Activity- and taxonomy-based knowledge representation framework

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Abstract: Elaborations of Competence-based Knowledge Space Theory (CbKST) incorporate skills that refer to the conceptual information of the domain as well as to the activities learners are expected to perform in this context. Thus, they are suggested as a formal knowledge representation framework that is able to take into account current activity-oriented pedagogical trends in designing effective Units of Learning (UoL). The broad array of required behaviour to be achieved by learners demands a search for instruments like taxonomies that allow for conceptualising activities, and consequently, skills and learning objectives. It is shown that the availability of such a taxonomy-based framework may be utilised in order to enhance the access and interface functionalities of learning systems. In particular, the selection of proper learning units and the delivery of effective feedback mechanisms on the teaching and learning progress are facilitated.

Keywords: knowledge representation; knowledge space theory; skills and competences; learning objectives; learning activities; taxonomies.

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1 Introduction

The learning effectiveness of a virtual learning environment depends to a large extent on how well the knowledge represented in the system is able to match the knowledge of a domain and of individual learners. At the first European Learning Grid Infrastructure (EleGI) conference in March 2005, we introduced the basic ideas of Competence-based Knowledge Space Theory (CbKST) (Heller *et al.*, 2005), which directly refers to the underlying skills required for solving problems or that are taught by learning objects. Moreover, their application in the context of distributed resources and Virtual Scientific Experiments (VSE) was discussed.

The present paper outlines how skills in terms of CbKST can be elaborated to adopt a more activity-oriented and learner-centred perspective which is currently predominant in the educational field. To this end, domain and learner knowledge are represented via skills that are characterised by both conceptual information and information related to the learning activities and objectives. Finally, the implications of using taxonomies that may underlie such a skill representation for enhancing the access and interface functionalities of learning systems (*e.g.*, within ELeGI) are presented.

2 Learning objectives

In the design of Units of Learning (UoL, *e.g.*, a lesson, a course), learning objectives play an essential role. Since recent developments in the educational field focus more on the teaching and learning processes than on the pure learning content, they are usually stated at a more fine-grained level than just at the conceptual dimension, as commonly practised in existing learning environments. Thus, learning objectives have to precisely specify the skills and competences that need to be acquired by the learner.

2.1 On the role of activity-oriented learning objectives

Instead of the traditional approach of directing instruction to the transmission of knowledge and defining objectives in terms of content to be learnt, learner-centred instruction acknowledges what the learner does.

Hence, learning objectives are formulated to express the intended learning outcome (*e.g.*, skills and competences) and what the learners will be able to do as a result of the instruction (Anderson *et al.*, 2001). Teaching consists in providing appropriate strategies that enable learners to achieve the respective knowledge and skills. The activity-oriented approach is also considered in the development of current standards, such as the IMS Learning Design (for details refer for example, to IMS Learning Design Best Practice and Implementation Guide, 2003).

In literature, much has been written about the nature of learning objectives. For example, Tyler (1949) suggested phrasing learning objectives in terms of the behaviour to be developed and the content in which this behaviour is to be operated. Another influential approach relies on three components: *behaviour*, *standard* and *condition*s (Mager, 1962; 1984). The behaviour describes what the learner is expected to be able to do and is expressed by specific verbs such as 'calculate' and 'differentiate'. Via the standard (also *criterion*), the acceptable level of performance is determined, for example, by a certain proportion of correct answers. The conditions indicate the constraints (*e.g.*, available resources) under which the learner will perform in the learning situation.

