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Supporting Teachers in Identifying Students' Learning Styles in Learning Management Systems: An Automatic Student Modelling Approach

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ABSTRACT

In learning management systems (LMSs), teachers have more difficulties to notice and know how individual students behave and learn in a course, compared to face-to-face education. Enabling teachers to know their students' learning styles and making students aware of their own learning styles increases teachers' and students' understanding about the students' learning process, allows teachers to provide better support for their students, and has therefore high potential to enhance teaching and learning. This paper proposes an automatic approach for identifying students' learning styles in LMSs as well as a tool that supports teachers in applying this approach. The approach is based on inferring students' learning styles from their behaviour in an online course and was developed for LMSs in general. It has been evaluated by a study with 127 students, comparing the results of the automatic approach with those of a learning style questionnaire. The evaluation yielded good results and demonstrated that the proposed approach is suitable for identifying learning styles. DeLeS, the tool which implements this approach, can be used by teachers to identify students' learning styles and therefore to support students by considering their individual learning styles.

Keywords

Learning styles, Felder-Silverman learning style model, Student modelling, Learning management systems

Introduction

In traditional learning, teachers can easily get an insight into how their students work and learn. However, in online learning, especially when using systems like learning management systems (LMSs), it is more difficult for teachers to see how individual students behave and learn in the system. LMSs such as Moodle (2009), Sakai (2009), and WebCT (2009) are commonly and successfully used in e-learning. They aim at supporting teachers in creating and managing online courses. However, with respect to providing teachers with information about their students, they mainly show how the overall class is using a course rather than focusing on individual students.

This paper focuses on supporting teachers in identifying their students' learning styles in LMSs. Learning styles can be seen as "a description of the attitudes and behaviours which determine an individual's preferred way of learning" (Honey & Mumford, 1992, p. 1). Many learning style models exist in literature, such as the learning style model by Kolb (1984), Honey and Mumford (1982), Pask (1976), and Felder and Silverman (1988). While there are still many open issues with respect to learning styles, the learning style models agree that learners have different ways in which they prefer to learn. Furthermore, many educational theorists and researchers consider learning styles as an important factor in the learning process and agree that incorporating them in education has potential to facilitate learning for students.

Knowing students' learning styles can help in many ways to enhance learning and teaching. First, teachers can benefit by getting information about how their students are used to learn, which provides them with a deeper understanding and might help when explaining or preparing learning material. Furthermore, making students aware of their learning styles and showing them their individual strengths and weaknesses can help students to understand why learning is sometimes difficult for them and is the basis for developing their weaknesses. In addition, students can be supported by matching the teaching style with their learning style. Providing students with learning material and activities that fit their preferred ways of learning can make learning easier for them. This matching hypothesis is supported by many educational theories, as stated and described by Coffield, Moseley, Hall, and Ecclestone (2004). Examples for studies which demonstrated supportive results of this hypothesis include those by Bajraktarevic, Hall, and Fullick (2003) and Graf and Kinshuk (2007).

For considering learning styles in education, the students' learning styles need to be known first. Brusilovsky (1996) distinguished between two different ways of student modelling: collaborative and automatic. In the collaborative approach, the learners provide explicit feedback which can be used to build and update a student model, such as filling out a learning style questionnaire. In the automatic approach, the process of building and updating the student model is done automatically based on the behaviour and actions of learners while they are using the system for learning. The automatic approach is direct and free from the problem of inaccurate self-conceptions of students. Moreover, it allows students to focus only on learning rather than additionally providing explicit feedback about their preferences. In contrast to learning style questionnaires, an automatic approach can also be more accurate and less error-prone since it analyses data from a specific time span rather than data which are gathered at one specific point of time.

In this paper, we propose an automatic student modelling approach for identifying learning styles in LMSs as well as a tool that implements this approach. Both, the approach and the tool are developed in a generic way and are therefore applicable for LMSs in general. For the theoretical basis regarding learning styles, a well-known and often used learning style model, especially in technology enhanced learning, has been selected, namely the Felder-Silverman learning styles model (FSLSM) (Felder & Silverman, 1988). As mentioned above, many learning style models exist in literature. FSLSM differs from other models since it combines major learning style models like the model by Kolb (1984) and Pask (1976). By combining these models, FSLSM describes learning styles in more detail through characterising each learner according to four dimensions: active/reflective, sensing/intuitive, visual/ verbal, and sequential/global. Furthermore, FSLSM considers learning styles as tendencies rather than obligatory types, as done by many other learning style models.

