

Enabling Learning Management Systems to Identify Learning Styles*

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Abstract:

Learning management systems (LMS) are very successful in e-education but provide only little adaptivity. Adapting courses to the needs of individual learners such as to their learning styles improves the learning progress of learners. However, a requirement for providing adaptivity is to know the needs of learners. In this paper, we describe an approach that enables LMS to identify the learning styles from the behaviour of learners in online courses. Since our approach is developed for LMS in general, it incorporates that different LMS may provide different features, track different behaviour, and store the data based on different database schemata. In order to provide a practical example, we demonstrate how to enable the LMS Moodle to identify learning styles and describe which extensions had to be done.

1 Introduction

Different learners have different ways of learning. Incorporating these different learning styles plays an important role in education. Matching the learning style of a student with the teaching style of the teacher results in better performance, makes learning easier, and increases the learning efficiency of the students [2]. Furthermore, students with strong preferences for a certain learning style may experience problems in the learning process if their learning style is not supported by the teaching style [6].

Learning management systems (LMS) such as WebCT [17], Blackboard [3] and Moodle [12] are commonly and successfully used in e-education, but most of the existing systems provide only little or in most cases no adaptivity [4]. Adapting to individual learning styles is not considered at all. To provide adaptivity with respect to learning styles, the learning styles of the learners need to be first known by the system. Various comprehensive questionnaires exist which can be used to identify the learning styles. Moreover, tracking functions are available in most LMS which track and store the behaviour of learners during the learning process. This data can identify what learners really do and prefer in a course. Instead of asking learners about their preferences by using a questionnaire, our investigations aim at an approach to infer the learning style from the behaviour of the learners in LMS.

Some recent research is done in the area of identifying learning styles based on the behaviour of learners in particular systems. García, Amandi, Schiaffino, and Campo [8] studied the use of Bayesian networks to detect students' learning styles in the educational system SAVER.

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They determined several patterns that fit to the system's abilities. According to the behaviour of the students in the online course, the probability of the preferred learning style was calculated by the use of Bayesian networks. Also Cha et al. [5] investigated the approach of identifying learning styles based on the behaviour of students. They used an intelligent learning environment and, again, incorporated suitable patterns regarding to this environment. The calculation process of the learning styles is based on decision trees and hidden markov models.

In this paper, we describe how LMS can be enabled to identify learning styles. As shown, some recent research works exist dealing with identifying learning styles from the behaviour of learners in a particular system. When investigating the identification of learning styles in LMS in general rather than in one system, two additional issues have to be considered: First, when choosing the patterns, on the one hand they have to be based on the considered learning style model but on the other hand, the patterns have to be chosen in a way that most LMS are able to gather the recommended data as well. Therefore, commonly used features in LMS such as forum or content objects have to be identified and the behaviour which is related to these features and is relevant for learning styles has to be considered as pattern. Second, the relevant data have to be extracted from the database of the LMS. When extracting the data, it has to be considered that different LMS have different database schemata. Subsequently, a system independent approach for calculating learning styles needs to be applied.

The rest of the paper is structured as follows. First, we describe the learning style model, namely Felder-Silverman learning style model, on which our work is based. In the next section, we introduce the investigated patterns which are considered for identifying learning styles in LMS. Then we propose a tool for extracting the relevant data from LMS and using them for calculating learning styles. After explaining the approach of identifying learning styles, we demonstrate a practical example, showing how to extend the learning management system Moodle to use the presented tool most effectively in terms of enabling Moodle to provide all recommended data.

2 The Felder-Silverman Learning Style Model

While several learning style theories exist in the literature, for example, the learning style models by Kolb [11] and Honey and Mumford [10], Felder-Silverman learning style model (FSLSM) [6] seems to be the most appropriate for use in computer-based educational systems [4]. Most other learning style models classify learners in few groups, whereas Felder and Silverman describe the learning style of a learner in more detail, distinguishing between preferences on four dimensions.

