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USAGE OF GRAPH PATTERNS FOR KNOWLEDGE ASSESSMENT BASED ON CONCEPT MAPS

GRAFU PARAUGU LIETOŠANA UZ KONCEPTU KARTĒM BALSTĪTĀ ZINĀŠANU VĒRTĒŠANĀ

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Graph, concept map, graph pattern, adaptive knowledge assessment, knowledge assessment agent

1. Introduction

Modern information and communication technologies (ICTs) penetrating in education have significantly changed the roles of main actors of teaching and learning process. Teachers nowadays should be guides and coaches while passive learners should turn into active ones. ICTs enable student centred and one-to-one learning in traditional education and technology enhanced educational systems. These technologies allow the construction of computational environments that aim at facilitating teaching, learning, and sometimes learning assessment, but with the dissemination of distance learning, however, learning assessment has become a constant concern [1].

It is important that both actors (a teacher and a learner) can keep track of learner's progress which requires systematic knowledge assessment. Nevertheless, even in traditional teaching where regular knowledge assessment may be carried out quite naturally, teachers have to cope with the assessment of hundreds of students. That is one of the main reasons why in practice they usually apply only final examinations. In e-learning a regular knowledge assessment, as a rule, is carried out using different kinds of tests. Unfortunately, tests allow assessing learners' knowledge only at the first four levels of Bloom's taxonomy which includes three levels of lower order skills: knowledge, comprehension, and application, and three levels of higher order skills: analysis, synthesis, and evaluation [2].

In this context concepts maps (CMs) have become a valuable tool of teaching, learning and assessment as they enhance learning, promote reflection and creativity and enable students to externalize their knowledge structure [3]. Approaches using CMs are based on the fundamental idea in Ausubel's cognitive psychology that learning takes place by the assimilation of new concepts and propositions into existing concept and propositional frameworks held by the learner [4]. Over the last years, the introduction of ICTs in the educational practice resulted into the development of a number of computer-based and web-based concept mapping environments [5]. Some environments based on CMs and aimed at assessment have already been described in literature [1, 5, 6, 7, 8, 9, 10]. The general tendency of these environments is to compare a CM developed by a learner (student) to a CM developed by a teacher or by a problem domain expert. The serious drawback is that the assessment accomplished through mere comparison of CMs is not in accordance with cognitive principles. It forces students to construct their knowledge in a way that mimics the knowledge constructed by the teacher or the expert [1]. This approach does not address the fact that humans construct knowledge in a number of different ways, for instance, some people prefer to specialize new concepts from more general ones while others prefer to do vice versa. An alternative is to compare students' CMs to population of CMs [1].

The paper presents the approach which recommends the use of so called graph patterns to generate a search space of possible correct CMs. This is the next step in the development of knowledge assessment system (KAS) [11, 12]. The approach is implemented in the developed adaptive KAS which supports both teacher's assessment and learner's self-assessment keeping track of person's progress, i.e., evolution of his/her understanding of the topic. The rest of the paper is structured as follows. In Section 2, the usage of CMs for knowledge assessment is discussed. In Section 3, an overview of the developed KAS is given. In Section 4, the notion of graph pattern is defined and different graph patterns are analyzed. The paper ends in Section 5, with conclusions and the outline of future work.

2. The use of concept maps for knowledge assessment

Concept maps as a pedagogical tool has been developed by Novak [3, 13]. According to Novak, a CM represents part of a person's cognitive structure, revealing his/her particular understanding of a specific knowledge area. This cognitive structure as held by the learner is also referred as the individual's knowledge structure [14]. CMs are semi-formal knowledge representation tools that are visualized by a graph and use natural language to represent concepts and propositions, i.e., to represent semantic knowledge and its conceptual organization. Mathematically defined, a CM is undirected or directed graph consisting of a finite, non-empty set of nodes which represent the concepts of a knowledge domain, and a finite, non-empty set of arcs (undirected, called also edges, or directed) which represent the relationships between pairs of concepts. Arcs may have the same or different weights, i.e. some relationships may be more important than others [15]. A CM can be defined also as an attributed graph where nodes are labelled by concepts and the set of arcs contains the attributes that can be words or linking phrases used to specify the kind of relationship between concepts [16]. A proposition is a semantic unit of CM, i.e., a concept-relationship-concept triple which is a meaningful statement about some object or event in a problem domain [17]. Variety of CMs visualized by different graphs is shown in Fig.1.

