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# AN APPROACH FOR DYNAMIC STUDENT MODELLING OF LEARNING STYLES*

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**ABSTRACT**

Knowing students' learning styles can contribute highly in supporting students in learning by making them aware of their learning styles and/or presenting them with personalised learning material and activities. In this paper, we propose a dynamic student modelling approach, which monitors students' behaviour in a course and notices once the learning styles stored in the student model do not reflect students' behaviour in the course any more. The proposed approach aims, on one hand, at updating the information in the student model as soon as possible once differences in students' behaviour were detected but, on the other hand, also considers deviations in students' behaviour. In an experiment with data from 75 students, appropriate parameter settings and the suitability of all considered components were tested, showing that the proposed dynamic student modelling approach yields good results. By using this dynamic student modelling approach, a system is therefore able to revise the information in the student model when required and thus enable systems to provide students with support, learning material and activities they currently need.

**KEYWORDS**

Dynamic Student Modelling, Learning Styles, Adaptivity in Learning Systems.

## 1. INTRODUCTION

Considering students' learning styles in education and especially in technology enhanced education can have many benefits for students such as making students aware of their learning styles and therefore helping them to understand why learning is sometimes difficult for them. Furthermore, providing students with learning material and activities that fit their preferred ways of learning can make learning easier for them, as studies such as those by Bajraktarevic et al. (2003) and Graf and Kinshuk (2007) demonstrated.

Student modelling can be classified as *static* or *dynamic*. Static student modelling refers to an approach where the student model is initialised only once. In contrast, a dynamic approach frequently updates the information in the student model and therefore allows a system to respond to changes of the investigated student characteristics immediately. With respect to learning styles, a dynamic approach has two advantages over a static approach. First, dynamic student modelling can extend static student modelling by initialising the student model through static student modelling and then applying dynamic student modelling to fine-tune and improve the gathered information. Second, many of the major learning style models argue that learning styles can change over time and only dynamic student modelling allows detection of these changes.

Recently, some research has been done on developing student modelling approaches that detect students' learning styles automatically from students' behaviour in a course (Cha et al., 2006, García et al., 2007, Graf et al., 2008). These approaches are still static but due to their automatic way of identifying learning styles, they are the basis for dynamic student modelling. In this paper, we propose an approach for dynamic student modelling which monitors the students' behaviour in a course and frequently updates the information in the student model, considering deviations in students' behaviour. In the next section, this approach is discussed in more detail. Subsequently, an experiment for verifying the approach is described and Section 4 concludes the paper.

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## 2. DYNAMIC STUDENT MODELLING

In our previous work (Graf et al., 2008), we developed and successfully evaluated a static student modelling approach that automatically identifies learning styles from the behaviour of students in an online course. Static in this context means that a certain amount of data can be used as input and the approach calculates learning styles based on these data. The approach identifies learning styles according to the Felder-Silverman learning style model (FSLSM) (Felder and Silverman, 1988), which characterises learners based on their preferences on four dimensions: active/reflective, sensing/intuitive, visual/verbal, and sequential/global.

In this paper, we focus on dynamic aspects of student modelling and use our previous work as basis. In dynamic student modelling, we can assume that at a certain point of time ($t$) a certain amount of data about students' behaviour is available and that additional data are frequently added once a student is using the system for learning. The aim of dynamic student modelling is to check frequently whether the new information about students' behaviour hints at revising the currently stored learning style. For deciding whether such a revision should be done, two partially conflicting objectives should be reached. On one hand, the currently stored information in the student model should reflect the current learning styles of students as good as possible and therefore should be updated as soon as a revision can be done. On the other hand, deviations of students' behaviour have to be considered and the student modelling approach should avoid situations where the learning styles of students are revised and then briefly afterwards this revision has to be taken back. To develop such a dynamic approach, the following three steps have to be performed.

First, data points ($d_t$) have to be calculated, representing the identified learning style of a student at a specific point in time $t$ based on his/her behaviour in an online course. As mentioned before, we already developed an approach for automatically calculating the current learning styles of students based on a certain amount of data about their behaviour in a course. This approach is used for calculating the data points.

Second, since considering deviations in students' learning styles is an important issue for dynamic student modelling, we do not only base the decision about whether the currently stored learning style ($L_s$) should be revised or not on the currently identified learning style ($d_t$) but also consider the history of the students' learning styles. We assume that a certain amount ($A$) of data points should be used in this calculation process. For calculating the average learning style based on current and past data, we calculate the mean value of the $A$ last data points. Therefore, deviations of students' behaviour can be softened, which leads to more stable information about students' learning styles. However, attention needs to be given to situations where one of the $A$ values is much lower or much higher than the others. Such an outlier should not have so much influence as to cause a change in the student model, but it should be included in the calculation, in case it is not an exception and provides additional information. Therefore, the student modelling approach needs to consider such data points and check whether they are exceptions or not based on the subsequent data points.

