Individualized Selection of Learning Object

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Abstract: It is becoming more necessary and possible to provide individualized help on selecting learning materials to learners in an online educational system because they usually face more choices. A framework for individualized learning object selection, called Eliminating and Optimized Selection (EOS), is proposed. This framework contains a suggestion on extending learning object metadata specifications and presents an approach to the selecting a short list of suitable learning objects appropriate for the learner and the learning context. The key features of the EOS approach are to evaluate the suitability of a learning object in its situated context and to refine the evaluation by using available historical information about the learner, the content, and the learning context.

1 Introduction

Rapidly evolved internet and web technologies have unlocked tremendous possibilities in the world. The movement towards web-based education is significant one among them. Through the internet, digital educational materials can be delivered by online learning systems effectively and affordably to a learner almost anywhere and at any time. Because of their convenience and flexibility, online learning systems have been increasingly gaining attention from both education providers and consumers.

A world wide effort has been made in developing learning object metadata standards and specifications. The focus of learning object metadata standardization is to improve reusability and interoperability of learning objects. Learning objects that comply with these standards and specifications can be easily discovered, acquired, and reutilized. This enables the sharing and exchange of learning objects across different learning systems and also provides learners access to multiple learning resources.

As a result of such ubiquitous access, learners in an online virtual course may have more diverse backgrounds than those in a traditional course. The traditional one-for-all approach to content selection becomes inadequate in an online learning environment. Different learners have their distinctive characteristics and learning styles. The resources individuals may have (bandwidth, software, hardware) can also vary. The expected benefit of a learning object and the learning effect gained from it are usually different from learner to learner. Because of the limitation of time and capability, however, it is almost impossible for a learner (or a teacher) to go through all available learning materials to find the most suitable one. Selecting the most suitable learning object among all candidates for individual learners becomes imperative for a learning management system.

In this paper, a framework for individualized learning object selection is proposed. This framework contains a suggestion on extending learning object metadata specifications and presents the Eliminating and Optimized Selection (EOS) approach. In the EOS approach, irrelevant learning objects are eliminated at first. Then the importance of each feature of a learning object is identified by examining the current context, and the associated weight is assigned dynamically. A composite score of all features determines the suitability of the learning object. Finally, the result of the selection is refined by using available historical information.

2 Background

As a result of international efforts on standardization of learning object metadata, several standards and specifications have been released. IEEE Standard for Learning object Metadata (LOM) [2], IMS Metadata Specifications [3], and Canadian Core Learning Resource Metadata Application Profile (CanCore) [1] are well known examples. The core of existing metadata specifications is LOM. Elements in nine categories have been defined in LOM to describe features of a learning object, such as general information, technical requirements, intellectual property rights, and educational characteristics. An instance of the specification can facilitate search, acquisition, and use of learning objects sufficiently, but it cannot provide enough information for individualized learning object selection.

The maturity of the standardization of leaning object metadata specification presents a new opportunity and challenge for researchers and developers in the area of intelligent educational systems. Various directions have been explored. For example, McCalla proposed the ecological approach for designing e-learning systems [4]. The key aspects of his approach involve gradually accumulating of information and focusing on end users. Mohan et al. investigated instructional planning processes in e-learning environments and recommended extensions to the current specifications [5]. Applying collaborative filtering and other techniques in web-based educational systems has also been explored [6, 7].

3 A Framework for Individualized Selection of Learning Object

The suitability of a learning object requires a comprehensive evaluation based upon its features. Whether a learning object is suitable depends on its own features and the context where it is used. The suitability of a learning object has various manifestations, such as its appropriateness with respect to the learning goals, its usefulness and helpfulness for learners, pedagogical value, popularity among learners, and endorsement by teachers.

A perfectly suitable learning object for a particular learner should possess the following features:

- It presents the knowledge that the learner wants to learn;
- It can be presented in the learner's environment, i.e. it is affordable in terms of cost and time to the learner, and it can be presented on the learner's platform;
- It is appropriate to the learner's knowledge level, which includes domain knowledge, reading capability, etc.;
- Its presentation style matches learner preferences as much as possible;
- It has high pedagogical value.

