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Abstract

A learner's knowledge is often the key aspect towards which personalized eLearning systems attempt to adapt. However, the assessment of their knowledge usually involves tedious and time consuming questionnaires or making stereotypical assumptions about what they know. The Knowledge Space Theory (KST) [Doignon and Falmagne, 1985; Albert and Held, 1999] offers a means of efficiently and effectively determining the current knowledge of a learner. By applying this theory to the analysis and determination of a learner's knowledge, highly configurable adaptive systems, such as APeLS [Conlan et al. 2002], can provide highly dynamic event driven personalized adaptations based on up-to-date information about the learner. This paper describes the culmination of collaborative research that has been carried out by Knowledge and Data Engineering Group of Trinity College, Dublin and the Cognitive Science Section of the University of Graz under the auspices of several European Commission funded projects.

Article

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Using Knowledge Space Theory to support Learner Modeling and Personalization

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Abstract: A learner’s knowledge is often the key aspect towards which personalized eLearning systems attempt to adapt. However, the assessment of their knowledge usually involves tedious and time consuming questionnaires or making stereotypical assumptions about what they know. The Knowledge Space Theory (KST) [Doignon and Falmagne, 1985; Albert and Held, 1999] offers a means of efficiently and effectively determining the current knowledge of a learner. By applying this theory to the analysis and determination of a learner’s knowledge, highly configurable adaptive systems, such as APeLS [Conlan et al. 2002], can provide highly dynamic event driven personalized adaptations based on up-to-date information about the learner. This paper describes the culmination of collaborative research that has been carried out by Knowledge and Data Engineering Group of Trinity College, Dublin and the Cognitive Science Section of the University of Graz under the auspices of several European Commission funded projects.

1 Introduction

Personalized eLearning systems [Brusilovsky, 1996; De Bra, 2001; Conlan et al. 2002] attempt to reconcile several pieces of information about a learner in order to produce a learning experience that is tailored towards their particular needs. For personalized eLearning or any learning experience to be effective, appropriate pedagogical and educational theories must be the fundamental drivers in designing and developing that experience. In contrast to this requirement, personalized eLearning systems are often developed from a purely technical perspective often leading to well engineered, but educationally inappropriate, or worse ineffective, systems. By developing the Adaptive Personalized eLearning Service (APeLS), and its predecessor the Personalized Learning Service (PLS), through cooperation with cognitive scientists and pedagogues, the Knowledge and Data Engineering Group (KDEG) of Trinity College, Dublin has produced a system that is both effective and pedagogically flexible. This paper describes the relationship between the Knowledge Space Theory (KST) and the development of APeLS.

The relationship between KST and APeLS is traceable through a number of European Commission funded Information, Society and Technologies (IST) projects from 2000 to the present. Namely there are three projects in which KDEG have collaborated with the Cognitive Science Section (CSS) of the University of Graz – EASEL (2000-2003), iClass (2004-present) and ELEKTRA (2006-present). During this time CSS have evolved their theoretical constructs for the Knowledge Space Theory, principally introducing the notion of skills [Heller et al., 2006] and confidence degrees [Leclercq et al., 1993] into the theory

In their own right neither KST nor APeLS are solutions for personalized eLearning – KST is a theory that describes and models how knowledge and skills are learned and related, while APeLS is a pedagogically flexible service for the reconciliation of multiple models towards producing tailored eLearning experiences. When combined, however, these approaches become the fundamental building blocks for a highly effective and flexible personalized eLearning solution. Pedagogical flexibility is still maintained as neither KST nor APeLS prescribe a pedagogical approach.

This paper describes the parallel evolution of both of these approaches, tracing their growth through a number of successful and innovative European Commission projects. The paper starts with an introduction and overview of the Knowledge Space Theory, which describes the fundamental elements of the theory. This is followed by a section that highlights the evolution of the relationship between KST and APeLS by describing case studies that snapshot their evolution over the last 6 years including their current state of the art use.

