Adapting e-learning contents based on navigation styles and preferences

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Abstract. Personalized access to e-learning contents is based on suggesting routes to users considering their preferences. Recent studies show that navigation styles can content much of the information related to cognitive learning styles and preferences. These navigation styles can be defined by means of different parameters. In order to develop a system that provides personalized learning contents, it is necessary to automatically extract student's characteristics and preferences. For that, we use data mining techniques that are methods that, basically, use indicators about student's activity to generate models that can direct the content selection process. In this paper, we address the problem of generating student's learning characteristics and preferences, which can make the task of designing adaptation models easier. This work classifies students in each of the next dimensions: (Active/Reflexive, Deductive/Inductive, Visual/Verbal, Sensitive/Intuitive and Local/Global).

Keywords. Navigation styles, e-learning, Data mining

Introduction

Environments that provide intelligent services based on the current situation and preferences of the user are becoming real. So far, most of these environments are physical environments, such as smart homes or intelligent classrooms that considering the principles of Ubiquitous Computing, are able to provide personalized services in an unobtrusive and proactive way. The same principles can be applied to virtual environments where without physical devices, the environment can provide intelligent and personalized services to users.

In the last decade, terms such as e-learning or lifelong learning have emerged introducing new concepts of learning, which demand new contents and tools. Access to e-learning contents creates many challenges, overall when the system has to provide personalized contents to each user. Personalized contents mean contents based on preferences and previous interactions of each user with the system, taking into account that different users have different preferences and habits of navigations.

In order to develop a system that provides personalized learning contents, the following steps are necessary:

1) Design the domain model where a hierarchy of learning goals is set.

2) Define the user model where the current knowledge of the user is calculated respect to goals and where the user's cognitive characteristics and preferences have to be set in order to better fill his needs.

3) Define the media space, where the educational resources description model is written.

4) Define the adaptation model where the concept selection rules are used for concept selection from the domain model.

After designing the Adaptive Educational Hypermedia System, following the above-mentioned steps, the adaptation engine is responsible for interpreting the adaptation rules specified in the Adaptation Model in order to generate personalized learning paths. This process is called adaptive educational hypermedia sequencing.

However, the design of adaptive educational hypermedia systems still requires significant effort from the system's designer. Adaptation rules can help, making their work easier, but there are some problems that have to be addressed since dependencies between educational characteristics of learning resources and users' characteristics are too complex. This complexity introduces several problems on the definition of the required rules [1], namely:

- Inconsistency, when two or more rules are conflicting.
- Confluence, when two or more rules are equivalent.
- Insufficiency, when one or more required rules have not been defined.

There are some approaches that try to avoid these problems [2]. For example courses where all possible paths that match the objective of a student are previously defined. Then the system, adaptively, selects one of the desired paths, at each moment.

The educational hypermedia sequencing process has different abstract layers. The concept identification layer, where some contents are identified as adequate by the knowledge space and defined as goals. The concept selection layer, that has to work over the objects previously identified. These two layers are complex to be defined because, in the first layer, the dependencies between learning concepts are difficult to be defined and, in the second layer, the decision has to be made based on student's characteristics and preferences, when the learning characteristics of the students are not clear yet.

Data mining techniques can be useful in this second step, in order to automatically extract student's characteristics and preferences. Data mining techniques are methods that, basically, use indicators about student's activity to generate models that can direct the content selection process.

In this paper, we address the problem of generating student's learning characteristics and preferences, which can make the task of designing adaptation models easier. This work classifies students in each of the next dimensions: (Active/Reflexive, Deductive/Inductive, Visual/Verbal, Sensitive/Intuitive and Local/Global).

This paper is organized as follows. Section 1 describes different learning styles and related works. Section 2 explains the process of discovering users' navigation styles. Section 3 provides the conclusions of this research.

1. Learning styles and models. Related works

Data mining has been used in web based learning systems in order to improve the learning process [3]. The information generated by web learning systems is so wide that is impossible to analyze this information manually. Some automatic methods can be useful to analyze this data. Data mining techniques can extract new knowledge in order to guide the student during the learning process. This guide can be transparent for the user, personalizing the environment to the student needs, recommending some contents or doing some modifications in the presentation tool. Different approaches can be used in this process in order to integrate data mining tools, for example algorithms can be integrated inside the learning platforms.

All these systems use three main elements to complete the process: a) data collected about the user, b) user model inferred from the collected data and c) adaptation tools that will show the selected elements. Content and link structures can be adapted to better achieve these goals, although the knowledge level and learning styles better define users.

1.1. Learning styles

Identifying learning styles can be fundamental in order to develop personalized learning models. Felder [4] proposes a taxonomy in a scale of 5 dimensions that defines different learning styles (See Table 1).