According to Krathwohl and Payne (1971), the specificity of learning objectives can vary from rather global to more specific objectives. They differentiate between *global*, *educational* and *instructional objectives*. Global objectives (as in curricula, for example) are identified with rather broadly stated learning outcomes, such as 'The student shall develop the fundamental skills of reading and writing.' More specific curricula can be defined at the level of educational objectives, which can be used by the teacher to plan their classroom activities for a longer period, for example, 'can name and recognise the letters of the alphabet'. In order to plan daily activities, still more specific instructional objectives are needed that focus on narrow teaching and learning in specific domains (*e.g.*, 'ability to discriminate between pairs of similar and easily confused letters, *e.g.*, P from R'). These are in line with Tyler's (1949) specification. Such specific instructional objectives can be identified with the skills and competences the students are going to achieve during a UoL. They can even be characterised by single learning objects in a virtual learning environment.

Including activity-related information into the specification of learning objectives emphasises the fact that content alone is only part of what is to be learnt. Many possible activities may be related to each content item. For example, a student may be requested to *explain* a concept or to *apply* it in a specific context. Thus, it is important that learning objectives refer to both – information on the content and required activities.

Note that learning objectives define *what* the learner is going to achieve, *not how* the learner learns and accomplishes them. The way to achieve these objectives (*i.e.*, learning activities) is mainly determined by the respective pedagogical approach the teacher relies on. In order to differentiate better between learning activities (*means*) and learning objectives (*targeted end states*), Anderson *et al*. (2001) suggest indicating learning objectives by the phrase '*to be able to'* or '*learn to*'.

To conclude, learning objectives are crucial for both the design process of effective teaching, on the one hand, and the assessment of the learning outcome (*i.e.*, skills and competences), on the other hand. The more specific these objectives are, the easier one can assess their achievement. The alignment between clearly stated learning objectives and learning activities rooted in the respective pedagogical background facilitates learning as well as its assessment, and hence the identification of the skills and competences gained by the learners.

2.2 Taxonomies for learning objectives

The use of learning objectives for designing and assessing learning is complicated by the availability of a broad range of possible activities that may be part of an objective. Thus, there is a need for a framework according to which learning objectives can be organised in order to increase their manageability. An instrument like a taxonomy can be used for planning instruction, learning and assessment.

A number of approaches have been devised for the classification of learning objectives and activities. The most popular taxonomy for the educational practice was developed by Bloom (1956), whose influential framework was later updated by Anderson *et al*. (2001). Bloom and his colleagues classified intended behaviours related to mental acts or thinking that occurred as a result of educational experiences. The purpose of this taxonomy was to enhance the exchange and communication of ideas and material by using a common language for educational objectives. The taxonomy should also serve as a tool for determining the congruence between objectives, learning activities and assessments related to a lesson, course, *etc*., as well as for revealing the array of possible instructional options. The taxonomy comprises six categories: *knowledge*, *comprehension*, *application*, *analysis*, *synthesis* and *evaluation*. These categories characterise different levels of cognitive processing and are assumed to form a cumulative hierarchy. Bloom's taxonomy has been used worldwide for designing educational instruction and has influenced many other researchers (*e.g.*, Ausubel and Robinson, 1969; Gagné, 1985; Marzano, 2001; Anderson *et al.*, 2001).

The revision of Bloom's taxonomy by Anderson *et al.* (2001) retains the six cognitive process categories. However, while the original framework uses nouns (*e.g.*, *analysis*), in the revised taxonomy verbs (*e.g.*, *analyse*) label the different categories, reflecting the prevalent activity-centred approach in teaching and learning. Moreover, Bloom's category *knowledge* was renamed to *remember*, *comprehension* to *understand*, and *synthesis* to *create*. Additionally, the order of the last two categories was reversed (see Table 1). Anderson *et al.* (2001) also introduced a second dimension, which lies along a continuum from concrete to abstract knowledge. It consists of four categories: *factual*, *conceptual*, *procedural* and *metacognitive* knowledge. The revised and activity-oriented version of the taxonomy remains hierarchical in overall complexity, too. It is also more applicable for the planning of educational instruction and assessment because the two dimensions, knowledge and cognitive process, displayed in a table form a useful representation of any UoL (Krathwohl, 2002).

