Metadata Driven Approaches to Facilitate Adaptivity in Personalized eLearning Systems

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Abstract
Personalized eLearning Systems tailor the learning experience to characteristics of individual learners. These tailored course offerings are often comprised of discrete electronic learning resources, such as text snippets, interactive animations, diagrams, and videos. An extension of standard metadata schemas developed for facilitating the discovery and reuse of such adaptive learning resources can also be utilized by the eLearning systems for realizing the adaptivity. An important feature of such reuse supporting adaptive systems is the clear distinction of separate models and components within the teaching process.

Keywords: Adaptive tutoring systems, Personalized eLearning, Metadata, System architecture.

1 Introduction

There are a number of reasons to utilize adaptive techniques to produce personalized eLearning courses. The primary of which is that no learners learn in the same way. In a traditional classroom situation learners are taught through a 'one size fits all' approach, where the teacher/lecturer aims not to alienate any of the learners with their pedagogical approach. With personalized courses, however, we can do better than trying not to alienate the learner – we can actively engage the learner with a teaching strategy and material that appeals to the learner's knowledge, style of learning, etc. It would be costly and unfeasible to ask a teacher/lecturer (the knowledge domain expert) to produce an individualized course for each learner in their course and to realize the private teacher approach.

Using hypermedia systems it is possible to deliver information outside the traditional bounds of a classroom, but unless the material is tailored to the learners requirements the learner may not be engaged by the material and suffer from the same problems as the 'one size approach'. By coupling the hypermedia technologies with personalization strategies we can deliver, to each individual learner, a course offering that is tailored to their learning requirements and learning styles [16]. The benefits of effective personalization is that

- Examples and case studies that appeal to the learner's background may be used.
- The time taken to learn the material may be reduced.
- The learner's retention may be improved.

Underlying any eLearning adaptation there should be sound pedagogical principles and the knowledge of a domain expert. Without the former any eLearning system can suffer from the polar problems of 'lost in hyperspace' [9] or the learners feeling they are being dictated to and constrained. The latter, i.e. the domain expert, ensures that the material presented is done in a coherent and structured manner.

The goal of the EASEL (Educator Access the Services in the Electronic Landscape) project [19], funded by the EC within its IST programme, was to develop a framework in which educators could assemble new educational course offerings from existing educational services and from material in local and remote content repositories. The key to the search and discovery aspects of such a system is effective, descriptive metadata. Metadata records include features of the learning resources such as title, description, keywords, author, technical requirements etc. These records describe the resource and facilitate inclusion of that resource in a new course offering. In EASEL, the primary resources considered were remote Adaptive eLearning Services and traditional eLearning content. In EASEL, Trinity College, Dublin [28] and University of Graz [14] were involved in the design and development of such services. This paper describes metadata-driven and model-based approaches to realizing Adaptive eLearning Systems developed as part of EASEL.

2 Realizing Adaptivity through Metadata

The vast amount of information online available has led to the development of metadata specifications that enable the cataloguing and searching of online resources more efficiently. While early approaches offered a non-standardized inline specification of metadata, e.g. in the HTML language [8], standardized schemas for separate metadata specifications were developed more recently for general [15] as well as for application specific purposes [e.g. 25,26]. So far, such metadata have had merely a descriptive function as they were mostly applied to static content.

In case of adaptive content, however, metadata also facilitate the description of the adaptive features of the resource, e.g. what is adapted and what it is adapted to. Such categories have been described in more detail in [6,20]. This information can not only be utilized for search, e.g. for finding material supporting certain adaptivity techniques but also for realizing the adaptivity when constructing courses from existing material. An adaptive engine may in this case select, sequence, and present resources based on the adaptivity metadata attached to these individual resources.

In the sequel, a first approach to realizing adaptivity through non-standardized metadata describing relationships between the learning objects of a course is described.

