such a neural net with a pattern to discriminate among students.

Schemata-related words in this type of semantic priming studies (with a lexical decision task) are obtained in some cases by using a so-called natural semantic net technique (e.g., Morales & Santos, 2015), as well as by using computer simulations of emergent self-organized schemata behavior (Gonzales *et al.*, 2013). This computer approach to simulated schemata behavior is based on the premise that long-term semantic priming relates to dynamic emergent processing of semantic information (Becker *et al.*, 1997). This is relevant since authors of long-term knowledge retention studies argue that students tend to retain a reduced knowledge schema of previously tested knowledge only (e.g., Conway, Cohen & Stanhope, 1991; 1992). Thus, the requirements for constructive methods of knowledge diagnosis are fulfilled by observing the effect of learned concepts over the schema course content, as well as by a semantic analysis of pre-post course concept organization in a semantic net. On the other hand, a responsive method of knowledge diagnosis is supported by a schemata priming effect, due to learning that allows implementation of a computer classifier to identify long-term knowledge acquisition by students. Since both approaches are mutually definitory, in the discussion section of this paper, it is argued that, by integrating both approaches, a more complete new educational tool for e-assessing students' e-learning can be built. However, some empirical evidence supporting these ideas is presented first.

2 Method

2.1 The constructive method

Most of the representative research under constructive scrutiny is based on analysing two mental representations. First, students´ semantic networks for course core concepts are obtained before and after course completion by using a technique called natural semantic network (e.g., Morales *et al.* 2015). Depending on the assessment goal, computer-simulated schemata behavior based on the obtained students´ semantic networks, in combination with indexes of semantic information, is used to analyze conceptual change.

Specifically, teachers participating in the current research project (from 15 different knowledge domains) were required to provide at least 20 core concepts to be learned in their courses. Then, students (940 from different education levels) were required to provide meaningful concept definers of these course target concepts (from the schemata to be learned). As an example, top left panel in Figure 1 provides students´ ten higher-ranked concept definers for ten schema target concepts from a computer science course on interface usability. Typically, some concepts would serve as definers for more than one concept. These concepts are called common definers and groups of definers are interconnected through them. High numbers of common definers tend to emerge whenever there is a close link among target concepts (Schema). Concept organization in this kind of mental representation resembles "Small World" semantic net structure (Morales & Santos, 2015).

It has been argued that, by using a Constraint Satisfaction Neural Network (CNN) such as the one adopted by Rumelhart et al (1986), emergent schemata behavior due to implicit schema relations among obtained student definitions can be analyzed (Lopez & Theios, 1996). Formally, in the appointed CNN, the weight association between two concepts is computed using the following Bayesian formula:

$$W_{ij} = -\ln\,[p(X=0\ \&\ Y=1)\ p(X=1\ \&\ Y=0)]\ [p(X=1\ \&\ Y=1)\ p(X=0\ \&\ Y=0)]^{-1} \qquad (1)$$

Thus, applying this formal specification to a natural semantic network, the CNN joint probability value $P(X=1\ \&\ Y=0)$ can be obtained by computing how many times the definer X of a pair of concepts appeared in a definers group from which Y was absent. The same approach can be adopted to obtain the other probability values (e.g., Lopez & Theios, 1992). The bottom left panel in Figure 1 shows a concept weight connectivity surface plot resulting from computing

Equation 1 over concept co-occurrence from the usability semantic network.

3 Some constructive method results

Weight connectivity surface plots for students´ semantic networks before and after course completion from three different knowledge domains are shown in the right panel of Figure 1: client service (23 participants; A), information systems (80 participants; B), and knowledge regarding music (60 participants; C).

