

Competence-based Knowledge Structures for Personalised Learning: Distributed Resources and Virtual Experiments

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The ELeGI project focuses on integrating technology-enhanced learning methodologies into a pedagogy-driven and service-oriented architecture based on Grid technology. It aims at a system that is capable of realising personalised, adaptive, and experiential learning. This requires to have available a framework that, on the one hand, allows for representing existing domain knowledge, and, on the other hand, provides a representation of the learner's current state of knowledge. It is shown that a competence-based extension of Knowledge Space Theory provides a representation of the conceptual organisation of a domain that not only allows for an adaptive assessment of an individual's knowledge, but also for generating personalised learning paths. The discussion of this framework emphasizes its application within an open distributed service model, and in the context of Virtual Scientific Experiments.

Keywords: adaptive eLearning, personalisation, learning Grid, knowledge structures, competencies.

1. INTRODUCTION

Personalisation, which became one of the key concepts in current education, reacts to the fact that students come to school with different knowledge and skill bases as well as varying learning preferences, interests, and aptitudes. Personalised learning presupposes high quality teaching that is adaptive to the different ways students achieve their knowledge and skills. Therefore, the teaching courses, curricula, and school organisations have to be designed in a way to reach as many students as possible with diverse needs and experiences for as much of the time as possible. Personalised courses actively engage the learners by providing teaching strategies and materials that appeal to the learners' knowledge and preferences etc. Since it would be costly and unfeasible for teachers to produce personalised courses that meet all of these requirements, hypermedia learning systems are of prime importance for education. Such systems allow for delivering information outside the traditional bound of a classroom situation, where learners are taught by a static one-fits-all approach. An educational system that responds to individual needs by creating a personal learning path enables individual students to experience excellence in his or her learning. Among the various benefits of a personalised learning environment that are mentioned is the fact that the time taken to learn is reduced, and that the learner's retention is improved.

The European Learning Grid Infrastructure (ELeGI) project sets out to develop an adaptive technology-enhanced learning system that integrates a new pedagogy paradigm concentrating on active, experiential, contextualised, and collaborative learning processes. Thus, the system should behave like a private teacher, who adapts the training to the individual learner. Learning paths allow the learning system to describe alternative ways from an individual starting knowledge state to the selected goal state by instructional interventions. The system should also provide a method for adaptive knowledge and skill assessment. A central aspect here is to uncover a learner's state of knowledge in the frame of an efficient questioning by selecting the problems in a way that takes into account the previous answers of a learner. All of these features have high technical requirements, which in ELeGI are addressed by building on the open distributed service model evolved as part of the Grid technology. Grid computing supports coordinating and sharing computing, application, data, storage, or network resources across dynamic and geographically distributed virtual locations. An eLearning system based on Grid Technology also provides an open learning environment, where educational content related to specific knowledge domains can be changed, added or deleted in local as well as in remote repositories. To ensure adaptivity, the technological aspects have to be complemented by pedagogical and psychological principles as well as by the knowledge of a domain expert to guarantee that the educational material is presented in an adequately structured way.

All these requirements demand to have available a framework for representing the existing domain knowledge as well as the learner’s current state of knowledge. Knowledge Space Theory is suggested as a formal framework that satisfies these needs. An extension of the originally behaviouristic approach that incorporates the underlying cognitive skills and competences can serve as a basis for implementing personalised learning into a technology-enhanced learning system.

The following section introduces the basic notions of Knowledge Space Theory, and illustrates its potential for an efficient adaptive assessment of a learner’s knowledge. Subsequently, this framework is extended by incorporating cognitive skills and competencies, which are to be derived from the ontological structure of the considered domain. This forms the basis for generating personalised learning paths, and assessing the learners’ competencies. Finally, we address some aspects that are especially relevant for ELeGI. This includes the integration of the approach into a Grid-based learning system, and discusses its application to Virtual Scientific Experiments.