In the following section, the concept for identifying learning styles is introduced. Subsequently, the evaluation of the proposed approach and its results are presented. Section 4 introduces the tool which implements the student modelling approach. Section 5 provides discussion about the proposed approach and the tool, and Section 6 concludes the paper.

A concept for identifying learning styles

The concept for identifying learning styles is based on patterns of behaviour which reveal certain preferences for a particular learning style. The approach is similar to the one of the Index of Learning Styles (ILS) questionnaire (Felder & Soloman, 1997), which is an instrument for identifying learning styles based on the FSLSM. However, while the questionnaire asks students about how they think they prefer to behave and learn, the proposed approach gathers data about how students really behave and learn by observing them during their learning process. The patterns of behaviour which are assumed to be relevant for each learning style dimension are discussed in the next subsection in more detail. Subsequently, the procedure about how to calculate learning styles from the data of the patterns is described.

Table 1. Relevant patterns for each learning style dimension of FSLSM

Active/Reflective	Sensing/Intuitive	Visual/Verbal	Sequential/Global
content_visit (-)	content_visit (-)	content_visit (-)	outline_visit (-)
content_stay (-)	content_stay (-)	ques_graphics (+)	outline_stay (-)
outline_stay (-)	example_visit (+)	ques_text (-)	ques_detail (+)
example_stay (-)	example_stay (+)	forum_visit (-)	ques_overview (-)
selfass_visit (+)	selfass_visit (+)	forum_stay (-)	ques_interpret (-)
selfass_stay (-)	selfass_stay (+)	forum_post (-)	ques_develop (-)
selfass_twice_wrong (+)	exercise_visit (+)		navigation_skip (-)
exercise_visit (+)	ques_detail (+)		navigation_overview_visit (-)
exercise_stay (+)	ques_facts (+)		navigation_overview_stay (-)
quiz_stay_results (-)	ques_concepts (-)		
forum_visit (-)	ques_develop (-)		
forum_post (+)	quiz_revisions (+)		
	quiz_stay_results (+)		

Relevant patterns of behaviour

In order to make our approach applicable for LMSs in general, only commonly used features in LMSs were selected to be the basis for the incorporated patterns. These features include: content objects, outlines, examples, self-assessment tests, exercises, and discussion forums. Furthermore, the navigation behaviour of students in the course was considered.

In the next subsections, the characteristics of each learning style with respect to the FSLSM are described and the relevant patterns for identifying learning styles for each dimension are presented, using the literature regarding FSLSM (Felder & Silverman, 1988) as basis. Table 1 provides a summary of the patterns per dimension, using "+" and "-" for indicating a high and low occurrence of the respective pattern from the viewpoint of an active, sensing, visual, and sequential learning style.

Active/reflective learning style dimension

According to FSLSM, this dimension distinguishes between an active and reflective way of processing information. Active learners learn best by working actively with the learning material, by applying the material, and by trying things out. Furthermore, they tend to be more interested in communicating with others and prefer to learn by working in groups where they can discuss about the learned material. In contrast, reflective learners prefer to think about and reflect on the learning material. Regarding communication, they prefer to work alone.

Identification of active/reflective learning style tendencies

Based on the different preferences regarding communication of active and reflective learners, the forum was used as a relevant feature for identifying students' learning styles. More specifically, the number of visits in the forum and the number of postings were considered. Based on the characteristics of active and reflective learners described by FSLSM, we can assume that active learners prefer to post more often in order to ask, discuss, and explain issues about the learned material. On the other hand, reflective learners are expected to participate more passively by carefully and frequently reading the postings but only rarely posting by themselves. Other features which help to indicate an active or reflective learning style are self-assessment tests and exercises which allow students to test their knowledge and try things out. A high number of visits of self-assessment tests and exercises as well as spending overall a high amount of time on exercises can give a hint towards an active learning style. On the other hand, due to their preference of reflecting and thinking about the learned material, reflective learners are expected to spend more time on reflecting about the results of their self-assessment tests and exercises as well as spending more time on answering questions of the self-assessment tests. As a consequence, they are expected to answer the same question less often twice wrongly, which is also used as a pattern for identifying a preference for active or reflective learning. Another hint can be gathered from the usage of examples. Active learners prefer to try things out and solve problems by themselves rather than looking at how someone else has solved a problem. Therefore, if students spend only little time on looking at examples, this behaviour can be interpreted as a hint for an active learning style. Furthermore, the usage of content objects and outlines can reveal indications about an active or reflective preference. Reflective learners are expected to visit and spend more time on reading and reflecting about the learning material as well as staying longer at outlines.