Table 1. Learning styles

DEFINITIONS	DIMENSIONS		DEFINITIONS
Do	ACTIVE	REFLEXIVE	Think
Learn facts	SENSITIVE	INTUITIVE	Learn concepts
Needs drawings	VISUAL	VERBAL	Needs read or dissertation
Derive facts from facts	INDUCTIVE	DEDUCTIVE	Derive results from principles
Step to step	LOCAL	GLOBAL	Global framework

Previously, Bloom had defined another taxonomy for learning styles [5], which sets a hierarchical classification of learning objects that was later redefined in [6] and can be seen in Table 2.

Table 2. Educational objects hierarchical classification

LEVEL	OBJETIVE	HABILITY
1	Knowledge	terminology, specific facts, ways and means of dealing with specifics, conventions, trends and sequences, classifications and categories, criteria, methodology, abstractions in a field, principles and generalizations, and theoretical structures
2	Comprehension	translation, interpretation, and extrapolation
3	Application	of concepts in the use of abstraction in particular and in concrete situations
4	Analysis	of elements, relationships, and organizational principles
5	Synthesis	of ideas in the production of unique communications and plans
6	Evaluation	leading to judgments about the value of materials and methods for given purposes

1.2. Modeling techniques

Different data mining methods have been used with different objectives in the user modeling task: grouping users by navigation pattern, grouping pages, grouping pages by their content, extracting relationships between pages, finding relevant information in pages, finding learning models, discovering visited page sequences, creating routes for users.

Regarding to the methods used to cover these objectives, visualization techniques are widely used to show information related to the user access to a course, a resource or the participation in a forum [7]. Classification techniques are used when some previously labeled cases belonging to different groups are available. The goal is to classify new cases, for which, the group is unknown. The users can be grouped by navigation patterns and the pages can be grouped by their content. Sometimes, a mixture of different data mining methods has been used but, usually, algorithms that can provide comprehensible output are better, such as Decision Trees (C4.5, C5.0) or Naive Bayes. Some educational data mining algorithms were also used [8] in order to discover groups of students with some similar characteristics with the purpose of determining pedagogical strategies, also for the student performance prediction and final rating. An example of applying modeling techniques can be found in [9].

Association rules are used to obtain rules that associate concepts that are located in different columns of a data base where the user activity has been registered. They have been widely used for extracting customer preferences, relating aspects that frequently occur together. In an e-learning context, it has been used as a way of finding out associations between learning activities. They can be useful to monitor students and

instructors' results in conjunction with alarm thresholds. These methods have been used to find relationships between concepts among the groups found by the clustering techniques and also to create automatic recommendations or finding out errors that occur together. They can be useful to optimize an e-learning content, taking into account what content is interesting for students. An example of this use can be found in [10] and [11].

AHA! is an example of an adaptive hypermedia system developed in the Technical University of Eindhoven in Holland [12], where the Apriori algorithm is used. The University of Cordoba has developed a tool that enables to use the resources (course, unit, lesson, exercise, etc.) and arrange the content by levels.

The sequence analysis process allows to analyze sequences of pages seen during a session or different sessions of the same user. It analyzes the order of the pages accessed by the user. These paths can be analyzed alone or aggregated after a clustering process. These results can then be used in order to reorganize the web content, personalize the resource delivery, doing suggestions to students with a similar profile, to evaluate the design of web pages or to identify sequences of interactions that can be indicative of success or problems.

Clustering techniques [13] have also been used in order to discover groups of objects with similar characteristics. The main goal is to discover groups of students with similar behaviors trying to thrust their collaboration and level of activity. Clusters can also be generated to establish different education journeys, fix personalized tutoring hours, etc.

A lot of another techniques are being used, XML and ontologies [14],[15], Neural networks[16], or methods that are feed by the labeling of the resources provided by the users[17], Semantic inference [18], rules [19], or variable definition [20], among others. Another system works providing information to the tutor [20], or selecting and synthesizing specific content documentation [21].

2. Discovering students' navigation styles in Moodle

In order to discover users' preferences when it comes to navigation styles, first of all, it is necessary to collect data. In Adaptive educational hypermedia systems, information referred to user logs, activities they have done, the quizzes they have tried, which ones they passed and level of knowledge, etc. is available. In order to collect data about the user, we used Moodle (Modular Object-Oriented Dynamic Learning Environment), which is a platform to show e-learning contents. Although this platform gives some information about the student interactions, we decided to extend it using log data and adding some extra indicators about user's activity, specifically for each student and course. Some of them are shown in table 3.

