

Developing Personalized and Adapted Medical Learning Objects for Healthcare Sector

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Abstract

Medical learning object deviates from traditional notion of learning object in that it is always in a digital form and relates to medication. They may include text, images, sound and video. They are introduced in order to facilitate the employees of healthcare sector and patients. In this article, we illustrate how medical learning objects can be personalized according to the user knowledge and adapted according to the working process in which the learning object is invoked. We believe that by introducing personalized and adapted medical learning objects we can optimally develop e-learning processes for healthcare sector that are just-in-time and are tailored to their specific needs. The variations of learning objects are produced by the XSLT-transformations. This approach significantly simplifies the management of the content of the learning objects as the updates have to be done only on the physical learning objects.

Keywords: learning objects, continued education, distance learning, e-health, ontologies, XSLT.

Introduction

The role of continued education and lifelong learning is becoming still more important as the fast development of technologies requires specialized skills that need to be renewed frequently. E-learning adopts well for continued education as it can be done in parallel to other work. Hence, e-learning sets new requirements for organizations: they have to build global learning infrastructures, learning material has to be in digital form, and learning material has to be distributed. In addition, organizations need learning processes that are just-in-time, tailored to their specific needs, and ideally integrated into day-to-day work patterns.

Healthcare is a field where the fast development of drug treatment and technologies requires specialized skills and knowledge that need to be renewed frequently. In addition, medical knowledge is expanding every day. As a result no physician can keep up without the help of modern informa-

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tion and communication technology (Puustjärvi & Puustjärvi, 2006). Ideally by integrating high-performance computers, high resolution video and fiber-optic information highways we could put the entire world of medical science at the fingertips of even the most isolated nurse and patient.

An interesting question arising from this vision is how medical knowledge should be organized and retrieved. In this article we focus on this problem.

The corner stone in our approach is the notion of medical learning object. It deviates from traditional notion of learning object (LOM, 2007) in that it is always in a digital form and relates to medication. It may include text, images, sound and video.

Traditionally the retrieval of learning objects is facilitated by introducing taxonomies and meta-data items (Puustjärvi & Pöyry, 2006). That is, learning objects are annotated by metadata items (keywords) taken from a taxonomy, and query expressions are constructed by connecting the keywords taken from the taxonomy. This approach has turned out to be useful (Puustjärvi, 2004), and it is also adapted to our approach. However, it has also turned out that in many cases keyword based approaches result learning objects which fit more or less to the query. Hence some kind of personalization and adaptation should also be done.

In order to increase the expression power of the information retrieval methods we have incorporated medical learning objects into medical ontologies. That is, in the medical ontology (Davies, Fensel, & Harmelen, 2002) we model the medical learning objects and other medical concepts (e.g., drug, disease and prescription) as well as their relationships.

The ultimate goal of this approach is that we can integrate medical learning objects as natural parts of the daily duties of the patients as well as the employers of the healthcare sector. For example, when a user is accessing a patient record including a statement of “diabetes” he or she can mark the word “diabetes” and clicks the button “give the learning object” and immediately the system returns the learning objects associated to diabetes. Moreover the content of the returned learning object depends on the familiarity of the user, i.e., whether the user is an expert (e.g. a physician, diabetes nurse, or a pharmacist), healthcare professional (e.g., a nurse) or a patient.

This kind of personalization requires that the system has different variations of the medical learning objects. For example a medical learning object focusing on diabetes should have at least the following variations:

- The expert variation includes the newest medical knowledge of diabetes.
- The professional variation includes useful information for all professionals of the healthcare sector whose work somehow relates to diabetes.
- The general variation includes information about diabetes that is understandable for an average patient.

It has turned out that in many cases the variations developed for personalization is not enough but also some kind of adaptation is needed. By adaptation we mean that the system is context-aware of the working process in which the learning object is invoked, and the returned learning object is adapted according to the working process. For example, if the diabetes learning object is invoked by a pharmacist in drug invoicing process, then the returned diabetes learning object should include information about the constraints under which the healthcare authority is obliged for paying antidiabetic drugs.

A consequence of introducing adaptation is that the number of required variations still increases giving rise for more complex management of learning objects. However, in our approach there is only a need for one physical copy of each topic (e.g., on diabetes) because its variations are produced on fly from it by the XSLT-transformations. An important gain of this approach is that the updates of a learning object have to be done only on the physical learning object but not on its variations.

We believe that by introducing personalized and adapted medical learning objects we can optimally develop e-learning processes for healthcare sector which are just-in-time and are tailored to their specific needs.

The rest of the paper is organized as follows. In the next section, we give an overview of the architecture of the Medical Learning Object Server that we are developing. Then we consider taxonomies and metadata (keywords) and illustrate how they can be used in annotating medical learning objects. We also consider the drawbacks of keyword-based learning object retrieving methods. Then, we give an overview of ontologies and illustrate how we exploit medical ontologies in increasing the expression power of information retrieval methods in supporting medical learning objects. The paper then illustrates how we use XSLT-transformations in producing the variations of medical learning objects. Finally, the paper concludes by discussing the advantages and limitations of our approach.