2. KNOWLEDGE SPACE THEORY

2.1. Basic Notions

Knowledge Space Theory [3] provides a set-theoretic framework for representing the knowledge of a learner in a certain domain, which is characterised by a set of assessment problems (subsequently denoted by Q). In this framework the knowledge state of a learner is identified with the set of problems this learner is capable of solving. Due to mutual (psychological) dependencies between the problems not all of the possible subsets of the set Q are plausible knowledge states. If a correct solution to a certain problem can be inferred given another problem is mastered then each knowledge state will contain the first problem whenever it contains the second one (i.e. the first problem may be considered a prerequisite to the second).

The notion of a surmise relation was introduced to capture the relationships between problems of a specific knowledge domain Q . Figure 1 illustrates a surmise relation defined on a set $Q = \{a, b, c, d, e\}$ of five assessment problems. Any surmise relation on a given knowledge domain can be illustrated by a so-called Hasse diagram. The relation is depicted by descending sequences of line segments. For instance, from a correct solution to problem b the correct answer to problem a can be surmised, while the mastery of problem e implies correct answers to problems $a, b,$ and c .

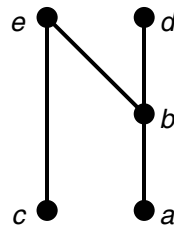


FIGURE 1: Example of a Hasse diagram illustrating a surmise relation on a knowledge domain Q .

A collection of knowledge states of a given knowledge domain Q is called a knowledge structure, whenever it contains the empty set \emptyset and the set Q . The knowledge structure induced by the surmise relation depicted in Figure 1 is given by

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

The resulting order on this collection of knowledge states, based on set-inclusion, is shown in Figure 2. Two main features of Knowledge Space Theory can be discussed with reference to this knowledge structure, namely the realisation of personalised learning paths and adaptive knowledge assessment.

As can be seen from Figure 2, there are various ways to move from the naive knowledge state (empty set \emptyset) to the knowledge state of full mastery (set Q). One of the possible learning paths is indicated by the upwards-directed dashed arrows. This path describes the possible steps of a learning process in the frame of a psychological learning theory. According to the given knowledge structure in the first step the content related to problems a or c should be learned. Dependent on the current knowledge state the next content is to be selected accordingly. It is

not a viable alternative to start with, for example, learning content related to problem b , because b has a as a prerequisite.

Aside from providing different learning paths supporting personalisation, based on a knowledge structure an efficient adaptive procedure for knowledge assessment can be devised. It allows for uniquely determining the knowledge state by presenting the learner with only a subset of problems. Supposing that the knowledge structure shown in Figure 2 has been obtained, in the beginning of an assessment phase all of these states may correspond to the knowledge state of an individual learner. According to a deterministic procedure, the assessment starts by selecting a problem that is contained approximately half of the states of this structure and by posing this problem to the learner. Dependent on the learner's previously given answers, the next problem will be selected.

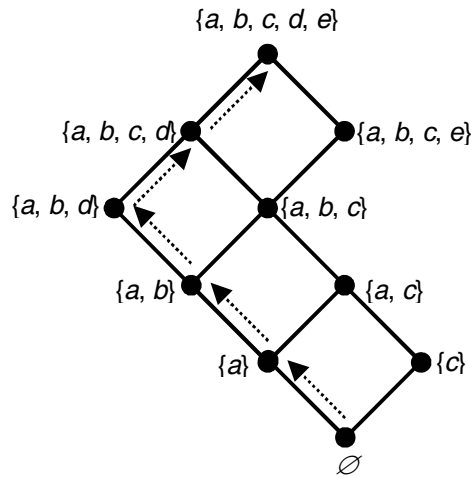


FIGURE 2: Knowledge structure induced by the surmise relation of Figure 1. The dashed arrows represent a possible learning path.

For example, if the learner is capable of solving problem b , then only the knowledge states containing problem b are still feasible. This reduces the number of still possible knowledge states from ten to six alternatives (for details see Table 1). If subsequently problem e is solved, states $\{a, b, c, e\}$ and $\{a, b, c, d, e\}$ remain. The learner's knowledge state is uniquely identified after presenting problem d . For instance, state $\{a, b, c, e\}$ results if problem d cannot be solved by this learner. Thus, for a set of five assessment problems, the presentation of only three problems allows for identifying the knowledge state of a learner. Formally, the knowledge state of a learner is determined in about $\log(|K|)$ questions.

TABLE 1: Adaptive assessment procedure.