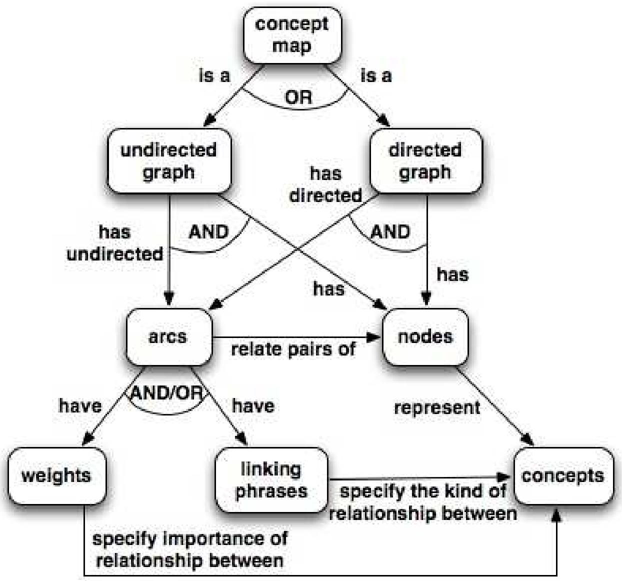

Fig.1. Variety of concept maps

A CM is constructed by the continued application of progressive differentiation and integrative reconciliation that, according to Ausubel's Assimilation Theory, is a fundamental necessity for human beings to learn meaningfully via acquisition and retention of concepts and propositions, which are stored in their cognitive structure [18]. The step-by-step construction of a CM and a sequence of CMs constructed by a student can illustrate the evolution of person's understanding of the topic [19]. Certainly, cognitive structures of student and teacher (expert) can be different and given the same

concepts they can draw different CMs. Buggy student model represents relation between student's and expert's knowledge. Student's knowledge is viewed as some subset of expert's knowledge as it is shown in Fig.2. The goal of tutoring is growing the student's subset of the expert's knowledge [20].
CMs are a viable, computable, and theoretically sound solution to the problem of assessing students learning [1]. The use of CM based tasks as test items for assessment allows seeing students' cognitive structure, i.e., their knowledge structure, promotes system thinking, and supports process oriented learning in which a teacher divides a study course into stages [21]. The latter is a prerequisite of regular and systematic knowledge assessment. Besides, CMs are easy to create and use. Concept mapping approach offers a reasonable balance between requirements to assess higher levels of knowledge and complexity of knowledge assessment system [21]. Moreover, CMs can be used as alternative to usual essays, decreasing the amount of work demanding from teachers during assessment [1].

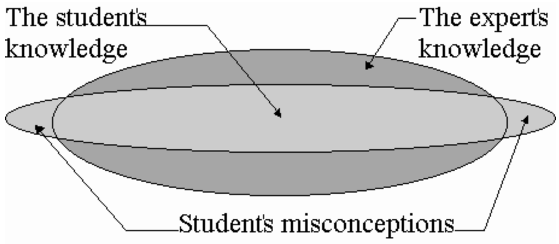

Fig.2. A representation of the perturbation or buggy student model (adapted from [20])

Realization of various learning concept mapping activities provides specific learning outcomes. An activity accomplishes specific educational functions, such as ascertaining students' prior knowledge, promoting knowledge construction/identifying conceptual changes, and assessing knowledge construction [22]. Depending on the outcomes and functions, the activities may employ various concept mapping tasks, such as, the completion of a given map, its extension, evaluation/correction, the construction of a map or combinations of the abovementioned tasks, each of which provides a different perspective of student's understanding [5].
The concept mapping tasks range from high-directed to low-directed depending on the support provided to students. All tasks are divided into "fill-in-the-map" tasks where CM's structure is given and "construct-the-map" tasks where students themselves must create a CM's structure and contents [23].
The CM tasks may be sorted in accordance with their degree of difficulty. At the one end of the scale there are located the most easy fill-in-the-map tasks which belong to high-directed tasks. In these tasks the structure with predefined and correctly placed linking phrases is given. Tasks of this group differ only with the number of teacher's predefined concepts which are correctly placed in the given CM. Students must fill-in blank nodes with concepts from the given list. The next group of high-directed tasks is composed of fill-in-the-map tasks where students must place concepts from the given list correctly in case when the structure of CM is given, too. It is possible to vary tasks in this group by inserting the definite number of teacher's predefined concepts, as well as to use weighted undirected graph, for example, defining important and less important arcs (also done by a teacher). Moving towards the most difficult fill-in-the-map tasks there are groups of tasks where only the structure of CM is given and students must fill-in blank nodes with given concepts and label arcs with linking phrases from the given list. From these tasks it is possible to derive tasks where linking phrases aren't given.
There is a variety of construct-the-map tasks the degree of difficulty of which depends on the support provided to students. Students may have a list of concepts and/or a list of relationships which, in their turn, may have weights. The underlying graph may be undirected or directed. In another group of tasks students may be free to add needed concepts and/or relationships to their CM. Yet more, the given lists may contain also concepts and/or relationships that are misleading, i.e. concepts and/or relationships that are superfluous or even incorrect. So, at the other end of the scale there are tasks with highest degree of difficulty, namely, those where students are free to define concepts and relationships with

linking phrases, and to construct the structure of CM corresponding to the underlying directed graph. The wide variety of different CM fill-in and construction tasks allows offering tasks with the degree of difficulty which corresponds to the current knowledge level of each individual learner. Consequently, CM tasks promote adaptive knowledge assessment.