The Medical Learning Object Server

The architecture of the system

The Medical Learning Object Server (Figure 1) provides an interface

- for the content provider for the creation and updates of medical learning objects
- for the user the taxonomy- and ontology based searching interface.
- for the medical applications an API (Application Programming Interface) for searching medical learning object.

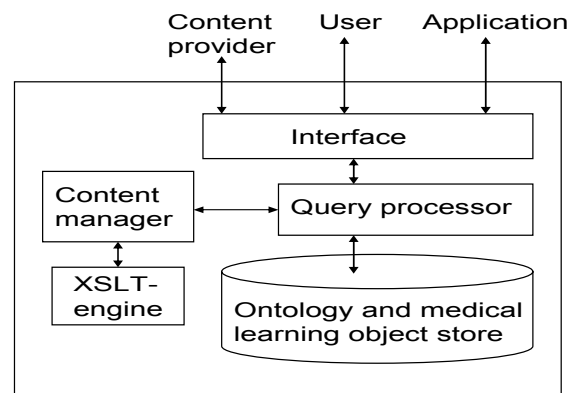


Figure 1. The Medical Learning Object Server.

The function of the components of the system is considered more detailed in the next section.

Taxonomy-based searching

In general, taxonomy is a way to classify or categorize a set of things into a hierarchy (Daconta, Obrst, & Smith, 2003). It is a tree like structure consisting of a root and branches where each branching point (i.e., a node) and leaf is an information entity. In the context of information technology taxonomy is generally understood as the classification of information entities in the form of a hierarchy, according to the presumed relationship of real-world entities that they represent.

The logic behind taxonomy is that when one goes up the taxonomy toward the root, the information entities become more general, and respectively when one goes down towards the leaves the information entities become more specialized. To illustrate this, a simply drug taxonomy is pre-

sented in Figure 2. The idea behind this classification is that the medical learning objects can be annotated by the metadata items (the branching points and the leaves) represented in the tree.

Applying the Boolean model (Baeza-Yate & Ribeiro-Neto, 1999) in searches requires that each medical learning object is augmented by a set of metadata items (keywords). A user can then query learning objects by Boolean expressions comprising of operands and operations. The operands are the used keywords and the operands are typically “and”, “or”, and “not”. For example, by using the taxonomy of Figure 2 the keywords attached to a learning object could be “Pain drugs for topical use” and “Prescription based pain drugs”.

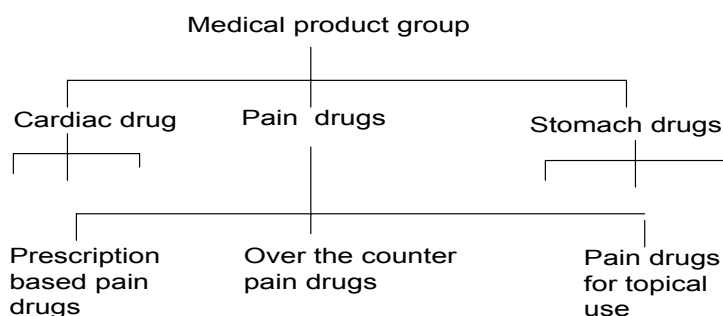


Figure 2. A simple Medical product group taxonomy.

The Boolean model is intuitive and clear. Moreover, it can be efficiently implemented even in the case of huge amount of objects. However, using this model in healthcare sector gives rise to following drawbacks:

- First, the model is based on a binary decision criterion, meaning that each learning object is predicted to be relevant or non-relevant. In reality, it is obvious that the resulting learning objects fit more or less to the query, i.e., some kind of grading should be possible.
- Second, expressing the requirements of learning objects by a Boolean expression may be difficult.
- Third, a typical problem concerning search engines based on the Boolean model is that either the result of the query includes too many or too few learning objects.

We next consider how these problems can be avoided by exploiting ontologies in searching learning objects.

Ontology-based searching

The term ontology originates from philosophy where it is used as the name of the study of the nature of existence. In the context of computer science, the commonly used definition is “An ontology is an explicit and formal specification of a conceptualization” (Gruber, 1993). So it is a general vocabulary of a certain domain. Essentially the used ontology must be shared and consensual terminology as it is used for information sharing and exchange. On the other hand, ontology tries to capture the meaning of a particular subject domain that corresponds to what a human being knows about that domain. It also tries to characterize that meaning in terms of concepts and their relationships.

Each ontology describes a domain of discourse. It consists of a finite set of concepts and the relationship between the concepts. For example, within healthcare sector patient, drug, and e-

prescription are typical concepts. These concepts and their relationships are graphically presented in Figure 3.