Table 1 The six categories of cognitive processes

Process categories	*Description and examples*
Remember	Retrieve relevant knowledge from long-term memory, *e.g.*, reorganise dates of important events in US history
Understand	Construct meaning from instructional messages, including oral, written, graphical communication, *e.g.*, classify mental disorders
Apply	Carry out or use a procedure in a given situation, *e.g.*, divide one whole number by another whole number
Analyse	Break material down into constituent parts and determine how parts relate to one another and to an overall structure, *e.g.*, differentiate between (ir)relevant numbers in a word problem
Evaluate	Make judgements based on criteria and standards, *e.g.*, judge which of two methods is the best way to solve a given problem
Create	Put elements together to form a coherent or functional whole; reorganise elements into a new pattern or structure, *e.g.*, plan a research paper on a given historical topic

Source: Adapted from Anderson *et al.* (2001)

A more recent approach for classifying learning outcomes is the Structure of the Observed Learning Outcome (SOLO) taxonomy developed by Biggs and Collis (1982; Biggs, 1999). This framework is primarily an assessment tool looking at the structure of the observed learning outcome. Its purpose is to provide a systematic way of describing how a learner's performance grows in complexity when mastering a range of tasks. It can be used to define objectives that describe performance goals or targets, as well as to evaluate the level of learning outcomes.

Still another approach for classifying learning activities was devised by Vermunt and Verloop (1999), who built their framework around cognitive, affective and metacognitive (regulative) dimensions. Since the categories of the cognitive process dimensions they distinguish are neither exhaustive nor mutually exclusive according to the authors, it can be seen as a framework rather than a taxonomy.

Since there are various frameworks and taxonomies available that focus on different aspects of learning and teaching, one has to define the criteria according to which the most appropriate approach can be selected, given particular interests and purposes. A comprehensive review and evaluation of existing frameworks for teaching, learning and thinking skills is provided in a report by Mosely *et al*. (2004). A hierarchical categorisation such as Bloom's revised taxonomy (Anderson *et al*., 2001) seems to be the most appropriate for the purpose presented in this paper.

3 Knowledge space theory and competence-based extensions

CbKST is a knowledge representation model that is able to incorporate the activity-oriented understanding of teaching and learning. After outlining the basic notions of Knowledge Space Theory and its competence-based extensions, recent activity – and taxonomy-based considerations are presented.

3.1 Basic notions of knowledge space theory

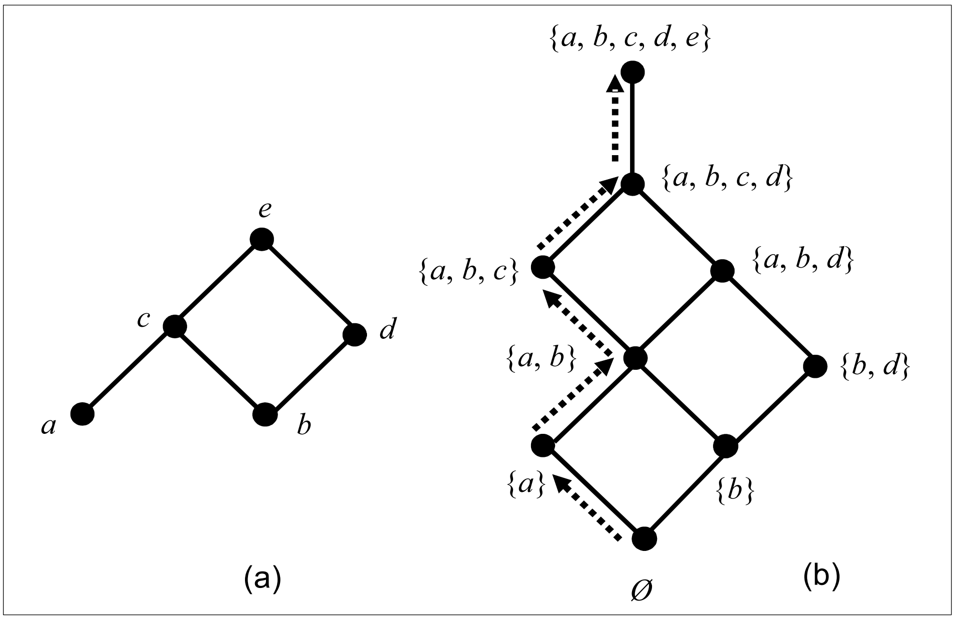
Knowledge Space Theory (Doignon and Falmagne, 1985; 1999) provides a set-theoretic framework for representing the knowledge of a learner in a certain domain, which is characterised by a set of problems (subsequently denoted by Q). The knowledge state of an individual is identified with the subset of problems this person is capable of solving. Due to mutual dependencies between the problems, which are captured by a so-called prerequisite relation, not all potential knowledge states will actually be observed.

