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Applying Ariadne: Practical Insights into Learning Style Identification via Hidden Markov Models

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Abstract

With the use of learning management systems students benefit from being recommended suitable learning elements based on their individual needs. In doing so, recommendation algorithms are applied which first query the student's learning style. To improve the recommendation of learning elements a continuous analysis of the individual's learning style is required. A frequent questionnaire assessment would however be too time consuming. Instead, in a prior study an algorithm has been designed to identify changes in learning styles from the student's selection of learning elements. In this paper, we investigate the functionality of that algorithm by applying it on real student data. In particular, we test if the algorithm correctly indicates changes in learning styles. The utilised data is collected in our learning management system. To be precise, the data is obtained from 22 students enrolled in a software engineering course during the winter term of 2023/24. The data comprises two types of information for each student: 1) learning style collected at the start and end of the term, and 2) the user's actual selection of learning elements inside the learning management system. The uniqueness of this study lies in the data and the evaluation strategy based on it. Having the learning style at the end of the semester period as ground truth allows us to test if the algorithm operates correctly with actual user data from our learning management system. The results validate the behaviour of our algorithm, yet they strongly suggest the need for an adaptation. Further research is required on how to parameterise the underlying models.

Keywords Learning Styles, Hidden Markov Models, Empirical Evaluation

Introduction

Nowadays, learning management systems (LMSs) can often recommend suitable learning material to students for an improved learning success. In doing so, the underlying algorithms initially query the learning style. To continuously update the students' learning styles, the Ariadne algorithm has been designed [1]. It analyses the user's chosen learning elements inside a LMS and quantifies with a metric, the so-called support value, how much the user behaviour aligns with the initial questionnaire assessment. Therefore, the support value can be utilised to improve the recommendation of learning elements. The aim of this study is to validate the Ariadne algorithm based on real student data and thus provide practical insights. To do this, data was collected from students inside our LMS for a software engineering course from the winter term 2023/24. The data contains the learning style assessed at the start and end of the term. Also, information about the chosen learning elements inside the LMS is included. The learning style queried at the end of the semester period serves as ground truth for evaluation. This allows us to benchmark the current implementation and furthermore formulate directions for improvement. In summary, the present paper adds the following contributions:

- C1 Demonstrate and validate the Ariadne algorithm when practically applied,
- C2 Test and evaluate the Ariadne algorithm,
- C3 Specify needs for adaptation in the Ariadne algorithm.

The paper is structured as follows. First, theoretical foundations are introduced. Section 4 then explains the methodology of this study. After, the results are highlighted and discussed. Following that, section 6 presents the limitations of this study. Finally, section 7 draws a conclusion and shows directions for future work.

Related Work

Several techniques already exist to identify learning styles from user behaviour in LMSs [2]. García et al. for example apply Bayesian statistics to detect learning styles [3]. On the other side, Bernard et al. deploy deep learning techniques for a more precise learning style identification from user behaviour [2]. However, the proposed techniques are limited in their interpretability or require a large amount of data. More importantly, none of these strategies addresses the challenge of detecting changes in learning styles. Thus, the uniqueness of our approach becomes clear: this study evaluates an algorithm for continuous analysis of learning styles based on user behaviour. Additionally, the given data allows to provide understandable results.

Theoretical Background

The following part introduces the foundations of the present work. First, the utilised learning style theories and learning elements are described. After, we briefly present the LMS used to collect the data for this study. Then, the key features of the Ariadne algorithm are highlighted.

Felder and Silverman formulated a way how learners perceive and understand information by defining four categories. To keep the attention of the reader, this paper only covers the Active-Reflective category. Active learners prefer practicing through exercises, whereas reflective learners tend to think about the content first. [4–7]

Consequently, the theories imply that given the choice and sequencing of learning elements conclusions about the learning style can be drawn. The learning element types used for this study refer to the ones defined by Staufer et al. [8]. To gather the students' learning styles, the Index of Learning Styles (ILS) questionnaire is used in this study. In addition to the bare classification, it also maps the strength of each learning style to a value between 1 and 11. Thus, learners show a mild (1 and 3), balanced (5 and 7) or strong (9 and 11) coherence to their learning style. [9]

Managing Learning Content with Pythia

The LMS employed in our research project is called Pythia. It is a Moodle based software implementation. Among other things, it facilitates the integration of algorithms recommending a sequence of learning elements - the learning path. Notably, it allows us as well to collect user data and learning analytics effectively. [10]

Learning Style Identification with Ariadne

The Ariadne algorithm has been designed to counteract weaknesses of the ILS when used for curriculum design [7] by updating learning styles from the learners continuously based on their actual choice of learning elements. To do this, Hidden Markov Models (HMMs) are deployed, which model learning styles as hidden states and learning elements as observable objects. In the case of this work, the applied HMM has the hidden states active and reflective. Consequently, a chosen learning element can be analysed to deduce the corresponding most probable learning style. Like stated in Equation (1), the support value then is used to quantify how often the initial learning style is identified by the algorithm ($learning\ styles_{algorithm}$) in reference to the length of the learning path ($l_{learning\ path}$).

$$support\ value = \frac{learning\ styles_{algorithm}}{l_{learning\ path}} \qquad (1)$$

This metric thus states how much the actual learning path aligns with the initial learning style assessment. The support value ranges from 0 (mismatch) to 1 (match). [1]

Methods

The following part first highlights the data used for this study. Then, the evaluation methodology is presented in brief.

Data

The data is obtained from 22 participants inside Pythia from a software engineering course of the winter semester period 2023/24. It contains results from the ILS rolled out in the start (Pre-Test) and the end (Post-Test) of the semester period as well as the students' learning paths inside Pythia. The data is made publicly available on Zenodo[2].

