AUTOMATIC STUDENT MODELLING FOR DETECTING LEARNING STYLE PREFERENCES IN LEARNING MANAGEMENT SYSTEMS*

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ABSTRACT

Providing adaptivity based on learning styles can support learners and make learning easier for them. However, for providing proper adaptivity, the learning styles of learners need to be known first. While most systems, which consider learning styles, use questionnaires in order to identify learning styles, we propose an automatic student modelling approach, which analyses the actual behaviour and actions of students during they are learning in an online course in order to infer students' learning styles. Such an automatic approach has the advantage that students do not have any additional effort for providing information about their learning styles. Additionally, an automatic approach can be more accurate by excluding extraordinary behaviour of students and adapting in the case that the learning styles changed over time. In this paper, we present an automatic student modelling approach for learning management system, which aims at identifying learning style preferences within the four dimensions of the Felder-Silverman learning style model (FSLSM). The approach is based on patterns derived from literature and a simple rule-based method for calculating learning styles from the students' behaviour. The proposed approach is evaluated by a study with 75 students, comparing the results of the learning style questionnaire with the results obtained by the proposed automatic student modelling approach. As a result, the approach is appropriate for identifying all learning style preferences within the active/reflective dimension of FSLSM and some learning style preferences within the sensing/intuitive and visual/verbal dimension. For the sequential/global dimension, results of learning style preferences show only moderate precision.

KEYWORDS

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

1. INTRODUCTION

According to Felder and Silverman (1988), learners with a strong preference for a specific learning style might have difficulties in learning if their learning styles are not considered by the teaching environment. On the other hand, providing courses that fit the learning styles of learners makes learning easier for them and

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leads to better progress. However, for provide adaptivity, the learning styles of students need to be known first. Therefore, student modelling is a crucial aspect of each adaptive system.

Brusilovsky (1996) distinguished between two different ways of student modelling: collaborative and automatic student modelling. In the collaborative student modelling approach, the learners provide explicit feedback which can be used to build or update the student model. With respect to learning styles, students can be asked, for example, to fill out a questionnaire to detect their learning styles. On the other hand, in the automatic student modelling approach, the process of building and updating the student model is done automatically based on the behaviour and actions of the learners when they are using the system for learning.

In this paper, we introduce an automatic student modelling approach for detecting learning style preferences according to the Felder-Silverman learning style model (FSLSM) (Felder and Silverman, 1988). Most learning style models provide a questionnaire in order to identify learning styles. For identifying learning styles based on the FSLSM, Felder and Soloman (1997) developed the Index of Learning Style (ILS) questionnaire. In contrast to the questionnaire, the proposed automatic student modelling approach identifies the students' learning styles based on their actual behaviour and actions in the online course. Therefore, students do not have any additional effort and just need to use the system for learning. Additionally, an automatic approach can be dynamic and therefore less error-prone, while a static approach such as questionnaires describe the learning style of a student at one specific point of time. Therefore, an automatic approach is robust towards extraordinary behaviour of students such as if they are in bad mood on one day. Furthermore, an automatic approach can dynamically adapt in the case the learning style of a student changed over time.

The approach is developed especially for learning management systems (LMS). LMS are commonly and successfully used in e-learning. They provide a variety of features to support teachers to create and manage their online courses. However, they provide very little or, in most cases, no adaptivity (Graf and List, 2005). An automatic student modelling approach for LMS provides on one hand teachers with more information about their students and is on the other hand an important issue for enabling LMS to provide adaptivity.

In the next sections, we introduce FSLSM as well as groups of learning style preferences within FSLSM, which are used as basis for the automatic student modelling approach. Section 4 introduces the automatic student modelling approach and Section 5 presents the evaluation of the proposed approach. Section 6 discusses related work and Section 7 concludes our paper.