2.1 A Non-standardized, Metadata-based Approach to Adaptive Hypermedia Services

The relational adaptive tutoring hypertext system RATH [22,24,31], funded by the EC within its HCM programme is a prototype of a system realizing adaptivity based on the metadata information of the content. Adaptivity in RATH is based on the theory of knowledge spaces [5,17,18]. This is a model from mathematical psychology for structuring a domain of knowledge based on prerequisite relationships between the individual items (e.g. learning objects or test problems). Knowledge space theory was connected to a relational formulation of the Dexter Hypertext Model [21] to obtain a hypertext tutoring system adapting to the individual user's current knowledge. Hyperlinks between the learning objects are adaptively hidden whenever a learner has not yet learned the contents of the prerequisite learning objects.

Technically, RATH expects metadata on prerequisite relationships for each learning object within the respective HTML (content) file through the HTML `<META>` tag, i.e. each HTML file within a RATH course should contain `<META>` entries of type `prerequisite` pointing to those other learning objects which are deemed as a necessary prerequisite for understanding the current object.

When a course is fed into the RATH system, all prerequisite relationship information are extracted from the individual files and stored in a relational database. While a learner browses through the course the learner model (i.e. the system's model of the learner's knowledge) is extended by each visited learning object. At certain points, test problems have additionally to be solved thus validating the learner model.

As RATH is a prototypical system, its implementation has been kept rather simple. Whenever a learning object is requested, the prerequisites for each linked document are retrieved from the database and compared to the current learner model. All communication between web server and database is done through the standard CGI interface and small programs for retrieving the necessary information from the database.

2.2 The competence-performance approach as a factor of reusability

Describing the prerequisite structure between the learning objects through direct prerequisite links as it was done in the RATH system involves difficulties in dynamic domains. Whenever learning objects are changed, added, or deleted, the prerequisite relationships to and from many other objects have to be rechecked for validity. This problem has already been discussed with respect to knowledge space theory without convincing results [4].

A solution to this can be found in Korossy's competence-performance approach [29,30]. Investigating the cognitive background of knowledge spaces, Korossy differentiated between observable performances and the underlying, not directly observable competencies. He defines a complete competence-performance structure by the structures within the sets of competencies and performances, respectively, and by the mappings between competencies and performances.

Based on experiences in developing a course for RATH [2,31], Hockemeyer takes up Korossy's approach in the form of mappings between learning objects and underlying competencies. Furthermore dividing the set of competencies assigned to an object into two subsets of required and of taught competencies he obtains *teaching structures* of competencies [23].

Such assignments of required and of taught competencies for a learning object can directly be expressed through metadata. An adaptive tutoring system can then use a learner model of competencies and can adapt to the learner's current knowledge by comparing the competencies required for the learning object in question with the learner's competence state.

This approach has been applied in the APeLS system described in Section 3 below. The benefits with respect to reusability of learning objects and to the dynamics of courses have been proven building a course on mechanics out of sections from two different courses. All learning objects were described with metadata on required and taught competencies. The new course could simply be built by feeding all the individual learning objects into the APeLS system.

2.3 Standardized Metadata for Describing and Realizing Adaptivity

As already mentioned above, standards for metadata describing eLearning resources have been developed in recent years [e.g. 26]. However, these standards are not capable of describing adaptivity of learning resources. Within the EASEL project [19], extensions of an existing metadata schema covering adaptivity information have been proposed [3,10]. The basic idea is an adaptivity block within the education related metadata that contains an arbitrary number of adaptivitytype entries, one for each type of adaptivity realizable with this piece of content. These adaptivitytype entries then contain *candidates* that may be hierarchically grouped by *sets* allowing, e.g., an and-or structure between the candidates. The candidates contain the real values, possibly in a sequence of langstrings allowing to specify the same values within multiple languages.

The following example shows an adaptivitytype entry describing the competencies required for understanding the current document. There exists a set of *candidates* of which all should be known. The *competence A* is described in two languages but the surrounding candidate block clearly states that *competence-A* and *Kompetenz-A* denote the same competence in different languages.

```
<adaptivitytype
name"competencies.required">
  <set type"all">
    <candidate>
      <langstring lang="en">
         competence-A
      </langstring>
      <langstring lang="de">
         Kompetenz-A
      </langstring>
    </candidate>
    <candidate>
      ...
    </candidate> ...
  </set>
</adaptivitytype>
```

Within the adaptivitytype tag it is also possible to specify a reference document explaining the terms used for the entries.