Any prerequisite relation can be illustrated by the so-called Hasse diagram, where the relation is depicted by ascending sequences of line segments. According to the diagram shown in Figure 1(a), for example, problems b and d are in a prerequisite relation, which means that problem b is a prerequisite to the solution of problem d. The collection of possible knowledge states of a given domain Q is called a knowledge structure, whenever it contains the empty set $\emptyset$ and the whole set Q. The knowledge structure induced by the prerequisite relation depicted in Figure 1(a) given by:

$$K = \{\emptyset, \{a\}, \{b\}, \{a, b\}, \{b, d\}, \{a, b, c\}, \{a, b, d\}, \{a, b, c, d\}, Q\}.$$

The resulting order on this collection of knowledge states is based on set-inclusion and is shown in Figure 1(b). A knowledge structure offers a range of possible learning paths from the naive knowledge state to the expert knowledge state. Besides offering personalised learning paths dependent on the knowledge state of an individual, a knowledge structure is at the core of an efficient adaptive procedure for knowledge assessment. It allows for uniquely determining the knowledge state by presenting the learner with only a subset of the problems.

Figure 1 Example of a prerequisite relation on a set of problems Q illustrated as a Hasse diagram (a) and corresponding knowledge structure (b) with the dashed arrows representing a possible learning path



3.2 Competence-based knowledge space theory

The original Knowledge Space Theory exclusively focuses on the observable solution behaviour of learners and does not refer to skills that are required for solving the problems or that are taught by learning objects. Since these issues are of special interest for practical application in educational settings, CbKST explicitly refers to learning objects as well as skills and competencies. The following considerations are based on work by Falmagne *et al*. (1990), Doignon (1994), Düntsch and Gediga (1995), Korossy (1997; 1999), Albert and Held (1994; 1999), Hockemeyer (2003) and Hockemeyer *et al.* (2003). The basic assumption is the existence of a set of skills that are relevant for solving the problems of a particular domain, and that are taught by the learning objects of the respective domain.

In CbKST, skills are assigned to both the problems and learning objects of a knowledge domain. Note that skills are meant to provide a fine-grained, low-level description of students' capabilities. Generally, these assignments represent the assignment of (semantic) metadata to the problems and learning objects. The relation between assessment problems and skills is realised by two mappings. The mapping s (skill function) associates with each problem a collection of subsets of skills. Each of these subsets (*i.e.*, each competence) consists of those skills that are sufficient for solving the problem. Assigning more than one competence to a problem takes care of the fact that there may be more than one way to solve it. The mapping p (problem function) associates with each subset of skills the set of problems that can be solved with it. It defines a knowledge structure K because the associated subsets actually are nothing else but the possible knowledge states (for an example, see Heller *et al*., 2005).

