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Software GOLUCA: Knowledge Representation in Mental Calculation*

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We present a new software, called Goluca (Godinho, Luengo, & Casas, 2007), based on the technique of Pathfinder Associative Networks (Schvaneveldt, 1989), which produces graphical representations of the cognitive structure of individuals in a given field knowledge. In this case, we studied the strategies used by teachers and its relationship with the perception expressed about their own abilities for mental calculation. First of all, the participants, 14 primary teachers, were asked what opinions they had about their own capabilities of mental calculation, classifying them as good, bad or moderate. Using the software Goluca, representations were obtained in the form of Pathfinder Associative Networks and the cognitive structure of these teachers concerning to the mental calculation strategies they used and calculated the consistency of such networks, denoted as "coherence". The results obtained allowed to identify which were the main strategies used by teachers and specify that teachers, who feel they have good skills in mental calculation, have more consistent cognitive structures.

Keywords: educational software, cognitive structure, pathfinder associative networks, mental calculation

Techniques for Knowledge Representation

Knowledge Representation

In our present state of knowledge about how the human mind works, it is widely assumed that the information and the concepts are stored in the memory according to a certain organization.

Of great importance in this context is the concept of cognitive structure. By this, it is meant the hypothetical construct that refers to the organization of the relationships between concepts in the semantic or long-term memory (Shavelson, 1972). During the learning process, with the formation of new relationships between existing knowledge and new knowledge, the cognitive structure is modified and becomes more comprehensive and coherent.

The graphical representation of the cognitive structure usually takes the form of what are known as semantic networks. These consist of nodes connected by different relationships and links (Norman, Gentner & Stevens, 1976). The nodes are concepts and groups of concepts (usually represented by words). For

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constructing these networks, we use its semantic similarity. Semantic similarity is a function of the number of properties that the concepts have in common. The more properties they have in common, the more strongly they will be linked.

In these techniques, it is assumed that someone can make a spatial representation of the concepts which describes the pattern of the relationship between those concepts in the memory. This representation can be constructed on the basis of a numerical score assigned to the similarity that a subject perceives among concepts and corresponds to their semantic distance.

Many researchers agreed that this procedure makes it possible to define the cognitive structure in an operational way (Fenker, 1975; Preece, 1976; Shavelson, 1972; Wainer & Kaye, 1974) and reveal the key concepts in a pupil's cognitive structure and the most important relationships between them (Jonassen, Beissner, & Yacci, 1993; Bajo & Cañas, 1994; Casas & Luengo, 2004; Davis & Yi, 2004; Da Silva, Mellado, Ruiz, & Porlán, 2006; Clariana & Wallace, 2007).

Pathfinder Associative Networks

The techniques used to construct these semantic networks include the use of questionnaires, protocols of thinking aloud, interviews with teachers and pupils, concept maps, card sorting, multidimensional scaling, cluster analysis and Pathfinder Associative Networks, amongst other similar approaches (Jonassen et al., 1993).

Pathfinder Associative Networks (Schvaneveldt, 1989) are representations in which the concepts appear as nodes and their relationships appear as line segments joining them. The line segments range their length depending on the weight or strength of their semantic proximity.

The way to assign a similarity score between concepts is the following: One begins by choosing the concepts; the subject is then presented in a random order with all the possible pairs of words that represent those concepts and asked to assign a score to each pair's similarity or difference. Then, it is calculated a correlation matrix like the following (which refers to a specific example), which represents the weights of the links between concepts.

	water	living b.	animals	plants	molecul.	motion	heat	phases w.	solid	liquid	gas
water	1										
living beings	0.7567	1									
animals	0.6833	0.7833	1								
plants	0.6767	0.7733	0.6900	1							
molecules	0.2500	0.3333	0.2433	0.3167	1						
motion	0.3433	0.5733	0.3633	0.3167	0.4000	1					
heat	0.2800	0.2000	0.4067	0.3033	0.5967	0.7767	1				
phases of water	0.7833	0.3300	0.1700	0.2700	0.6833	0.7100	0.7933	1			
solid	0.2667	0.2467	0.2833	0.2667	0.3467	0.2267	0.3333	0.7100	1		
liquid	0.8767	0.2500	0.3033	0.3200	0.1867	0.3267	0.3100	0.7833	0.6200	1	
gas	0.3167	0.1967	0.1767	0.1467	0.3267	0.3067	0.2633	0.7833	0.3800	0.6033	1

Figure 1. Correlation data matrix.