3. Overview of the developed knowledge assessment system

From CMs comparison perspective the developed KAS consists from three interacting agents: teachers, learners and the intelligent knowledge assessment agent as it is depicted in Fig.3.

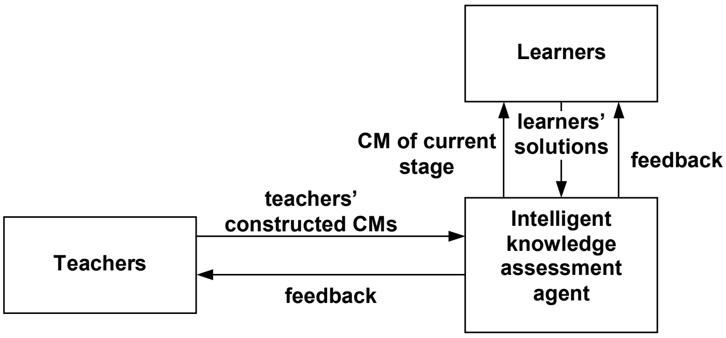

Fig.3. Three interacting agents of KAS

The system supports the following scenario. A teacher divides a study course into *N* stages and defines concepts and relationships between them which are taught at each stage. Using the system's graphical user interface, a teacher prepares CMs for each stage. During creation of a CM for the first stage, a teacher can freely edit it. At the next stages he/she can freely operate only with new elements of the current CM, because the system maintains the previous CM unchanged. The system supports teacher's action for drawing CMs on the working surface. At the knowledge assessment or self-assessment phase a learner receives a CM that corresponds to the task (fill-in-the-map or construct-the-map) of current stage. After finishing the task a learner confirms his/her solution and the intelligent knowledge assessment agent compare corresponding CMs. The intelligent knowledge assessment agent is a multiagent system as it is shown in Fig.4.

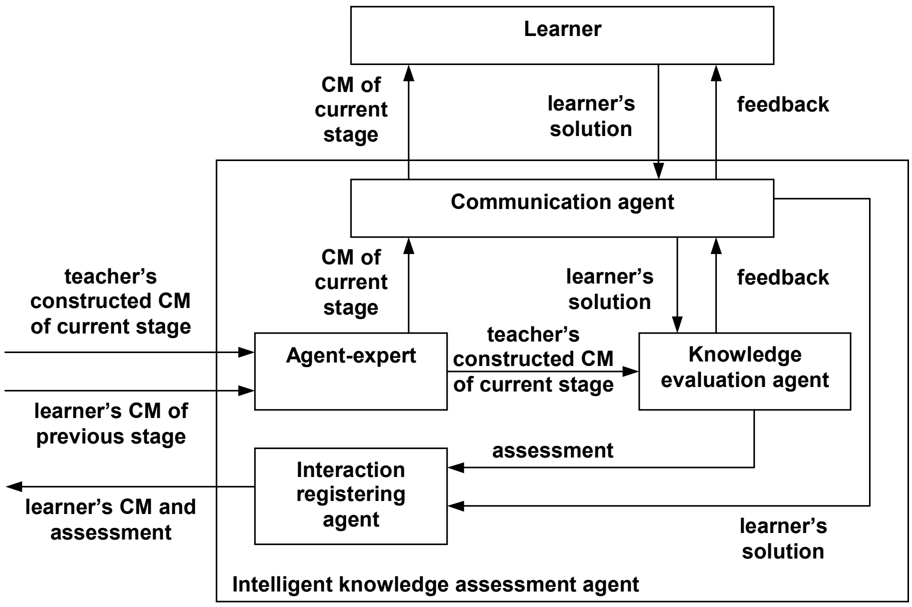

Fig.4. Intelligent knowledge assessment agent as a multiagent system

The duty of the agent-expert is to form a CM of a current stage using a teacher's constructed CM and a learner's CM of a previous stage in which only correct solutions are left while concepts and/or relationships placed incorrectly are returned back in the corresponding lists. The agent-expert sends a learner's CM of a previous stage to the communication agent for visualization, and a teacher's constructed CM to the knowledge evaluation agent. The latter compares a learner's solution (CM) with a teacher's constructed CM, recognizes graph patterns described in the next section, and gives an assessment. The communication agent visualizes a CM of a current stage, perceives a learner's CM, sends it to the knowledge evaluation agent, gets a feedback from it and passes this feedback to a learner. The interaction registering agent, after receiving a learner's solution and its assessment, stores them into the database. The functioning of KAS in details is described in [11, 12, 21, 24].