ILS Pre- and Post-Test

The results from Fig. 1 suggest the need for a continuous update of the learning style during the semester period. Four students change from Active to Reflective and seven students from Reflective to Active learning style.

Fig. 1 Pre- (left) to Post-Test (right) Development of Learning Styles for the Active Reflective Learning Style Dimension

[2] 10.5281/zenodo.12594911

Moodle Learning Paths

The students' learning paths inside Pythia are chronological sequences of the learning elements with the Moodle status marked as done. After pressing the corresponding button, an event is triggered. This information is stored over the semester period and then used as data source for this study.

Evaluation Methodology

The evaluation methodology is displayed in Fig. 2. The Pre-Test learning style is used to initialise the HMM of the Ariadne algorithm. Then, the student's learning path serves as input for the algorithm to calculate the support value. Finally, we check if the outcome aligns with the Post-Test learning style. The results are obtained using the Python packages *hmm-learn 0.3.2* and *numpy 1.26.4*.

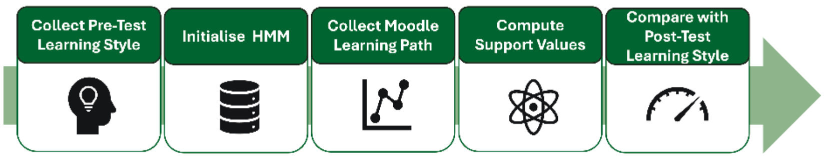

Fig. 2 Workflow for the Evaluation of the Ariadne Algorithm

Results and Discussion

The results are listed in Table 1 and clustered based on Pre- and Post-Test outcomes. The questionnaire assessments show that mostly students with a mild learning style expression tend to change between Active and Reflective behaviour. On the contrary, students with a balanced or strong characteristic prefer to stay in their learning style. For these participants the support value mostly aligns with the questionnaire information. More importantly, the findings show that the algorithm is able to identify changes in the learning styles for specific students.

ID	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
Change	–	–	–	–	–	–	–	–	↘	↘	↘	↘	–	–	–	↗	↗	↗	↗	↗	↗	↗
Pre-Test	3	9	9	7	5	5	3	5	3	1	5	5	3	9	1	5	1	1	1	1	1	1
Post-Test	5	7	9	7	5	5	5	3	1	1	1	3	3	9	3	1	1	1	3	5	3	3
SV	0.98	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.67	0.99	1.00	0.99	0.98	0.20	1.00	0.98	0.80	0.69	1.00	0.00	0.6

* The – symbol refers to a remain between Pre- and Post-Test learning style, whereas ↘ and ↗ indicate a change from Active to Reflective and Reflective to Active respectively

* Green entries indicate that the SV correctly suggests a change or remain of the learning style

Table 2 Support Values (SVs) from the algorithm for the learning paths from 22 students along with their ILS Pre- and Post-Test results.

For a better understanding, Fig. 3 illustrates the learning path for the student with ID 22. As stated in Table 1, the algorithm correctly doubts the Pre-Test learning style. Like shown in the learning path, the selection of quizzes leads to the algorithm suggesting that the student has Active learning tendencies as well. This is indicated by the support value of 0.60.

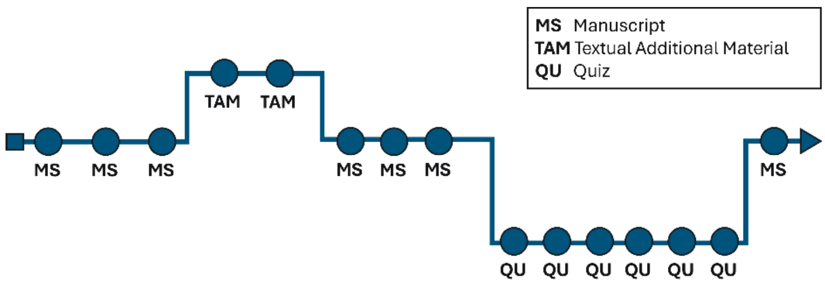

Fig. 3 Learning Path for ID 22

In summary, the results provide valuable insights into the behaviour of the algorithm. The findings imply that the Pre-Test learning style used to parameterise the HMM strongly influences the decision-making. We assume that the algorithm is overfitted to learners with a mild characteristic as correctly classifying these students is very important. Though, in this case the algorithm would not produce sensible outcomes for balanced and strong learners. More research is however required to confirm this statement.

Limitations

The major source of limitation to this study concerns the collected learning path data. Neither have the students been taught the right use of

Pythia, nor are we able to resolve whether the state *mark as done* has been applied correctly after the completion of a learning element. The users interact differently with our LMS. Hence, the learning path data for the Ariadne algorithm varies in input size and thus the findings are hard to compare. Also, we only analysed the data after completion of the term. However, the results can be different when running the algorithm during the semester period. Another limitation to the data is due to the fact that not all learning element types were equally present in the LMS. Hence, the data is biased to the given variety of learning elements. Finally, the questionnaire results are in general limited in their reliability. Students might have misunderstood questions or have not answered the questions consciously due to a lack of interest.

Conclusions and Future Work

In summary, this study practically evaluates the Ariadne algorithm and presents valuable insights into its behaviour when applied to real student data. The findings demonstrate that the Ariadne algorithm can be deployed to identify changes in the learning style and thus update learning path recommendation algorithms. Though, further adaptation is needed to refine the underlying computations. In particular, the results suggest that future work has to address how the learning style from the questionnaire affects the parameters of the HMM. Also, it is necessary to facilitate the extraction of more meaningful learning path data. Checking the usage time when accessing a learning element or analysing the user interaction with the learning element can provide more meaningful input data for the Ariadne algorithm.

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