The association of skills with the problems of a domain allows uncovering a learner's skills in the frame of an efficient assessment. The collection of skills a person has available is then called the competence state of this individual. It is not directly observable but can be inferred on the basis of the knowledge state. Once the knowledge and competence state of an individual is identified, low-level learning objectives may indicate the targeted skills to be learned next. To bridge the gap between the actual knowledge and competence state and the targeted learning objectives, in CbKST skills are also associated with the learning objects of a domain. This relationship is mediated by two mappings. The mapping r associates with each learning object a subset of skills (required skills), which characterise the prerequisites for dealing with it, or understanding it. The mapping t associates with each learning object a subset of skills (taught skills), which refer to the content actually taught by the learning objects. Given the competence state of a learner, personalised learning paths can be built that teach the skills this learner is ready to learn next.

A further extension is to assume dependencies between the skills (*e.g*., Korossy, 1999), inducing a competence structure on the set of skills. A competence structure further restricts the number of possible knowledge states that can occur and may be explicitly established by identifying relationships between skills, for example, by querying experts, or indirectly via the assignments of skills to the problems of a domain as described above. Obviously, pedagogical aspects, *e.g*., curriculum frameworks, educational standards and learning objectives, also have to be taken into account when building a competence structure.

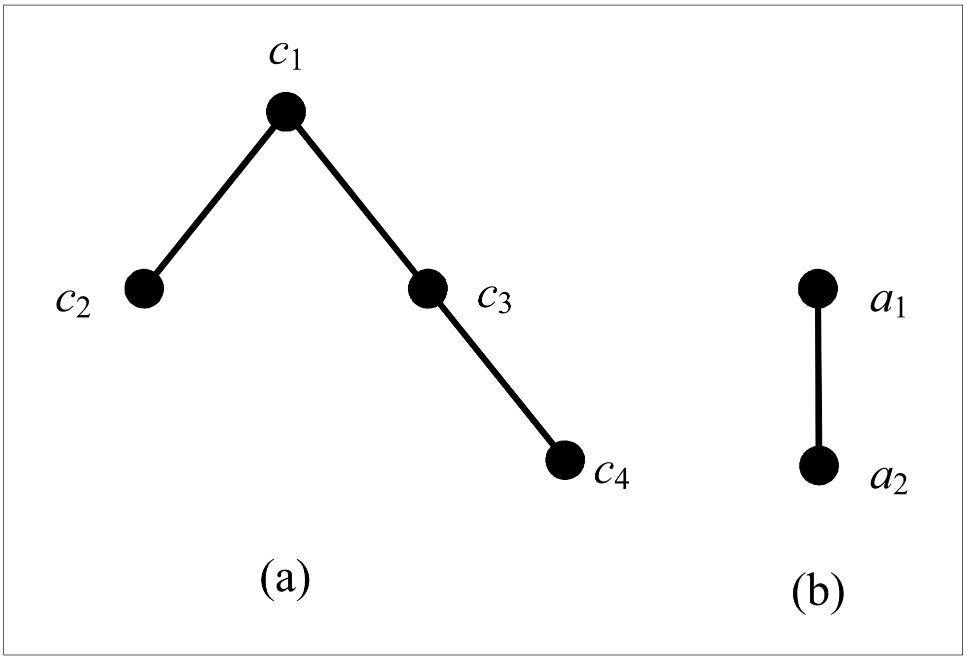
3.3 Activity-based skill characterisation

As mentioned above, fine-grained learning objectives can be identified with the skills and competences learners are expected to achieve as a result of a UoL. Since learning objectives refer to both the information on the content and the required activities, the representation of skills has to reflect this characterisation, too. Thus, we suggest characterising a skill as a pair consisting of a concept and an activity (*e.g*., *apply Pythagorean Theorem*). Both entities hold structural information, which has to be combined in order to derive a structure of the set of skills (Heller *et al*., 2006).

The concepts for the skill definition may be derived from a domain ontology. Common tools for representing the ontological information of a domain are concept maps, which depict structural relations between the basic concepts. For example, a concept map may illustrate that the concept (c_2) *Pythagorean Theorem* is a prerequisite to the concept (c_1) *Altitude Theorem*. This induces an order on the set of concepts, which can be graphically represented as in Figure 2(a).