Since all the concepts are related to a greater or lesser degree in the data matrix, there is a corresponding geometrical network in which they all are also linked to each other. The criterion, used by the Pathfinder Associative Networks to determine which links will be included, is that a given link is only incorporated into the network, if there is no indirect path through other nodes whose sum of weights would be less than the direct link.

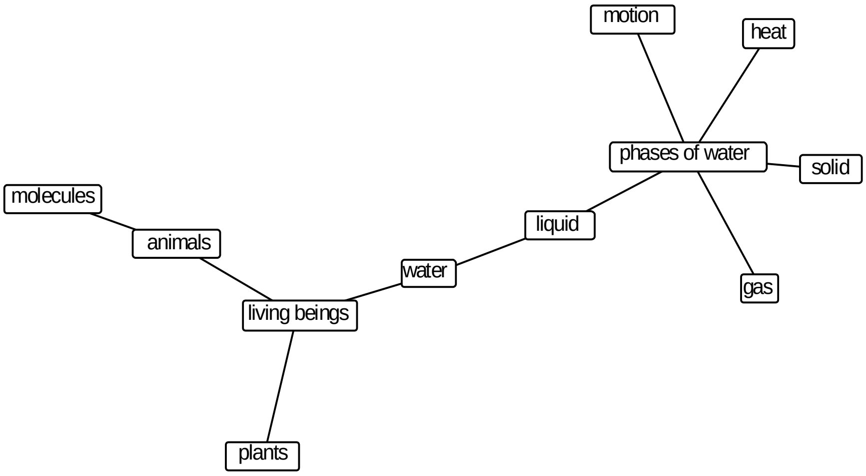

Figure 2. Network of the relation between concepts.

A detailed account of the above can be found in Schvaneveldt (1989), Casas (2002a; 2002b; 2004) and Casas and Luengo (2004).

Pathfinder Associative Networks are used in a wide variety of fields of research (Jonassen et al., 1993; Gonzalvo, Cañas, & Bajo, 1994; McGaghie, 1996; Eckert, 1997; Chen, 1999; Ramey, Smith, Barile, Bihm, & Poindexter, 2001; Moya-Anegón, Vargas-Quesada, Herrero-Solana, Chinchilla-Rodríguez, Corera-Álvarez, & Muñoz-Fernández, 2004).

Software for Knowledge Representation: GOLUCA Software

The procedure described above can be accomplished using the KNOT (knowledge network organizing tool) computer program (KNOT Software, 1989). There are two versions of this program: for Macintosh and for Windows operative systems. The Macintosh version is not yet available and there is a trial version, called Pathfinder, which has been sent us by its author, Roger Schvaneveldt, but only available for PC. This version fixes some shortcomings of the previous version and offers new possibilities, but it continues with two limitations we believe very important.

The first limitation is that it does not allow assign proximity values continuously, but only integer values between one and ten, which means that when calculating the paths values, many ties occur, making it appear that the networks obtained more complex. This problem did not occur with the Macintosh version.

The second limitation is that the program does not have a user-friendly interface. This aspect, which may not be important for the researcher, is important for the experimental subjects that use them. Again, this problem was not the case with the Macintosh version, which was more comfortable to use.

In view of these limitations and to improve possibilities of Pathfinder and KNOT programs, we designed a kind of software called Goluca (Godinho, Luengo, & Casas, 2007) which will be described briefly and with which we have done the research presented in this work.

Mental Calculation

As a result of our teaching and after reviewing the scientific literature (Thompson, 2009; B. Clarke, D. Clarke, & Horne, 2006; Gómez, 1995), we have found that there are students who demonstrate good mental math skills from an early age, just as there are adults who also have regardless of their level of education.

As we have also seen, there is a limited number of strategies for mental calculation that are commonly used for the good calculators, which are discovered at an early age, most often self-taught, apart from formal education.

The difference between novices and experts and between good and bad calculators lies not only in the knowledge of these strategies, but in the best organization of such knowledge into their cognitive structure (Chi, Feltovich, & Glaser, 1981; Ferguson-Hessler & De Jong, 1990).

Abundant research agrees that among these strategies are the following: count forward, count backward, count the missing to reach to, do the double, do the half, etc..

Our hypothesis is that these strategies can be identified and efficiently taught to all students. In order to teach them, it was selected a set of activities that were conducted during a school year with a project of educational innovation aimed to improving outcomes for students in mental calculation.

Method

Our study sample consisted of 14 primary school teachers who taught in various courses from first to sixth. These teachers participated in an educational innovation project, whose goal was to teach mental calculation strategies to their students.