Sensing/intuitive learning style dimension

The second dimension of the FSLSM deals with sensing and intuitive learning. Learners with a sensing learning style like to learn facts and concrete learning material, using their sensory experiences of particular instances as a primary source. They like to solve problems with standard approaches and also tend to be more patient with details. Furthermore, sensing learners are considered as more realistic and sensible; they tend to be more practical than intuitive learners and like to relate the learned material to the real world. In contrast, intuitive learners prefer to learn abstract material, such as theories and their underlying meanings, with general principles rather than concrete instances being a preferred source of information. They like to discover possibilities and relationships and tend to be more innovative and creative than sensing learners.

Identification of sensing/intuitive learning style tendencies

For identifying a sensing or intuitive learning style, self-assessment tests and exercises play an important role. Since sensing learners prefer to learn concrete material like facts while intuitive learners prefer to learn abstract material such as theories, the learners' performance on questions about facts as well as questions about theories and concepts was used as hints for identifying their learning styles. Furthermore, sensing learners prefer to solve problems by applying standard procedures, which they have learned before, and thus like to be well-prepared for tasks such as assignments and exams. Therefore, we can assume that they perform a higher number of self-assessment tests and exercises in order to check their acquired knowledge and practise to apply it. In contrast, intuitive learners tend to be more creative and like to solve problems in new ways. Therefore, a good performance on questions which ask for developing new solutions can give an indication for an intuitive learning style. Furthermore, a basic understanding of the underlying concepts and theories is important for developing new solutions, which can be seen as another argument for intuitive learners to yield on average better results on such questions. Since sensing learners tend to be more patient with details and work carefully but slowly, the time students take for self-assessment tests can be used as another pattern. Since sensing learners also like to check their answers carefully before submitting them, another pattern is the number of revisions performed before submitting a test or exercise. In line with these characteristics, sensing learners are also expected to spend more time on reviewing their results on self-assessment tests and exercises. Furthermore, by looking at students' performance on questions about details, the sensing learners' preference for being careful with details can help them in achieving better results on such questions and is therefore used as another pattern. Besides self-assessment tests and exercises, the students' behaviour regarding content objects and examples can contribute to identifying their preference regarding sensing or intuitive learning. Since sensing learners prefer to learn from concrete material, we can assume that they prefer learning from examples. Therefore, the number of visits and the time spent on examples can act as other patterns. Another argument for the preference for learning from examples for sensing learners is that they like to solve problems based on standard procedures and examples can help them to learn existing approaches for solving problems. On the other hand, intuitive learners are supposed to learn from more abstract material such as content objects and use examples only as supplementary material. Therefore, we can assume that they visit content objects more often and tend to spend more time on them.

Visual/verbal learning style dimension

The visual/verbal dimension deals with the preferred input mode. The dimension differentiates learners who remember best what they have seen (e.g., pictures, diagrams, flow-charts and so on), from learners who get more out of textual representations, regardless of whether they are written or spoken.

Identification of visual/verbal learning style tendencies

A main feature for identifying a visual or verbal learning style is the forum, where verbal learners are expected to use the forum more often and more intensive in order to discuss and communicate with others. Therefore, the number of visits of forum messages, the time spent in the forum, and the numbers of postings are considered as relevant patterns for this dimension. Furthermore, we expect visual learners to perform better on questions about material which was presented in a visual way using, for example, figures and graphics. On the other hand, verbal learners are expected to yield better results on questions about learning material which has been presented in textual format. Another feature which can provide information about students' preference for either visual or verbal learning is content objects. Based on the preference for textual representation, verbal learners are expected to visit reading material such as content objects more often, which can be used as another pattern.

Sequential/global learning style dimension

In the sequential/global dimension, the learners are characterised 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 they have learned enough material they suddenly get the whole picture. Then they are able to solve complex problems and put things together in novel ways; however, they have difficulties in explaining how they did it. Because the whole picture is important for global learners, they tend to be more interested in overviews and in a broad knowledge, whereas sequential learners are more interested in details.