Unfortunately, such an ideal learning object can rarely be found in the real world. Usually, a learning object has only some of those desired features. Moreover, some features of a learning object contribute positively to its suitability, while the others contribute negatively. In a more complicated situation, a learning object whose features apparently match a learner's preferences might not be the best choice for the learner on the basis of other similar learners' negative evaluations and/or instructors' negative endorsements — information that can be retrieved from the usage history of learning objects.

3.1 Information Requirements for Individualized Selection

The existing learning object metadata specifications have a defined set of attributes that describe learning objects. The suitability of a learning object for a given learner and learning situation is, however, a contextual feature. It can be decided only when the learning object is situated in a certain context. To determine the suitability of a learning object, some information about the context is necessary in addition to the information about the learning object itself. Besides feature and requirement matching, the suitability of a learning object depends on some features that are more difficult to describe and measure. Historical usage of learning objects can provide valuable help in optimizing selection. As a first approximation, we have taken a pragmatic approach to identifying attributes that may be important in selecting suitable learning objects. We have identified attributes that are relatively easy to obtain, attributes that (based on the educational literature) seem to have maximal discriminatory power, and attributes that link content to context of learning.

3.1.1 Information about Learning Objects

The current existing specifications focus on promoting reusability and interoperability through defining text-based tags for categorizing and annotating learning objects, which facilitate learning object discovery and exchange across different learning objects repositories. To achieve individualized selection, however, extension and modification are required. The following is some examples.

> ***Pedagogical Objective:*** describes the concept that the learning object presents and what is expected to be achieved. This is a critical attribute for determining the suitability of a learning object. In current existing specifications, pedagogical objectives of learning objects are not addressed, and they might be indirectly inferred from attributes such as *keyword* and *description*. *Description* is difficult to be used for automatic learning object comparison and selection. *Keyword* is not sufficient and sometimes could mislead to unexpected results. An ontology-based representation of pedagogical objectives may serve much better.
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> ***Expected Reading Level:*** indicates the reading capability that the learning object requires the learner to have. In the current existing specifications, the expected reading level is not defined. Instead attributes *context* (the level of education) and *typicalagerange* are used. Learners in the same level of education or in the same age, however, may have different reading ability. Their reading ability actually plays a more important role.
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> ***Prerequisite:*** specifies the knowledge needed by the learning object. The gap between the prerequisite of a learning object and a learner's knowledge level may cause frustration. This attribute is not defined in the existing specifications, but it is a very important factor for deciding the suitability of a learning object for a specific learner.

3.1.2 Information about Context

The suitability of a learning object may change when it is presented in a different context. An excellent learning object can become totally useless in the wrong context. For example, a well designed video clip is not profitable for a learner who doesn't have enough time to download it. A vivid animation of DNA replication won't do any good for a learner who has just seen three other vivid animations of DNA replication. The information about context determines the requirements for current learning.

> ***Learning Objective:*** indicates what the current learner wants to intent to learn. Learning objects with irrelevant pedagogical objectives are useless.
>
> ***Resources:*** define restrictions that may affect the learner's access to learning objects. For example, the *Financial Situation* attribute gives information about the learner's possible financial restrictions, i.e. how much money will the learner be able to pay for access to a particular proprietary resource. If the learner obtains learning materials via an organization, this will refer to how much the organization would spend for this purpose. The *Time* attribute provides information about the time the learner is willing to spend on a learning object. A lengthy learning object is probably not a good choice for a learner who can devote only very limited time.
>
> ***Learner Characteristics:*** provides information about the learner. The learner is central to the context. Learner characteristics play a significant role in learning object selection. The information about the learner can be used to decide the degree of the match between learning object features and the learner's preferences. It determines the features of learning objects that have stronger effects on learning in various contexts. More important, sufficient learner information enables applying data clustering and collaborative filtering techniques to gain benefits from others' experience. Theoretically, the more that is known about a learner, the better the selection that can be made for him/her. However, many criteria and constraints may interfere with the selection, and sometimes situational variables add a great deal of complication to the decision. Exactly what attributes should be included is a question yet to be answered.