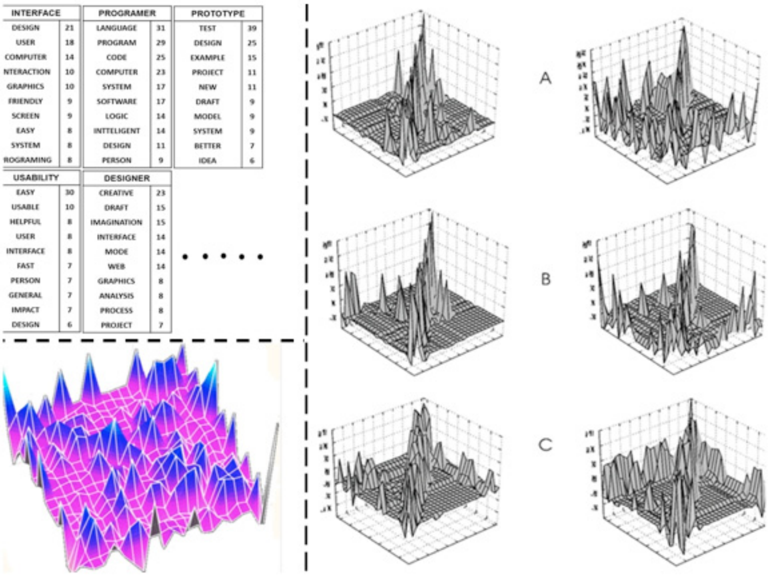

Fig. 1 - Weight connectivity surface plot (bottom left) of concepts defining ten schema target concepts (interface usability; left panel). The right panel provides surface plots for three different courses at the beginning and the end of a course (adapted from Lopez, 2002).

As can be seen from the right panel surface plots, schemata computer simulations will produce different concept organization due to learning. Interestingly, computer screen outputs of simulated schemata concept activation based on these weight connectivity matrices produce results similar to those yielded by other robust tools used in mental representation analysis (e.g., PathFinder analysis; Figure 2).

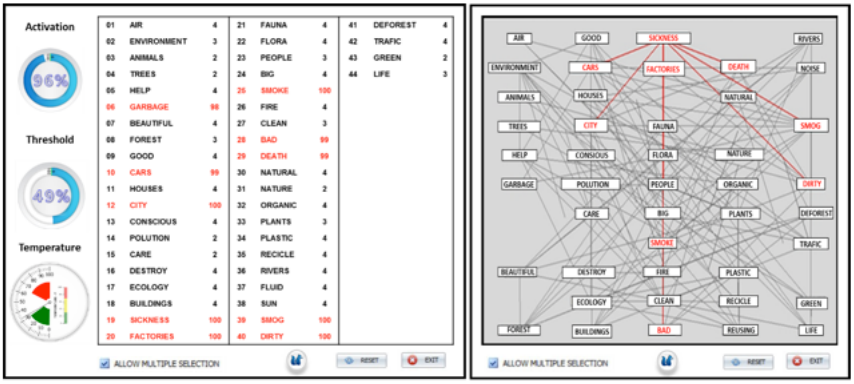

Fig. 2 - The left panel shows simulated ecology schemata behavior (constrained Satisfaction Neural Network (CSNN); Boltzman machine) based on the input from 80 bachelor biology students. The right panel shows a pathfinder analysis (for a review, see Jonassen *et al.*, 1993) of the same students' conceptual definitions. Both systems produce identical outputs if Equation 1 is used as a distance index among concepts.

Using a CSNN approach provides additional advantages for analyzing emergent schemata behavior relative to other semantic net analysis tools. For example, by affecting activation of schemata relevant concepts (e.g., clamping concepts), it is possible to select core concepts underlying schemata organization. It has been argued that these schemata-related concepts (such as Microwave-House, brick-house for the schema of a room; Lopez, 1996) do indeed exist at the level of the human lexicon. Thus, if they are stored in long-term memory, their semantic relation can be detected by using semantic priming techniques (Lopez & Theios, 1996). As will be described next, the potential for schemata priming was used to develop a form of reactive e-assessment. However, regarding the appointed constructive approach, a computer system capable of using at least 50 indexes of semantic organization has been developed to empower a teacher with visual analysis of a report of schemata behavior due to learning. As will be discussed later, this cognitive report has a particular value when incorporated into a reactive assessment of student learning.

4 The reactive method

Either by choosing core concepts of a simulated schema or by choosing common definers to target concepts in a natural semantic network, it is possible to obtain a set of schemata-related concepts to implement a semantic priming study. Put simply, the objective is to use such cognitive experimental studies to explore the extent of student learning of course content only by analyzing the time they take to recognize course schemata-related concepts.

5 Some reactive method results

The left panel in Figure 3 shows response latencies (in milliseconds) of two groups of students´ recognition times associated with 15 moral schemata-related word pairs. One high school group (experimental) took a course on moral development, whereas the other one did not (Gonzales *et al.*, 2013). It is noteworthy that only the experimental group showed priming effects over schema-related words at the end of the course. On the other hand, the right panel shows recognition times pertaining to schema-related concepts from a course on computer usability for two groups of students. Both groups process automatically schema-related concepts, and do so differently from other kinds of semantic-related word pairs. However, second-semester students seem to have acquired course content indirectly, due to other academic activities in their career as engineers. The teacher (the same individual for both groups) did not know that the knowledge schema she was trying to teach would not have a significant impact on her students' long-term memory.