The relations between activities associated with the respective skills may be based on a proper taxonomy, according to which they can also be organised. The revised taxonomy by Anderson *et al*. (2001) seems to be appropriate for at least two reasons. First, the cognitive process dimension focuses directly on learning and required cognitive efforts. Second, the hierarchical structure of the framework provides the desired information on the relation between given activities. For example, the prerequisite relation between an activity *(a_2) state* (*a certain theorem*) and *(a_1) apply* (*a certain theorem*) may be derived by contrasting these verbs with the categories of the taxonomy. In doing this, it may be revealed that *state* can be associated with the category *remember* and *apply* with the category *appl*y. Since, according to the structure of the taxonomy, *remember* is a prerequisite to *apply*, this information can be adopted for the relation between *state* (a_2) and *apply* (a_1), as can be seen from the graphical representation shown in Figure 2(b).

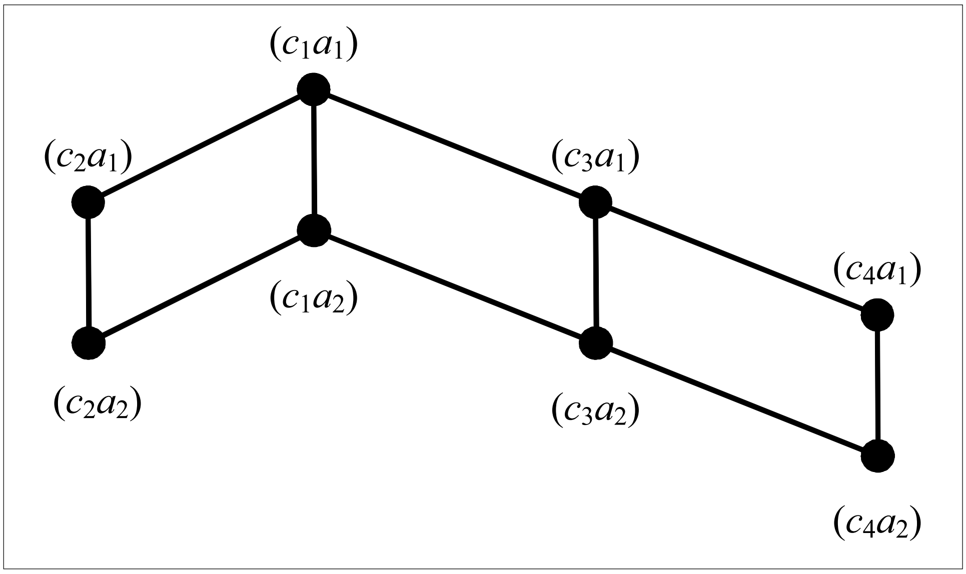
Figure 2 Concept structure (a) and structure on activities (b)



Obviously, the principle for classifying activities (verbs) into categories or levels of the cognitive process dimension is not a straightforward procedure. It requires the definition of clear features that characterise each category, possibly enabling an automatic assignment of activities to appropriate categories. Further research is required on such issues as how to determine such features.

Another crucial question is how the structures on the concepts and activities can be merged in order to derive the competence structure. We suggest resolving this issue by using the component-attribute approach (Albert and Held, 1994; 1999). Within this approach, components are understood as dimensions, and attributes are the different values the dimensions can take on. For the given context, the set C of concepts and the set A of activities can be seen as the components, and the attributes can be identified with the different elements (*e.g.*, c_1, c_2 in C and a_1, a_2 in A). For each component a relation is defined according to which the attributes are ordered. The structure of the set of skills is then built by forming the direct product of the components, inducing a prerequisite relation on the Cartesian Product C x A by component-wise ordering. The product of the two graphs shown in Figure 2 is the structure illustrated in Figure 3. From this it can be read off, for example, that the skill (c_2a_2) is a prerequisite to skills (c_2a_1), (c_1a_1) and (c_1a_2).