4. Comparison of concept maps based on graph patterns

The main attractiveness of CMs is easiness of creation and use. At the same time, this ease of use causes an ambiguity, which makes it difficult to assess knowledge expressed in CMs [25]. As mentioned in introduction, the assessment accomplished through pure comparison of CMs is not in accordance with cognitive principles, as it forces students to construct their knowledge exactly in the same way as it was done by a teacher. Some alternatives are discussed in literature. In [26] an approach is presented based on Artificial Intelligence techniques, such as ontologies and genetic algorithms allowing personal ways of constructing knowledge. A scheme that adopts the relational method by examining the accuracy and completeness of the presented propositions on the student map, taking into account the missing ones, with respect to the propositions represented on the expert map is proposed in [27]. Different approach is proposed in [16]. In this work, CMs are described as attributed graphs and their comparison is performed using graph isomorphism. A heuristic algorithm is used to automatically compare CMs and compute their similarities. All abovementioned approaches are targeted towards more flexible and adaptive knowledge assessment for CM tasks, using rather time-consuming procedures. It is needed to stress, that the determination of graph isomorphism which is computationally hard task, may be used only as indicator finding out are there mistakes in a learner's CM or not, and only for construct-the-map tasks, because it is clear, for example, that if both CMs have different number of nodes, some concepts are "lost" in a learner's CM.

This paper presents the algorithmic approach based on comparison of so called graph patterns found in a learner's and a teacher's CMs. A graph pattern is defined as a subgraph, in fact, a path with limited length. In the developed KAS only two classes of graph patterns are used, namely, those containing two related concepts and those containing three concepts and two relationships.

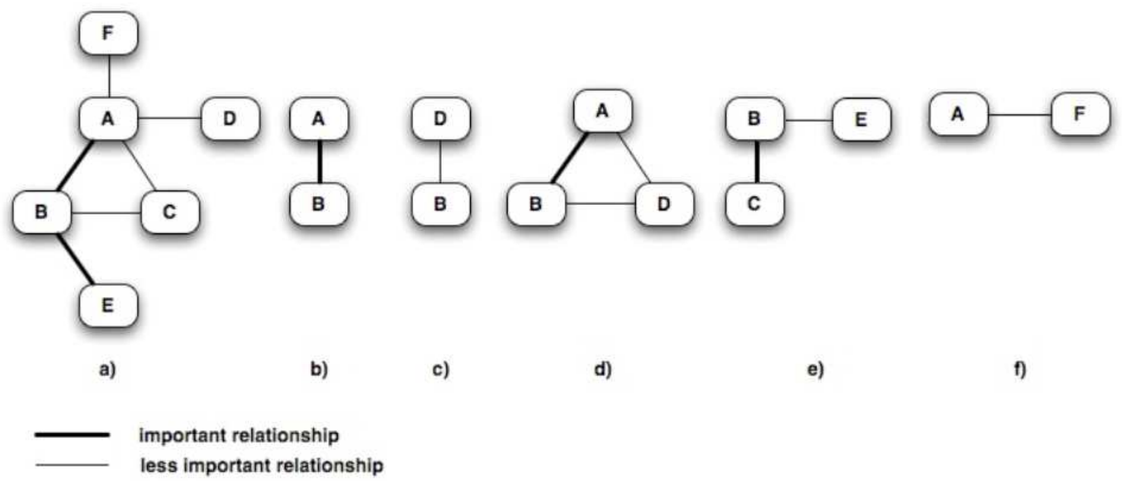

Fig.5. Five graph patterns

First, let's consider high-directed fill-in-the-map tasks. The comparison is based on the assumption that understanding of existence of a relationship is more important than knowledge about weight of a relationship and places of concepts in a CM. In case if the structure of a CM is given and only two types of undirected links are used, 5 graph patterns have been defined [12]. In Fig.5a an abstract example of a CM is given. Fig.5b represents correct solution, while Fig.5c corresponds to completely incorrect solution. In Fig.5d is shown a solution: correct relationship, incorrect place (*D* instead of *C*). Fig.5e depicts a solution: incorrect type of relationship, incorrect place (*E* instead of *C* and vice versa), and Fig.5f represents a solution: incorrect place (*F* instead of *D*), but the place is not important, and actually the solution is correct.
In case when linking phrases are added the knowledge evaluation agent uses the algorithm which distinguishes 9 graph patterns [28]. In Fig.6a an example of a CM is given.