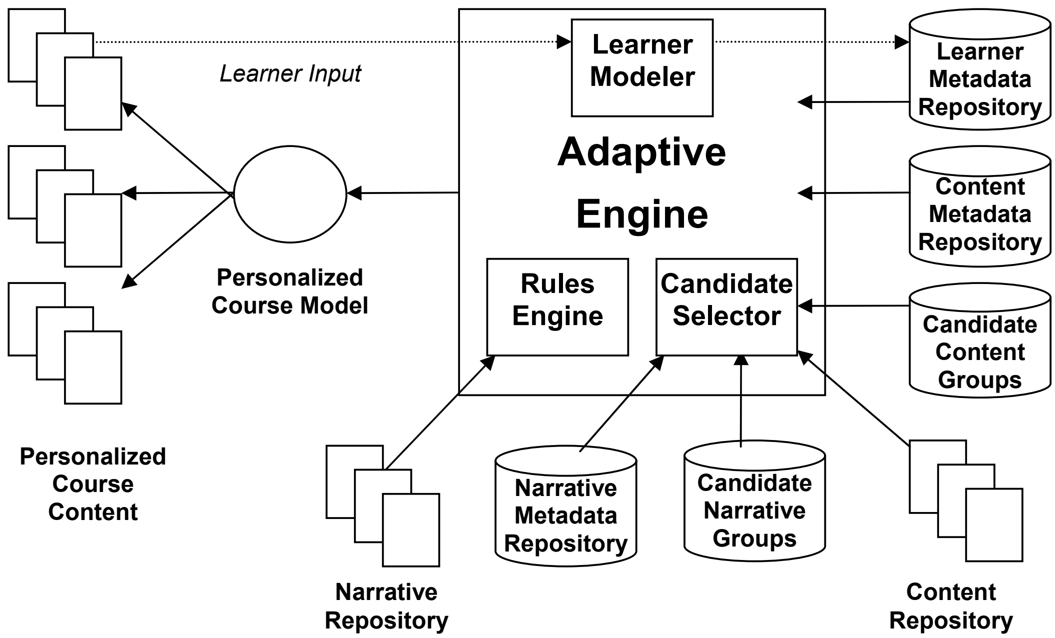

Figure 1 – Architecture of the PLS [Conlan et al, 2002a]

3 Models and Candidacy in Adaptive eLearning Systems

In this section, an architecture for an adaptive system based on separate data models and on separation of concepts and contents is introduced which may help solving the problems mentioned in Section 2.1 above.

The principle element of any eLearning system is the learner, or more accurately how precisely the system models the learner. Most eLearning Systems that support adaptive techniques have two other models – Content Model and Narrative Model, though these models are often intertwined. The content model represents the learning resources within the system and the narrative model embodies the ways in which that content may be sequenced for the learner. It is the reconciliation of these three models that produces personalized courses.

The Personalized Learning Service (PLS) [12], developed by Trinity College, Dublin, separates these three models into discrete elements of the service.
The advantage of this separation into discrete models (see Fig. 1) is that the content is now independent of the narrative and can be reused in other eLearning services or courses. The PLS also supports a *candidacy architecture* [12] that enables the narrative to refer to learning concepts, rather than individual pieces of content. This approach enables an individual concept to be fulfilled by an appropriate candidate at runtime (see 3.4 Metadata and Candidates as a basis for Adaptation).

3.1 Generic Standards-based Approach to Adaptive Hypermedia Services

As part of EASEL, two approaches to developing adaptive hypermedia services were explored. [11] detail the service architecture and describe the differences between explored Adaptive Hypermedia Services and Adaptive Hypermedia Systems. The first approach, the Personalized Learning Service [12] explored many of the basic principles employed and enhanced in the second iteration. The primary goals of the second adaptive hypermedia service, called the Adaptive Personalized eLearning Service (APeLS), were to

- Ensure that the flexibility of the rules engine was maintained.
- Expand the candidacy approach to cater for n models (rather than just three).