Figure 3 Example of the prerequisite relation induced by the structures shown in Figure 2



If learning objectives are formulated at the level of skills, and skills are associated with the problems and learning objects of a knowledge domain, it can easily be assessed whether the respective learning objectives have been achieved by learners. This may provide the basis for identifying the gaps that are to be filled, by devising a personalised learning path. Moreover, the association of skills to a sound taxonomy may also provide a method for describing skills in an aggregated form. In the next section the practical implications for using taxonomies and a skill characterisation, as outlined above, within a virtual learning environment will be outlined.

4 Application of an activity- and taxonomy-based skill representation

The relation of skills to conceptual information and required activities, as well as to the concrete learning objects and assessment problems that make up a learning system, can be utilised in order to enhance the access and interface functionalities of e-learning applications. In fact, the skills' association to taxonomies of cognitive processes facilitates the selection of a proper UoL and the delivery of effective feedback mechanisms.

4.1 Access modalities: building units of learning

In virtual environments, the options for selecting a UoL are commonly limited to the conceptual level. CbKST can provide additional options for defining a learning unit that are driven by the above-introduced skill assignments.

First of all, the learner or teacher may choose a certain skill to be taught. In this case there are two options for building a UoL. First, based on the selected skill, the set of learning objects that actually teach that skill can be identified. Then it has to be checked whether the learner has already acquired the skills needed for understanding these learning objects. If this is not the case, the learning objects that teach these required skills have to be selected. This procedure recursively builds up a structure of learning objects, and thus a collection of possible learning paths. This procedure continues until the required skills in at least one of the resulting paths match the learner's competence. The second way of producing a UoL is to identify the respective concepts associated with the chosen skill. Which option actually is selected depends, for example, on didactical considerations (*e.g.*, the type of knowledge that is to be learnt).

Due to the broad range of possible skills and learning objectives, respectively, their identification for building a UoL may be facilitated by the availability of a taxonomy as described in Section 2.2. Based on such a framework, teachers or even learners may simply choose the level of the skills and objectives with respect to specific concepts instead of defining particular skills. The system then has to search for available skills and associated learning objects or concepts to build up a UoL.

4.2 Interface modalities: reporting mechanism

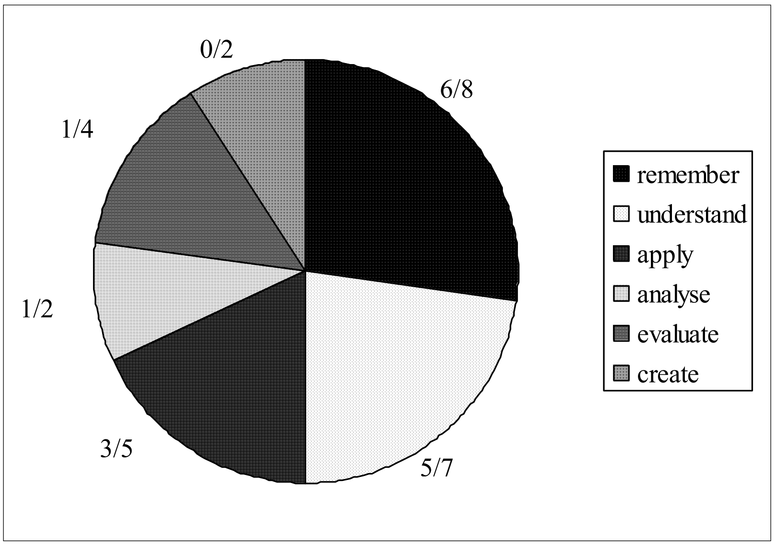
A taxonomy underlying the skills and learning objectives may be useful for teachers and learners in getting an overview of either the spectrum of their teaching and/or their learning progress. These considerations are mostly in line with the purpose for which Bloom (1956), and later Anderson *et al.* (2001), introduced the taxonomy of educational objectives.