Identification of sequential/global learning style tendencies

Regarding identifying students' preferences for a sequential or global learning style, mainly the performance on specific questions, the usage of outlines and the course overview page, as well as students' navigational behaviour was considered. Based on sequential learners' preference for details and global learners' preference for overviews and seeing the "big picture", the performance on questions dealing with details and the performance on questions dealing with overview knowledge and connections between concepts were used as patterns. Furthermore, global learners' interest in relating and connecting topics to each other helps them in interpreting predefined solutions and developing new solutions. Therefore, a better performance on respective questions can be seen as another hint for a global learning style. Another indication for a global learning style with respect to the students' interest in getting the "big picture" and overview of the learning material can be retrieved from students' behaviour regarding outlines of chapters and the course overview page. If students use these features often, in terms of visiting and/or spending much time on them, hints for a global learning style can be concluded. Furthermore, students' navigational behaviour can reveal information about their learning style. According to FSLSM, sequential learners prefer to go through the course step by step, in a linear way, while global learners tend to learn in large leaps, sometimes skipping learning objects and jumping to more complex material. Therefore, the number of skipped learning objects was considered as another pattern.

From behaviour to learning styles

The previous section described the patterns which are incorporated for each dimension as well as whether a high or low occurrence indicates a specific learning style. Based on this information, data about students' behaviour can be used to get hints for calculating students' learning styles. For example, if a student visited exercises often, this gives us a hint that the learner prefers an active learning style. Hints ($h_{dim,\,i}$) are gathered for each dimension (*dim*) and each pattern (*i*) which includes relevant information for this dimension. Hints are stated by four values: 3 indicates that the student's behaviour gives a strong indication for the respective learning style (e.g., active), 2 indicates that the student's behaviour is average and therefore does not provide a specific hint, 1 indicates that the student's behaviour is in disagreement with the respective learning style and therefore hints for a preference towards the other pole of the learning style dimension (e.g., reflective), and 0 indicates that no information about the student's behaviour is available. In order to classify the behaviour of students into these four groups, thresholds from literature are used as basis, considering additionally the characteristics of the respective course. For example, such characteristics can include that the discussion forum is mainly used for asking questions to teachers rather than discussing about topics with other students. Another example is that a course may provide printed learning material and/or lectures so that students use content objects mainly for looking up something rather than learning from them.

By summing up all hints and dividing them by the number of patterns that include available information (p_{dim}), a measure for the respective learning style (ls_{dim}) is calculated, as stated in formula 1. This measure is then normalised on a range from 0 to 1 as stated in formula 2, resulting in a measure nls_{dim} where 1 represents a strong positive preference and 0 represents a strong negative preference for the respective learning style. If no pattern includes available information, no conclusion can be drawn.

$$ls_{\dim} = \frac{\sum_{i=1}^{p_{\dim}} h_{\dim,i}}{p_{\dim}} \tag{1}$$

$$nls_{\dim} = \frac{ls_{\dim} - 1}{2} \tag{2}$$

Evaluation

The proposed student modelling approach was evaluated by a course about object oriented modelling in the Information System and Computer Science curriculum, held at a university in Austria. 127 students participated in the study. However, only data from 75 students were used for the study since we included only data from students who spent more than 5 minutes on filling out the ILS questionnaire, submitted more than half of the assignments, and attended the final exam.

The course included all types of learning objects described in the previous section, namely content objects, outlines, examples, self-assessment tests, exercises, and discussion forums. Moodle (2009) was used for hosting the course. Since Moodle already has a comprehensive tracking mechanism, only one extension was necessary in order to gather data for all above introduced patterns, dealing with tracking how often students are revising their answers in a self-assessment test or exercise. Furthermore, few additional extensions were performed in order to make gathering of data easier, mainly dealing with distinguishing between particular types of learning objects and questions which would also be possible to do without extension but by giving teachers guidelines about how to name particular types of learning objects and questions.

In order to classify the occurrence of behaviour with respect to the investigated patterns, thresholds were used for each pattern. In the next subsection, these thresholds are discussed. Subsequently, the evaluation method and the results of the evaluation are described.

Classifying the occurrence of behaviour

The thresholds for distinguishing whether students have a high, moderate, or low occurrence of behaviour regarding each pattern were determined from literature and adjusted based on the characteristics of the course rather than depending on the students' average behaviour in the class. Thus, the approach is also applicable for small classes, where the average distribution of learning styles might not apply due to its small size.

The thresholds regarding discussion forum were based on recommendations from Rovai and Barnum (2003), but were lowered since the forum was mainly used for asking questions which were then answered by tutors rather than discussing with other students. Therefore, for the number of visits, thresholds of 7 and 14 visits per week were used, for the time students spent on the forum, thresholds of 5 and 10 minutes per week were used, and for the number of postings, thresholds of 2 and 4 postings per course were used.