They were asked first to rate subjectively his own capacity for mental calculation, choosing among three levels: “Bad (1)”; “Moderate (2)”; and “Good (3)”.

Then, we conducted a test using the software Goluca, so that similarity scores were assigned to each pair consisting of the following 16 terms which correspond to strategies used for the mental calculation: collect, remove, count forward, count backward, count the missing to reach to, do the double, do the half, subtract as opposite to add, divide as opposite to multiply, seek complementary, count by tens and hundreds, ..., compensate, add, subtract, multiply and divide.

These terms were selected because they corresponded to the most frequently used strategies for mental calculation and had been previously identified in the context of the educational innovation project.

Using the Goluca software, the representations were obtained in the form of Pathfinder Associative Networks to reflect the cognitive structure of teachers about the importance of different strategies and the relationship among them.

By using the Goluca software, we calculated the value of the coherence of each network of participants. The coherence measure of a set of data reflects their consistency. In particular, given two concepts A and B, if they are both related in the same way with the rest of the set of concepts, they must be very similar concepts. The way to compare the type of relationship between A and B is by obtaining the correlation coefficient between the proximity values (from the data matrix) of A with all the other concepts (except itself and B) and the proximity values of B with all the other concepts (except itself and A). If this is done for all the concepts, one obtains an indirect measure of the proximities. This measure is again correlated with the original proximity data, yielding a new correlation coefficient in the range of -1 to +1. The greater the value of this correlation, the more consistent the data and thus the greater the coherence are. It often corresponds to the level of experience (or level of learning) and also indicates whether the values of proximity are assigned conscientiously or at random.

Results

We obtained 14 graphic representations in the form of Pathfinder Associative Networks of the teachers involved. Graphic representations are as the following.

In these networks, we can see how some strategies are more important than others, which are corresponded to what in our theory (Casas & Luengo, 2004) called “Nuclear Concepts”. In the networks shown in Figures 3 and 4, these strategies are clearly highlighted with a logical relationship established with the other strategies, while in other networks, as in Figure 5, appear more intricate and relationships do not seem logical. The value of coherence for the first network corresponds to what we considered as coherence “good (3)”, while the second and third correspond to networks with values of coherence “moderate (2)” and “bad (1)”, respectively.

The summary of the data obtained, in terms of capacity for mental calculation perceived by participants (mental calculation skills), coherence of Pathfinder Associative Networks and degree of coherence, was as follows (see Table 1).

With these data, using the SPSS statistical program we calculate the Spearman’s correlation (see Table 2).

As previous results indicate, there is a statistically significant association (p = 0.000) between the degree of capacity for mental calculation perceived by the participating teachers and the coherence calculated for its Pathfinder Associative Networks. This partnership is important, as indicated by the value of 0.839 in the Spearman’s Rho.