2 Overview of Knowledge Space Theory

Knowledge Space Theory provides a theoretical framework within which the knowledge or competence state of a learner can be determined through an efficient adaptive assessment procedure, presenting the learner with only a subset of all possible problems. A personalized learning system requires the availability of a framework that allows for the formal representation of a whole body of knowledge while providing a representation of the learner's current state of knowledge. Based on such a framework, methods for adaptive knowledge assessment and for suggesting a personalized learning path can then be developed. Knowledge Space Theory, introduced by Doignon and Falmagne [1985], is proposed as a basic framework that meets these requirements. A state-of-the-art report on Knowledge Space Theory is presented in Doignon and Falmagne [1999], for an introduction into the theory and its applications we refer the reader to Falmagne, et al. [1990].

The fundamental approach taken in KST is to reduce the number of possible questions asked of a learner to an optimal set. In this way the Knowledge State of a learner may be assessed through the minimum number of queries, thus achieving maximum efficiency. This is only possible by examining the domain in which the questioning is occurring and identifying the underlying prerequisite relationships that exist between concepts. For example, in the domain of algebraic multiplication it may be assumed that the concept of *multiplying whole numbers* is a prerequisite to *multiplying decimal numbers*. If it is determined that a learner cannot multiply whole numbers then it may be extrapolated that they cannot multiply decimal numbers without questioning them further. Continuing the example, the knowledge domain $Q = \{a, b, c, d, e\}$ consists of the problems –

- | | |
|----------|--|
| <i>a</i> | $378 \times 605 = ?$ |
| <i>b</i> | $58.7 \times 0.94 = ?$ |
| <i>c</i> | $1/2 \times 5/6 = ?$ |
| <i>d</i> | What is 30% of 34? |
| <i>e</i> | Gwendolyn is $3/4$ as old as Rebecca. Rebecca is $2/5$ as old as Edwin. Edwin is 20 years old. How old is Gwendolyn? |

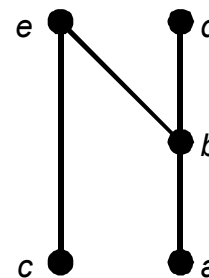


Figure 1

Table 1

The empirically observed solution behavior on a given knowledge domain Q will exhibit some dependencies. One way to identify these kinds of dependencies is by drawing upon domain knowledge, for example, by querying an expert (possibly a mathematics teacher or professional curricula developer in the above example). A surmise relation is a binary relation \leq on the set Q . Referring to the above example, the expression $p \leq q$ means that whenever problem q is solved correctly then we can surmise a correct solution to problem p . In other words, the mastery of problem q implies the mastery of p . Any surmise relation on a given knowledge domain can be illustrated by a so-called Hasse diagram, in which the mutual relationships between the problems are depicted in an economical way. The Hasse diagram in figure 1 presents a surmise relation defined on the knowledge domain Q from the above example. The relation \leq is depicted by ascending sequences of line segments. For instance, from a correct solution to problem b a correct answer to problem a can be surmised. The mastery of problem e implies correct answers to problems a , b , and c , and the mastery of problem d implies the mastery of problems a and b . From a correct solution to either problem c or problem a no inferences regarding the solution of the remaining problems can be made.

From the above we have a formal framework for introducing pre-requisites in a knowledge domain. The central question of how to represent the learner's knowledge within this framework still remains. The state of knowledge of an individual is identified with the subset of problems of the knowledge domain Q , which this individual is capable of solving. This means that for a knowledge domain of n problems there exist no less than 2^n potential knowledge states. Due to the mutual dependencies between the problems, however, not each of the subsets of the set Q is a plausible knowledge state.