Based on the assumptions of García, Amandi, Schiaffino, and Campo (2007), the thresholds for visiting exercises were set to 25% and 75% of available exercises. For self-assessment tests and examples, we used a threshold of 50% and 100% since both types of learning objects were designed in a way that each object might be visited more than once. For outlines, thresholds of 75% and 150% were used. Regarding content objects, students had additionally the possibility to download the learning material for print. Therefore, the content objects were mainly used for looking up information when students were conducting, for example, some exercises or were reflecting about a topic. Therefore, the thresholds for visiting content objects were set to 10% and 20% of all available content objects. Furthermore, the thresholds for visiting the course overview page was determined with 10% and 20% of all visited learning objects.

The thresholds for the time spent on examples, exercises, self-assessment tests, content objects, outlines, and the course overview page were determined as 50% and 75% in relation to the expected learning time of students with high interest in the respective type of learning object, following the recommendation of García et al. (2007). For the time spent on the results of an exercise or self-assessment test, thresholds of 30 seconds and 60 seconds were assumed. Thresholds for the performance of specific question types were assumed as 50% and 75% of correctly answered questions, based on the applied grading system. With respect to revisions of self-assessment tests and exercises, thresholds were determined as 2.5% and 5% of performed self-assessment tests or exercises. The thresholds regarding how often students answered a self-assessment question twice wrong were assumed as 25% and 50% of times a student is asked the same question twice.

Regarding skipping learning objects, we looked at how often students skipped learning objects in relation to the total number of visited learning objects. Thresholds of 1% and 2% of times students used the navigation menu to skip learning objects were assumed.

Method of evaluation

In order to evaluate our approach, its results were compared with the results of the ILS questionnaire (Felder & Soloman, 1997). The proposed approach aims at detecting learning styles for each dimension of the FSLSM on a 3-item scale, distinguishing, for example, between an active, balanced, and reflective learning style. Therefore, the measure introduced above (nls_{dim}) was divided into three groups using values of 0.25 and 0.75 as thresholds. These thresholds are based on experiments, showing that using the first and last quarter for indicating learning style preferences for one or the other extreme of the respective dimension and using the second and third quarter for indicating a balanced learning style yields better results than dividing the range into 3 equal parts. Similarly, results of the ILS questionnaire were divided into three groups. For measuring the precision of the proposed approach, including also how close the predicted learning style ($LS_{predicted}$) is to the learning style detected by the ILS questionnaire (LS_{ILS}), the following measure proposed by García et al. (2007) was used:

$$\text{Precision} = \frac{\sum_{i=1}^{n} Sim(LS_{predicted}, LS_{ILS})}{n} \cdot 100, \qquad (3)$$

where n is the number of students. The function Sim compares its two parameters $LS_{predicted}$ and LS_{ILS} and returns 1 if both are equal, 0.5 if one represents a balanced learning style and the other represents a preference for one of the two poles of the dimension, and 0 if they are opposite.

Results

Table 2 shows the results of the comparison between the proposed approach and the ILS questionnaire. The achieved results range from 73.33% to 79.33%, demonstrating a high precision of the proposed approach for all four dimensions of the FSLSM, and therefore, show that the proposed approach is suitable for identifying learning styles.

Table 2. Results of the comparison between the proposed approach and the ILS questionnaire

act/ref	sen/int	vis/ver	seq/glo
79.33%	77.33%	76.67%	73.33%

DeLeS – A Tool for Detecting Learning Styles

DeLeS stands for “Detecting Learning Styles” and is developed based on the approach for automatically identifying learning styles, introduced in the previous two sections. The tool extends this approach by a user interface which allows teachers to easily specify required information and therefore enables them to detect students’ learning styles, in an automatic way, by using data from students’ behaviour in a course in a LMS. DeLeS is a standalone tool and is developed in a way that it can be used for any LMS. In the next section, the architecture of the tool is described in more detail. Subsequently, the tool is introduced by showing the required and possible user interactions for teachers in order to use the tool.

Architecture

Figure 1 shows the architecture of the tool. The tool consists of two components, the *data extraction component* and the *calculation component*.

The data extraction component is responsible for extracting the relevant data from the LMS database in order to calculate learning styles with respect to the four dimensions of FSLSM. The relevant data are based on the above introduced patterns of behaviour, which are derived from several commonly used features in LMSs. Since one of the main aims of the tool is to be applicable for LMSs in general rather than only for one specific system, heterogeneity of database schemata in different LMSs had to be considered. Therefore, a global schema was built. This can be done by a bottom-up approach, using one LMS database schema as a basis, or by a top-down approach, where the required information acts as a basis. Because the databases of LMSs usually include much more information than required for detecting learning styles, and the database schemata from different LMSs have different structures, the top-down approach was applied. Therefore, a global schema was built where each table in the schema includes data representing one pattern of behaviour. To keep the extraction process as simple as possible, the representation of the data in each table is based on the event-based way data are typically stored in LMS databases. For example, a table includes data about each visit of a learner on examples and stores how much time a student spent at each visit. The overall time a student spent on examples is then calculated automatically by the tool and used as raw data for the calculation component. Figure 2 depicts the process of data extraction.