3.1.3 Information about Learning Object Usage History

Some features relating to quality and appropriateness of a learning object, which may impact its suitability in the given context, may not be readily describable by an author or evaluator. Much useful information can be indirectly gathered from prior experiences with the leaning object by learners and instructors. This kind of information should be recorded in the learning object usage history.

Previous Learners: contains models and/or records of learners who have accessed the learning object in the past as well as their actions, evaluation, cognitive state, and achievement related to the learning object.
Previous Instructors: consists teachers who have accessed the learning object and their evaluation or endorsements of the learning object.
Statistics: records accumulated information about the access of the learning object. This can be helpful when more detailed information is not available.

Information about learning object usage history may provide very useful information for optimized selection, and in some situations such information is of the utmost importance. It is valuable to attach historical usage information to every learning object.

Table 1. Information about Context

Attribute Name	Explanation
Learning Objective	The subject or topic the current learner is going to learn
Learner Characteristics	Information about the learner. It is composed by sub-attributes.
Learner Type	Learner's category (e.g. high school student, university student, or non-credit)
Background	Information about related knowledge or experiences of the learner (e.g. major of a university student)
Knowledge in Related Area	Learner's level of domain related knowledge (e.g. experience with programming)
Details of Domain Knowledge	Model of learner's domain specific knowledge (e.g. knowledge about JavaScript and HTML)
Preferred Language	Languages that the learner prefers
Reading Level	Learner's capability of understanding written materials
Listening Level	Learner's capability of understanding vocal materials
Reading Speed	Learner's speed of reading
Preferred Presentation Style	Learner's preference about the way in which the content is presented
Learning Style	Learner's way of learning new concepts or knowledge
Study Attitude	Learner's attitude towards studies
Academic Achievement Goal	The academic goal the learner wants to achieve
General Academic Achievement	Information about the learner's academic performance
History of Using Learning Objects	Learning objects visited by the learner
Resources	Restrictions that may affect the learner's access to learning objects
Computer Environment	Hardware, software, and other related condition
Financial Situation	Financial restriction
Time	Time the learner wishes to spend

Table 2. Information about Learning Objects

Attribute Name	Explanation
Pedagogical Objective	The concept presented in the learning object and what is expected
Environment	The technical requirements needed for presenting the learning object
Cost	The price of the learning object
Language	The language in which the content is presented
Expected Reading Level	The reading capability required by the learning object
Prerequisite	The knowledge needed by the learning object
Typical Learning Time	Time needed for working with the learning object
Presentation Style	The way of presenting the content of the learning object

Table 3. Information about Learning Object Usage History

Attribute Name	Explanation
Previous Learners	Information about previous learners
Accessing Time	The time when the learning object is accessed by the learner
Learner Status	Snap shots of the learner's state before and after accessing the object
Interactions	Actions the learner makes while accessing the learning object
Evaluation	The learner's opinions about the learning object
Achievement	The assessment result of the learner after working with the object
Previous Instructors	Teachers who have accessed the learning object and their evaluation
Statistics	Accumulated information about the learning object
General Popularity	How often the learning object is selected for all types of learners
Categorized Popularity	How often the learning object is selected for certain type of learners

Table 1, 2, and 3 summarize attributes related to the three areas required by the individualized selection. It is not necessary to get explicit input for every attribute in order to perform the individualized selection. Some of them can be inferred from other attributes, and also sometimes the selection has to be done while some information is lacking. We believe that attributes important to learning object selection in adaptive systems should also become part of learning object metadata, and the results of this research will hopefully influence future work on metadata standards.

3.2 The Eliminating and Optimized Selection (EOS) Approach

According to their roles in learning object selection, attributes of a learning object are categorised into two groups, eliminating attributes and selecting attributes. The learning object becomes unsuitable and is eliminated out of hand if an eliminating attribute cannot match the corresponding requirement of current context; while a selecting attribute helps choose among candidate learning objects by a weighted analysis of the features surrounding the learning object or the context of its use.

