Usage of Semantics of Links as the Basis for Learner's Knowledge Structure Assessment. The Pros and Cons

Maija Strautmane[1]

[1] *Riga Technical University, Riga, Latvia, maija.strautmane@rtu.lv*

Abstract

A concept map provides an external representation of its creator's internal mental structures. As a form of knowledge representation it stresses the structural aspects of learner's knowledge representing it as a network of interconnected concepts. No concept has a meaning by itself because the meaning of a concept arises from its relationships with other concepts in the domain. Links between concepts can be directed or undirected and may be or not be labelled with linking phrases to further explain the type of connection between concepts (thus defining semantics of the links). There has been continuous debate about the necessity of using labelled links and usefulness of including the analysis of correctness of linking phrases as a criterion for a concept map assessment. Ignoring linking phrases makes the assessment of a concept map easier, but the risk is that by simplifying the assessment process in this way important aspects of knowledge are left out of the picture. The paper discusses the pros and cons of analysing linking as a part of a student's knowledge structure assessment. It also describes the results of an experiment, which was conducted to prove that inclusion of linking phrases as a criterion for a concept map assessment gives meaningful information about a concept map creators' knowledge that cannot be obtained using other assessment criteria.

Keywords: *Concept maps, Concept relationships, Knowledge structure, Linking phrases, Knowledge assessment*

1. Introduction

Practitioners in the field of teaching and learning are seeking for ways to adapt educational processes to the latest advances in information and communication technologies (ICT) for the enhancement of effectiveness of knowledge acquisition. Technologies can be used also to support e- and m-learning, adaptive and intelligent knowledge assessment and self-assessment. They provide various means for presenting information and various kinds of tasks for training that were not possible before. One of the means for presenting knowledge in technology supported teaching/learning process is usage of concept maps (CM). CMs can be used for presenting knowledge structure and also as a basis for exercises and tasks for knowledge assessment and self-assessment.

CMs are used both with and without technological support, but the main advantage of using technologies is the ability to automatically generate representation of knowledge in the form of a CM, to compare these representations and give an assessment of represented knowledge. That is why CMs can be utilised as a part of e-assessment system to reduce a teacher's workload.

J.D. Novak and his research team introduced concept maps in 1970's at Cornell University. [1] Usage of structural diagrams like CMs in teaching and learning process is backed up by ideas from Ausubel's hierarchical memory theory and Deese's associationist memory theory. [2] According to Ausubel's theory, meaningful learning takes place by the assimilation of new concepts and their interrelationships into existing concept and propositional frameworks also known as a cognitive structure held by the learner. [1] Ausubel insisted on hierarchical arrangement of this cognitive structure. This structure changes over time as a result of learning through processes of progressive differentiation and integrative reconciliation. [3] Deese postulated that a cognitive structure may contain hierarchically arranged segments, but such order is not obligatory. [2]

Externalisation of internal mental structures in a form of a CM gives an insight into its creator's mental models. Authors of [4] call CMs a "measurement technique that provides window into the structure of our students' minds". As a geographical map is not the territory that it represents, a CM also is just an approximation of the knowledge that it portrays. CMs represent an important property of knowledge – its interconnectedness [5] [6] whether it is hierarchically arranged or not. Authors of [7] claim that well-structured knowledge is an aspect of a competence in a particular field. CMs can be used for assessing that aspect.

Structure as a property of knowledge characterises all kinds of knowledge: declarative, procedural, schematic and also strategic knowledge. [4] At the same time, the source [8] provides a different subdivision of knowledge categories where structural knowledge is mentioned as a category on its own in addition to declarative (factual) and procedural (knowing how to do something) knowledge. Structural knowledge describes the interrelatedness between facts and procedural elements. [8] It interlinks the declarative knowledge with procedural knowledge and facilitates their application. CMs represent declarative as well as structural knowledge [9] because each proposition is a fact, and their arrangement creates the structure. The more intensely interconnected the structure, the easier it is to retrieve relevant knowledge when needed so the utility of well organised knowledge is higher than that of a poorly organised knowledge structures. [10]

It is agreed among users of CMs that interconnectedness is an important trait of a CM that characterises the quality of represented knowledge, but there are still conflicting views whether semantics of relationships needs to be evaluated or not. This paper discusses the pros and cons of including assessment of the semantic meaning of relationships into the scoring algorithm. First section of this paper describes usage of CMs for knowledge assessment purposes. Advantages and drawbacks of implementing assessment of relationships' semantics are discussed in the second section, while the third section contains results of an experiment that was conducted to test the hypothesis that relationship semantics provides important information that cannot be obtained otherwise. The paper ends with conclusions.

