Using Artificial Neural Networks to Identify Learning Styles

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Abstract. Adaptive learning systems may be used to provide personalized content to students based on their learning styles which can improve students' performance and satisfaction, or reduce the time to learn. Although typically questionnaires exist to identify students' learning styles, there are several disadvantages when using such questionnaires. In order to overcome these disadvantages, research has been conducted on automatic approaches to identify learning styles. However, this line of research is still in an early stage and the accuracy levels of current approaches leave room for improvement before they can be effectively used in adaptive systems. In this paper, we introduce an approach which uses artificial neural networks to identify students' learning styles. The approach has been evaluated with data from 75 students and found to outperform current state of the art approaches. By increasing the accuracy level of learning style identification, more accurate advice can be provided to students, either by adaptive systems or by teachers who are informed about students' learning styles, leading to benefits for students such as higher performance, greater learning satisfaction and less time required to learn.

Keywords: Artificial neural network · Felder-silverman learning style model · Identification of learning styles

1 Introduction

Adaptive mechanisms may be used to personalize content to students based on different characteristics such as their learning styles, knowledge level, cognitive traits, and others. Although there is some controversy on the use of learning styles, especially in technology enhanced learning several benefits were found when adapting courses to learning styles of students [e.g., 1,2]. However, identifying learning styles in a reliable and non-intrusive way is still an open issue. In order to avoid disadvantages of

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questionnaires such as additional time that students need to spend and the influence of factors such as lack of motivation to fill out the questionnaire, over the past few years, research has been conducted on automatic approaches where the behavior of students is analyzed to identify their learning styles automatically. Such approaches use either an artificial/computational intelligence technique [e.g., 3,4,5] or are based on rules retrieved from literature [e.g., 6,7]. Current approaches achieve results that are typically lower than 80% of precision, with most results being around 70% or even lower.

In this paper, we introduce LSID-ANN, a novel approach using artificial neural networks to identify students' learning styles based on the Felder-Silverman learning style model (FSLSM) [8]. While there exist many learning style models, we selected the FSLSM due to several advantages of this model, such as describing learning styles in much detail and using scales to represent the strength of learning style preferences instead of learner types. To do so, FSLSM uses four dimensions (active/reflective (A/R), sensing/intuitive (S/I), visual/verbal (V/V) and sequential/global (S/G)), where a learner has a preference on each of these four dimensions. Furthermore, FSLSM is one of the most often used learning style models in technology enhanced learning and considered as one of the best models to use in adaptive systems [9,10]. Besides focuses on achieving highly accurate results, LSID-ANN also aims at providing a solution that is generalizable, so that it can be used in different learning systems.

The remainder of the paper is structured as follows: Section 2 provides a brief overview on how the artificial neural networks are built. Section 3 describes the evaluation of LSID-ANN and Section 4 concludes the paper.

2 Building ANNs to Identify Learning Styles

LSID-ANN uses four artificial neural networks (each for one of the four learning style dimensions) with a 3-layer perceptron configuration.

As a first step to build an ANN, the input values of the ANN have to be determined, which are behavior patterns in the case of LSID-ANN. As our approach aims at being applicable in different learning systems, it was important to use generic behavior patterns. Graf et al. [6] have investigated the use of generic behavior patterns and used such patterns in their automatic learning style identification approach, achieving one of the highest precision results in literature so far. Thus, for LSID-ANN, we used the same behavior patterns.

Next, we need to determine how to assess the output of the ANN. To calculate the back propagation error, the output of the ANN is compared to the learning style as identified by the Index of Learning Styles (ILS) questionnaire [11], a questionnaire that has been proven to be valid and reliable to identify learning styles based on the FSLSM [12]. The difference between the result from the ANN and the result from the ILS questionnaire is used as back propagation error.

The parameters of the ANN were optimized through experimentation using suggested values/ranges from literature. As a result, the number of hidden nodes was set to 1 for A/R, 5 for S/I, 8 for V/V and 2 for S/G. The learning rate was set to 0.08 for A/R, 0.06 for S/I, 0.08 for V/V and 0.07 for S/G. The momentum was set to 0.1 for A/R, 0.09 for S/I, 0.06 for V/V and 0.01 for S/G. The training mode was set to individual mode for all four learning style dimensions. Furthermore, two techniques for reducing overfitting were investigated and used. Stratification is improving results for A/R, S/I and V/V and therefore is used for these dimensions. Weight decay is used for all dimensions with a weight decay of 0.05 for A/R, 0.05 for S/I, 0.01 for V/V and 0.1 for S/G. These settings were again determined through experimentation.

Parameter optimization, overfitting reduction analysis and obtaining final results were done using 10 fold cross validation to ensure generalization of our results to independent datasets.

3 Evaluation

To evaluate LSID-ANN, data from 127 computer science undergraduate students were collected, including their behavior data in a university course and their results on the ILS questionnaire. Only 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 were considered for this study, leading to a dataset of 75 students.

Two performance metrics are used to demonstrate the performance of LSID-ANN. The first metric is SIM, a metric commonly used for measuring the performance of learning style identification in literature [4-6]. SIM divides the learning style values into high, low and balanced regions and returns 1 when the actual (LS_{actual}) and identified ($LS_{identified}$) learning style values are in the same region, 0.5 when they are in adjacent regions, and 0 when they are in opposite regions. SIM values are calculated for each student and then an average SIM value is built to measure the overall precision.

SIM has a drawback of reduced accuracy due to classifying results when the actual and/or identified learning style values are near the region edges. With neural networks, the exact difference between LS_{actual} and $LS_{identified}$ can be measured, leading to a more accurate performance metric, which we call ACC. ACC is calculated for each student, and an average ACC is built to measure the overall precision.

As can be seen from Table 1, LSID-ANN and DeLeS [6] are the two approaches that achieved the best results using SIM, with LSID-ANN outperforming other approaches in the A/R and S/G dimensions and DeLeS outperforming other approaches in the other two dimensions. Since the SIM metrics is not as accurate as ACC and DeLeS is the leading approach using SIM, raw results from DeLeS were obtained to calculate ACC for DeLeS. As can be seen in Table 2, using ACC, LSID-ANN outperforms DeLeS clearly in V/V and S/G, achieves little higher results in A/R and achieves the same results in S/I.

Table 1. Comparison of SIM results

	A/R	S/I	V/V	S/G
LSID-ANN	**0.802**	0.741	0.727	**0.825**
DeLeS [6]	0.793	**0.773**	**0.767**	0.733
Bayesian [4]	0.580	0.770	-	0.630
NBTree [5]	0.700	0.733	0.533	0.733

Table 2. Comparison of ACC results

	A/R	S/I	V/V	S/G
LSID-ANN	**0.802**	**0.790**	**0.840**	**0.797**
DeLeS [6]	0.799	**0.790**	0.788	0.702

4 Conclusions

This paper introduced LSID-ANN, an artificial neural network approach for identifying students' learning styles based on the Felder-Silverman learning style model [8]. LSID-ANN was evaluated with real data from 75 students, showing that it outperforms the leading approach, DeLeS, in three out of four dimensions of the FSLSM and achieved the same results for the fourth dimension. By identifying students' learning styles with higher accuracy, adaptive learning systems can use this learning style information to provide more accurate personalization. Furthermore, teachers can use this learning style information to provide more accurate advice to their students.

In future work, we plan to investigate other artificial intelligence / computational intelligence approaches as well as hybrid approaches for learning style identification.

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