2. FELDER-SILVERMAN LEARNING STYLE MODEL

While several learning style theories exist in the literature, for example, the learning style models by Kolb (1984) and Honey and Mumford (1982), Felder-Silverman learning style model (1988) seems to be the most appropriate for use in computer-based educational systems (Carver et al., 1999, Kuljis and Liu, 2005). Most other learning style models classify learners in few groups, whereas FSLSM describes 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 by applying the material and trying things out. Furthermore, they tend to be more interested in working in groups and discussing the material with others. In contrast, reflective learners prefer to think about and reflect on the material. Regarding communication, they prefer to work alone or maybe in a small group together with one good friend.

The second dimension covers sensing versus intuitive learning. Learners who prefer a sensing learning style like to learn facts and concrete learning material. They like to solve problems with standard approaches and also tend to be more careful and patient with details. Furthermore, 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 learning material, such as concepts and theories. 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 representations, regardless of the fact whether they are written or spoken.

In the fourth dimension, the learners are characterised according to their understanding. Sequential learners learn in small incremental steps and therefore have a linear learning progress. 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, find connections between different areas, and put things together in novel ways. Because the whole picture is important for global learners, they tend to be interested in overviews and a broad knowledge whereas sequential learners are more interested in details.

The ILS questionnaire (Felder and Soloman, 1997), consisting of 44 questions, is an instrument for identifying learning styles based on FSLSM. As mentioned, each learner has a personal preference for each of the four dimensions of FSLSM. These preferences are expressed with values between +11 to -11 per dimension. This range comes from the 11 questions that are posed for each dimension. When answering a question, for instance, with an active preference, +1 is added to the value of the active/reflective dimension, whereas an answer for a reflective preference decreases the value by 1.

3. GROUPING OF LEARNING STYLE PREFERENCES

As can be seen from the description in the previous section, each learning style dimension seems to include different characteristics. In an empirical study (Graf et al., 2007), the groups of preferences within each dimension of FSLSM were analysed and their relevance for each dimension was investigated. Table 1 shows the proposed groups as well as the related answers of ILS questions (Felder and Soloman, 1997) for each group. A question may appear twice in the table, if the two possible answers to the question point to two different groups.

The semantic groups within the dimensions provide relevant information in order to be able to identify learning styles. For example, if a learner has a preference for trying things out and tends to be more impersonal oriented, he/she would have a balanced learning style on the active/reflective dimension. However, a learner has also a balanced learning style if he/she prefers to think about the material and tends to be more social oriented. Although both learners have different preferences and therefore different behaviour in an online course, both are considered equally according to the result of ILS. Considering the proposed semantic groups leads therefore to more accurate information about learners' preferences and to a more accurate model for identifying learning styles based on the behaviour of learners in an online course.

Table 1. Semantic groups associated with the ILS answers

Style	Semantic group	ILS questions (answer a)	Style	Semantic group	ILS questions (answer b)
Active	trying something out social oriented	1, 17, 25, 29 5, 9, 13, 21, 33, 37, 41	Reflective	think about material impersonal oriented	1, 5, 17, 25, 29 9, 13, 21, 33, 41, 37
Sensing	existing ways concrete material careful with details	2, 30, 34 6, 10, 14, 18, 26, 38 22, 42	Intuitive	new ways abstract material not careful with details	2, 14, 22, 26, 30, 34 6, 10, 18, 38 42
Visual	Pictures	3, 7, 11, 15, 19, 23, 27, 31, 35, 39, 43	Verbal	spoken words written words difficulty with visual style	3, 7, 15, 19, 27, 35 3, 7, 11, 23, 31, 39 43
Sequential	detail oriented sequential progress from parts to the whole	4, 28, 40 20, 24, 32, 36, 44 8, 12, 16	Global	overall picture Non-sequential progress relations/connections	4, 8, 12, 16, 28, 40 24, 32 20, 36, 44

4. AUTOMATIC DETECTION OF LEARNING STYLES

According to a study by Graf and Kinshuk (in press), students with different learning styles behave also differently in online courses in LMS. Furthermore, the study shows some correlations between patterns of behaviour and answers of the ILS questionnaire. These findings indicate that the behaviour in an online course can be used to get information about the students' learning styles. In this section, we introduce an approach for automatic student modelling of learning style preferences in learning management systems.