Whenever a problem b is contained in a knowledge state $K \subseteq Q$, and from solving b we can surmise solving problem a (i.e. we have the surmise relation $a \leq b$), then a should be contained in the knowledge state K , too. For the surmise relation of figure 1 the set $\{a, b, c\} \subseteq Q$ is a possible knowledge state, while the subset $\{b, c, d\} \subseteq Q$ is not a possible knowledge state (b is in $\{b, c, d\}$, and we have $a \leq b$, but a is not in $\{b, c, d\}$). A collection \mathcal{K} of knowledge states for a given knowledge domain Q is called a knowledge structure, whenever it contains the empty set \emptyset and the set Q . In other words the collection \mathcal{K} contains all of the possible knowledge states that a learner may be in for a given knowledge domain. The knowledge structure \mathcal{K} , consisting of the knowledge states induced by the surmise relation of Figure 1, is given by –

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

This representation of knowledge only focuses on the actual solution of the problems, and does not refer to any underlying latent constructs (skills, competencies, problem demands, etc.) that may be responsible for the observable behavior. There have been various extensions that integrate the consideration of latent constructs into Knowledge Space Theory. By assigning to a problem the skills or competencies that are relevant for mastering it, the solution behavior is linked to some underlying cognitive constructs. Moreover, any such assignment completely specifies the possible knowledge states in the considered knowledge domain. Various approaches have been devised that differ in their assumptions concerning what are the necessary and sufficient skills for solving a problem. A number of approaches are outlined in Falmagne et al. [1990] and developed further in Doignon [1994], or later in Düntsch and Gediga [1995]. Korossy [1997; 1999] proposes an independent but similar skill-based approach, the so-called competence-performance approach. Albert and Held [1994; 1999] devised a method for constructing problems from components that are based on skills and demands the problems pose to an individual.

Case Studies in Modeling Learner Knowledge using KST

There are two main approaches to developing adaptive systems; the first is through the use of embedded strategies, which are either embedded in the engine and/or the media it operates across. This was the approach taken in early Intelligent Tutoring Systems (ITS) in the domain of eLearning. The resulting systems, while possibly effective in their adaptation, were very difficult to modify or repurpose. The second approach, and that advocated in the design and implementation of APeLS, is the separation of all of the constituent parts of the adaptation process into discrete models. Significantly, this includes the model of strategy, referred to as ‘narrative’ in this paper. This second approach requires a generic adaptive engine that is capable of reconciling the narrative with other models. This reconciliation is at the core of the adaptation process.

The Knowledge and Data Engineering Group of Trinity College, Dublin has been developing such a generic adaptive engine that supports the execution of adaptive strategies [O’Keeffe et al., 2006] for the past six years. The initial versions of the adaptive engine (AE) were tightly coupled to their use in the eLearning domain. However, in the last couple of years this domain dependency has lessened to the point where the current version of the engine, Adaptive Engine 3 (AE3), is independent to any specific application domain. AE3 is the generic adaptation engine at the core of the Adaptive Personalized eLearning Service (APeLS), while its predecessor, the original AE, was the engine integrated at the centre of the Personalized Learning Service (PLS).

2.1.1.1 Case Study 1: Personalized Course on Mechanics

The first iteration of a KST informed adaptive system produced by the Knowledge and Data Engineering Group, developed in 2001, was based on the PLS and developed as part of the EASEL [EASEL] project. This project examined the discovery and integration of eLearning content and services into consolidated offerings. One such service offered was an adaptive course to teach the Physics subject of Mechanics. The course adapted to a learner’s prior knowledge by only offering material they were capable of learning based on a pre-requisite analysis of their understanding. The adaptivity in the course was divided into the following phases –

1. **Pre-test:** When a learner first entered the system they were asked to answer four basic questions about Mechanics. These questions did not use KST-based optimization and as such the same questions were presented to every learner. Correct answers given to these questions were used to build a basic model of the learner's knowledge.
2. **Dynamic Personalization:** Once the pre-test had been completed the learner was presented with learning material that the system determined they were capable of learning. This decision was based on the surmise relationship between the concepts in the content. For example, if a learner had knowledge of *collisions in 2D spaces* then they have the pre-requisite competency necessary to learn about *collisions in 3D spaces*. The narrative executed in the PLS would determine that content covering collisions in 3D spaces was now suitable to add to the learner's personalized course (but does not add it yet).
3. **Dynamic Modeling:** Modeling of the learner's evolving competencies was performed by making the assumption that once a learner had accessed and read content pertaining to a competency that they knew it. This is obviously a major simplification. This information about the new competency is added to the learner's model.
4. **Learner chooses to expand the course:** The course does not change unless the learner explicitly decides they are ready to learn more. When they are ready all of the dynamically modeled information is processed and any further content they are capable of learning is presented.