These indicators were added by means of a plug-in to the Moodle platform, so that they could be used by teachers and tutors. Table 3 shows the list of indicators that the tutor can use in Moodle in order to monitor each student, each course and the activity of each student in each course.

Table 3. Observatory indicators extracted from moodle.

1. Number of pages seen	4.Use of discussion forum	7. Consumed multimedia resources	10.Comment a entry in the glossary
2. Number of unique pages seen	5.Attempts to do the quiz	8. Number of glossary entries	11.Use of the chat
3. Unique records	6.Sequentiality	9.Actualize an entry in the glossary	12. Use of the Wiki.

2.1. Relating indicators with navigation and learning styles

It is not easy to decide what indicators better characterize students and their learning style. In order to select the most representative ones, a previous interaction of the experts with the system was identified as necessary. Teachers and tutors have information and experience that can be useful in this process. In order to interactively change and evaluate these indicators, a web application has been developed where a tutor can establish relationships between activity indicators, navigation styles and learning styles(obtained by filling questionaries or by some other ways). This has been understood as a validation process of the observatory indicators and a first approach to identify the best indicators in order to discover user learning models. The developed architecture for the whole process can be seen in Figure 1.
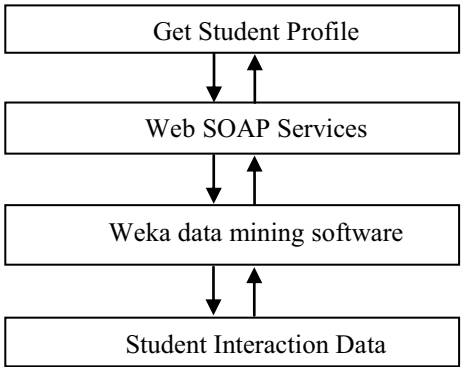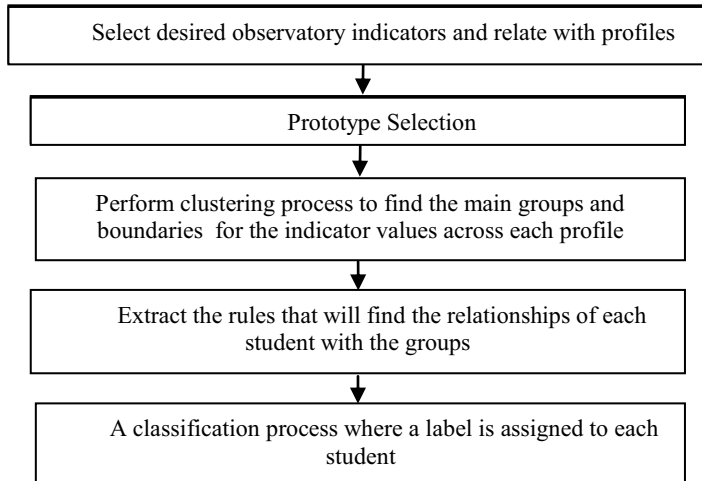

Figure 1: Developed architecture

2.2. Modeling Users

Once indicators have been selected, they are used to model users' learning styles. As mentioned previously we consider different learning styles, also called dimensions (see Table 1). Based on the indicators, the algorithm we have developed classifies students in each one of these dimensions. Figure 2 shows the steps carried out by the algorithm in order to discover the learning style of each student.

Using the dataset and clustering techniques, data across the defined dimensions are divided in different clusters. Each cluster groups students with similar values for such dimensions. Before the clustering process, a prototype selection step (used in data mining to select the cases to build the model) gives the possibility to generate the

model using filtered data, discarding noisy data (for example, data from students that begins the course later than the others or that finishes before).

Select desired observatory indicators and relate with profiles

↓

Prototype Selection

↓

Perform clustering process to find the main groups and boundaries for the indicator values across each profile

↓

Extract the rules that will find the relationships of each student with the groups

↓

A classification process where a label is assigned to each student

Figure 2: Discovering students' learning styles

Then, once clusters are defined, the algorithm extracts the set of rules that better defines the relationship between the dimensions and the clusters. These rules establish the boundaries for the values of each cluster. Finally, considering each student's indicators and using classification techniques, each student is characterized in each dimension. .

3. Conclusions and Future work

Providing personalized contents based on preferences and navigation styles is a necessary step to provide intelligent services in virtual environments. For that, different techniques can be applied. We have developed a system that models user's navigation styles using clustering and classification techniques. As an initial approach, we have considered the parameter that defines if a user's navigation style is either local or global.

This work is being extended in order to generate more accurate patterns. In that sense, one of the challenges is the validation of the models, due to the fact that it demands the contribution of teacher, tutors, as well as the collaboration of the students.