2. Concept Maps as Knowledge Assessment Tool

A CM is a graphical representation of knowledge in a form of graph where nodes correspond to concepts and arcs represent relationships between them. Concepts are mental representations of categories of objects, events, or other entities that allow storing information economically so that it can be used to describe and reason about every instance of the category. [11] No concept can be explained without referring to other concepts from the domain. The meaning of each concept depends on the relationships that it has with other concepts in the cognitive structure. [2] CMs are capable of representing various kinds of relationships between concepts in terms of their semantics (in this paper only binary relationships $a\ R\ b$ are considered where "a" and "b" correspond to the concepts and R to the labelled link between them).

Some of the practitioners in the CM field describe using CMs without labelled relationships (as, for example, authors of [12] and [13]), while others insist on using labelled arrows to clarify the nature of each relationship because describing the link between two concepts aid in comprehending their interrelation [14] and inability to provide label is a sign of weak understanding. [15] There is even such a radical opinion that relationships without linking phrases are not creating propositions [16] [17]. These labels are often called linking phrases although terms like "relationships" and "arcs" are used as well. Linking phrases are usually verbs [6] or phrases that contain verbs. Semantics of relationships may be homogenous throughout the whole CM, but it can also be heterogeneous. Homogenous relationships are used in case of pure taxonomies and partonomies (hierarchical arrangements of whole and its parts), and in such cases it is not necessary to label the relationships. [18] There may also be CMs that represent only causal, temporal or other type of relationships. In most cases, though, CMs contain various kinds of relationships (see for example Figure 1).

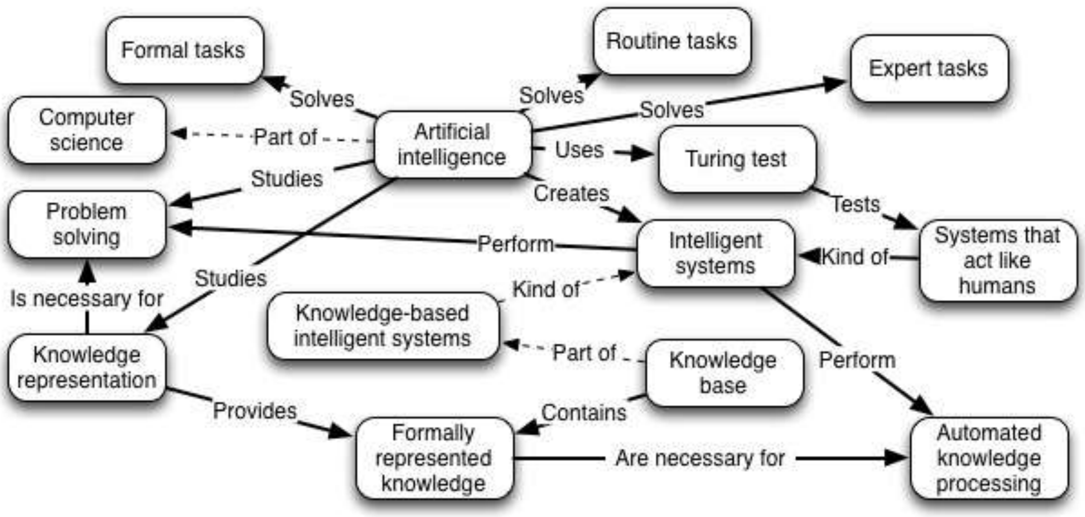

Figure 1. A fragment from a concept map about artificial intelligence.