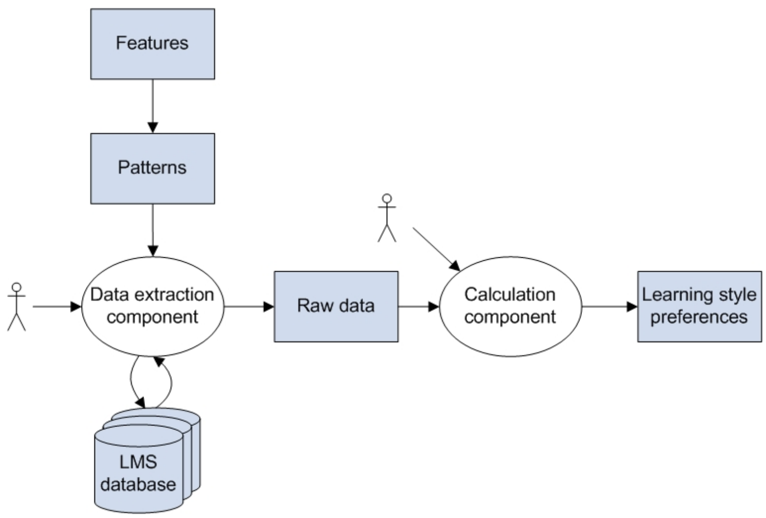

Figure 1: Tool architecture

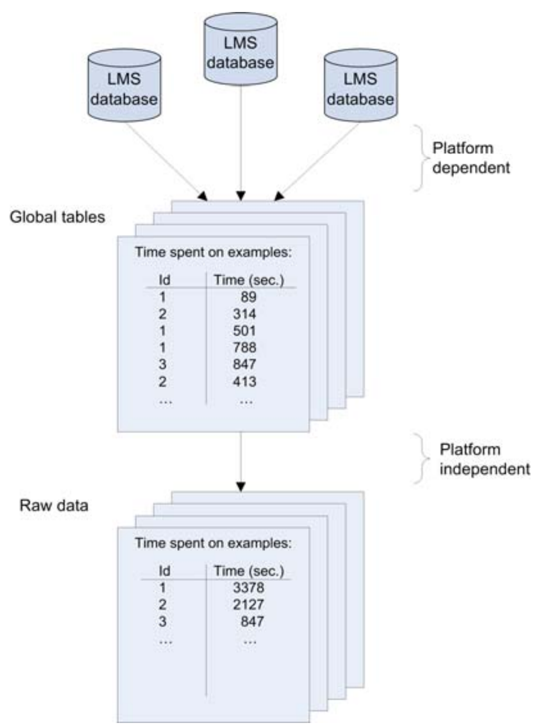

Figure 2: Process of data extraction

As a result, the data extraction component delivers raw data which represent the behaviour of the learners regarding the determined patterns. These raw data are then passed to the calculation component, which is responsible for calculating learning styles. The calculation component conducts two steps: First, ordered data are calculated from the raw data based on thresholds which classify the occurrence of behaviour. As argued, for example, by Alberer et al. (2003) and Roblyer and Wiencke (2003), these thresholds can vary from course to course depending, for example, on the structure of the course and the subject. Therefore, the proposed tool recommends thresholds which can be changed by the teachers if necessary. Second, based on the ordered data the learning styles of each student are calculated as described in the proposed approach above and the results are stored as text file.

User interaction for specifying information

In order to use the tool, teachers need to provide some information as well as be able to configure the tool so that it is better adjusted to the characteristics of the investigated course. When starting DeLeS, a configuration file is created, stored in xml format and based on a standard set of information, which includes predefined thresholds, parameters, and settings. The teachers are then asked to provide a name for the configuration file, the name of the LMS as well as information for establishing a connection to the LMS database. For opening the same configuration file at a later point of time, the configuration name and the LMS name need to be entered again.