Phases 2-4 may be repeated continuously enabling the learner to gradual expand the set of content to learn. The technical approach taken in implementing this adaptive service violated one of the rules of model driven adaptivity [Conlan et al., 2002]. The systems used three models – learner, content metadata and narrative. The narrative embodied the generic rules for Knowledge Space Theory, i.e. that a piece of content should not be added until all of its pre-requisite concepts had been met and the learner model kept track of the learner's competencies. It was the content metadata model that violated one of the key concepts of the model driven approach – separation of concerns.

The metadata representing the individual pieces of content contained pre-requisite information that identified which concepts needed to be understood in order to understand this piece of content. In this way the domain model, or Knowledge Space, was distributed across all of the content metadata. This did not impact the effectiveness of the course or the effectiveness of KST as an approach to personalization. It did, however, adversely impact the ability of course authors and designers to expand the course. As part of the EASEL project the Mechanics course was extended using material supplied by the Open University [OU]. In order to add more content the course designer needed an intricate knowledge of all of the content metadata to ensure the pre-requisites of the new content could be met. For example, the designer needed to ensure that cyclical dependencies weren't introduced, i.e. that one piece of content was a pre-requisite of another and vice versa, without there being an appropriate piece of content that fulfilled a pre-requisite that would act as entry point into the cycle.

2.1.1.1.2 Case Study 2: Personalization in iClass

Personalization technologies are a central theme in the iClass project [iClass] with particular consideration given to the complete life cycle of a personalized experience. At the centre of the project are a number of services that support the personalization of concepts, activities and content as well as services that monitor and profile the learner. The adaptive engine has seen its most dramatic evolution through the course of this project. So too has the implementation of the Knowledge Space Theory.

The key challenges with respect to knowledge assessment in iClass were to incorporate the notion of confidence degrees [Leclercq, D. et al. 1993; Leclercq and Poumay, 2003] and to examine the importance of assessing skills (as against concepts). The former involves including an important meta-cognitive check point into the assessment procedure. For every question asked of a learner, using the KST approach, an associated confidence degree is also solicited. For example, if a learner is asked *What is the capital city of Australia?* and they answer *Sydney* the previous knowledge assessment techniques would only see this as an incorrect answer. In iClass the learner would also be asked to determine their confidence in this answer. Continuing the above example, if the learner stated that they were highly confident in their answer then this highlights a serious misconception. If, however, they stated that they had little confidence in their answer then it may indicate that they merely guessed the answer. From the KST perspective this information can be incorporated into the procedures for determining the knowledge state of the learner by giving an associated probability of them being in a particular knowledge state. This

probability is based on the confidence expressed in the evidence used to determine the knowledge state. From a personalization perspective the main benefit of this approach is that the personalization mechanisms can compensate for low probabilities by providing additional learning material.

The second challenge regarding knowledge assessment addressed in iClass was to examine knowledge not only in terms of the concepts known by the learner, but also in terms of the skills they had acquired. This challenge arose from a pragmatic consideration – many national curricula in Europe are expressed both in terms of concepts and the associated skills acquired. For the iClass context, a skill was defined as a concept with an action verb. In an attempt to bring a common understanding to the set of verbs used Bloom's Taxonomy [Bloom, 1956] is being investigated as a means of constraining the vocabulary and understanding. The structures and mechanisms of KST are not heavily impacted by the adoption of skills instead of concepts alone. The onus is very much on the monitoring of the learner's interaction with the system and on the types of questions asked in order to determine the learner's skill level. Again confidence degrees may be used.