Theoretically there are more than 700 CM-based tasks possible although, as revealed in extensive study on most frequently used kinds of CM-based tasks, only seven of them are often used. [19] They range from "fill-in-the-map" tasks where a learner has to choose or generate labels for just some elements in a given CM structure to "construct-a-map" tasks where no structure is given, and the learner has to construct the CM according to his/her understanding of how the concepts are interrelated in a particular domain. The type of a task depends on what is provided and what the learner has to generate to complete the task. There can be provided a complete structure of CM, fragments of it or none at all. If the structure is given, then the student may have to indicate the orientation, type (importance of a relationship in the domain being represented) and/or linking phrases of relationships, if they are not already provided in the structure. Complete, partial or empty set of concept labels and linking phrases may be provided to choose elements for creating CM. Sets of concept labels and linking phrases may or may not contain misleading elements that are not supposed to be included in the CM.

CM-based tasks are used both in traditional paper-based knowledge assessments and in technology enhanced knowledge assessment systems. Scoring of a CM may be carried out manually, in a semi-automated manner, where only a part of the CM may be assessed by a system or as a completely automated process. The first CM scoring scheme that still serves as a basis for developing scoring mechanisms for CM assessed four aspects of a CM: the number of meaningful propositions, the number of valid levels of hierarchy, the number of crosslinks and the number of examples. [20] Generally, propositions are concept-relationship-concept triples that make meaningful statements about the domain, but here propositions are relationships between concepts within the same hierarchical segment of the map. All the relationships that connect concepts from different hierarchical segments of the map are called crosslinks. The crosslinks are scored higher than other relationships because these links indicate creative ability [20], and they are evidence of knowledge integration. [21] The levels of hierarchy show where on the general-specific continuum each concept lays in respect to the domain being represented. The number of levels of hierarchy is related to extent to which the individual subsumes more specific knowledge under more general knowledge. [21] Examples are specific events or objects that are instances of concepts. [20] There are a lot more characteristics that can be and have been used for assessing CMs, see, for example, list of criteria in [19].

The evaluation of quantitative criteria of CMs such as the number of concepts, the number of levels of hierarchy, intensity of interrelation (relationships per concept) and the average distance between concepts in the CM can be automated rather easily. Besides, if a learner uses some technology enhanced environment to create the map it is also useful to do so because counting elements of a CM and calculating lengths of paths between concepts are routine tasks that automated systems can do much faster than humans. At the same time, there are quite a few criteria that are considered to reflect important aspects of knowledge, but whose automatisation is not an easy task. One of such criteria is the level of correctness of a proposition. Propositions may consist of such components as a link itself, its direction, its type (weight or degree of importance) and linking phrase. Based on the correctness of these four components, a relationship can be completely correct, completely incorrect or somewhere in between those two. There are several approaches of how much should be awarded for each of the components starting with those that give the same credit for each of them [2], [22] and ending with those that give greatly more credit for correct linking phrases [23] and even those that do not award any points for other components if the linking phrase is missing [24] [25] or incorrect. [26] [27] Time that is necessary for manually scoring a CM using assessment procedure that awards score based on the levels of correctness of its relationships in [28] is estimated to be moderately high compared to the time needed for holistic (expert gives an assessment about the overall quality of a CM) and structural (Novakian) assessment procedures. The time increases not due to the assessment of the first three components of a relationship, but because of the last one. Linking phrases are expressed in a natural language which is not unambiguous. If linking phrases are not provided for a CM creator, than he/she may use any expression that he/she feels is appropriate to describe the nature of the relationship between each two concepts that are connected. To automate the assessment of the linking phrases, the system needs a mechanism to cope with these situations. Next section discusses the advantages and drawbacks of including the analysis of relationship semantics in CM assessment procedure.

3. Analysis of Relationship Semantics

Usually in those cases where a CM assessment mechanism analyses relationship semantics, an expert's map is prepared beforehand to serve as a standard against which learners' maps are compared both in a manual and technology enhanced assessment. Then, a learner's map is scored based on how precisely it mimics relationships included in the expert's map. CMs creator generates linking phrases according to his/her understanding of how concepts are related in a particular domain. As humans use different vocabularies and have their preferred style of expressing thoughts and opinions, they may describe relationships with the same meaning using different phrases. The semantics of interrelation of the same two concepts can also vary depending on the context in which they are used. [10] Moreover, there can even be cases when it is meaningful to represent more than one relationship between two concepts [2] [10]. If no more than one relationship is allowed, then the CM creator has to choose only the most important one.