The first dimension distinguishes between an active and a reflective way of processing information. Active learners learn best by working actively with the learning material, e.g. working in groups, discussing the material, or applying it. In contrast, reflective learners prefer to think about and reflect on the material.

The second dimension covers sensing versus intuitive learning. Learners with preference for sensing learning style like to learn facts and concrete learning material. They tend to be more patient with details, more practical than intuitive learners, and like to relate the learned material to the real world. Intuitive learners prefer to learn abstract learning material, such as theories and their underlying meanings. They like to discover possibilities and relationships and tend to be more innovative and creative than sensing learners.

The third, visual-verbal dimension differentiates learners who remember best what they have seen, e.g. pictures, diagrams and flow-charts, and learners who get more out of textual representation, regardless of the fact whether they are written or spoken.

In the fourth dimension, the learners are characterized according to their understanding. Sequential learners learn in small incremental steps and therefore have a linear learning progress. They tend to follow logical stepwise paths in finding solutions. In contrast, global learners use a holistic thinking process and learn in large leaps. They tend to absorb learning material almost randomly without seeing connections, but after learning enough material they suddenly get the whole picture. Then they are able to solve complex problems and put things together in novel ways but find it difficult to explain how they did it

3 Investigated patterns of behaviour

As mentioned in the introduction, we investigated an approach to detect learning styles based on the behaviour of learners during an online course in LMS. When investigating such an approach for one specific system, the patterns can be adjusted to the features of the particular system and to the ability of its tracking functions. For example, the approach proposed by García et al. [8] incorporates only patterns for three dimensions (active/reflective, sensing/intuitive, and sequential/global) of FSLSM since the system supports only features that are related to these dimensions rather than to visual/verbal learning. Similarly, Cha et al. [5] did not consider the active/reflective dimension because no specific features were provided in their learning environment regarding this behaviour. Since our approach is applicable for LMS in general rather than for only one specific system, it has to be considered that different LMS may provide different features. Therefore, we chose patterns that focus on commonly used features which on the one hand are available in most LMS and on the other hand are relevant for learning styles according to literature [6]. Nevertheless, it has to be considered that not all LMS may be able to deliver data for all recommended patterns. However, the more data are available, the more reliable is the identification process of the learning styles.

The incorporated features include *content objects* presenting the content of the course. Regarding content objects, we considered the time learners spent on content objects. Additionally, the time learners spent on content objects including graphics is used as a pattern. Also patterns regarding *outlines* of chapters are included since they are explicitly mentioned in FSLSM. Therefore, we looked at the number of visits of outlines and the time learners spent on it.

Another feature is *examples* which illustrate the theoretical content in a more concrete way. Again, the number of visits and the time learners spent on these objects are used as patterns.

Furthermore, *tests* are included whereby we distinguish between marked tests, which are compulsory, and tests for self-assessment, where students can check their acquired knowledge, for example, to prepare for an exam. Regarding these tests, we considered information such as the results a learner achieved, how often a learner revised his/her answers before submitting, and how long a learner spent on the tests. For self-assessment tests, we additionally included the number of tests a learner has performed as pattern. Furthermore, the questions contained in a test can be about facts or concepts, refer to an overview or to details, or can be based on graphics rather than on text. The results learners achieved on each kind of questions act as a pattern as well.

Another feature deals with *exercises* which serve as practice area where students can try things out or answer questions about interpreting predefined solutions or developing new solutions. The number of visits and the time student spent on exercises is considered as pattern.

For communication issues, *discussion forum* and *chat* are considered. As patterns, we incorporated the number of visits to the forum or the chat and how many messages learners posted.

Additionally, we incorporate the *navigation* between learning objects. We considered how often learning objects were skipped in the course sequence as well as how often and how long learners stayed at the course overview page.

4 Extracting data and identifying learning styles

The data about the above defined patterns can act as indications for specific learning style preferences. In this section, we present a tool that focuses on extracting the recommended data from the database of an LMS and uses these data to calculate learning styles. The architecture of the tool can be seen in Figure 1. The tool consists of two components, the data extraction component and the calculation component.