Analyzing the characteristics of the learning objects that can fit better the preferences of the students for each learning style is a big goal. This way, we can focus not only on the learning content that is shown to the student, but on how it looks the page that he will see.

We also expect to add some extra indicators to our systems, some of them related with engagement, other ones related with emotional status.

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References

[1] H. Wu, P. De Bra, (2001). Sufficient Conditions for Well-behaved Adaptive Hypermedia Systems. Lecture Notes in Computer Science, 2198, 148-152.

[2] P. Karampiperis, D. Sampson, Adaptive Learning Resources Sequencing In Educational Hypermedia Systems. Educational Technology & Society, 8 (4), 128-147

[3] S. Preidys, L. Sakalauskas, Analysis Of Students' Study Activities In Virtual Learning Environments Using Data Mining Methods. Technological And Economic Development Of Economy. Baltic Journal on Sustainability.2010.

[4] R. M. Felder, and L. K. Silverman, Learning and Teaching Styles in Engineering Education, Engineering Education, 78(7): 674-681, 1988

[5] Bloom ,Taxonomy of Educational Objectives: The Classification of Educational Goals; pp. 201-207; B. S. (Ed.) Susan Fauer Company, Inc. 1956.

[6] D. R. Krathwohl. A Revision of Bloom's Taxonomy: An Overview. Theory Into Practice, Volume 41, Number 4, Autumn 2002 Copyright C) 2002 College Of Education, The Ohio State University

[7] Nachimas & Hershkovitz , A case study Using visualization for Understanding the Behaviour of the online learner. Proceedings of the International Workshop on Applying Data Mining in e-Learning 2007.

[8] B. Minaei-Bidgoli, D. A. Kashy, G. Kortemeyer, and W. Punch, Predicting Student Performance: an Application of Data Mining Methods with an Educational Web-Based System (LON-CAPA), Frontiers in Education Conference 2003.

[9]   S. Baldiris, G. Moreno, R. Fabregat, I. Guarín, R. Llamosa, J. García, Extensiones en SHABOO: sistema hipermedia adaptativo para la enseñanza de la programación orientada a objetos. Enlace Informático 6 .2007.

[10] A. Merceron and K. Yacef, Measuring Correlation of Strong Symmetric Association Rules in Educational Data, chapter in Handbook on Educational Data Mining, C. Romero, S. Ventura, M.Pechenizkiy and R.Baker (Eds). CRC Press,2010.

[11] E. García, C. Romero, S. Ventura y T. Calders. Drawbacks and solutions of applying association rule mining in learning management systems. International Workshop on Applying Data Mining in e-learning (ADML'07). Crete (Greece), 2007.

[12] P. de Bra, AHA! The adaptive hypermedia architecture Conference on Hypertext and Hypermedia archive. Proceedings of the fourteenth ACM conference on Hypertext and hypermedia. 2003.

[13] A. Klasnja-Milicevic, B. Vesin, M. Ivanovic, Z. Budimac: E-learning personalization based on hybrid recommendation strategy and learning style identification. COMPUTERS & EDUCATION . 2011

[14] F. Lazarinis, S. Green, E. Pearson: Focusing on content reusability and interoperability in a personalized hypermedia assessment tool. MULTIMEDIA TOOLS AND APPLICATIONS.

[15] F. Liu , X. Li , G. Gao : Ontology-based personalized recommendation technology research of learning resources. ETP/IITA Conference on System Science and Simulation in Engineering. 2010.

[16] A. Baylari; G. A Montazer: Design a personalized e-learning system based on item response theory and artificial neural network approach. EXPERT SYSTEMS WITH APPLICATIONS 2009.

[17]   N. Escudeiro, P. Escudeiro, D. Remenyi: Organizing web Educational Resources According to Specific User Needs. 8th European Conference on e-Learning. 2009.

[18] Y. Blanco-Fernandez, Jose J.Pazos-Arias, Alberto Gil-Solla, Manuel Ramos-Cabrer,

[19] G. Fernandez, A. Sterbini, M. Temperini,   Learning objects: A metadata approach. International Conference on Computer as a Tool. 2007.

[20] T. Roselli, V. Rossano, Describing learning scenarios to share teaching experiences. 7th International Conference on Information Technology Based Higher Education and Training. 2006.

[21] S. Abidi, C. Han, S. Abidi, V. Patel, R. Rogers, R. Haux, Patient empowerment via 'pushed' delivery of personalised healthcare educational content over the Internet. 10th World Congress on Medical Informatics (MEDINFO 2001).

[22] P. Clough, N. Ford, M. Stevenson, Personalizing Access To Cultural Heritage Collections Using Pathways. 2011 Workshop on Personalized Access to Cultural Heritage. 2011.