A so-called reporting tool may inform the teacher about the range of skills and objectives with respect to certain concepts that they already covered in the prepared UoL. It may quote the levels of skills the teacher has never considered as well as dominant skill levels. Such a report may foster a teacher's metacognition about his or her teaching strategies and may inspire the teacher to build an effective UoL covering a broad range of possible learning objectives and skills. Via a taxonomy, it would also be possible to notify the teacher in an aggregated way about the skills related to the particular concepts the learners have achieved so far. This may also influence the selection of skill levels for designing subsequent instructional units.

Via an underlying taxonomy, the learner could also be notified about the amount of achieved skills and competences in an efficient way, promoting the learner's metacognitive reflection on his or her learning progress. In case that the learner uses the learning system to edit new learning units, he or she may also be notified about the range of disregarded and preferred skill levels, in order to consider this information for the next time.

For both teachers and learners, a concise way to deliver and represent the feedback may be to visualise the report information on achieved and/or covered skill levels with respect to certain concepts. Two kinds of information are of interest. Since the total sum of skills contained in each category will likely vary, first, it is relevant to know the amount of skills contained in each category. Second, for the teacher or learner the number of actually achieved and/or covered skills per category or level is of significance.

Figure 4 Example of a possible visualisation (pie chart) for reporting covered or achieved skills per taxonomy level for a particular UoL. The whole UoL comprises 28 skills. The fractions next to each slice indicate how many of the available skills per category have already been achieved and/or covered



For illustrating this information at a glance, histograms or pie charts seem to be favourable. In the diagram shown in Figure 4, each slice corresponds to one category of the taxonomy (*i.e.*, skill level, *remember*, *understand*, *apply*, *etc*.). The fraction per slice shows how many of the available skills per category have already been covered by a teacher or achieved by a learner. For example, according to Figure 4, a learner has achieved six out of a total of eight skills that are associated with the first level (*i.e.*, *remember*) of the taxonomy and three out of the five skills that are contained in the category *apply*. The information on the skills can be provided either for a particular concept, closely interrelated concepts, or even a whole UoL. In each case the aim is to increase the number of covered and/or achieved skills for each skill level of the taxonomy.

5 Conclusion and implications

The paper shows that learner and content knowledge modelling based on CbKST is able to take into account current pedagogical trends in designing effective UoL, by incorporating skills that refer to the conceptual information of the domain as well as to the activities learners are expected to perform in this context. Via the component-attribute approach, it is possible to merge these two kinds of structural information into a unified representation of the skill structure. This type of skill characterisation is further in line with the definition of fine-grained learning objectives for building narrow instructional units. The broad array of possible verbs that express the required behaviour to be achieved by learners requires a search for mechanisms that allow for conceptualising activities and consequently, skills and learning objectives. The revision of Bloom's taxonomy by Anderson *et al*. (2001) is suggested as a tool for organising and structuring learning objectives and skills. It was shown that the availability of such a framework may facilitate building a UoL (see Section 4.1), as well as the reporting on the teaching and learning progress (see Section 4.2) with respect to covered and achieved skills, respectively.

However, there is a need for further research. Principles have to be elicited according to which activities can be associated with one of the six levels of cognitive processing. The aim is to find features for each category in order to be able to differentiate between them. Based on such characteristics, it would also be possible to automatically assign activities to certain levels of the taxonomy. Obviously, it is not reasonable to assume that there will be always clear and unambiguous assignments. There may be some overlaps between the categories, which means that a single activity may possibly be associated with more than exactly one level. In this case, mechanisms like fuzzy assignments according to predefined criteria may be useful. Another option would be to ask the teacher for clarification about the category the respective activity should be assigned to. Another open research question is whether, at all times, all levels of the taxonomy have to be included for defining learning objectives and skills. The coverage of the different levels of cognitive processing may, for example, depend on what is to be achieved for different groups of learners in a class.

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