Third, based on the abovementioned data, decision has to be taken whether the learning style in the student model has to be revised. This decision is based on three conditions which need to be fulfilled in order to revise the student model. The first condition aims at making the student model reflect the current learning style of a student as close as possible. The second and third conditions aim at considering deviations in students' behaviour, especially with respect to giving single outliers not enough influence to change the information in the student model.

The first condition compares the currently stored learning style in the student model ($L_s$) and the average learning style from current and past data. If the difference between these two values is greater or equal than a certain parameter $x$, this condition is fulfilled and data argue for a revision in the student model.

The second condition checks whether the difference between the currently identified learning style ($d_t$) and the previously identified learning style ($d_{t-1}$) is smaller than $2*x$. The parameter $x$ represents the difference between learning styles that is acceptable and does not cause the need for a revision. We assume that if the difference between the currently identified learning style and the previously identified learning style is greater than two times of this acceptable difference, the current behaviour of the student can be considered as exceptional behaviour and the resulting learning style is treated as extreme value. In this case, the second condition is not fulfilled and no revision should be conducted. On the other hand, if the condition is fulfilled, the difference between both values is considered as normal and data argue for a revision in the student model.

The third condition follows up with the second one and compares the difference between the previously identified learning style ($d_{t-1}$) and the learning style stored in the student model ($L_s$) with the difference between the currently identified learning style ($d_t$) and the learning style stored in the student model ($L_s$). If the difference is greater than *x/2*, the previously identified learning style can be seen as an exception and the currently identified learning style is already relatively close to the learning style stored in the student model. In this case, no revision should be done in the student model. Otherwise, the third condition is fulfilled and data argue for a revision in the student model.

If all three conditions are fulfilled, the learning style in the student model should be revised by calculating the mean value of the last $A$ data points. Formula 1 formally describes when and how the student model is updated.

$$\textit{If} \quad \left| L_s - \frac{\sum_{i=t-A+1}^{t} d_i}{A} \right| \geq x \quad \text{AND} \quad \left| d_t - d_{t-1} \right| < 2x \quad \text{AND NOT} \quad \left[ \left| d_{t-1} - L_s \right| - \left| d_t - L_s \right| > \frac{x}{2} \right] \quad \textit{Then} \quad L_{s+1} = \frac{\sum_{i=t-A+1}^{t} d_i}{A} \qquad (1)$$

## 3. VERIFICATION OF THE PROPOSED APPROACH

In this section, we describe an experiment for verifying our approach, which is based on data from 75 students who took a course about object oriented modelling at a university in Austria. The course was taught via Moodle (2009) and students' behaviour within Moodle was tracked and used for this experiment. In the next section, the method of evaluation is described. Subsequently, the results of the experiment are discussed.

### 3.1 Method of Evaluation

Our approach has been tested by calculating learning styles with respect to the Felder-Silverman learning style model (Felder and Silverman, 1988) from students' behaviour in the Moodle course. The dynamic student modelling approach was applied for each of the four learning style dimensions of the learning style model. Based on the usage of the course, we assumed that 20 actions constitute a reasonable number for calculating a new data point, representing the current learning style of a student based on his/her behaviour.

This experiment has two goals. First, suitable values for two parameters should be determined: the accepted difference between the average learning style from past and current data and the learning style stored in the student model (*x)*, and the amount of data points included in the calculation process of learning styles (*A)*. Second, the three conditions in formula (1) should be tested with respect to their suitability.

To reach these two goals, a fitness function representing the quality of a given solution of dynamic student modelling needs to be formulated. As mentioned above, the dynamic student modelling approach aims at two objectives which lead to two criteria in the fitness function. The first criterion represents the average difference between the learning styles stored in the student model and the average learning styles from past and current data, including data from all data points and all students. The second criterion deals with how many times the currently stored learning style changes in one direction and after 3 or less data points changes back towards the former learning style, considering data from all students. We assume that both criteria are equally important. The multi-objective fitness function is based on both criteria and normalised based on minimum and maximum values, using 0 as minimum values for both criteria, $x$ as maximum value for the first criterion and the number of students as maximum value of the second criterion. Since FSLSM includes four dimensions and the dynamic student modelling approach is applied for each of them separately, the overall fitness is calculated by the average of the fitness values of each dimension.