The first step of the EOS approach is eliminating irrelevant objects. Eliminating attributes are usually constraints and therefore are binary variables (e.g. 1 or 0). If the feature of a learning object represented by an attribute satisfies the requirement of the current context, it has value 1 (true), and the learning object will be selected to perform further comparison; otherwise, its value is 0 (false), and the learning object is eliminated. Attributes in this category could be pedagogical objective, the language, environment condition (e.g. hardware and software), or the financial cost. Let $a_{eliminate\ i}$ be the value of an eliminating attribute, the evaluation result of eliminating step, $e_{eliminate}$, is

$$e_{\text{eliminate}} = \prod^{i} a_{\text{eliminate } i} \qquad \text{where } a_{\text{eliminate}} \in \{0, 1\}$$

If any eliminating attribute does not fit in the current context, the learning object is omitted. The eliminating attributes should be chosen very carefully. When the quantity of available learning objects is limited, some constraints can be relaxed in this step to adjust the selection range.

After the range for learning object selection is reduced, the suitability of all relevant learning objects has to be decided. The contribution of an attribute to the suitability of the learning object depends on its importance in the context and the degree it matches the requirement. If the importance of an attribute *i* is represented by its weight (w_i) and the degree of the match is indicated by a value between 0 and 1 ($a_{select\ i}$). The result of this step for a learning object (e_{select}) can be reflected by the sum of evaluation of all attributes.

$$e_{\text{select}} = \sum^{i} w_i \times a_{\text{select } i} \qquad \text{where } w_i, a_{\text{select}} \in [0, 1]$$

In different contexts a learning object feature affects the suitability in various ways. A very important feature may become a nonentity when the target learner or the environment where the learner resides changes. It is not feasible to define a fixed weight for each feature that applies to all contexts. In the EOS approach, the important features are identified by examining the current context and applying pedagogical principles, and their associated weight is assigned dynamically.

The individualized learning object selection is not simply finding the best match between the features of a learning object and the requirements of the context because in some situations a learning object whose features apparently match a learner's preferences might not be the best choice for the learner. The selection of the most suitable learning object is optimized by using information about previous usage of learning objects, such as experts' evaluation, similar learners' experience, and popularities of learning objects. Influences from these aspects can be negative, and they may also be assigned with different weights to distinguish their importance.

Let $e_{optimize}$ be the result of total optimized adjustment, and e_{final} be the final evaluation result of the learning object, we have:

$$e_{\text{final}} = e_{\text{eliminate}} \times (e_{\text{select}} + e_{\text{optimize}})$$

The learning object that has the highest e_{final} value is the most suitable object.

4 Validating the EOS Approach

The implementation of an EOS selector based on the individualized learning object selection approach is under way. First an evaluation of the attributes will be performed in terms of the ease of operationalizing variables and gathering data and in term of the educational relevance. Then we will evaluate the overall system performance by comparing the selection made by the EOS selector with human experts' judgements. The EOS selector and invited experts will perform selection in parallel on the same simulated test bed, which includes a number of created instances of learning object metadata, a number of artificial learners, and simulated usage history of the learning objects. Finally a sensitivity analysis will be performed on the attributes to determine if some can be collapsed or need to be modified.

5 Conclusions

This research aims at exploiting and improving techniques that were developed in Intelligent Tutoring Systems, Recommender Systems, and Semantic Web technologies to enhance web-based educational systems with intelligent functionalities. While currently at a relatively early stage, this research is aimed at improving our ability to select dynamically an appropriate learning object for a given contest. We are investigating the use Multi-Attribute Utility Theory in our selection computations. We are also examining the educational literature to identify additional pedagogical principles that may also be applied to improve the systems' performance. As more and more learning materials come online, the EOS selector should be able to help learners by recommending the most suitable learning objects for their individual learning needs and we hope this type of enhancement may become a core component in the next generation of learning management systems.

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