The data extraction component requires the patterns of behaviour derived from common features in LMS for providing information about the learning styles. Based on the defined patterns, data need to be extracted from the database. Because the tool is generated for learning management systems in general, heterogeneity of database schemata needs to be considered. Section 4.1 describes the data extraction component and how it supports the teacher in providing the required information about the location of the data.

As a result, the data extraction component delivers raw data which represents the behaviour of the learners regarding the defined patterns. These raw data are used for calculating the learning styles in the calculation component. User interaction is needed in this component for adjusting thresholds of patterns, which are recommended by the tool but can be changed by the user. Section 4.2 describes the calculation component in more detail.

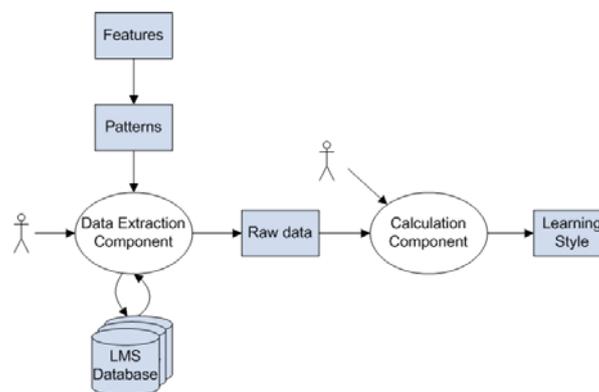


Figure 1. Tool architecture

4.1 Data extraction

Heterogeneity of databases is a well know issue in the research area of schema integration, interoperability, and also data extraction. According to Sheth [15], information heterogeneity can be classified into three types: Syntactical heterogeneity involves different data formats and representations, structural heterogeneity deals with different data models and schemata, and semantic heterogeneity incorporates different interpretations. In our case, the main considerations deal with different database schemata and additionally different representation formats need to be considered.

The process of data extraction is illustrated in Figure 2. To extract data from different database schemata, first a global schema has to be built. This can be done by a bottom-up approach, using the LMS database schemata as a basis, or by a top-down approach, where the required information acts as a basis. Because LMS databases can include much more information than we need for detecting learning styles, and database schemata from different LMS have quite different structures, the top-down approach was applied. As can be seen in Figure 2, each table of the global schema includes data representing one pattern.