4.1 Investigated patterns

Different LMS provide teachers and course developers with the opportunity to integrate different features in an online course. For providing an automatic student modelling approach that can be used by LMS in general, we used only patterns related to those features which are implemented in most LMS and which are also commonly used by teachers and course developers. The incorporated features include *content objects*, which represent the learning material, and *outlines*, which provide a summary of a chapter. Furthermore, we used *self-assessment tests*, which provide students with the opportunity to check their acquired knowledge, and *exercises*, where students can practise. Moreover, *examples* and *discussion forums* are included.

Regarding content, outline, and examples, the number and time students spent on these objects are used as patterns. With respect to the self-assessment tests, the total number of answered questions and the time spent on self-assessment tests is considered as pattern. Furthermore, the students' performance on questions dealing with facts or concepts, referring to details or overviews, being about graphics or text, and asking about interpreting a given solution or developing a new one is incorporated as pattern. Moreover, a pattern is included dealing with whether a learners is answering the same question twice wrong. Additionally, the number of revisions on answers in self-assessment tests is considered as patterns. Another pattern dealing with self-assessment tests is the time students spent on reviewing their results. Regarding exercises, also the performed number and the time spent on exercises is used as patterns. Furthermore, the performance on questions about interpreting a given solution and developing a new solution, the number of performed revisions, and the time students reflected on the results of the exercise is combined with the behaviour in self-assessment tests. With respect to the forum, the number of visits, the time students spent in the forum, and the number of postings is included. Regarding navigational behaviour, patterns deal with how often students skipped learning objects via the navigation menu as well as how often they visited and how much time they spent on the course overview page.

4.2 Relevance of patterns for groups of learning styles

In this section, we describe relevant patterns for each group of learning style according to the literature (Felder and Silverman, 1988) and related behaviour of learners with a preference for a specific group.

Learners who prefer to *try things out* focus more on an active way of learning. Therefore, they are expected to visit exercises more often, spent in general more time on exercises, and perform more self-assessment tests. Furthermore, they tend to have a weak preference for reflecting about the learned material. This lack of reflection can be seen, for example, when looking at how often learners answer the same self-assessment question twice wrong or when looking at how much time they spend on reflecting about results in self-assessment tests or exercises. Furthermore, they do not like to spend much time on examples, which illustrate how others have solved a problem. Also, they do not like to learn from content, which results in a low number of visits as well as a low amount of time spent on content objects and outlines. In contrast, learners who prefer to *think about the material* focus more on a reflective way of learning rather than an active one. They like content objects, which can be seen from a high number of visits and a high amount of time spent there, and they tend to spend more time on outlines, reflecting about the content of the topic. Due to their preference for reflecting, they tend to take more time on self-assessment tests, spend more time on reflecting on the results of their tests, and tend to answer less often the same question twice wrong. On the other hand, learners with a preference for thinking about the material are less interested in exercises, which can be seen from a lower number of visits and time spent on exercises.

In online learning, the behaviour of learners in discussion forums can give indications about their tendency for social orientation. Learners who are *social oriented* tend to post more often messages then learners who are more *impersonal oriented*. On the other hand, learners with an impersonal preference tend to focus more on reading what others have written, which results in more visits of forum entries.

Learners who prefer solving problems based on *existing ways* and with standard procedures are expected to like to practice by performing a high number of self-assessment tests and exercises. Furthermore, they tend to like to visit and spend time on examples, which show ways to solve specific problems. Moreover, they are expected to perform poor in questions about generating new solutions. On the other hand, learners who prefer challenges and solving problems in *new ways* tend to perform well in questions asking for generating new solutions. Since they get easily bored by solving the same kind of problems always with the same procedures, they tend to perform only a low number of self-assessment tests and are expected to have low interest in examples (visits and time spent on examples)

Learners who prefer *concrete material* such as facts and data tend to like to learn from examples rather than from the content objects. Therefore, a high number of visits and a high amount of time spent on examples as well as a low number of visits and a low amount of time spent on content objects can indicate a preference for concrete material. Furthermore, they are expected to perform better on questions about facts. In contrast, learners with a preference for abstract material such as concepts and theories tend to like to learn from content objects, which results in a higher number of visits and more time spent on content objects, and use examples only as complementary information, resulting in a low number of visits and a low amount of time spent on examples. Furthermore, they are expected to perform better on questions about concepts and on questions about generating new solutions, where they need the knowledge about the concepts and theories.