- Utilize an approach that can use this metadata as a means to produce adaptive effects.
- Maintain the standards-based metadata for describing the content model.

3.2 Flexible Rules Engine

The rules engine employed is based on JESS [27], as was the original PLS rules engine. The narrative paradigm, where an individual narrative embodies the flow and conditions for assembling a personalized course offering, was extended to facilitate

- Open course structure
- Reusable sub-narratives
- Metadata-based decision making
- Re-usable selection processes

The original PLS was constrained to the course model represented internally in the adaptive engine implementation. This model was of a traditional course-section-unit-content form. In APeLS it was decided that this model was too restrictive to represent the variety of pedagogical approach that the course (narrative) author may wish to express. To this end, APeLS was designed to allow narratives to build any DOM (Document Object Model) they required directly from the narrative rules. The DOM could then be expressed in XML and passed through a transformation, as in the PLS, to produce a rendering of that course.

APeLS was also designed to utilize the capability of JESS to call other sets of rules, called batches, from within another rule set. This translates to narratives being able to call sub-narratives. As all narratives have associated metadata the *calling* of sub-narratives can use the same principles of candidacy used in the narrative selection and content selection processes of the PLS. The ability to use finer grained narratives to constitute a larger narrative enables the course author to produce re-usable narratives and build a repository of such narratives (described by their associated metadata). If the design DOM hierarchy is replicated at different levels within the course produced then, in theory, the sub-narrative could be inserted at any point in the course and still produce a valid DOM.

3.3 N Models and Collections

The original PLS was based on three models – Learner, Content and Narrative. This approach, however, precluded the possibility of expanding to other models. For example, it may be desirable to represent aspects pertaining to the learning environment, learning device (PDA, WAP, eBook etc.), learner's peers or overall curricula. Separate models that the narratives can reference, if required, should represent each of these aspects. With the capabilities of metadata-based decision making it is possible to query any metadata model. The problem remains, however, of how to organize the models in such a way that the metadata is accessible and the principle of candidacy is maintained.

The data storage of the PLS was based on a relational database model that was capable of storing any XML structure in a generic fashion. The downside of this approach is that for large numbers of records the tables grew very large with no mechanism for segregating and identifying the different models represented. For multiple models to be feasible it is necessary to collect like models together to ease querying of the metadata. To this end, Xindice [7] was chosen as the data storage facilitator. Xindice (originally dbXML) is a database that thinks in terms of XML. Most relational databases offer XML import and export facilities, but the underlying structure is still relational. Xindice utilizes relational principles, but natively understands XML and offers XPath query services. It is also capable of organizing XML documents into collections, facilitating the dynamic creation of such collections as well.

Using Xindice it is possible to have n models, each distinctive model being stored in a separate collection. For example, APeLS could be used with four models – Learner, Content, Device and Narrative. The Device model may represent aspects of the learning device such as, screen real estate (resolution), network bandwidth, input device (stylus, mouse or touchpad). The narratives can access this metadata information and use it as a basis for modifying the course structure or at the content selection stage they can choose a candidate that best suits the device. As the modification or addition of models and collections does not require a recompilation of the engine the course author who can decide to add or change models as required when developing a new course.

3.4 Metadata and Candidates as a basis for Adaptation

Using the mechanisms outlined above one can use the descriptive metadata of any of the models as a basis for adaptation. This enables the course author to create narratives that add either candidate groups of content or candidate groups of sub-narratives to a narrative based on the comparison of their metadata with that on the learner. The execution of the narrative may utilize any metadata relating to the content for realizing the adaptation. For example, the metadata may describe required and taught competencies (in accordance with a model such 17,18]) and its cognitive extensions [5] and compare these values with the learner's learned competencies as the basis for adaptation.

When a personalized course is created the first step creates a personalized course model that details the candidate groups, from which candidates will later be selected, that fulfil the learners learning objectives. This is a *fuzzy* form of the adaptive course as, in the example of content for instance, it says what concept should be delivered, but not which content candidate will be delivered at runtime. Similarly sub-narratives do not need to be reconciled until runtime enabling changes in the learner model to influence later candidate selection without impacting on candidates already selected. If the course author desires this approach can support an evolving form of adaptivity, where the whole course is not recompiled, but the *blanks* (candidate groups) are filled as required allowing the decisions that fill those *blanks* to be made using the latest user information.

