ISSN 2395-1621

Automatic Student Profiling Based on Learning Style Models in eLearning - A Survey

[#1]Ritesh R. Dhote

[1]ritesh.dhote@gmail.com
[#1]ME Computer
Department of Computer Engineering,
JSPM's Imperial College of Engineering & Research, Wagholi, Pune

.

ABSTRACT

In the world of e-learning, personalized learning is hot cake now days. Learner centric approaches are becomes one of the primary goals for Learning management systems (LMS). Personalization in learning can be approached optimally, if we have access to the method or approach by which a learner can gain the max. The trainer can get better opportunity to harvest the strength and overcome weaknesses of the learner. Hence the researchers in the domain are taking deep dives to dig in the learning style identification process. As many approaches were studied and identified to detect the way student learns at his best based on questioner or assessment test. Size of learner pool with access to e-learning and some of the issues in formal approach gives a rise to need for automating the learning style identification process. Over few decades the different ways to identify and overcome the problem of identification of learner style detection are been imparted. This paper presents a look over and analysis over some shortcomings, and scope of work in the present methods.

Keywords— e-Learning, student profiling, learning style.

ARTICLE INFO

Article History

Received :28th December 2015

Received in revised form :

31st December 2015

Accepted :5th January , 2016

Published online :

6th January 2015

I. INTRODUCTION

In e-learning scenario one size never fits all so the personalization can play a vital role with expectation of provide tailor made environment. Personalise learning environment precision depends upon its adoptability to the learner approach i.e. learning style. Even if there is no standard definition to the phrase "learning style", but one of the comparatively accepted is defined by Keefe [1] which defines learning style as "the composite of characteristic cognitive, affective, and psychological factors that serve as relatively stable indicators of how a learner perceives, interacts with, and responds to the learning environment". In simple work learning style can be expressed as the approach which with student can learn at his best.

Student learning styles are categorically distinguished as different models. These model driven learner classifications are base on top of the question set that are scaled. A learning style model classifies students according to where they fit on a number of scales belonging to the ways in which they receive and process information [2]. Models for learning style categorically provide a thin degree of overlapping with reference to dimensions, terminology, proposed outcome etc. Still pin pointing learning style gives a great edge to student as well as teacher to understand how to process the learning work to get optimal result. Learning style identification is also important as it can help to improve performance, motivation and decrease the learning duration [3].

The traditional approach has some side fall to it like, formal approach turns tedious as the size of question set increases, set of questioner assume considers that the students are well aware of their learning preferences but this is not a real world case, learning style expected to change over the time which results in invalidating the previous model assessment and lastly the students answering has great chance of getting influenced.

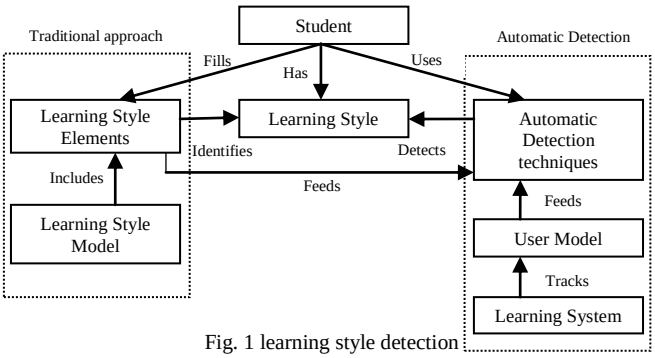

Fig. 1 learning style detection

To overcome the shortcoming of traditional approach different approaches for auto detecting a learning style are been proposed. In this paper we will analyse these approaches on the basis of various aspects depicted in Fig.1. Thus is section II we discuss the learning models in brief. In section III we review various approaches that are proposed to automate the process of learning style identification. In section IV we discuss future scope in the field and present our conclusion.

II. MODEL FOR LEARNING STYLES

A learning style model classifies students according to where they fit on a number of scales pertaining to the ways they receive and process information [2]. A small number of dimensions that collectively provide a good basis for designing effective instruction are specified by these models [4]. In continuation to this learning style models also help in identifying strength and weakness of learner, which would be valuable input to system for optimally personalise the system and get the better results from learner. For such ideal implementation the centre of attraction is the learning style model that will be the guideline in the LMS. The base ideas for detecting learning style used by various approaches are as follows:

A. Kolb's model of learning style[5]

This model has Experiential Learning Theory (ELT) [5] as a base. In the process concrete experience tailed with reflection and observation that moves to abstract concept formulisation, that is actively tested under experimentation. Kolb's lists four cyclic stages as Concrete Experience - (CE), Reflective Observation - (RO), Abstract Conceptualization - (AC)Active Experimentation - (AE). On the basis of these following styles of learning are defines:

- Diverging (CE/RO): Student in this style tends to resolve the problem with use of imagination. They try to gather information preferable by watching rather than doing.
- Assimilating (AC/RO): Student with this learning style goes well with abstract idea, theoretical models and concepts.
- Converging (AC/AE): Student having this learning style tends to use learning to solve practical issues. They prefer technical task.
- Accommodating (CE/AE): Student in this style likes "hands-on" and relays on intuition rather than logic. They prefer team work to complete the task.

