Analyzing Learning Styles using Behavioral Indicators in Web based Learning Environments

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Abstract. It is argued that the analysis of the learner's generated log files during interactions with a learning environment is necessary to produce interpretative views of their activities. The analysis of these log files, or traces, provides "knowledge" about the activity we call indicators. Our work is related to this research field. We are particularly interested in automatically identifying learners' learning styles from learning indicators. This concept, used in several Educational Hypermedia Systems (EHS) as a criterion for adaptation and tracking, belongs to a set of behaviors and strategies in how to manage and organize information. In this paper, we validate our approach of auto-detection of student's learning styles based on their navigation behavior using machine-learning classifiers.

1 Motivation

Several studies are currently being done on measuring Learning Styles (LS) by the analysis of learners' interaction traces (*eg*. DeLeS [6], Welsa [7], and Chang et al. [5]). Their general criticism is related to the use of a specific environment, and therefore specific traces and indicators. Our ambition is to develop an approach and interpretable indicators as independently as possible from the learning environment. What leads us to deal with Web-based learning environments widely used by EHS. The problem is to infer automatically high-level information about the learner preferences (behaviors and LS) from low-level ones: the navigation traces (visited URLs, clicks, etc.).

2 Approach

To validate our assumption that it is possible to deduce LS from navigational behavior, we made an experiment with 45 graduate students at the Higher National School of Computer Science (ESI-Algiers). They worked on machines equipped with a trace collection tool, with a web-based learning course. Based on their navigation traces, we calculate the five indicators we propose [2] to describe the learner's browsing behavior, to identify two attributes of the learning process layer of our LS model [1]: information processing and understanding. Their values correspond to two dimensions of the FSLSM [3]: active/reflective, and sequential/global. We used supervised classification methods to compare the psychological questionnaire ILS [4] results to those of four classifiers (K-Nearest Neighbor, decision trees, Bayesian Networks, and neural networks). We used the Weka tool and the cross validation method using 10 partitions, to address the sample size problem. Table 1 summarizes the obtained results, using the recall metric (number of correctly classified participants by the classifier over the number of participants that it should find according to ILS).

Table 1. LS Classification results

LS Attribute / Classification Method	Information Processing			Understanding		
	Active	**Reflective**	**ACT/REF**	**Sequential**	**Global**	**SEQ/GLO**
K-NN (K=3)	78.6%	41.2%	64.4%	47.4%	84.6%	68.9 %
Decision Trees C4.5	92.9%	0%	57.8 %	63.2%	73.1%	68.9 %
Bayesian Networks	82.1%	11.8%	55.6 %	42.1%	65.4%	55.6 %
Neural Networks	60.7%	64.7%	62.2%	63.2%	80.8%	73.3 %

Through Table1, we notice that for the information processing LS' attribute, all the classifiers learn the active style better than the reflective one, except for Neural Networks. This is due to the stronger presence of active learners than reflective ones. Concerning the understanding LS' attribute, the global style was better learned by all classifiers than the sequential one for the same reason as the first attribute, where neural networks give the best total results. We observe that the total results are all over 50%. Thus, we can strengthen the hypothesis of the possibility to deduce information about learner preferences using simple navigational information that we can apply on any learning environment on the Web, without having to consider evaluation scores or the communication tool traces that allow us to give more details. We plan to continue the development of other indicators to improve the LS' identification results.

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