The created xml file is divided in three parts, including the login data to the LMS database, data about parameters, and data about features and patterns. Data about parameters as well as features and patterns can be specified in the main page of DeLeS (illustrated in Figure 3). Besides the data for the database connection, teachers have to provide some information about parameters, including the number of self-assessment questions, exercises, examples, content objects, and outlines in the respective course. These values are required in order to use meaningful thresholds for the number of visits of these types of learning objects, for example, using 25% and 75% of the performed exercises over all available exercises as thresholds. Furthermore, other parameters, mainly for improving the accuracy of patterns about time spans, can be changed by teachers if they feel the predefined values do not fit their course.

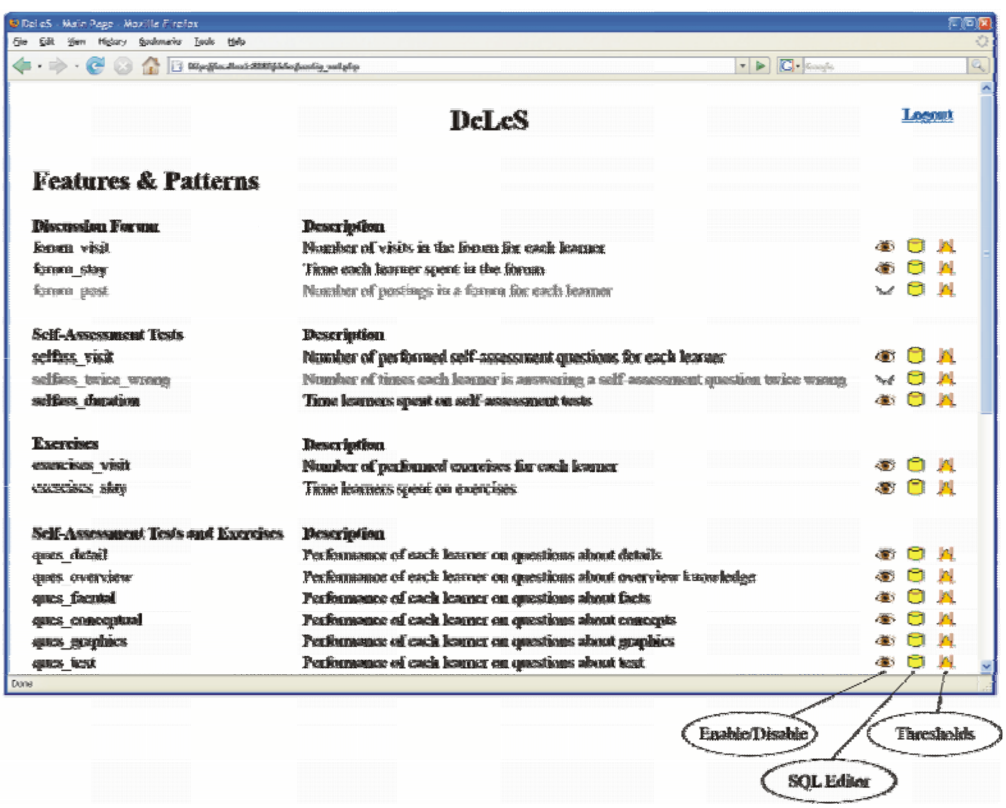

Figure 3: Main page of DeLeS

As can be seen in Figure 3, the main page shows all features and patterns, including a brief description of each pattern. Each pattern can be disabled if the LMS or the course does not provide information regarding the respective pattern. This can be done by clicking on the first symbol behind the respective pattern. After doing so, the pattern is written in grey font and the symbol changes, allowing enabling the pattern again.

For each pattern, thresholds for classifying the occurrence of behaviour are predefined (Graf, 2007). These thresholds can be adjusted in order to fit better the characteristics of the respective course. This can be done by clicking on the last symbol in each line, which leads to a page that shows the current thresholds and allows changing and saving the new ones in the configuration file.

Furthermore, the tool needs to know where the required data for each pattern is stored in the database in order to extract it. One way to provide this information is to use a predefined template where the information about where to find the relevant data is already specified. Such a template is currently available for Moodle version 1.6 and Moodle version 1.4. Another way is to define a new template via the tool. However, for specifying the location of all required data in the database, the teacher (or administrator) needs to be familiar with the database of the LMS. Specifying the location can be done by using the SQL editor, which is reachable via the second symbol in each line. In the first step, the SQL editor shows the required fields for providing information about the respective pattern and asks the teacher to specify which tables are needed to extract the required data. In the second step, three kinds of information are asked: all required fields in the tables for extracting data regarding the pattern, how to connect the tables with each other if more than one table is necessary, including the kind of join as well as the required fields for connecting the tables, and conditions which can optionally be provided and are based on the SQL syntax. After submitting the required information, the editor builds a SQL statement and shows the statement as well as its result when applying it to the database. After confirming, the SQL statement is stored in the configuration file. Besides using the SQL editor, teachers can also write the SQL statement directly in the respective text field on the first page of the editor.