Posed problem	Answer	Feasible knowledge state(s)
-	-	Q
b	solved	$\{a, b\}, \{a, b, c\}, \{a, b, d\}, \{a, b, c, d\}, \{a, b, c, e\}, \{a, b, c, d, e\}$
e	solved	$\{a, b, c, e\}, \{a, b, c, d, e\}$
d	not solved	$\{a, b, c, e\}$

Once the knowledge state of a learner has been determined it may serve several purposes. Based on the learner's current state the learning material to be presented next can be selected according to the learning paths. Given the assessed state $\{a, b, c, e\}$ of the knowledge structure shown in Figure 2, in the next step content related to problem d have to be selected. If previously learned material has to be reviewed then the content related to problem e seems to be a natural choice. To provide another example, assume that the learner's knowledge state is $\{a, b, c\}$. In this case in the next learning step material related to problem d or e can be presented. Since it is not

known whether content associated to problems b or c has been learned in the last step of the learning process, content related to problems b and c have to be selected when previously learned material has to be rehearsed.

So far Knowledge Space Theory is discussed from a deterministic point of view. For practical applications it seems reasonable to assume that knowledge states may occur in a population with different frequencies, and that a learner sometimes may be careless in solving a problem or may guess the correct answer. To integrate this approach into a probabilistic framework the notion of a probabilistic knowledge structure was introduced [4]. It assumes a probability distribution on the knowledge states in a given knowledge structure and uses the well-known assumption of local stochastic independence to relate the conditional probability of observing a response pattern given a knowledge state to problem-specific probabilities of a careless error, or a lucky guess, respectively. Notice that in this approach the knowledge state is a latent construct that is distinguished from the observable response pattern.

2.2. Competence-based Extensions

Although there is a commercial learning system that is based on Knowledge Space Theory, which is the ALEKS system (<http://www.aleks.com>), this approach suffers from its limitation to a purely behaviouristic perspective. Knowledge Space Theory focuses completely on the observable solution behaviour, and does not refer to both learning objects and skills or competencies that are to be taught. Moreover, an open learning environment should enable teachers to assemble new learning courses from existing ones and from material in local and remote repositories as well as to change or add new educational content.

In the ALEKS system the procedure to assess the knowledge state of a learner is based on the dependency relations defined on the problems. Enlarging the set of problems is not straightforward in case of such a problem-based system. Whenever the problems in a knowledge domain are changed, added or deleted, all the prerequisite relationships between these problems will change and, therefore, the prerequisite information attached to each of the problems will have to be revised. This issue can be resolved by assigning skills to the problems that are relevant to its solution. This skill assignment to a particular problem is independent of the skills associated to other problems. Adding new problems to a knowledge domain then does not require revising all the problems, it only calls for a re-computation of the knowledge structure. When implementing this approach the assignment of skills to problems has to be reflected by the metadata assigned to them.

Thus, Knowledge Space Theory has to be extended so that it incorporates explicit reference to learning objects and underlying skills and competencies. The subsequent consideration is based on previous work by [6], [2], [5], [10], [1], [7], [8]. It not only integrates these different contributions, but also derives the implications for implementing a personalised learning system, and clarifies the approach's relation to domain ontologies.

Besides assessment problems there are learning objects (LO), which impart the knowledge and skills associated with the educational material. Therefore, extended Knowledge Space Theory deals with three different sorts of entities, which are

- the set Q of assessment problems
- the set L of LOs,
- the set S of skills relevant for solving the problems, and taught by the LOs.

Notice that the skills in the set S are meant to provide a fine-grained, low-level description of the student's capabilities. Usually, it is a whole bunch of skills that is tested by an assessment problem, or taught by a LO. Each of these basic sets is assumed to be endowed with a structure, which we conceive as a collection of subsets of the respective set. In particular, we consider

- a knowledge structure on the set Q of assessment problems,
- a learning structure on the set L of LOs,
- a competence structure on the set of skills S .

The knowledge structure forms the basis of the problem-based assessment of a student's competency. The learning structure together with a student's current competence state (subset of available skills, element of

competence structure) is used to generate a personalised learning path. Learning and competence structures are defined in complete analogy to the knowledge structure introduced above. The main goal is to identify the pieces of information that are needed for establishing all those structures.