In some initial stage of automatic learning style detection this model were used but in present scenario other optimized models are more preferable.

B. Gardner's Model[6]

This model is based on Multiple Intelligence Theory [6] proposed by Gardner. In this Gardener classifies eight intelligences:

- Linguistic: This intelligence relates to ability to listen, write, read and speak. This intelligence relay on language base for interpretation and explanation of ideas and information.
- Logical/Mathematical: This intelligence reflects skill of pattern identification, logical thinking, perform mathematical calculation.
- Musical: This intelligence linked to musical ability, awareness and emotional aspect of the music.
- Bodily-Kinesthetic: This intelligence relates to ability of body control and goal oriented action
- Spatial/Visual: This intelligence related to visual precision to perform modification through mental strength.
- Interpersonal: This intelligence related to ability to relate to other, emotional self management, and self correction.
- Intrapersonal: This intelligence relate to ability to orient oneself to the world and capability to understand oneself.
- Naturalist: This intelligence relates the conception of living entities and nature.

The Gardner's approach relies only on intelligence i.e. things one can very well do. This approach is singular and value directional. It is exactly opposite to learning style approach which bipolar and value differentiated as it refers to learners preference to do things.

C. Felder and Silverman Model[2]

This model is based upon the work outcome of Kolb and Myers-Briggs. Felder suggested that the learning process can be optimised if teaching methodology matches learning style. This model quantifies student learning style on the basis of its four dimensional characterization that shows how student learn. These dimensions are as follows:

- Processing: This dimension is related to the approach by which information is transformed in to knowledge. The learning styles in this dimension are Active and Reflective. Active learn are more of experiment oriented and they are good team worker. Whereas Reflective learner do well by themself.
- Perception: This dimension is related to the preference of student in the type of information that he wants to recognise. Learning style in this dimension are Sensitive who likes facts, data and standard approach to solve problem where as Intuitive prefer theory and principle.
- Input: This dimension is related to the preference of learner to receive information. Learning styles in this dimension are Visual and Verbal. A visual learner recognises and remembers pictorial data preciously where as Verbal learner good with the thing they hear and say.
- Understanding: This dimension is related to the way learner understands the things. The learning styles in

this dimension are Sequential and Global. Learner belonging to sequential style is more optimal towards the linear processes of reasoning. On other hand Global learner prefer hops in the learning path.

This model is very popular in the research of automation with its variations the work is majorly performed by theoretical perspective rather than evaluating approach with simulated data or empirical evaluation.

D. Biggs Model[7]

This model is more oriented toward what student do and why they do so when they go for learning. Three learning approached were identified by Biggs model listed as:

- Surface: learner with this style primarily motivated by fear of failure. Equilibrium is tried to be achieved between hard work and failure.
- Deep: learner belonging to this style tries to actuate interest in academic subject.
- Achieving: Competition is the base of this style, achievement with high grade whether or not material is interesting.

Many of educational researchers applied this model as it deal with the learning process a bit profoundly. In this model also students are classified in fix categories and not consider preferences of learning as criteria.

E. Custom Models

This call of learning style is bit difficult to categorized but still popular amongst the researcher in the field. Model belonging to this class are caring properties of two or more formal approaches custom model are well know to cater issues like multitude model learning style, concept overlapping and correlation between learning style. Custom models are well carrier of the extended dimension in learning but still due to weak theoretical support.

III. METHODS FOR AUTOMATIC LEARNING STYLE IDENTIFICATION

Various approached were crafted to serve the purpose of automatic learning style detection in the learning domain. Several approached were driven with core or custom models or combination of them but artificial intelligence (AI) get the clean swipe due to the humanly nature of the problem. There several AI techniques are used by researchers in the field. Section bellow will discuss current out of them and technique they apply to classification.

There mainly two way for automatic learning style detection were identified by Graf [8].

A. Data Driven

In this approach the role of classifier is crafted in a manner so that it can imitate a learning style element. AI classification algorithms to which user model is an input and resultant output is a preferences of student learning style. This approach is more advantages and accurate with real data. So for this approach to act accurately data set play a vital role in it. this approach is popular in computer researchers as it require collecting relevant information and then apply AI classification on to it.