When comparing the relationships in expert's and learner's maps in respect to the labels used, there can be several situations: (a) the labels are the same in both maps; (b) the labels are different, but they represent the same semantics; (c) the labels represent slightly different semantics; (d) one of the labels is more specific or general than the other one; (e) the labels represent very different semantics. In the first two cases the relationship must be scored as completely correct, in the cases (c) and (d) as partially correct, but in the case (e) as incorrect unless it represents other meaningful relationship in the domain. In addition, every time when there exists a relationship in one direction, there also exists an inverse relationship that has a different label in case of asymmetric relationship, but it is just as correct as the first one. Therefore, an automated scoring mechanism needs an algorithm for analysing the semantics of relationships to discriminate between these cases and assess a learner's CM appropriately. This task is not an easy one because the variance of phrases is virtually indefinite. The author of this paper has done some research on what linking phrases are used in various sources for describing relationships, and it turned out that for an inheritance relationship alone there are more than 50 ways to label it. It is especially important in cases as [5] where researchers encouraged learners to use as many words as they wanted for labelling relationships.

It would be easier if a variety of linking phrases was restricted and there existed few attempts to create a set of linking phrases that would be useful for all kinds of situations, for example [10]. At the same time, there is an opinion that restricting a CMs' creator in how he/she can express his/her internal knowledge structure would counteract the aim of an assessment – to find out what exactly the learner knows and what not. The approach where an assessment mechanism uses predetermined set of linking phrases relationships between which (synonyms, hypernym-hyponym, indirect replacements or inverse relationships) are also defined in advance would also depend on the natural language used for labelling.

To sum up, it takes more preparation to assess semantics instead of only counting concepts, levels of hierarchy and calculate such measures as the interrelatedness of concepts etc. because experts' CM must be prepared and the mechanism that could determinate whether a linking phrase represents the same, slightly different or completely different semantics also needs to be developed. Another drawback, comparing these two assessment approaches, is the dependence on the natural language used for labelling. As seen in the example with the inheritance relationships, it is also not realistic to predetermine all possible labels and their interrelationships if it is allowed to generate any linking phrase that the learner feels is appropriate for a particular relationship in a given domain. On the other hand, it is claimed that analysing relationship semantics is the only way to assess the deep understanding [29] that is crucial for successfully applying the knowledge instead of just being able to replicate certain constructs.

There is one study reported in [30] that has tested whether a more complex CM scoring mechanism gives better results than a simpler one. The complex scoring mechanism has included the analysis of relationship semantics, but the simpler one has only checked whether there exists a relationship between the same two concepts in the expert's map or not. It has been found that both approaches give very similar results (the correlation between these two methods was 0.966). So, if the gain (increase in the accuracy of knowledge assessment) is not worth the effort needed to build assessment systems that could score CMs based also on the semantics of relationships, then it is not useful to try to build such systems. Next section describes an experiment that was conducted to find out if this is the case.

4. Experiment

For the purpose of determining whether a relationship semantics analysis gives different information about learners' knowledge structure an experiment was conducted. There were altogether 201 participants. They all were third year bachelor program students at Riga Technical University, Faculty of Computer Science and Information Technology that had the course "Fundamentals of Artificial Intelligence" in spring semester of the year 2013. All the participants had previous experience in using CMs in this and other courses, so there was no need for training. Each participant received partial credit (max 10% of the final grade in this course) for taking part in the experiment depending on the quality of his/her CM. Thus, the participants were not only interested in taking part, but also creating as qualitative CMs as possible.

For the assessment each participant had to do the CM-based "construct-a-map" task with a given list of 41 concepts that was composed of the concepts discussed during the course. No structure was provided. The participants were reminded of such typical linking phrases as "is a", "part of", "characterises", "is an example" and "kind of", but they were also encouraged to use what ever linking phrases they feel are appropriate for describing relationships that they have created.

The expert's map that served as a reference point for scoring students' CMs contained 55 relationships out of which 22 were considered to be more important and, thus, worth 5 points each if completely correct, but 33 were considered to be of a lesser importance and worth 2 points each (a fragment of this map is shown in Figure 1). If the learner included correct relationships in his/her CM that were not present in the expert's CM, they were scored 1 point each if all its components were correct because although they represented correct proposition in the domain, expert did not consider them to be important enough to be included into CM.