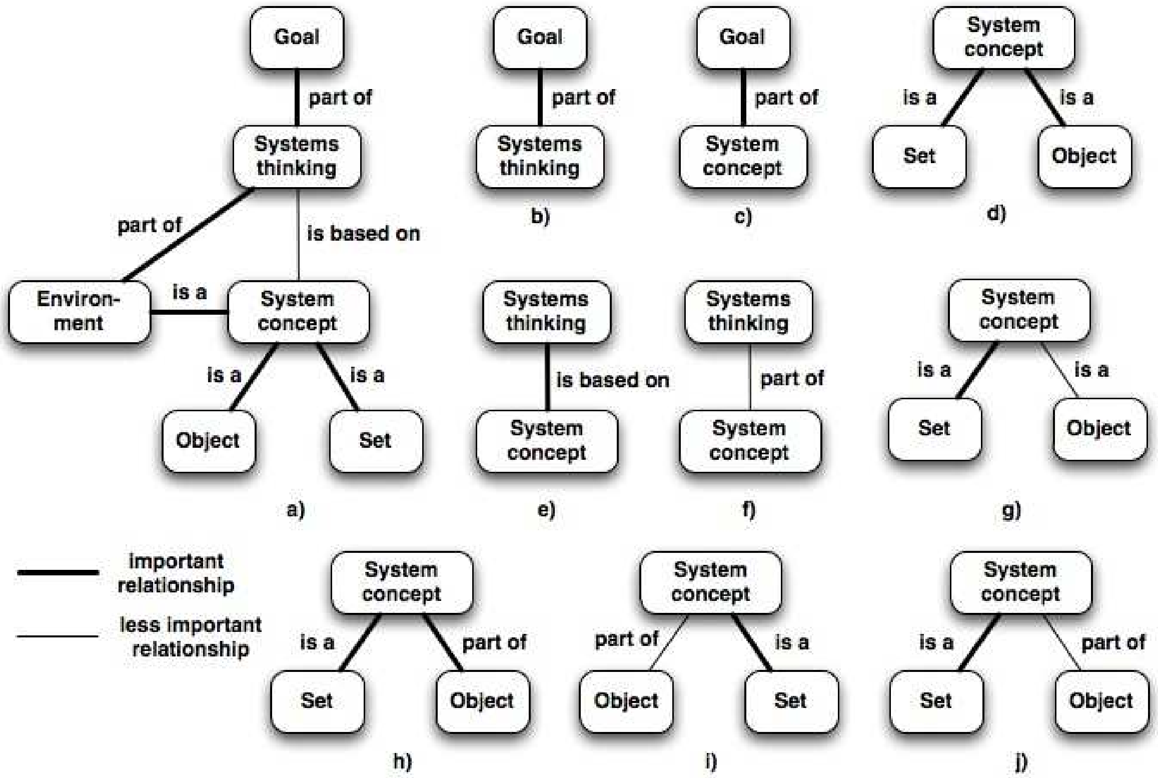

Fig.6. Nine graph patterns

The following solutions are considered: Fig.6b – correct; Fig.6c – completely incorrect; Fig.6d – correct relationship, incorrect places of concepts "object" and "set"; Fig.6e – incorrect type of relationship; Fig.6f – incorrect linking phrase; Fig.6g – incorrect type of relationship, incorrect place of concept "object"; Fig.6h – relationship exists, a linking phrase is incorrect, place of concept "object" is incorrect; Fig.6i – relationship exists, but both its type and linking phrase are incorrect; Fig.6j – relationship exists, but its type and a linking phrase is incorrect and at least one of concepts is placed incorrectly.
The abovementioned 9 patterns are characteristic for both fill-in-the-map tasks and construct-the-map tasks. If the underlying graph is directed, the number of patterns grows up to 36 [24].
In those construct-the-map tasks where learners are given freedom to define concepts and linking phrases the number of possible patterns is high. The reason is that synonyms of concepts should be taken into account using corresponding ontologies as well as many new relations which are "hidden" in a teacher's CM may appear in a learner's CM [29]. In fact, the algorithm must compare a population of CMs and assess correct solutions. In this case to increase the level of automation of knowledge assessment and, as a consequence, to increase the adaptability of KAS, it is useful to inspect larger graph patterns.

In Fig.7 the situation is shown where some relations are "hidden". There are only 3 relations in the expert's CM (Fig.7a), but 2 more relations can be derived from it (Fig.7b). These derived relations may be permitted in a student's CM and should be accepted as correct, too. So, it is necessary to define the mechanism according to which the KAS could detect extra relations and thus make the assessment more flexible and automated.