Let us first consider the assignment of skills to both assessment problems and LOs. The relationship between assessment problems and skills can be formalised by two mappings. The mapping s (skill function) associates to each problem a collection of subsets of skills. Each of these subsets (i.e. each competency) consists of those skills that are sufficient for solving the problem. Assigning more than one competency 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 to each subset of skills the set of problems that can be solved in it. It defines a knowledge structure because the associated subsets actually are nothing else but the possible knowledge states. It has been shown that both concepts are equivalent, which means that, given the skill function, the problem function is uniquely determined, and vice versa. Consequently, only one of the two functions needs to be known in order to build the respective knowledge structure. Consideration is confined to the skill function, because it may be interpreted as representing the assignment of metadata to the problems. It follows that assigning (semantic) metadata to assessment problems puts constraints on the possible knowledge states that can occur. In principle, the skill function for a given set Q of assessment problems may also introduce dependencies between skills. These dependencies, however, may only crop up in the given set Q , and it remains unclear whether they are valid in general. If capitalising on incidental dependencies between problems is to be avoided then the constraints the skill function puts on the possible subsets of skills should be neglected.

The relationship between the set L of LOs and the skills in S is mediated by two mappings. The mapping r associates to each LO a subset of skills (required competency), which characterise the prerequisites for dealing with it, or understanding it. The mapping t associates to each LO a subset of skills (taught competency), which refer to the content actually taught by the LO. In a similar way as outlined above, the mappings r and t may be exploited to induce a learning structure on the set of LOs, which plays a central role for generating personalised learning paths. The pair of mappings r and t also imposes constraints on the competence states that can occur. Again, these constraints are tied to the given set L of LOs, and may not be valid in general.

The identification of skills and their relationships is a crucial aspect for generating competence structures. Identifying skills by only analysing LOs or assessment problems leads to specific skill sets associated to these LOs or problems, which is problematic in the context of an open learning system. Other sources for establishing competence structures have to be determined.

Structural information regarding skills may be provided by ontologies or concept maps related to a specific knowledge domain. On the one hand, ontologies may serve as a kind of lexicon including the relevant “vocabulary” (skills, concepts, ...), for example, to facilitate the process of adding new content. On the other hand, ontologies may provide structural information regarding the relations between the concepts and skills relevant for solving assessment problems, for example. These ontological structures on skills or concepts can be based on curricula analysis, and therefore they are not restricted to a particular set of LOs. Moreover, these relations between skills have an impact on the corresponding knowledge structures.

3. DISTRIBUTED RESOURCES

Since the Grid technology is based on distributed services, in this context the concept of *distributed skill functions* [11] is of particular interest. In a Grid-based system learning objects can reside on different locations, where every location has access to both, local and remote learning objects.

As outlined above, a knowledge structure may be induced by a skill function. If several skill functions are available, they can be merged into a single skill function (*distributed skill function*), which then induces a knowledge structure. The notion of a distributed skill function thus entails a distributed representation of a knowledge structure.

As an example consider the skill functions s_1 and s_2 defined on $Q_1 = \{a, b, c, d\}$, $S_1 = \{x, y, z\}$ and $Q_2 = \{a, b, e, f\}$ and $S_2 = \{w, x, y\}$, respectively.

$$\begin{aligned}
 s_1(a) &= \{\{x, y\}, \{x, z\}\} \\
 s_1(b) &= \{\{x\}, \{z\}\} \\
 s_1(c) &= \{\{x\}, \{y\}\} \\
 s_1(d) &= \{\{y, z\}\}
 \end{aligned}$$

$$\begin{aligned}
 s_2(a) &= \{\{x, y\}, \{w, y\}\} \\
 s_2(b) &= \{\{w, x\}\} \\
 s_2(e) &= \{\{x\}, \{w, y\}\} \\
 s_2(f) &= \{\{y\}, \{w, x\}\}
 \end{aligned}$$