B. Literature Based

This model fetch hints out of user modal with target to identify the learning preferences of the learning style and afterwards final output, rule-based mechanism is used to calculate preference for matching hints. Due to the generic nature this approach is advantages for data collected for any course. Though summing-up importance factor related to each hint stand tall as challenge in this approach to identify learning style preferences. Sangineto et al [9] Popescu [3] and Latham et al [10] are some of the recent work related to literature based approach. In this approach some knowledge of a psychology and cognitive science can help to get better result.

Following session reviews the AI techniques imparted in identification process.

A. Bayesian networks

They are modelled as acyclic directed graph with probability distribution, where each arc represent probabilistic correlation and node random number. The table containing coordinal state are called as coordinal probability table (CPT). Two stapes are needed to build, first defining network structure and parameters of the network is to be set. Second, when structure is in place CPT must be set.

This approach is used in work of Alkhuraiji et al [11] and Ahmad and Shamsuddin [12].

B. Decision Tree

Decision tree algorithm imparted in two stages. Stage one is a building stage followed by pruning stage. In this method training set of data is recursively partitioned until all the participant categorised to some class. Because of its simplicity, readable output, this method is frequently used for the purpose of classification in the process of automatic learning style detection. Decision tree were used in the work of Crockett et al [13], Ahmad and Shamsuddin [12].

C. Other AI Techniques

Other frequently used AI techniques for automatic learning style detection consist of:

- Hidden network: to infer student style of learning, where in student action series considered to track progress in learner behaviour.
- Generic algorithm: This is heuristic search algorithm based on Darwin's evolution theory where leaner solutions evolve towards better ones.
- Case-Based reasoning: In this approach every new case is matched to previous monitored one.
- Graphical probabilistic model: it works like K-Nearest Neighbour where in student action plotted on k dimensional space and student near to each other considered to have similar learning style.

IV. SCOPE FOR WORK

One of the major area in automatic learning style detection process is the characterized by small-scale application model. This clearly depict that future work should be carried with bigger population size as knowledge and environment may influence the preferences. Another issue is related to comparative evaluation in case of population with varying sizes comes in to the picture, so for further work population selection must be derived from size

parameter. Another issue with automatic learning style detection is computation and precision of the automated process. Unless and until accuracy jumps upwards of threshold use of the outcome will not be effective.

V. CONCLUSION

This paper studied different learning model and some recent techniques for automation of the process to automatically identifying respective categories. It also highlighted shortcomings in the respective technique and pin pointed the scope for future work. So this study provides a basic outline of the present techniques to identify learner style.

REFRENCES

[1] Keefe, J.W. (1979), “Learning style: An overview”. NASSP's Student learning styles: Diagnosing and proscribing programs (pp. 1-17). Reston, VA. National Association of Secondary School Principles

[2] Felder, R.M., Silverman, L.K.: Learning and teaching styles in engineering education. Engineering Education 78(7), 674–681,1988.

[3] Popescu E, “Diagnosing students’ learning style in an educational hypermedia system”. Cognitive and Emotional Processes in Web-based Education: Integrating Human Factors and Personalization 1:187–208, 2009.

[4] Felder R.M., Are learning styles invalid? (Hint:No!), On-Course Newsletter, 2010.

[5] Kolb DA Experiential learning: experience as the source of learning and development. Prentice Hall, Englewood Cliffs, NJ 1984.

[6] Gardner H, “Frames of Mind: The Theory of Multiple Intelligences”. Basic Books 1993.

[7] Biggs J, “Student Approaches to Learning and Studying”. Australian Council for Educational Research 1987.

[8] Graf S, Kinshuk, Liu TC, “Identifying learning styles in learning management systems by using indications from students’ behaviour”. In: ICALT, IEEE, pp 482–48, 2008.

[9] Sangineto E, Capuano N, Gaeta M, Micarelli A Adaptive course generation through learning styles representation. Universal Access in the Information Society 7(1-2):1–23, 2008.

[10] Latham A, Crockett KA, McLean D, Edmonds B,"A conversational intelligent tutoring system to automatically predict learning styles". Computers & Education 59(1):95–109, 2012.

[11] Alkhuraiji S, Cheetham BMG, Bamasak O (2011) "Dynamic adaptive mechanism in learning management system based on learning styles". In: 11th IEEE International Conference on Advanced Learning Technologies, IEEE Computer Society, pp 215–217, 2011.

[12] Ahmad NBH, Shamsuddin SM, "A comparative analysis of mining techniques for automatic detection of student’s learning style". In: Proceedings of the 2010 10th International Conference on Intelligent Systems Design and Applications, ISDA’10, pp 877–882, 2011.

[13] Crockett K, Latham A, Mclean D, Bandar Z, O’Shea J, "On predicting learning styles in conversational intelligent tutoring systems using fuzzy classification trees". In: IEEE International Conference on Fuzzy Systems, pp 2481–2488, 2011.