In the figure, ellipses are classes and boxes are properties. The ontology includes for example the following information: Medical learning object is a class and due to its subClassOf-property its instances may comprise a hierarchical structure. For example there may be a medical learning object instance Diabetes having subclasses Type 1 Diabetes and Type 2 Diabetes B. (Type 1 diabetes or insulin-dependent diabetes, is usually first diagnosed in children, teenagers, or young adults while Type 2 diabetes or noninsulin-dependent diabetes, is the most common form of diabetes.)

Note that this subClassOff structure has nothing to do with the learning objects variations discussed earlier. All these three diabetes learning objects' instances may have several variations that are produced by XSLT-transformations (Daconta et al, 2003).

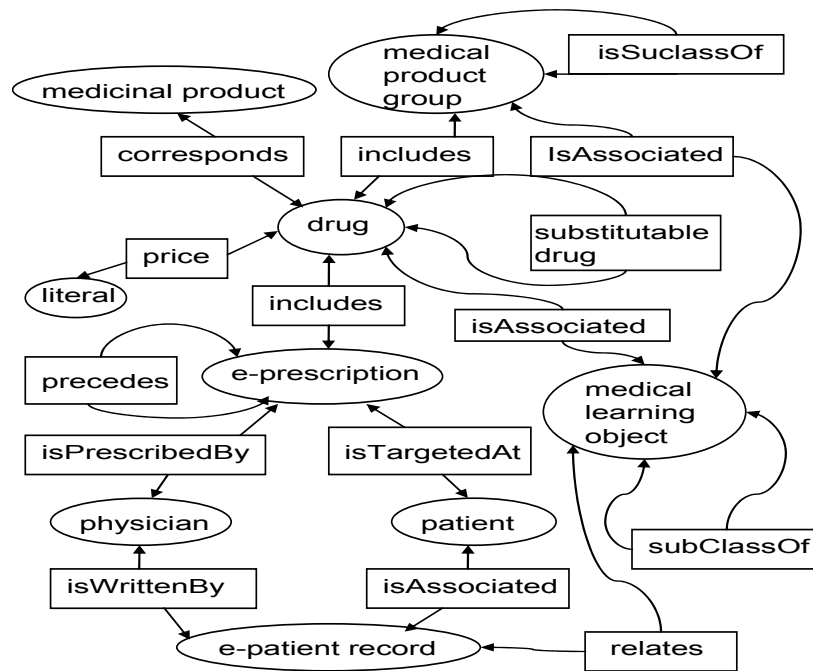


Figure 3. A medical ontology.

In Figure 4, the part of the ontology of Figure 3 is taken and instance acetylsalicylic acid is inserted to class drug and the instance Aspirin is inserted to class medicinal product. That is, an ontology may include concepts as well as their instances.

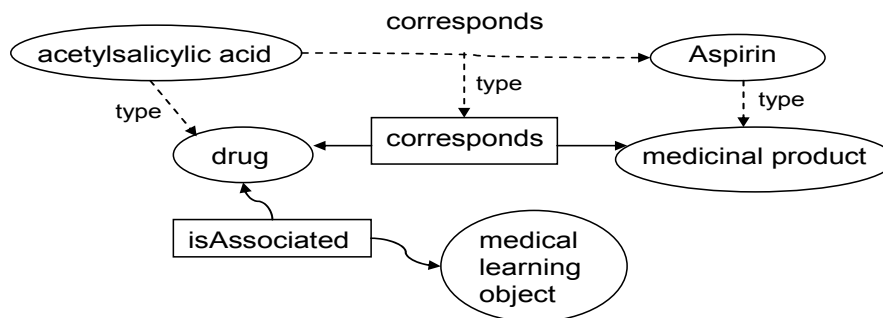


Figure 4. Including instances in the ontology.

Based on this ontology we can make for example the following queries (e.g., by using RQL):

- Give me the learning object that is associated to the drug acetylsalicylic acid.
- Give me all medicinal products that corresponds the drug acetylsalicylic acid.

The graphical ontologies of Figure 3 and 4 are presented by ontology languages in a machine processable form. We now shortly present these languages and illustrate how we can use them.

XML (Extensible Markup Language) (Harold & Scott Means, 2002) is a metamarkup language for text documents. It is the syntactic foundation layer of the Semantic Web (Antoniou & Harmelen, 2004). All other technologies providing features for the Semantic Web will be built on top of XML. Particularly XML defines a generic syntax used to mark up data with simple human readable tags. An important feature of XML is that it does not have a fixed set of tags but it allows user to define tags of their own.

RDF (RDF, 2007) provides a means for attaching semantics to a resource (e.g., to any concept represented in Figure 3 and 4) without making any assumptions about its structure. The relationship of XML and RDF is that XML provides a way to express RDF-statements. A statement describes the relationships among resources. For example, a RDF-statement can be used to express that Aspirin is a type of medicinal product.