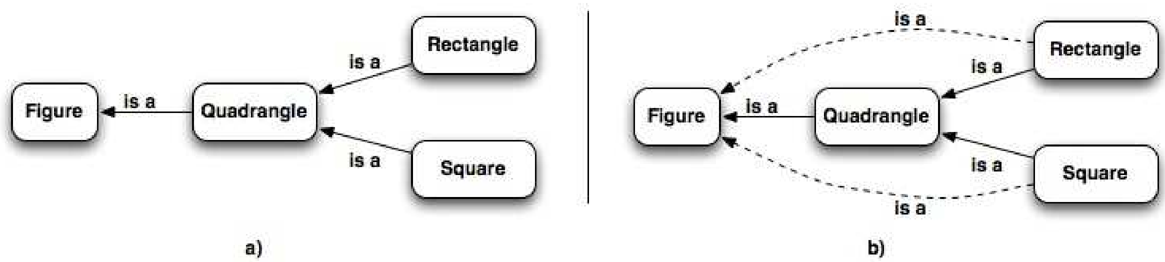

Fig.7. Hidden relations

Inspecting patterns that consist of three concepts and two relations shown in Fig.8, three situations can be fixed:

a) Combination is allowed but an extra relation cannot be added;
b) Combination is allowed and extra relation can be added;
c) Combination is not allowed.

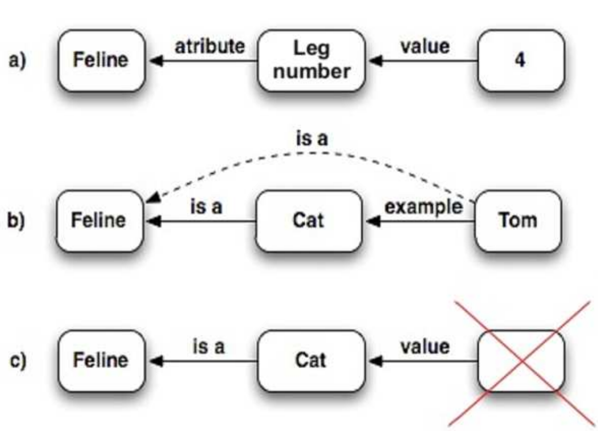

Fig.8. Three pattern types

Using these patterns, system does not have to look through the semantics of concepts because only a relation type and placement is relevant. It is a significant benefit because analyzing syntactic structures for artificial systems is much easier than working with semantics.
When talking about patterns in CMs, 6 types of relations can be examined:

- "is a" – a relation between concepts meaning that one is a subclass of another;
- "part of" – a relation between concepts meaning that one of them is a part of another;
- "attribute" – a relation between a concept and its attribute;
- "example" – a relation between a general concept and a particular example of it;
- "value" – a relation between an attribute and its value;
- "kind of" – a relation between levels of hierarchy.

Of course, there are many other linguistic relations as well, but due to the scope of this paper, they are not considered.
Structure of patterns discussed in Table 1 is shown in Fig.9. The pattern has two main relations (Relation 1 and Relation 2) which are of types mentioned previously. An extra relation (Relation 3) can be formed using a corresponding production rule from Table 2. In some cases a combination of relations is not allowed and a production rule given in Table 2 is of proscriptive nature. Column

“Combination allowed” identifies either a combination between Relation 1 and Relation 2 is allowed or not.

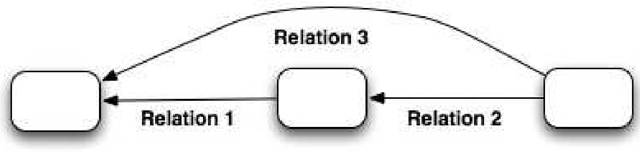

Fig.9. Structure of pattern

Table 1

Patterns containing three concepts and two relations

	Relation 1	Relation 2	Combination allowed	Relation 3	Rule No.
1	Is a	Is a	Yes	Is a	R1
2	Is a	Part of	Yes	Part of	R2
3	Is a	Attribute	Yes	Can’t be specified*	–
4	Is a	Example	Yes	Is a	R3
5	Is a	Value	No	–	R4
6	Is a	Kind of	Yes	Is a	R5
7	Part of	Is a	Yes	Part of	R6
8	Part of	Part of	Yes	Part of	R7
9	Part of	Attribute	Yes	Can’t be specified*	–
10	Part of	Example	Yes	Part of	R8
11	Part of	Value	No	–	R9
12	Part of	Kind of	Yes	Part of	R10
13	Attribute	Value	Yes	No extra relation**	–
14	Attribute	Any other except “Value” and linguistic	No	–	R11
15	Example	Is a	Yes	No extra relation**	R12
16	Example	Part of	Yes	No extra relation**	R13
17	Example	Attribute	Yes	Can’t be specified*	
18	Example	Example	No	–	R14
19	Example	Value	No	–	R15
20	Example	Kind of	Yes	No extra relation**	R16
21	Value	Any other except linguistic	No	–	R17
22	Kind of	Part of	Yes	Part of	R18
23	Kind of	Is a	Yes	Is a	R19
24	Kind of	Kind of	Yes	Is a	R20
25	Kind of	Example	Yes	Example	R21
26	Kind of	Attribute	Yes	Can’t be specified*	–
27	Kind of	Value	No	–	R22

* There can be situations when extra relation can be added, but not always.
** No additional relation of considered 6 types.