The preference for being *careful with details* can be seen especially from the behaviour and performance in self-assessment tests. Learners who are careful with details tend to check their answers more carefully, therefore tend to spend more time on tests and do more revisions on their answers. Furthermore, they are expected to perform better on questions about details. The same patterns, with opposite values, were used for identifying a preference for being *not careful with details*.

A *visual* preference can be identified by looking at the performance on questions about content that was presented in graphics. Furthermore, visual learners tend not to prefer to visit content objects that often, since these objects contain mainly of written words. Moreover, they are expected to use the forum only little for discussing learning material, in terms of posting a message in the forum. For the preference for *spoken words*, no suitable patterns exist based on the incorporated features in our approach. Therefore, we excluded this group from the identification process. Learners who prefer to learn from *written words* tend to prefer using the forum, in terms of visiting, staying, and posting. They are expected to learn from content objects, indicated by a high number of visits, and tend to be good in answering questions about text. *Difficulties with visual material* can be identified by looking at the performance of students on questions about content that was presented in graphics.

Learners who can be considered as *detail oriented* are expected to be good in answering questions dealing with details. However, they tend not to focus on getting an overview of the topic, which is indicated by little interest in outlines (visits and time) and the course overview page (visits and time). On the other hand, learners who prefer to get an *overall picture* of the course tend to visit outlines and the course overview page more often and spend more time there. Furthermore, learners who focus on the overall picture tend to be good in answering questions dealing with overview knowledge.

Learners who prefer a *sequential progress* tend to go through the course step by step. This behaviour can be seen from the number of skipped learning objects via the navigation menu and the number of visits of the course overview page, which offers access to all learning objects. In contrast, a preference for a *non-sequential progress* can be indicated by a high number of skipped learning objects and a high number of visits of the course overview page.

The preference of first focussing on understanding all *parts* of the course in order to get the whole picture can be seen by the tendency to focus not on getting an overview but on the learning material itself. Therefore, a low interest in outlines (visits and time) and in the overview pages (visits and time) can act as indications.

Learners who focus on *connections and relations* between topics are expected to be good in questions dealing with overview knowledge as well as with questions about interpreting and developing solutions, where in both cases the knowledge about different topics is essential. Furthermore, they tend to have a higher interest in the overview page (visits and time), where they can see the different topics and can access them.

4.3 From behaviour to learning style preferences

In order to conclude from the students' behaviour to their preferences of semantic groups, we used a simple rule-based method, similar to the approach used in the ILS questionnaire.

In a first step, the behaviour of students is gathered from the database of the LMS and for each pattern, data are mapped onto a four-item scale. More formally, let O be the matrix of ordered data, including in rows all students and in columns all patterns, values between 0 and 3 are assigned in order to classify the behaviour of each student for each pattern. Values between 1 and 3 indicate the occurrence of a certain behaviour (e.g., number of visits), where 1 represents a low occurrence, 2 a moderate one and 3 a high one. 0 indicates that no information about the respective pattern is available. The mapping of values between 1 and 3 is based on thresholds which are mainly derived from literature (García et al., in press, Rovai and Barnum, 2003, Wang, 2004), however, the thresholds can be adapted to the specific characteristics of the respective online course.