Once all information is specified, the teacher can start the detection process, where the tool extracts data from the LMS database, uses it to calculate learning styles, and stores the results in a text file.

Discussion

DeLeS allows detecting learning styles by extracting relevant data about students’ behaviour in an online course from the database of an LMS. The calculation process applies a simple rule for calculating learning styles based on these data, assuming that each pattern of behaviour can give relevant indications for identifying students’ learning styles. The underlying concept of this approach is similar to the concept of a questionnaire, expect that in the automatic approach information from students’ behaviour is used rather than asking students about their preferences.

While the calculation procedure of the proposed approach is based on the learning style literature (Felder & Silverman, 1988), related works deal with using a data-driven approach, building models for calculating learning styles from the data about students’ behaviour and data about students’ learning styles gathered by the ILS questionnaire. For example, Cha et al. (2006) used Decision Trees (Dunham, 2002) and Hidden Markov Models (Rabiner, 1989) in order to detect learning styles according to the FSLSM. The results were promising, however, only data from the ILS questionnaire indicating a strong or moderate preference on a specific learning style dimension were considered and data indicating a balanced learning style were excluded. Therefore, further investigations towards a more accurate approach are necessary. Another study was conducted by García et al. (2007), using Bayesian networks (Jensen, 1996) in order to detect learning styles for three dimensions of the FSLSM. They achieved results of 58% for the active/reflective dimension, 77% for the sensing/intuitive dimension, and 63% for the sequential/global dimension, using the same measure as used in this study. Comparing these results to those of our evaluation, it can be seen that the approach presented in this paper achieved similar results for the sensing/intuitive dimension and higher results for the active/reflective and sequential/global dimension.

Apart from using a different concept for calculating learning styles from the behaviour data of students, our approach is different from related work in another important way. While related works aim at identifying learning styles in a specific learning system, our approach is developed for LMSs in general. However, making the approach applicable for LMSs in general is more challenging than developing it only for one specific system. It requires consideration that different LMSs support different features and even if an LMS supports a specific feature and is able to provide data regarding the patterns related to this feature, teachers also need to use the feature in their courses. Therefore, features in our study were selected in consideration of whether they are commonly available in LMSs and commonly used in online courses. In addition, the procedure for calculating learning styles is developed in a way that it allows missing data in case that information for a pattern cannot be retrieved from the course. However, the more data are available the more accurate the approach is. In this context, our approach includes a relatively high number of patterns of behaviour for each learning style dimension, compared to those of related works, such as the model introduced by García et al. (2007) as well as one of our previous research work (Graf & Kinshuk, 2006). On one hand, a high number of patterns gives more detailed information for identifying learning styles and, on the other hand, it contributes to the general applicability of the approach, considering that some patterns might not be available in all LMSs. Another difference to related works is the tool which has been developed for supporting teachers to use the proposed approach for identifying learning styles in LMSs.

Conclusions

This paper introduced an automatic student modelling approach for identifying learning styles based on the Felder-Silverman learning style model in LMSs as well as a tool that implements this approach and makes it applicable for teachers. The proposed approach uses the behaviour of students while they are learning in order to gather hints about their learning styles. By applying a simple rule-based mechanism, learning styles are calculated based on the gathered indications. The evaluation of the approach yielded good results, showing that the approach is suitable for identifying learning styles with respect to the FSLSM and therefore demonstrating the functionality of the tool.

The proposed approach as well as the tool was developed for LMSs in general rather than for one specific system. LMSs are widely used in online and blended education and therefore, the developed tool is widely applicable and can support many teachers in identifying students' learning styles. The information about students' learning styles can be used for providing teachers with more information about their students, showing them that their students have different preferences and ways in which they learn. Furthermore, the information about students' learning styles can help teachers in understanding why and when students may have difficulties in learning. In addition, the information can be used for making students themselves aware of their own learning styles, helping them to better understand their strengths and weaknesses in the learning process. Furthermore, identifying learning styles in an automatic way is an important step for enhancing adaptivity in LMSs, enabling these systems to present students with courses that fit their learning styles based on their prior behaviour in the course.

Future work will deal with developing a concept for dynamic automatic student modelling, where data from students' behaviour will be used on the fly for modifying and updating the student model and therefore, allowing the system to immediately respond on students' needs. Furthermore, future work is planned on improving and evaluating the usability of DeLeS in order to provide teachers with better support.

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