Each participant was given a blank A3 paper for constructing a CM and another paper with an alphabetically ordered list of concepts and task demands. The participants were also reminded to use such components of relationships as direction and type (importance) designated by arrow and thicker line accordingly. Participants had been drawing more detailed CMs for subtopics of this course, but not for this course as a whole. Thus, the CM for this experiment was of a higher level of abstraction, and they had no possibility to redraw some previously created structure. Participants had 1 hour and 30 minutes for completing the task.

The author of this paper performed evaluation of each CM manually. Each CM was evaluated using 6 different scoring schemes (see Table 1). When using one of the first four scoring schemes (E, P, T and D), only one component of a relationship has been evaluated by each of them (existence of such a relationship, correctness of a linking phrase, type of a relationship or its direction accordingly). If it matches with a relationship from the expert's CM that is marked as important (marked with a bold line in Figure 1), the student receives 5 points. If it matches with a relationship that is marked as less important (marked with a dashed line in Figure 1), the student receives 2 points. If the student has created a relationship that represents correct proposition in the domain, but was not included in the expert's CM, then the student receives 1 point for that. Last two scoring schemes evaluate all four components of a relationship, but with different weight. Scoring scheme that has been denoted as E EPTD treats all components as equally important. Thus, if the expert has marked a relationship as important, and the student has drawn that relationship in his/her CM, then he/she gets 5*0.25=1.25 points for each correct component. In case of a less important relationship, it is 2*0,25=0.4 points for each correct component. If such a relationship does not exist in the expert's CM, but it represents a correct knowledge, then the student may receive 1*0.25 = 0.25 points for each correct component. The scoring scheme that has been denoted as E EPTD treats the existence of all relationships as the most important component awarding, linking phrase – as a second most important, type − as third and direction − as the least important component. The weight of each component is chosen to reflect the weight that is used in IKAS (**I**ntelligent and adaptive **K**nowledge **A**ssessment **S**ystem) that uses CM-based tasks and has been developed in Riga Technical University since 2005. [31]

Table 1. Weight of relationship components in various CM scoring schemes.

Denotation	Existence	Linking phrase	Type	Direction
E	100%	Not evaluated	Not evaluated	Not evaluated
P	No points awarded	100%	Not evaluated	Not evaluated
T	No points awarded	Not evaluated	100%	Not evaluated
D	No points awarded	Not evaluated	Not evaluated	100%
E EPTD	25%	25%	25%	25%
P EPTD	42,1%	31,6%	15,8%	10,5%

The components of relationships are not completely independent because the linking phrase, type of relationship and its direction can only be awarded with points if it exists, meaning that such connection of concepts makes a correct statement about the domain being represented. Also the direction is somewhat related to the linking phrase because the choice of the linking phrase depends on the direction of a relationship. In case of symmetric relationships (for example, "is near to" or "coocurrs with") the direction of the arrow can be drawn in ether way, but there are also asymmetric relationships (for example, "is part of" or "located in") for which changing the direction means also changing the label.

The students' scores were normalised expressing them as a percentage of maximum score that could be gained for completely correct CM. Afterwards, Pearsons's correlation coefficients were calculated for pairwise comparing of all four simple scoring schemes that award points based only on correctness of one of the components and for comparing their results with two complex scoring schemes results. In addition, the correlation of CM scores with the final grade was checked for those 95 students who had met all the requirements for passing this course up until June 5th of the year 2013. There are altogether four parts that make up the final grade: the points gained at the theoretical part of the exam give 35% of the final grade, the points gained at the practical part of the exam give 25% of the final grade, the points gained by completing practical tasks during the semester give 30% of the final grade and 10% of the final grade may be received for successfully participating in the experiment described in this paper. For the calculation of the correlation coefficients the following formula was used:

$$r_{x,y} = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2 * \sum_{i=1}^{n}(y_1 - \overline{y})^2}} \quad (1)$$

Where x_i and y_i are the scores for CM with number i that are obtained with scoring schemes to be compared, $\bar{x}$ and $\bar{y}$ are average scores gained with these schemes. The results of these calculations are represented in Table 2.

Table 2. Correlations of scores obtained with various CM scoring schemes and with final grade.