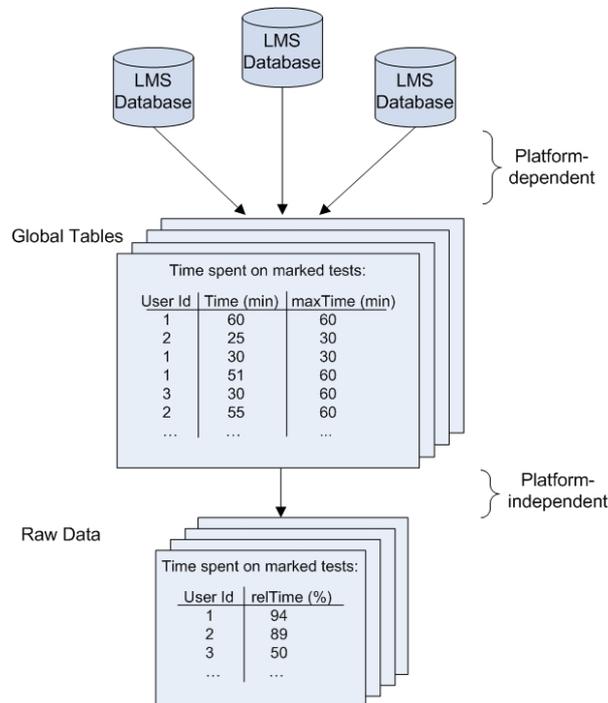


Figure 2. Process of data extraction

Because it is not possible to find the required information for the global schema automatically in each LMS database, teachers need to be supported as much as possible in specifying where the required information is located. Therefore, the information needed for the global schema should be easy to extract from the LMS database schemata. In most LMS databases the required information is stored in an event-based way. For example, for each visit of a specific learning object or each posting in a forum, an entry is added. However, the raw data which are needed for calculating the learning styles are cumulated, presenting e.g. how often each learner has visited a specific learning object in relation to the total number of such learning objects or how much time he/she spent on these learning objects in relation to the predefined maximum time. For keeping data extraction from the LMS database to the global tables as simple as possible, we adapt the top-down approach in the way that global tables store data in a non-cumulated, event-based way rather than in the cumulated form required for raw data (see Figure 2).

For supporting the teacher in specifying the location of the required information for the global schema, an editor is provided. For each pattern, names for required tables and attributes, possible constraints, as well as necessary information for connecting tables are specified. Additionally, it is possible to write an SQL statement instead of using the question-based editor.

As soon as the information for the global schema is extracted, the values for the raw data can be calculated by the tool automatically.

4.2 Calculation of learning styles

For calculating learning styles, the raw data acts as input for the calculation component. In this component, there are two main steps: (1) ordered data are calculated from the raw data and (2) learning styles are calculated for each dimension based on the ordered data.

Ordered data can take the values +1, 0, and -1, indicating, for example, an active, balanced, or reflective preference. For building these data out of the raw data, thresholds for all patterns need to be determined. As is argued, for example in [1] and [13], these thresholds can vary from course to course depending on the structure of the course, the subject, and also on the experiences of the students. Therefore, the proposed tool recommends thresholds which can be changed by the teachers if necessary. The recommended thresholds are based on other research work dealing with the usage of the respective features [8, 14, 16].

The calculation of learning styles itself is based on the approach used in the Index of Learning Styles (ILS) [7], a questionnaire for identifying the learning style according to Felder-Silverman learning style model. According to this approach, for each dimension the ordered data (+1, 0, or -1) which are relevant for the respective dimension are summed up. The result of each dimension is converted to a 3-item scale, indicating e.g. an active, balanced, or reflective learning style.

5 Extensions in Moodle in order to provide all recommended data

There are three requirements for getting information about patterns in LMS. First, if the pattern is based on a certain feature (e.g. example or forum), this feature needs to be supported by the LMS. Since patterns are chosen in awareness of commonly used features, most LMS should be able to provide learning material according to the proposed features.

Second, the LMS must be tracking the required behaviour and storing this information in its database. For instance, the number of postings and the time each student spent on an example object may need to be stored. Again, most LMS include the option to track certain behaviour of the learners but what exactly is tracked by the system may differ. As mentioned above, identifying learning styles is based on gathering indications from the learner's behaviour which are relevant to his/her learning style. The more information is available, the more reliable is the identification of the learning style.

Finally, the authors need to include the respective features in the online course. The authors do not need to be familiar with learning styles theories but for certain patterns they have to describe the created learning material by the use of meta-data, e.g. specifying whether graphics are included in the learning object.

In the following two subsections, some extensions to Moodle are described. These extensions enable Moodle to use the proposed tool for identifying learning styles (described in Section 4) most effectively. The extensions are performed for Moodle version 1.4.4 as well as 1.6.1 (current version) and are available as add-ons.

5.1 Extensions regarding incorporating all proposed features

Moodle provides a number of different features to include in an online course. For our investigations and with respect to the above introduced patterns, only some of these features are of particular interest, namely the resources, which can be included as text page, web page or as a link to a file or website, the quiz, the forum, and the chat. These are types of learning objects that are commonly used also in other LMS and relevant for learning styles. In Moodle, learning material regarding all proposed features can be created by using these three different

types of learning objects. But for extracting data regarding the learners' behaviour, the learning material have to be distinguished with respect to the proposed features, and for some features, an additional description of the material is necessary. In most cases, this differentiation and additional descriptions are not supported by Moodle. Our extensions address these issues.