The second advantage of candidate groups is that more candidates may be created for a candidate group as required. As narratives refer to candidate groups, rather than individual candidates, the narrative requires no re-authoring if more candidates are created. This is true for both sub-narrative candidates and content candidates. If required the selection process may be updated to account for the new candidates, but this is often unnecessary if the candidates are described using the same metadata schema. This way, also the problem with dynamic domains experienced with the RATH system (see above, Section 2.1) is solved.

As both candidates are described using standards-based metadata they may be incorporated into many courses or added to a content repository for searching and discovery. This dramatically increases the contents potential reuse [13]. As quality eLearning material is expensive, both in terms of time and financially, to produce the disadvantage of having to author accompanying metadata is outweighed by the potential for reuse. The fact that aspects of this metadata may be used as part of the adaptive process increases its value.

4 Conclusion

In this paper, we have presented an approach to realize adaptivity in eLearning systems in a metadata and model driven way. Thus, metadata originally developed for the description of adaptivity can also be applied for its implementation. An important element for this is the application of a candidacy architecture, i.e. the separation of abstract concepts to be taught from their concrete instantiation as learning objects. This separation corresponds to the distinction between competencies and performances in the psychological theory of knowledge spaces which facilitates the application of that theory for adaptive and personalized elearning.

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References

1. Albert, D. & Hockemeyer, C.. Adaptive and dynamic hypertext tutoring systems based on knowledge space theory. In du Boulay, B. & Mizoguchi, R., editors, *Artificial Intelligence in Education:*

Knowledge and Media in Learning Systems, volume 39 of *Frontiers in Artificial Intelligence and Applications*, pp. 553-555, Amsterdam, 1997. IOS Press.