	P	**T**	**D**	**E EPTD**	**P EPTD**	**Grade**
E	0.6815	0.7499	0.7663	0.8988	0.8988	0.2953
P		0.5809	0.8116	0.8957	0.9051	0.3735
T			0.6131	0.8029	0.7617	
D				0.7747	0.8997	
E EPTD						0.3675
P EPTD						0.3653

The values of the correlation coefficient in Table 2 show that all CM scoring schemes correlate to some extent, but they are not interreplacable because they do evaluate different aspects of knowledge structure. The correlation coefficient of schemes E and P is only 0.6815, which means a moderate positive correlation. This is in conflict with the results of the experiment described in [30] where 0.966 correlation was calculated. This result means that not all the students that are capable of indicating the correct linking lines between concepts are able to explain correctly the nature of each relationship between the concepts. They remember that these concepts are somewhat related, but cannot explain how, and this means they do not completely comprehend the connection between them. The correlation coefficients of the scoring schemes E and T and E and D show a strong correlation (0.7499 and 0.7663 respectively), which means that the ability to provide the correct type and direction of a relationship is strongly related to the ability to indicate which concepts have meaningful connections in the domain being mapped. The correlation of the schemes P and D is even higher (0.8116), which affirms the previously postulated fact that a linking phrase and the direction of the arc are not completely independent, and if a student can correctly label the link, then he/she usually can indicate the appropriate direction of the relationship. This may be due to the fact that the direction of the arc matches with the direction of reading this proposition, so that it forms a sentence in a natural language. The least correlation between simple scoring mechanisms is between schemes P and T. This is due to the fact that the students were not always able to discriminate between important and less important relationships. One part of them marked almost all, while some marked only few relationships as important. This inability is related to the fact that it takes a deep comprehension of a domain to be able to distinguish an important connection from a less important one. [32]

When comparing results of the simple scoring schemes with the scoring scheme that evaluates all four relationship components with equal weight (E EPTD), the correlations show a strong positive relationship ranging from 0.7747 to 0.8988. The highest correlation is between E EPTD and E and nearly the same between E EPTD and P, which means that including two other components (type and direction) does not give much of a difference and that the existence of a relationship and the usage of a correct label has the main impact on the final result. The situation is likewise when comparing the simple scoring schemes with the scoring scheme that evaluates all four relationship components with the weight that is proportional to the one used in IKAS (P EPTD).

For all the CM scoring schemes the correlation with the final grade in this course is rather low. It means that CMs measure different aspects of knowledge than exams and practical tasks that are being used for assessment purposes in course “Fundamentals of Artificial Intelligence”. It conforms with the view expressed in [33] and [9] that CMs and traditional measures like essays and other kinds of tasks are not interreplacable and both of them must be used to gain a comprehensive assessment of learners’ knowledge. The fact that the simple scoring scheme E has a lower correlation with the final grades than the scoring scheme P does not necessarily mean that the ability to generate the correct label for a relationship is a better indicator of deep knowledge than the existence of a relationship. It only means that it measures such aspects of knowledge that are more similar to the ones measured by the present assessment system in this course. The fact that the correlation between a final grade and a scheme that only evaluates the existence of a relationship is only 0.2953 means that the assessment methods used in this course do not measure structural knowledge. The correlation of the final grade with the scheme that only evaluates correctness of a linking phrase is higher (0.3735 which shows a weak relationship between the two) because generating linking phrases is more similar to expressing one's thoughts in a written form that is necessary for answering the questions in the theoretical part of an exam.

5. Conclusions

Theoretical discussion at the first part of this paper describes why including the analysis of relationship semantics into the CM scoring mechanism is important and what are the obstacles that are faced when trying to develop such a mechanism. The conducted experiment proves that a linking phrase as a component of relationship gives additional information about a CM creator's knowledge and, thus, it is reasonable to develop such scoring mechanisms that would evaluate the semantics of a relationship instead of just evaluating the structural conformance between the expert's and learner's CMs. Both the correctness of a linking phrase and existence of a relationship should be included as components for evaluating the quality of a learner's knowledge structure in a comprehensible scoring scheme because they reflect different aspects of CMs creators' knowledge. While the existence of a relationship refers to the overall interconnectedness of the concepts of the domain, the ability to attach appropriate linking phrase demonstrates deeper understanding of each particular connection between them. This experiment has once more certified that CMs evaluate different aspects of knowledge than traditional knowledge measurements do and that they can be used as an addition to the traditional measures to reveal learners' structural knowledge.