From the personalization perspective the tailoring of an educational experience is split between two different services – the Selector service and the LO Generator service [O'Keeffe et al., 2006]. Both of these services are based on the third iteration of the adaptive engine, evolved as part of iClass, yet adapt different things; the Selector is responsible for adapting the concepts and activities presented to a learner based on their knowledge and preferences while the LO Generator is responsible for selecting or assembling new learning objects from atomic content assets. It is the Selector, therefore, that has the most interaction with the knowledge assessment service of iClass, referred to as the Monitor [Muehlenbrock et al., 2005].

The primary advancement made through iClass has been a further separation of concerns with respect to personalized eLearning. This is manifest in the creation of the Selector and LO Generator services as the central services for personalization. This separation may also be seen in the disaggregation of all of the other elements of personalized eLearning, such as the modeling of learner knowledge, maintenance of learner preferences, the separate storage of the modeled information and the distributed nature of content and activities [O'Keeffe et al., 2006]. This separation has enabled the evolution of the knowledge assessment to be carried out independently to the evolution of the personalized eLearning, thus enabling different pedagogical approaches to be adopted for different learners while still using the same knowledge assessment facilities. This contrasts with the approach highlighted in Case Study 1 where the adaptation mechanism and knowledge assessment approach were inextricably tied.

2.1.1.1.3 Case Study 3: Generic Strategy for Assessing Knowledge State

With the evolution of the Adaptive Engine to its third iteration (AE3) the opportunity arose to create a narrative that could handle any Knowledge Space and assess learner knowledge generically. By generically it is meant that the assessment performed is not tied to a specific knowledge domain. This possibility came about with the inclusion of service handling facilities into AE3. The engine would no longer have to rely on an embedded domain model, as it did in Case Study 1, or on a completely separate and specialized service as was the case in Case Study 2.

With the capacity to call external services AE3 could now utilize the advantages of ontology reasoning services. The role of the narrative in this version of the engine, referred to as the Knowledge Assessment Engine (KAE) in the ELEKTRA project [ELEKTRA], is to produce meaningful queries to pass to an ontology reasoning service. The functionality of the narrative may be extended, but currently it can perform three functions –

- Add/remove a concept to/from the model of the learner's current knowledge
- Enquire about the possible knowledge states of a learner based on their current knowledge
- Ask what the next concept that should be questioned of the learner

The KAE, again because of the AE3 implementation, can be offered as a service itself, thus allowing external services to utilize the operations it exposes. As part of the ELEKTRA project the KAE is invoked by another adaptive engine that is attempting to ensure that the educational experience of a learner offers a sufficient challenge. This separate Adaptive Engine invokes the KAE as a service to determine the current possible knowledge states of the learner.

Architecturally this approach is very similar to that taken in the production of the Personalized New Service [Conlan et al., 2006], indeed both implementations required no code changes to the AE3 and just needed additional narratives reflecting the different forms of adaptivity required to be developed. Figure 2, below, shows the architecture of the KAE with a sample workflow for how a learner may be questioned –

1. A third party learning service invokes one of the operations offered by the KAE; in this case it is asking for an appropriate question to ask the learner. In the ELEKTRA project the third party learning service is also based on AE3.
2. The adaptive engine at the core of the KAE retrieves the known current knowledge for the learner. Building on the example from the *Overview of Knowledge Space Theory* section the learner model shows that the learner has the knowledge state of $\{a, c\}$.
3. The narrative for asking for the next appropriate question is triggered (based on the invocation). This complex and highly involved narrative executes in the AE3 and assembles an appropriate SPARQL [SPARQL] query by including information about the learner's current known knowledge state. This is where the true intelligent capabilities of AE3 are used. It is combining model information with the complicated processing rules of the query language in order to create a bespoke and appropriate query.
4. The Ontology Reasoning Service, which is based on Jena [Jena], is invoked and the SPARQL query is passed to be processed. This service may either have the appropriate ontology loaded into memory; if not it will load the ontology for reasoning.
5. The SPARQL query is processed and the result set is returned as a response to the AE3. The response is in the form of one or more concepts related to the ontology. In this example the concept relating to b is returned as the next most appropriate concept to be questioned.
6. Based on this response the AE3 calls a third party questioning service (such as QuizPACK [Sosnovsky et al., 2003]). The only proviso on this invocation being successful is that the metadata associated with the questions must use the same vocabulary as the ontology. The appropriate question may then be returned to the learning service.