Table 2

Corresponding rules

Rule No.	IF...THEN Rule
R1	IF Relation (X, Y, "is a") AND Relation (Y, Z, "is a") THEN Relation (X, Z, "is a")
R2	IF Relation (X, Y, "part of") AND Relation (Y, Z, "is a") THEN Relation (X, Z, "part of")
R3	IF Relation (X, Y, "Example") AND Relation (Y, Z, "is a") THEN Relation (X, Z, "is a")
R4	IF Relation (X, Y, "is a") THEN NOT Relation (Z, X, "value")
R5	IF Relation (X, Y, "kind of") AND Relation (Y, Z, "is a") THEN Relation (X, Z, "is a")
R6	IF Relation (X, Y, "is a") AND Relation (Y, Z, "part of") THEN Relation (X, Z, "part of")
R7	IF Relation (X, Y, "part of") AND Relation (Y, Z, "part of") THEN Relation (X, Z, "part of")
R8	IF Relation (X, Y, "example") AND Relation (Y, Z, "part of") THEN Relation (X, Z, "part of")
R9	IF Relation (X, Y, "part of") THEN NOT Relation (Z, X, "value")
R10	IF Relation (X, Y, "kind of") AND Relation (Y, Z, "part of") THEN Relation (X, Z, "part of")
R11	IF Relation (X, Y, "attribute") THEN NOT Relation (Z, X, "part of") AND NOT Relation (Z, X, "example") AND NOT Relation (Z, X, "is a") AND NOT Relation (Z, X, "attribute") AND NOT Relation (Z, X, "kind of")
R12	IF Relation (X, Y, "is a") AND Relation (Y, Z, "example") THEN NOT Relation (X, Z, "part of") AND NOT Relation (X, Z, "is a") AND NOT Relation (X, Z, "example") AND NOT Relation (X, Z, "attribute") AND NOT Relation (X, Z, "value") AND NOT Relation (X, Z, "kind of")
R13	IF Relation (X, Y, "part of") AND Relation (Y, Z, "example") THEN NOT Relation (X, Z, "part of") AND NOT Relation (X, Z, "is a") AND NOT Relation (X, Z, "example") AND NOT Relation (X, Z, "attribute") AND NOT Relation (X, Z, "value") AND NOT Relation (X, Z, "kind of")
R14	IF Relation (X, Y, "example") THEN NOT Relation (Z, X, " example")
R15	IF Relation (X, Y, " example") THEN NOT Relation (Z, X, "value")
R16	IF Relation (X, Y, "kind of") AND Relation (Y, Z, "example") THEN NOT Relation (X, Z, "part of") AND NOT Relation (X, Z, "is a") AND NOT Relation (X, Z, "example") AND NOT Relation (X, Z, "attribute") AND NOT Relation (X, Z, "value") AND NOT Relation (X, Z, "kind of")
R17	IF Relation (X, Y, "value") THEN NOT Relation (Z, X, "part of") AND NOT Relation (Z, X, "is a") AND NOT Relation (Z, X, "example") AND NOT Relation (Z, X, "attribute") AND NOT Relation (Z, X, "value") AND NOT Relation (Z, X, „kind of")
R18	IF Relation (X, Y, "part of") AND Relation (Y, Z, "kind of") THEN Relation (X, Z, "part of")
R19	IF Relation (X, Y, "is a") AND Relation (Y, Z, "kind of") THEN Relation (X, Z, "is a")
R20	IF Relation (X, Y, "kind of") AND Relation (Y, Z, "kind of") THEN Relation (X, Z, "is a")
R21	IF Relation (X, Y, "example") AND Relation (Y, Z, "kind of") THEN Relation (X, Z, "example")
R22	IF Relation (X, Y, "kind of") THEN NOT Relation (Z, X, "value")

In production rules relations between concepts are written in the following form: Relation (<concept_1>, <concept_2>, <relation_type>). "Concept_1" and "concept_2" are not particular concepts but they are needed to specify directions of relations in a pattern. "Relation_type" represents semantics of a relation between concepts.

Production rules from Table 2 are used to expand expert's CM adding all possible extra relations. Afterwards this expanded structure is compared with a CM drawn by a student. This technique allows assessing student's knowledge more precisely. Production rules from Table 2 can also be used to reveal additional relations in graph patterns that consist of more than three concepts and two relations between them. In such case the algorithm must iteratively go through the CM searching for patterns and adding extra relations whenever rules order it. The algorithm stops when no new relation has been added during the last iteration.