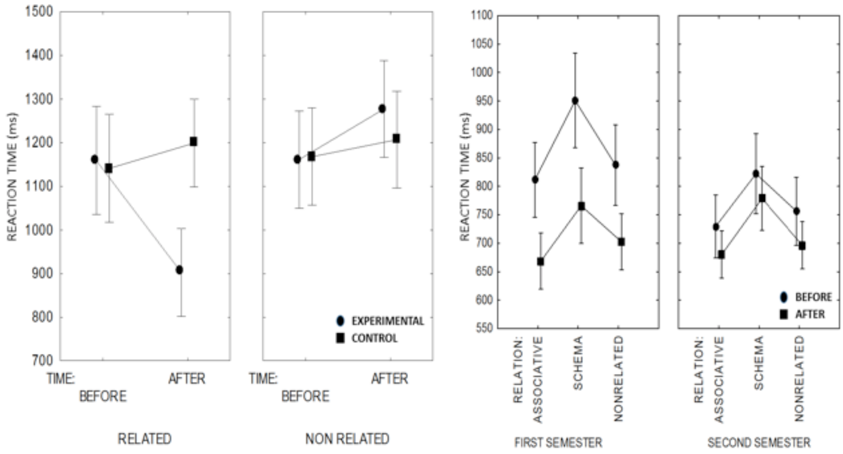

Fig. 3 - Students' recognition of moral-related words is faster only after a course on moral development (left panel). If students possess previous knowledge of a course content (right panel, second semester), no priming effects are obtained due to attending the course, while the course has an effect on the beginners (right panel, first semester).

A supervised feed-forward three-layered neural net with back propagation error has been trained (using a genetic algorithm) to successfully recognize 95% to 100% of cases where a student seems to integrate schemata-related concepts in her/his lexicon based on her/his recognition times to schemata related concepts (see Lopez *et al.*, 2014). It does this after been presented thousand times with hundreds of different cases of students´ priming effects due to schema-related words from different knowledge domains. When this neural net categorizer is integrated into a computer user interface, a report is generated that can be used as a form of reactive assessment of different students' learning states (e.g., students already having course schemata knowledge before a course, or students that have integrated knew knowledge in their long-term memory).

At least two immediate advantages are obtained through this kind of reactive assessment. First, in contrast to other standard cognitive constructive assessment approaches employed to test schemata knowledge retention (e.g., Conway, Cohen & Stanhope, 1991; 1992), the reactive assessment allows the test administrators to comply with the standard testing objectives by providing immediate report on students´ knowledge acquisition. Second, some students only retain information as a means of passing tests. Thus, they will not acquire relevant long-term schemata relations in their lexicon to be noticed by a priming effect even if they succeed in testing. Since semantic priming relates to cognitive automatic processing, faking knowledge acquisition is out of their control.

Discussion and conclusion

As it can be observed from the discussions of constructive and reactive methods, both approaches are perceived as a circular continuum. Mental representations of teachers and students serve to elaborate concept stimuli to be tested in reactive assessment of learning. In turn, reactive assessment facilitates a teacher´s calibration of what is taught. However, a significant difference exists between the current approach to assessing learning and other mental representation techniques employed to evaluate knowledge acquisition (Holley & Danserau, 1984; Rainer, 2005; Hyerle, 2009; Clariana, 2010b). Mainly, natural semantic networks are used to analyze how people signify an event or an object (Figueroa, Gonzales & Solis, 1975). That is, rather than focusing on structural knowledge change, this technique emphasizes analysis of changes as a means of establishing what is learned. This does not imply that metrics of semantic organization cannot be obtained by using the current semantic network technique (e.g. Morales & Santos, 2015); rather, assessment of learning by the current approach must be seen as a means of identifying students´ very personal new conceptualizations of a topic.

It is too early to postulate what impact this technology will have on curriculum and teaching in educational institutions. More research is required to determine how this alternative to e-assessment will complement current e-testing, or how it will affect e-instruction. It is clear, however, that this kind of innovation opens numerous new possibilities for innovating educational technology and establishing new empirical directions for research e-assessment. Presently, the developed software system is a transfer technology prototype (not a toy program) to be implemented on a large scale in distance learning courses through Mexico at the end of this year. Cognitive reports nationwide to teachers accessing the system to obtain information on mental representations due to learning will be implemented by the end of next year.

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