2. Albert, D. & Hockemeyer, C. Applying demand analysis of a set of test problems for developing an adaptive course. *Proceedings of the International Conference on Computers in Education ICCE2002,* accepted for publication.
3. Albert, D., Hockemeyer, C., Conlan, O. & Wade, V. Reusing Adaptive Learning Resources. In C.-H. Lee et al. (Eds). *Proceedings of the International Conference on Computers in Education/SchoolNet2001.* Incheon, Korea: Incheon National University of Education. Vol. 1, pp. 205-210.
4. Albert, D. & Kaluscha, R. Adapting knowledge structures in dynamic domains. In Herzog, C., editor, *Beiträge zum Achten Arbeitstreffen der GI--Fachgruppe 1.1.5/7.0.1 ``Intelligente Lehr--/Lernsysteme'', September 1997, Duisburg, Germany*, pp. 89-100. TU München, 1997.
5. Albert, D. & Lukas, J.: *Knowledge Spaces: Theories, Empirical Research, and Applications.* Berlin: Springer, 1999.
6. Albert, D. & Mori, T. (2001). Contributions of cognitive psychology to the future of e-learning. *Bulletin of the Graduate School of Education, Hiroshima University, Part I (Learning and Curriculum Development), 50,* 25-34.
7. *Apache Xindice*. http://xml.apache.org/ xindice.
8. Berners-Lee, D. & Connolly, D.: HyperText Markup Language Specification – 2.0. *IETF Request for Comments 1866,* 1995.
9. Conklin, J.. Hypertext: An introduction and survey. *IEEE Computer*, *20*(9), 17-41, 1987.
10. Conlan, O.; Hockemeyer, C.; Lefrere, P.; Wade, V.; Albert, D.. "Extending Educational Metadata Schemas to Describe Adaptive Learning Resources." *Hypertext '01: Proceedings of the Twelfth ACM Conference on Hypertext and Hypermedia.* New York: ACM, 2001. pp.161-162.
11. Conlan, O.; Hockemeyer, C.; Wade, V.; Albert, D.; Gargan, M. An Architecture for integrating Adaptive Hypermedia Service with Open Learning Environments. *Proceedings of ED-MEDIA 2002, World Conference on Educational Multimedia, Hypermedia & Telecommunications*, Denver, Colorado, June 2002.
12. Conlan, O.; Wade, V.; Bruen, C.; Gargan, M. Multi-Model, Metadata Driven Approach to Adaptive Hypermedia Services for Personalized eLearning. In: de Bra, P., Brusilovsky, P., & Conejo, R. (Ed.), *Adaptive Hypermedia and Adaptive Web-Based Systems*, pp. 100 – 111. New York: Springer.
13. Conlan, O.; Dagger, D.; Wade, V. Towards a Standards-based Approach to e-Learning Personalization using Reusable Learning Objects. *E-Learn 2002, World Conference on E-Learning in Corporate, Government, Healthcare and Higher Education,* Montreal, September 2002 (paper accepted).
14. *Cognitive Science Section,* Department of Psychology, University of Graz, Austria. URL: http://wundt.uni-graz.at/.
15. *Dublin Core Metadata Initiative*. URL: http://dublincore.org.
16. De Bra, P., Brusilovsky, P., & Conejo, R. (ed.) (2002). *Adaptive Hypermedia and Adaptive Web-Based Systems.* New York: Springer-Verlag.
17. Doignon, J.-P. & Falmagne, J.-C. Spaces for the assessment of knowledge. *International Journal of Man-Machine Studies*, *23*, 175-196, 1985.
18. Doignon, J.-P. & Falmagne, J.-C. (1999). *Knowledge Spaces*. Springer-Verlag, Berlin.
19. *EASEL: Educators Access to Services in the Electronic Landscape.* EC project IST-1999-10051. URL: http://www.fd group.co.uk/easel.
20. Easel Consortium. *D03 Requirements Specification, v. 1.4.* URL: http://www. fdgroup.co.uk/easel/documents/D3-Update.doc.
21. Halasz, F. & Schwartz, M.. The Dexter hypertext reference model. In Moline, J., Benigni, D., & Baronas, J., editors. *Proceedings of the Hypertext Standardization Workshop*, volume 500-178 of *NIST Special Publications*, pp. 95 - 133. Gaithersburg, MD: National Institute of Standards and Technology.
22. Cord Hockemeyer. *RATH --- A Relational Adaptive Tutoring Hypertext WWW--Environment*. Technical Report 1997/3,

Institut für Psychologie, Karl-Franzens-Universität Graz, Austria, 1997.
23. Hockemeyer C., Held, T., & Albert, D. RATH - a relational adaptive tutoring hypertext WWW-environment based on knowledge space theory. In Christer Alvegård, ed., *CALISCE`98: Proceedings of the Fourth International Conference on Computer Aided Learning in Science and Engineering*, pp. 417-423, Göteborg, Sweden: Chalmers University of Technology, 1998.
24. Hockemeyer, C. *Extending the Competence-Performance-Approach for Building Dynamic Adaptive Tutoring Systems.* Talk at the 33rd European Mathematical Psychology Group Meeting EMPG 2002.
25. *IEEE Learning Technology Standards Committee (LTSC).* URL: http://ltsc.ieee.org.
26. *IMS Learning Resource Meta-data Specification.* URL: http://imsproject.org/metadata/index.html.
27. *JESS: Java Expert System Shell,* Version 6.0, URL: http://herzberg.ca.sandia.gov/jess/.
28. *Knowledge and Data Engineering Group*, Department of Computer Science, Trinity College, Dublin. URL: http://kdeg.cs.tcd.ie.
29. Korossy, K.tending the theory of knowledge spaces: A competence-performance approach. *Zeitschrift für Psychologie*, *205*,53-82, 1997.
30. Korossy, K. Modelling knowledge as competence and performance. In Albert, D. & Lukas, J., editors, *Knowledge Spaces: Theories, Empirical Research, Applications*, pp. 103-132. Lawrence Erlbaum Associates, Mahwah, NJ, 1999.
31. *RATH (Relational Adaptive Tutoring Hypertext),*URL: http://wundt.uni-graz.at/rath/.