RDF however, provides no modeling primitives for describing the ontology. Representing such ontology is the role of RDF vocabulary description language RDF schema. It defines classes (e.g., drug, learning object and e-prescription) and properties (e.g., subclass, includes, and corresponds).

OWL Web Ontology Language (OWL, 2007) has more facilities for expressing meaning and semantics than RDF Schema. In particular, it adds more semantics for describing properties and classes, for example relations between classes, cardinality of relationships, and equality of classes and instances. For example using OWL we can define that “the classes medicinal product and drug are disjoint” and that “each drug may include in many medicinal product group”.

Managing the Content of Learning Objects

Content Manager is a Web-based system to manage the production and distribution of medical learning objects to various users. It uses XML-technologies in separating content (physical learning object) from its presentation variation. Content can be transformed on the fly via the Extensible Language Transformation (XSLT) (Daconta et al., 2003) to users' browsers or to a user application.

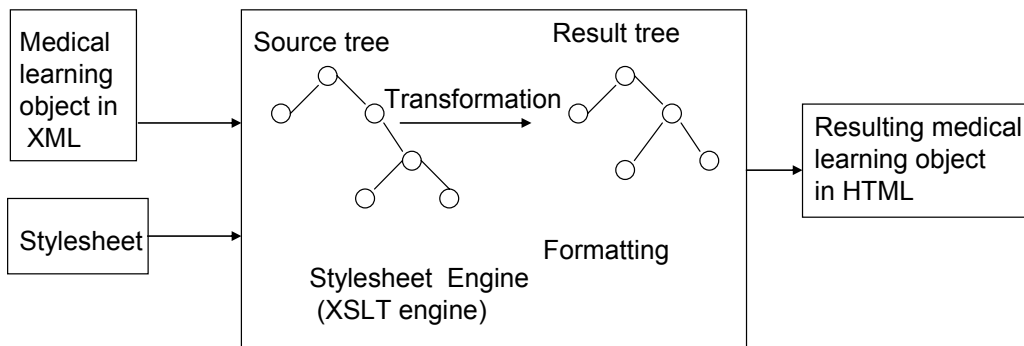


Figure 5. Transforming a medical learning object.

Figure 5 illustrates the transformation and formatting process. The Stylesheet Engine takes an original (physical) medical learning object (XML-document), loads it into a DOM (Document Object Model) (Daconta et al., 2003) source tree, and transforms that document with the instructions given in the style sheet. In specifying those instructions, style sheet use XPath (Antoniou, & Harmelen, 2004) expressions to reference portions of the source tree and capture information to place it into the result tree. The result tree is then formatted, and the resulting learning object (XML-document) is returned. Although the original document is XML document, the resulting document may be any format, e.g., in HTML, PDF or RTF.

Conclusions

Medical knowledge is expanding every day. As a result neither the physicians nor other workers in the health care sector can keep up without the help of modern information and communication technology. At the same ever expanding set of patients are interested to have more medical knowledge.

By using traditional information retrieval methods retrieving medical information is frequently a long lasting and frustrating process because the returned medical information is not relevant, is overly superficial or overly specific. In our solution medical information is personalized according to user background and adapted according to the working process in which the information is invoked. We believe that in this way we can avoid many of the problems related to the quality of medical information retrieval.

A drawback of our approach is that style sheets have to be produced for each variation of a medical learning object. On the other hand, the gain of this approach is that when medical learning objects are updated no updates on style sheets have to be done. However, the only way to evaluate definitively our solution is to test it thoroughly in the healthcare sector. Anyway a consequence of introducing our solution is that it changes the daily duties of the employees of the healthcare sector. Therefore the most challenging aspect will not necessary be the technology but rather the training to utilize the new technology.

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Biographies



J. Puustjarvi obtained his B.Sc. and M.Sc degree in computer science in 1985 and 1990, respectively, and his PhD degree in computer science in 1999, all from the University of Helsinki, Finland. Currently he is a professor of information society technologies at the Technical University of Lappeenranta. He is also a docent of eBusiness technologies at the Technical University of Helsinki, and a docent of computer science at the University of Helsinki. His research interests include eLearning, eHealth, eBusiness, knowledge management, semantic web and databases.



L. Puustjarvi obtained her M.Sc degree in pharmacy in 1981, and her professional development exam in community pharmacy in 2005, both from the University of Helsinki, Finland. She has worked in several pharmacies as well as in research groups focusing on medicinal information systems. Currently she is pharmacy owner in Kaivopuisto Pharmacy in Helsinki. In addition, she participates in many medicinal researches and advises thesis focusing on medicinal information systems. Her current research interest includes electronic prescriptions, medicinal ontologies and medicinal information systems.