5. Conclusions

Concept maps have become a rather popular tool of teaching, learning and assessment because they are easy to construct and use. At the same time mere comparison of teacher's created and a learner's completed CM does not satisfy cognitive principles. Moreover, it does not allow students to construct their knowledge in different ways which, in its turn, results as a population of CMs. The paper presents the approach based on graph patterns targeted towards more adaptive and flexible knowledge assessment. The already developed adaptive KAS supports both fill-in-the-map and construct-the-map tasks. The running prototype (fourth in a row) is under the development. All described graph patterns will be implemented in the knowledge evaluation agent of this prototype.

Future work is directed towards extension of the developed KAS. The scoring mechanism for compared CMs where all defined graph patterns are considered should be developed. More flexible and adaptive feedback to learners based on student models is investigated, too.

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Grundspeņķis J., Strautmane M. Grafu paraugu lietošana uz konceptu kartēm balstītā zināšanu vērtēšanā

Rakstā ir apskatīta konceptu karšu lietošana zināšanu vērtēšanai. Konceptu kartes ir grafi, kuru virsotnes atspoguļo konceptus, bet loki attieksmes starp tiem. Konceptu kartes atklāj apmācāmo zināšanu struktūru un ļauj novērtēt viņu zināšanu līmeni. Konceptu kartes ir viegli pakāpeniski konstruēt un ērti lietot. Tomēr eksperta veidotās konceptu kartes un apmācāmo veidoto konceptu karšu tieša salīdzināšana ierobežo apmācāmos, jo viņi ir spiesti sekot eksperta zināšanu struktūrai, lai gan valda uzskats, ka indivīdi savas zināšanu struktūras veido visai dažādi. Izstrādātās adaptīvās zināšanu vērtēšanu sistēmas, kas ir realizēta kā daudzaģentu sistēma, zināšanu vērtēšanas aģents veic minēto konceptu karšu salīdzināšanu. Rakstā izklāstīta jauna pieeja konceptu karšu salīdzināšanā, izmantojot grafu paraugus. Grafu paraugi ir apakšgrafi, t.i., ceļi ar ierobežotu garumu. Ir doti grafu paraugi gan uzdevumiem, kuros apmācāmais aizpilda konceptu karti, ja ir iepriekš definēta tās struktūra, gan konceptu kartes konstruēšanas uzdevumiem. Grafu paraugiem atbilstošie produkciju likumi ļauj paplašināt eksperta konstruēto konceptu karti, tādējādi nodrošinot elastīgāku un adaptīvu zināšanu vērtēšanu.

Grundspenkis J., Strautmane M. Usage of Graph Patterns for Knowledge Assessment Based on Concept Maps

The paper discusses application of concepts maps (CMs) for knowledge assessment. CMs are graphs which nodes represent concepts and arcs represent relationships between them. CMs reveal learners' knowledge structure and allow assessing their knowledge level. Step-by-step construction and use of CMs is easy. However, mere comparison of expert constructed and learners' completed CMs forces students to construct their knowledge exactly in the same way as experts. At the same time it is known that individuals construct their knowledge structures in different ways. The developed adaptive knowledge assessment system which is implemented as multiagent system includes the knowledge evaluation agent which carries out the comparison of CMs. The paper presents a novel approach to comparison of CMs using graph patterns. Graph patterns are subgraphs, i.e., paths with limited length. Graph patterns are given for both fill-in-the-map tasks where CM structure is predefined and construct-the-map tasks. The corresponding production rules of graph patterns allow to expand the expert's constructed CM and in this way to promote more flexible and adaptive knowledge assessment.

Грундспенькис Я., Страутмане М. Использование графовых образов для оценки знаний на основе сетей понятий

В статье рассмотрено использование сетей понятий для оценивания знаний. Сети понятий являются графами, вершины которых представляют понятия, а дуги соответствуют отношениям между ними. Сети понятий позволяют видеть структуру знаний обучаемого. Пошаговое конструирование сетей понятий и их применение весьма просто. Однако прямое сравнение сети понятий эксперта и обучаемого ограничивает последнего, так как вынуждает его следовать структуре знаний эксперта. В то же время известно, что индивиды строят свой структуры знаний весьма отлично. Разработанная адаптивная система оценивания знаний, которая является многоагентной системой, содержит агента оценки знаний, который осуществляет сравнение сетей понятий. В статье предлагается новый подход для сравнения сетей понятий, в котором используется графовые образы, т.е., пути ограниченной длины. Даны графовые образы как для задач, в которых обучаемый заполняет сеть понятий, если дана его структура, так и для задач, в которых обучаемый сам строит сеть понятий. Продукции, соответствующие графовым образам дают возможность расширить сеть понятий эксперта и таким образом обеспечить более эластичное и адаптивное оценивание знаний.