References

[1] J.D. Novak, A.J. Canas, *"The Theory Underlying Concept Maps and How to Construct and Use Them"*, January 2006 http://cmap.ihmc.us/publications/researchpapers/theorycmaps/theoryunderlyingconceptmaps.htm, Last accessed 20 February 2014.

[2] R.J. Shavelson, H. Lang, B. Lewin, "*On Concept Maps as Potential 'Authentic' Assessments in Science: Indirect Approaches to Knowledge Representation of High School Science*", 1994, http://www.eric.ed.gov/PDFS/ED367691.pdf, Last accessed 20 February 2014.

[3] M.A. Ruiz-Primo, R.J. Shavelson, "*Problems and Issues in the Use of Concept Maps in Science Assessment*". Journal of Research in Science Teaching, Vol. 33, No. 6, pp. 569-600, 1996, http://www.stanford.edu/dept/SUSE/SEAL/Reports_Papers/ProblemsIssuesCMScience.pdf, Last accessed 20 February 2014.

[4] J.R. Shavelson, M.A. Ruiz-Primo, E.W. Wiley, "*Windows into the mind*". Higher Education, Vol. 49, pp. 413–430. 2005.

[5] M.A. Ruiz-Primo, R.J. Shavelson, *"Concept-map based assessment on possible sources of sampling variability*", Report ED422403, 1997, http://files.eric.ed.gov/fulltext/ED422403.pdf, Last accessed 20 February 2014.

[6] K.M. Fisher, J.H. Wandersee, D.E. Moody (ed.) "*Mapping Biology Knowledge*", Kluwer Academic Publishers, Hingham, MA, USA, 2000.

[7] M. A. Ruiz-Primo, "*On the use of concept maps as an assessment tool in science: What we have learned so far*", Revista Electronica de Investigacion Educativa, Vol. 2 No. 1, pp. 29-52, 2000.

[8] D. Ifenthaler, "Scope of Graphical Indices in Educational Diagnostics". *Computer-Based Diagnostics and Systematic Analysis of Knowledge*, D. Ifenthaler, P. Pirnay-Dummer, N.M. Seel (eds.), New York, Springer, 2010, Chap. 12, pp. 213-234.

[9] L.A. Freeman, A. Urbaczewski, "*Concept Maps as an Alternative Technique for Assessing Students' Understanding of Telecommunications*", Journal of Informatics Education Research, Vol. 5, No. 2, pp. 41-54, 2002

[10] D.H. Jonassen, "*Computers as mindtools for schools: engaging critical thinking*", 2nd edition, Prentice-Hall, Upper Saddle River, New Jersey, 2000, pp. 58-82.

[11] D.H. Jonassen, "*On the role of concepts in learning and instructional design*", Educational Technology: Research & Development, Vol. 54, No. 2, pp. 177-196, 2006.

[12] M. Lay-Dopyera, B. Beyerbach, "*Concept mapping for individual assessment*", Paper presented at the Annual Meeting of the American Educational Research Association, April 1983.

[13] C. Eden, "*Analyzing cognitive maps to help structure issues or problems*", European Journal of Operational Research, Vol. 159, pp. 673-686, 2004.

[14] K. Oliver, "*An investigation of concept mapping to improve the reading comprehension of science texts*", Journal of Science Education and Technology, Vol.18, pp. 402-414, 2009.

[15] L.B. Austin, B.M. Shore, *"Using concept mapping for assessment in physics",* Physics Education, Vol. 30, No. 41, pp. 41-45, 1995.

[16] T. Stoddart, R. Abrams, E. Gasper, D. Canaday, "*Concept Maps as Assessment in Science Inquiry Learning - A Report of Methodology*", International Journal of Science Education, Vol. 22, No. 12, pp.1221- 1246, 2000.

[17] E. Gouli, A. Gogoulou, K. Papanikolaou, M. Grigoriadou, "Evaluating Learner's Knowledge Level on Concept Mapping Tasks", *Proceedings of the Fifth IEEE International Conference on Advanced Learning Technologies,* ICALT '05, 2005, pp. 424-428.