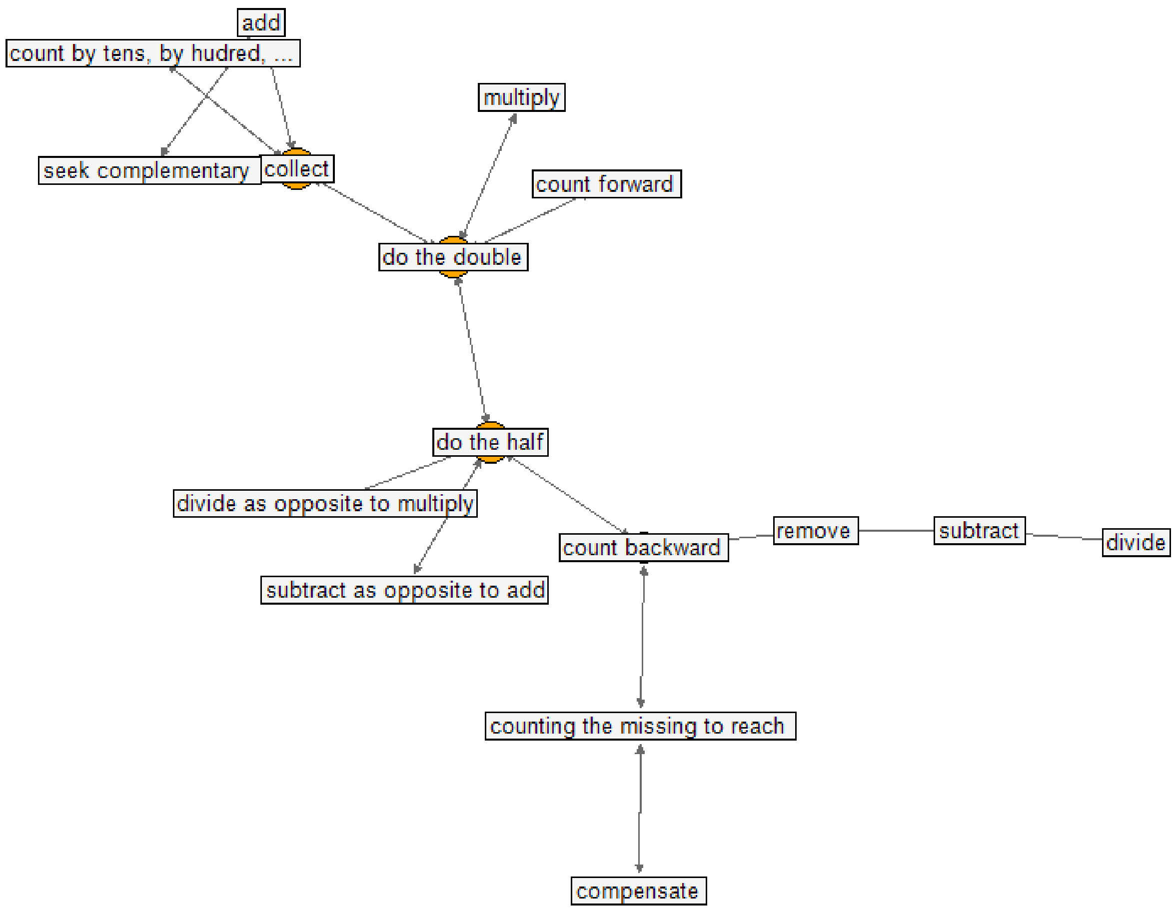

Figure 3. Pathfinder Associative Network (Subject 5).

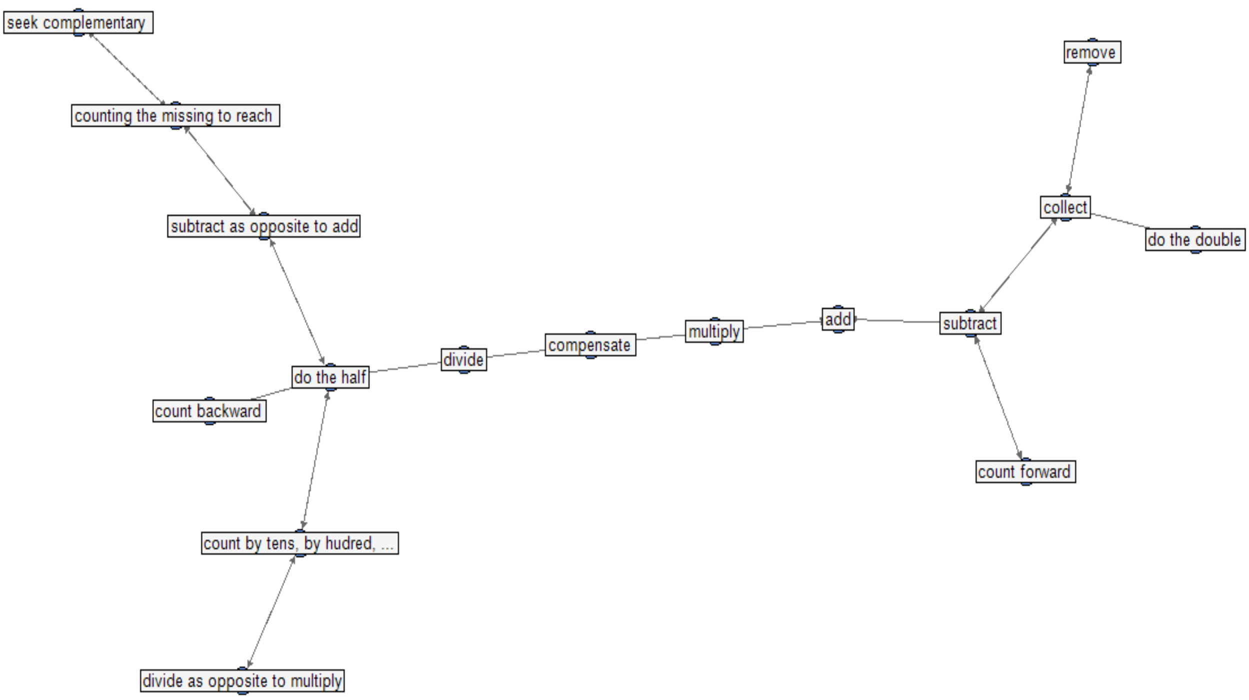

Figure 4. Pathfinder Associative Network (Subject 10).