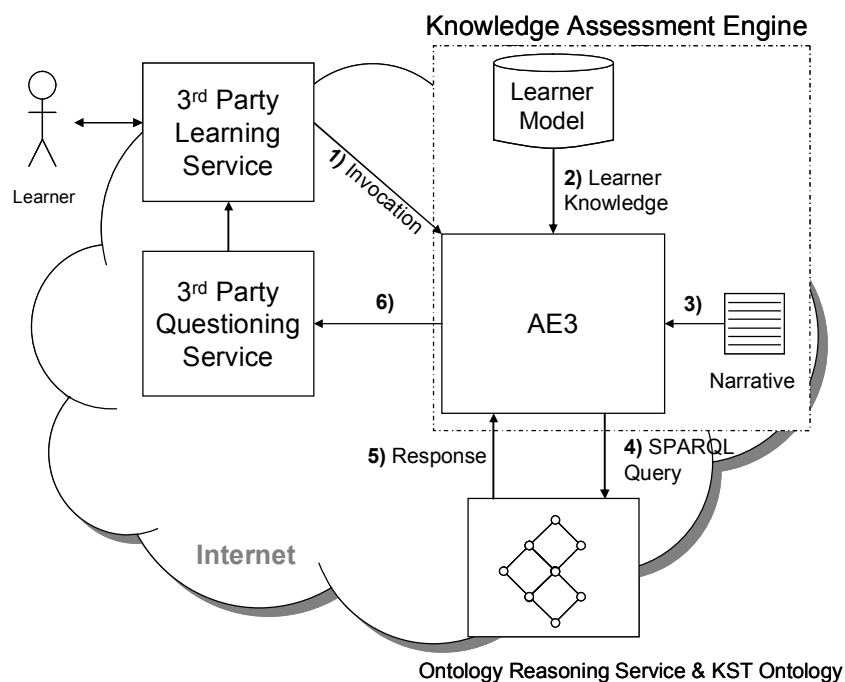


Figure 2

The primary benefit of this approach is that different ontologies may be loaded into the Jena service enabling the knowledge of learners to be assessed across a wide variety of domains. The narratives used in the KAE are both generic and extensible, making them agnostic to the domain for which they are assembling queries. The extensibility enables more functionality to be added to the KAE as it is required.

The use of SPARQL and ontologies described using OWL [OWL] ensures that the approach is conformant with current best practice in knowledge representation. However, since the ontology reasoning is performed by a service the possibility to replace it with an alternative exists. The example in this section has concentrated on assessing the concepts known by the learner, but the approach is equally applicable to the skills assessment as described in Case Study 2.

3 Conclusion

This paper has described the evolution of the application of the Knowledge Space Theory for personalized eLearning through three collaborative research projects since 2000. It has highlighted the significant steps made in assessing learner knowledge both in terms of how the theory has evolved and in terms of how the technical implementations have progressed. These steps have been shown through a series of illustrative case studies.

The Knowledge Space Theory has been shown as a useful mechanism for efficiently assessing the knowledge state of a learner. The case studies showed different mechanisms for realizing the theory culminating in a generic service driven approach that enables third party learning services to utilize the power of KST. This approach builds upon the most up to date technologies coming from the Semantic Web community and it is envisaged that as these technologies mature so to will their associated tools. For example, in the case on ontologies the authoring tools available are progressing all of the time. With the capacity to author ontologies that represent knowledge spaces the generic approach applied by the Knowledge Assessment Engine has much potential.

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