The concept of resources in Moodle can be used for presenting content, an outline for a chapter or the course, and an example. Regarding examples, additionally the text within the examples has to be displayed exactly in the way it is written. This is especially important if the example includes source code that can be executed within the browser. Since the source code in an example should be displayed as it is instead of executing it and displaying the result of the source code, we created a new type of learning object based on the type resource but with the difference that every text in an example is displayed exactly as it is. For distinguishing between content and outlines, the resource type is extended by meta-data which indicate whether the resource presents content or an outline. When creating a resource, authors can therefore choose between these two types. Furthermore, additional meta-data for content objects are included regarding graphics in order to get indications about visual and verbal learning preferences. Therefore, authors are asked to indicate whether a content object includes graphics or not.

In Moodle, quizzes can represent self-assessment tests, marked tests as well as exercises. The difference between exercises and self-assessment tests is that former is more practically oriented with the aim that learners solve tasks and get feedback for their solutions. In contrast, self-assessment tests focus on theoretical issues and can be used to check whether a learner understands the learning material. Both, exercises and self-assessment tests are voluntary, in contrast to marked tests which are a compulsory part of the course. While the purpose of all these three kinds of quizzes is different, their structure might be same. Therefore, it is necessary to distinguish between these kinds by the use of meta-data. So, our extensions provide the possibility for authors to choose between self-assessment test, marked test, and exercise. Additionally, each question in a quiz can be specified according to whether it is about facts or concepts, refers to an overview or to details, or is based on graphics rather than on text. This detailed specification provides information about which kind of question a learner handles easily or with difficulty. Again, the authors are asked to specify their created questions by the use of meta-data.

Regarding the forum and the chat, no modifications have to be done since Moodle provides a forum and a chat with several functionalities.

Due to these extensions, Moodle is able to distinguish all recommended features and provide additional meta-data to describe them. These extensions are a requirement for tracking the behaviour of learners regarding the proposed features.

5.2 Extensions regarding tracking activities

Moodle provides comprehensive tracking functions. For each action a learner performs, e.g. visiting a particular learning object, an entry is done in a log table in the database, including several information such as the user-id, the action itself, the learning object, and a timestamp. Based on the tracked data in Moodle, for most of the proposed patterns the required data can be extracted from the database. Only one extension was necessary. This extension deals with the pattern about revisions when learners answer questions of self-assessment tests or marked tests. Moodle only tracks the final answers to questions. In order to get more detailed information about what learners are doing during a test, we extended the tracking function by storing each answer which is given by a learner, even if this answer is revised later. When the question asks for a textual answer rather than for choosing between predefined options,

additionally the sequence of keys is tracked with attention to the delete and backspace key. This additional data provides information about how often students are revising their answers.

6 Conclusion and future work

In this paper, we described an approach that enables learning management systems to identify learning styles. A tool was presented that extracts relevant data from the database of an LMS and uses this data to calculate learning styles. To provide a practical example, we showed how the learning management system Moodle can be extended in order to be able to provide all recommended data and therefore use the proposed tool more effectively.

Applying the proposed approach allows LMS to detect learning styles from the behaviour of learners. Therefore, learners do not have to fill out comprehensive questionnaires to provide information about their learning styles. Instead, the detection can be done by the LMS automatically. Another advantage is that the approach supports dynamic student modelling by using data gathered during the online course. The calculated learning styles can be included in the student model of the LMS and provide the basis for adaptivity regarding learning styles.

At the current stage, the extended version of Moodle has been used for teaching courses about XML at Vienna University of Technology and another course about object-oriented modelling will be held next semester. Future work deals with analysing the gathered data and comparing the results of the tool with the results from the ILS questionnaire that learners had additionally filled out.

Although our proposed calculation approach can handle missing data and can calculate learning styles based on partial information, future work will also deal with the issue of partial information. We will investigate calculation approaches that concentrate more on this issue and compare them with the proposed calculation approach.

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