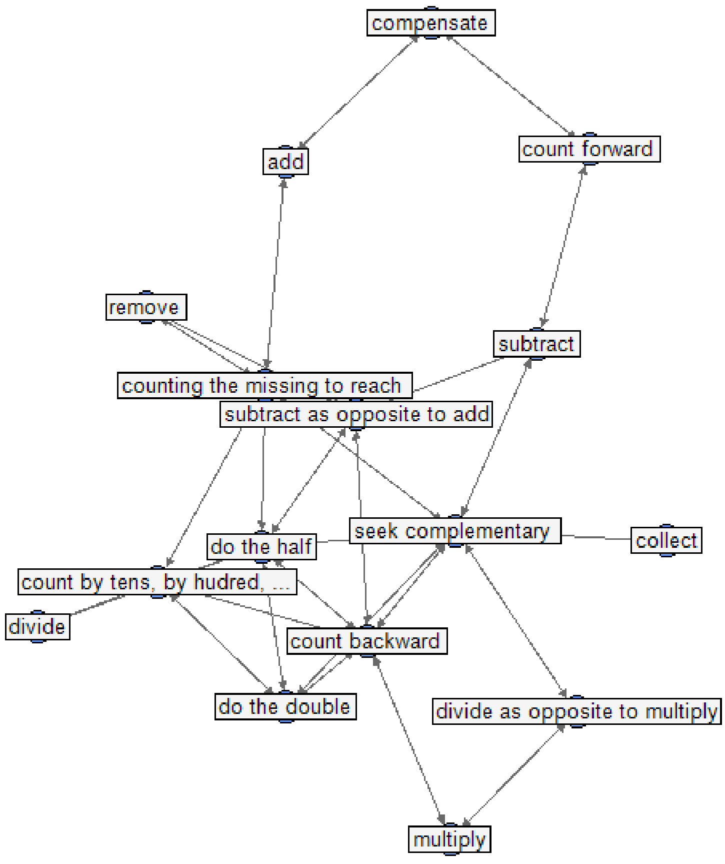

Figure 5. Pathfinder Associative Network (Subject 11).

Table 1

Coherence and Mental Calculation Skills

Subject	Mental calculation skills	Coherence
Subject 1	Bad	0.213
Subject 2	Good	0.564
Subject 3	Good	0.614
Subject 4	Moderate	0.395
Subject 5	Moderate	0.421
Subject 6	Bad	0.250
Subject 7	Good	0.491
Subject 8	Moderate	0.519
Subject 9	Bad	0.434
Subject 10	Good	0.678
Subject 11	Bad	0.284
Subject 12	Bad	0.326
Subject 13	Moderate	0.311
Subject 14	Good	0.569

Table 2

Spearman's Rho Correlation Test

			Mental calculation skills	Coherence
Spearman's Rho	Mental calculation skills	Correlation coefficient	1.000	0.839
		Asymptotic Sig. (bilateral)	.	p = 0.000
		N	14	14
	Coherence	Correlation coefficient	0.839	1.000
		Asymptotic Sig. (bilateral)	p = 0.000	.
		N	14	14

Discussion and Conclusions

The results obtained allow us to ensure that the technique of Pathfinder Associative Networks can represent the cognitive structure of the subjects in different fields of knowledge. Our results are in line with other studies using similar techniques (Jonassen et al., 1993; Eckert, 1997; Chen, 1999; Moya et al., 2004).

The graphical representation of knowledge structure allows us to recognize what its main elements are and also evaluate important features of this structure. The applications of this technique, as we showed in our work, can be extended to areas, such as mental calculation.

In our case, we have shown that teachers, who believe they have good capacity for mental calculation, have cognitive structures more coherent, centered around a few strategies for calculation, but well-organized. These results are in line with those obtained by Chi, Feltovich, and Glaser (1981) in connection with problem solving.

Our proposal is that recognizing these strategies in the most competent individuals, we can convey students to learn them more effectively.

As for the software Goluca that we used to represent the Pathfinder Associative Networks allows a similar way to other programs, such as Knot and Pathfinder, it represents the cognitive structure of the subject and get data from it, but it has other possibilities including that we emphasize its greater ease of use, friendly interface, potential in working with different data types (verbal, graphic...) and different modes of acquisition of proximity values, so that the process of acquiring information about the cognitive structure can be extended to many different themes and subjects.

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