### 3.2 Results

The first goal of this experiment deals with determining suitable parameter values for the accepted difference between the average learning style from past and current data and the learning style stored in the student model (*x)* and for the amount of data points included in the calculation process of learning styles (*A*). For $x$, we tested the following values: 1/22, 1/11, and 2/11. These values are based on FSLSM, which measures learning styles on each dimension by values between +11 and -11, in steps of +/- 2. For $A$, we tested 2, 3, 4, and 5 as test values. Table 1 presents the results of this comparison, indicating that the combination $x$=1/11 and $A$=3 is the best parameter setting under the given conditions.

Table 1. Comparison of different parameter settings

| Accepted difference bet. calculated and stored learning styles (x) | Amount of data points included in the calculation process of learning styles (*A*) 2 | 3 | 4 | 5 |
|---|---|---|---|---|
| 1/22 | 0.521 | 0.563 | 0.588 | 0.602 |
| 1/11 | 0.640 | 0.656 | 0.645 | 0.617 |
| 2/11 | 0.615 | 0.584 | 0.558 | 0.532 |

Table 2. Verification of conditions in formula (1)

| | x=1/11, A=3 |
|---|---|
| only first condition | 0.646 |
| first two conditions | 0.642 |
| all three conditions | 0.656 |

The second goal of this experiment deals with checking whether all three condition in formula (1) help to improve the overall result of the dynamic student modelling approach. Therefore, we used the parameter setting $x$=1/11 and $A$=3 as identified to be the most suitable, and calculated the overall fitness values when using only the first condition, the first two conditions, and all three conditions. As can be seen in Table 2, using all three conditions achieves better result than using only one or two conditions. This confirms our expectations that balancing deviations and considering extreme values in students' behaviour, as done when incorporating all three conditions, is worth to be considered and has potential to improve dynamic student modelling.

# 4. DISCUSSIONS AND CONCLUSIONS

The dynamic student modelling approach presented in this paper allows learning systems to frequently update the information about students' learning styles in the student model based on students' recent behaviour in an online course accurately and by considering deviations in students' behaviour. An experiment with 75 students was performed to investigate the most suitable parameter setting and to verify the approach, using the respective parameter setting. The experiment shows that the approach leads to good results, enabling learning systems to notice the need of revisions in the student model and to revise the information respectively. Such revisions can be caused by a change in students' learning styles or can be necessary if dynamic student modelling is used for improving and fine-tuning the information in the student model. By using the proposed approach, the system is able to identify students' learning styles more accurately and therefore can meet students' current needs. The proposed approach can be integrated in systems that plan to incorporate dynamic student modelling. Although the approach is based on FSLSM, it can be applied to other learning style models with similar structure after few revisions. Future work will deal with implementing the proposed student modelling approach in an adaptive system and evaluating the benefits of dynamic student modelling.

# REFERENCES

Bajraktarevic, N., Hall, W. and Fullick, P., 2003. Incorporating Learning Styles in Hypermedia Environment: Empirical Evaluation. *Proceedings of the Workshop on Adaptive Hypermedia and Adaptive Web-Based Systems.* Nottingham, UK, Eindhoven University, pp. 41-52.

Cha, H.J., Kim, Y.S., Park, S.H., Yoon, T.B., Jung, Y.M. and Lee, J.-H., 2006. Learning Style Diagnosis Based on User Interface Behavior for the Customization of Learning Interfaces in an Intelligent Tutoring System. *Proceedings of the 8th International Conference on Intelligent Tutoring Systems,* Berlin, Heidelberg, Springer, pp. 513-524.

Felder, R.M. and Silverman, L.K., 1988. Learning and Teaching Styles in Engineering Education. *Engineering Education,* Vol. 78, No. 7**,** pp. 674–681.

García, P., Amandi, A., Schiaffino, S. and Campo, M., 2007. Evaluating Bayesian Networks' Precision for Detecting Students' Learning Styles. *Computers & Education,* Vol. 49, No. 3**,** pp. 794-808.

Graf, S. and Kinshuk, 2007. Providing Adaptive Courses in Learning Management Systems with Respect to Learning Styles. *Proceedings of the World Conference on E-Learning in Corporate, Government, Healthcare, and Higher Education (E-Learn).* Chesapeake, VA, AACE Press, pp. 2576-2583.

Graf, S., Kinshuk and Liu, T.-C., 2008. Identifying Learning Styles in Learning Management Systems by Using Indications from Students' Behaviour. *Proceedings of the International Conference on Advanced Learning Technologies.* Santander, Spain, IEEE Computer Science, pp. 482-486.

Moodle, 2009. Retrieved 6 September, 2009, from http://www.moodle.org.