The approach for calculating learning style preferences is based on the idea that each relevant pattern gives a hint about the respective preference. The relevant patterns for each semantic group as well as whether a high or low value is supporting a specific group is described in the previous section. Based on this information, we can calculate how many hints match based on the students' behaviour. More formally, based on the matrix O, for each semantic group i, a matrix G_i is calculated. G_i has in rows all students and in columns all relevant patterns for the respective semantic group. G_i consists of values between 0 and 3. 3 indicates that the student's behaviour gives a strong indication for the respective semantic group (e.g., a high number of visits of exercises or a low number of visits of content objects are strong hints for the preference of trying things out), 2 indicates that the student's behaviour is average and therefore does not provide a specific hint, and 1 indicates that the student's behaviour is in disagreement with the respective learning style preference (e.g., a low number of visits of exercises or a high number of visits of content objects for the preference of trying things out). 0 indicates that no information about the student's behaviour is available.

By summing up the values in G_i and dividing them by the number of patterns that include available information (value>0), we calculate an measure for the preference for the respective semantic group, indicated by a value between 1 and 3, where 3 represents a strong preference for the respective semantic group and 1 represents a strong negative preference for the respective semantic group. In order to make this measure more interpretable we normalized it to lie between 0 and 1. If no pattern includes available information, no conclusion can be drawn with respect to the semantic group.

5. EVALUATION

In order to evaluate the proposed approach, we conducted a study with 75 students. The students participated in a university course about object oriented modelling at Vienna University of Technology in Austria. The course consists of a lecture and a practical part, where students had to submit 5 assignments. The whole course was managed via Moodle. The students' interactions with Moodle were tracked in order to get information about their learning behaviour. Furthermore, we asked the students to fill out the ILS questionnaire to get information about their learning styles via a collaborative student modelling approach.

In the next subsections, we provide information about the course structure, the method of evaluation, and the results of the evaluation.

5.1 Course structure

The online course consisted of 7 chapters. Five chapters dealt about the main concepts of object oriented modelling, where each concept was introduced in one chapter. Furthermore, an introduction chapter and a chapter about the practical use of object oriented modelling were provided. Overall, the course included 424 content objects. Moreover, each chapter included one or two files providing all content objects as print-version. For all chapters, an outline, a conclusion, and a self-assessment test was available. Overall, the seven self-assessment tests included 114 questions. For each of the 5 chapters dealing with the main concepts, 5 examples and 5 exercises existed. The exercise included overall 181 questions. Furthermore, a forum was provided for the course. To examine the knowledge of the students, 5 marked assignments were included within the 7 chapters. The assignments had to be done in groups of two. Few days after the submission, each student was examined on the solution individually. At the end of the course, each student had to pass a written exam. Although parts of the assignments were done in groups of two, the course was designed in a way that all students needed to learn everything and they were examined on all topics; hence the course was appropriate for investigation of individual learning.

5.2 Method of evaluation

For evaluating the automatic student modelling approach, results from the ILS questionnaire are compared with the results from the automatic student modelling approach. For the calculation of ILS preference, every answer has been considered equal to 1 when contributing to the semantic group, and equal to 0 otherwise (according to Table 1). Therefore, the average preference of each group provided by ILS answers is always between 0 and 1.

Due to the different number of patterns and questions and subsequently the different number of possible states per results (for patterns and questions), we used a measure that aims at reducing this inaccuracy. Let s_{min} be the number of states in the range with the lower number of states, either for patterns or for questions, ls_{min} be the results in terms of preferences on semantic groups on the range with the lower number of states, and ls_{max} be the result on the range with the higher number of states. In order to reduce the inaccuracy from the different number of states, an area with the width $1/s_{min}$ is build around ls_{min}. If $ls_{min} - 1/(2s_{min}) \leq ls_{max} \leq ls_{min} + 1/(2s_{min})$, then an absolute difference of 0 is assumed since ls_{min} is the best match for ls_{max}. In all other cases, the absolute difference is calculated by $abs(ls_{min} - ls_{max})$. The absolute difference is calculated for each student, values are summed up, and divided by the number of students. The result is used as measure.

5.3 Results

The results for all semantic groups are shown in Table 2. Based on the used measure, results smaller or equal than 0.25 can be interpreted as good results, indicating that our approach is suitable to identify the preference for the respective semantic group.