The knowledge structure K_1 induced by the s_1 is given by

$$K_1 = \{\emptyset, \{b\}, \{c\}, \{b, c\}, \{a, b, c\}, \{b, c, d\}, Q_1\},$$

while the knowledge structure K_2 induced by s_2 reads

$$K_2 = \{\emptyset, \{e\}, \{f\}, \{a, e, f\}, \{b, e, f\}, Q_2\}.$$

Merging the skill functions s_1 and s_2 results in the following distributed skill function s defined on $Q = \{a, b, c, d, e, f\}$, $S = \{w, x, y, z\}$.

$$\begin{aligned}
 s(a) &= \{\{x, y\}, \{x, z\}, \{w, y\}\} \\
 s(b) &= \{\{x\}, \{z\}, \{x, w\}\} \\
 s(c) &= \{\{x\}, \{y\}\} \\
 s(d) &= \{\{y, z\}\} \\
 s(e) &= \{\{x\}, \{w, y\}\} \\
 s(f) &= \{\{y\}, \{w, x\}\}
 \end{aligned}$$

The knowledge structure K induced by s is given by

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

Mild consistency criteria have to be met (e.g. in case of overlapping basic sets) for defining a distributed skill function. Notice that, in the above example, the knowledge structure K_1 is 'contained' in K (to be more precise, $K_1 \subset K \cap Q_1$), while K_2 is *not* 'contained' in K (i.e. $K_2 \not\subset K \cap Q_2$). This shows that further research is needed to elaborate this approach in order to clearly understand the interrelation between the knowledge structure induced by a distributed skill function and those associated to its components.

4. APPLICATION TO VIRTUAL SCIENTIFIC EXPERIMENTS

Extended Knowledge Space Theory can also form the basis for representing the learning processes that occur in the context of Virtual Scientific Experiments (VSEs). VSEs represent a way of inquiry teaching, in which the educational material is explored by the learner. Extended Knowledge Space Theory knowledge can be applied to either a single VSE or various VSEs within a specific course. Establishing knowledge structures for VSEs follows the same procedure as for assessment problems or LOs outlined above. For each VSE the relevant skills and concepts for solving it have to be identified and assigned to it. The skills and their mutual relationships can again be derived from a domain ontology.

In a VSE learning environment, a learner has to perform several sequences of actions or manipulations. For instance, a learner may want to identify which of several variables (e.g. length, mass, angle) has an impact on the

period of a pendulum. To solve this task the relevant parameters have to be manipulated and the respective effects have to be observed and recorded. Possible skills that are associated to this pendulum-VSE might be to know that 'period does not depend on mass' or to know that 'period does depend on length'. To accommodate with such a dynamic learning situation, Knowledge Space Theory has to be integrated into a dynamic framework.

In a VSE a learner navigates through a space of LOs (identified with single activities). Selecting from several alternative activities available at a point in time the learner creates an individual sequence of LOs. This individual learning path is directly observable. Analogous to this observable behaviour the existence of cognitive states is assumed. The cognitive states may comprise skills and competencies as well as preferences and prior knowledge. The observable sequence of actions or LOs is supposed to depend on these cognitive states. Conversely, the visited LOs and performed manipulations determine what can be learned, and thus change the latent cognitive state of the learner. The dependencies between the observable and latent learning paths may be captured in a stochastic process model (e.g. Markov Chain Model, [9]). The state of the dynamic system can be represented by a compound consisting of the currently chosen activity (or, LO) and the current knowledge or competence state. The specification of the transition probabilities between the compound states forms the core of a Markov chain model. It is an important advantage of this Markov chain model is that, given an initial assessment, the current knowledge or competence state of the learner can be inferred from observing the sequence of chosen activities or learning objects. It is not necessary to continuously assess the learner during his or her interaction with the virtual experiment.

5. CONCLUSIONS

This paper discusses the application of extended Knowledge Space Theory as a formal framework for the knowledge representation within a technology-enhanced learning system based on Grid technology. The mutual implications and relationships between assessment problems, LOs, and related skills or competencies are outlined. It is shown that this approach allows for generating personalised learning paths, and for an efficient adaptive assessment of knowledge and competencies, respectively. Moreover, it addresses various issues that are essential for an application of the approach. In particular, it discusses the question of how to integrate domain ontologies, the handling of distributed resources as required by the Grid technology, and how to represent the learning process that occurs in experiential learning through VSE.

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