[18] S. Whiteley, "*Memletics Concept Mapping: Learn How to Use Powerful Mind and Concept Mapping Tools to Further Enhance Your Learning and Memory Skills*", Advanogy Publishing, 2005.

[19] M. Strautmane "Concept Map-Based Knowledge Assessment Tasks and Their Scoring Criteria: an Overview" *Concept Maps: Theory, Methodology, Technology: Proceedings of the Fifth International Conference on Concept Mapping*, Valletta, Malta, 2012, pp. 80-89.

[20] J.D. Novak, D.B.Gowin, "*Learning how to learn*", Cambridge University Press, p. 216. 1984.

[21] E.J. Borda, D.J. Burgess, C.J. Plog, N.C. DeKalb, M. M Luce, *"Concept Maps as Tools for Assessing Students' Epistemologies of Science".* Electronic Journal of Science Education, Vol. 13, No. 2, 2009, http://ejse.southwestern.edu/article/view/7804/5571, Last accessed 20 February 2014.

[22] L. Zhang, Y. Wang, B. Dong, Z. Zhou, "*The comparison study of Chinese and American secondary school students' knowledge structure- an experimental research based on concept map assessment technique*", Frontiers of Education in China, Vol. 4, No. 2, pp. 286-297, 2009.

[23] L. Roberts, "*Using concept maps to measure statistical understanding",* International Journal of Mathematical Education in Science and Technology, Vol. 30, No. 5, pp. 707-717, 1999.

[24] D.B. Hay, I.M. Kinchin, *"Using concept maps to reveal conceptual typologies",* Education and Training, Vol. 48, No. 2/3, pp.127-142, 2006.

[25] D.B. Hay, "*Using concept maps to measure deep, surface and non-learning outcomes*", Studies in Higher Education, Vol. 32, No. 1, pp. 39–57, 2007.

[26] S.-C. Lin, K.-E. Chang, Y.-T. Sung, G.-D. Chen, "*A New Structural Knowledge Assessment Based on Weighted Concept Maps*", *Proceedings of the International Conference on Computers in Education*, ICCE-2002, 2000, pp. 679-680.

[27] K.E. Chang, Y.T. Sung, R.B. Chang, S.C. Lin, "*A New Assessment for Computer- Based Concept Mapping",* Educational Technology and Society, Vol. 8 No. 3, pp. 138-148, 2005.

[28] J. Keppens, D. Hay, "*Concept map assessment for teaching computer programming*", Computer Science Education, Vol. 18, No. 1, pp. 31–42, 2008.

[29] L.A. Bolte, "*Assessing mathematical knowledge with concept maps and interpretive essays*". Paper presented at the Annual Meeting of the American Educational Research Association, March 24 1997.

[30] M.E. Harper, R.M. Hoeft, A.W. Evans, F.G. Jentsch, "Scoring concepts maps: Can a practical method of scoring concept maps be used to assess trainee's knowledge structures?" *Proceedings of the Human Factors and Ergonomics Society Annual Meeting 2004*, Vol. 48, pp. 2599-2603, 2004.

[31] A. Anohina-Naumeca, J. Grundspenkis, M. Strautmane, *"The Concept Map Based Assessment System: Functional Capabilities, Evolution, and Experimental Results"*. International Journal of Continuing Engineering Education and Life-Long Learning, Vol. 21 No 4, pp. 308-327, 2011.

[32] Y. Yin, J. Vanides, M.A. Ruiz-Primo, C.C. Ayala, R.J. Shavelson, "*Comparison of Two Concept-Mapping Techniques: Implications for Scoring, Interpretation, and Use.*" Journal of Research in Science Teaching, Vol. 42, No. 2, pp.166–184, 2005.

[33] C. Schau, N. Mattern, R.J. Weber, K. Minnick, C. Witt, *„Use of fill-in concept maps to assess middle school students connected understanding of science"*. Paper presented at the Annual Meeting of the American Educational Research Association, 1997, http://files.eric.ed.gov/fulltext/ED408200.pdf, Last accessed 20 February 2014.

Author

Principal author: Maija Strautmane holds an MSc degree in computer systems from the Riga Technical University and a BSc degree in computer control and computer science from Riga Technical University. At present she is a doctoral student and a researcher at Institute of Applied Computer Systems, Riga Technical University.