As can be seen from Table 2, all semantic groups of the active/reflective dimension yield good results. Regarding the sensing/intuitive dimension, the groups referring to concrete material and a preference for being careful with details yield good results and therefore the proposed approach seems to be appropriate to detect preferences with respect to these two groups. The moderate result for the group referring to the preference of being not careful with details might come from the inaccuracy due to the existence of only one relevant question. For the groups referring to a preference for existing ways, new ways, and abstract material, the proposed approach is only able to detect these preferences with a moderated precision. This might come from the issue that the incorporated features and patterns might not provide enough information to detect these preferences with high precision. Further investigations are necessary with respect to identify data which provide highly relevant information about these preferences. With respect to the visual/verbal learning style dimension, the groups referring to pictures and written words yield good results. The group indicating difficulties with a visual style achieved only a moderate result which was expected since only one pattern is considered as relevant for this group and the information about the learning style preference from the ILS questionnaire is also based on one question only. For the sequential/global dimension, the approach yields less accurate results which can be explained by the overlapping of patterns within groups, where the patterns mostly pointing to a general sequential/global preference, while ILS questions point to different semantic groups. Therefore, further investigations are necessary, dealing with the extension of the proposed course structure in order to find more relevant information for the respective semantic groups.

Table 2. Results of the comparison between preferences from patterns and ILS answers

Style	Semantic group	Result	Style	Semantic group	Result
Active	trying something out	0.233	Reflective	think about material	0.242
	social oriented	0.201		impersonal oriented	0.218
Sensing	existing ways	0.318	Intuitive	new ways	0.282
	concrete material	0.230		abstract material	0.274
	careful with details	0.227		not careful with details	0.305
Visual	pictures	0.228	Verbal	spoken words	-
				written words	0.227
				difficulty with visual style	0.263
Sequential	detail oriented	0.399	Global	overall picture	0.293
	sequential progress	0.275		non-sequential progress	0.303
	from parts to the whole	0.309		relations/connections	0.344

6. RELATED WORK

Few research works exist on automatic student modelling for identifying learning styles. García et al. (2007) proposed an automatic approach for the system SAVER, considering 3 dimensions of FSLSM and overall 11 patterns. Based on the data from these patterns, Bayesian networks are used to learn the dependencies of the model. Another approach for automatic detection of learning styles was investigated by Cha et al. (2006). Again, they observed the behaviour of learners during an online course in an intelligent learning environment based on several patterns. In an experiment, they tested the effectiveness of Decision Trees and Hidden Markov Models for detecting learning styles according to FSLSM.

In both research works, an approach strictly depending on available data is used in order to build a model for calculating learning styles. Furthermore, the approaches are developed for specific systems, using only those features and patterns that are incorporated in the system. Our proposed approach considers preferences within the learning style dimensions and aims at providing a general concept for identifying learning style in LMS, based on a simple rule-based method, similar to the one used in ILS, to calculate learning styles.

7. CONCLUSION

This paper introduced an automatic student modelling approach for identifying learning style preferences according to FSLSM in learning management systems. The proposed approach is based on the idea that students' behaviour can give relevant hints for identifying their learning style preferences. Relevant patterns were derived from the learning style literature (Felder and Silverman, 1988) and conclusions about the students preferences were calculated based on a simple rule-based method, similar to the one used in the ILS questionnaire, an instrument to identify learning style based on the FSLSM. The proposed approach was evaluated by a study with 75 participants. The study compares the results of the proposed automatic student modelling approach with the results of the ILS questionnaire. Results show that the approach is suitable for identifying all preferences of the active/reflective dimension and some preferences of the sensing/intuitive and visual/verbal dimension. For the sequential/global dimension, results show only moderated precision.

Future work will deal with extending the proposed course structure in order to find patterns that give more accurate information about the preferences where only moderate results were achieved. Furthermore, future work will deal with investigating the use of automatic student modelling for dynamically updating the information in the student model by considering the behaviour of students in an online course.

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