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Automatic Detection of Learning Styles on Learning Management Systems using Data Mining Technique

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Abstract

Objectives: Automatic detection of E-learners' learning styles is an important requirement for personalized e-learning. The present study proposes the detection of students' learning styles automatically on Learning Management System (LMS). **Methods/Analysis:** The present study proposes different technique of automatic detection of learning styles on LMS using Data Mining technique Bayesian Network (BN). A large survey data is used to map the class room learning styles to E-learning environment which provide significance to incorporated LS model on E-learning systems. Standard questionnaire called Kolb's Learning Style Inventory (KLSI) is used to identify the students' learning styles in a class room environment but the proposed technique can automatically detect the learning styles on LMS. **Findings:** The BN resulted probability values were used as threshold values to detect the learning styles of students in an experiment in which the students of a public university of Pakistan were participated. The participants' learning styles were found using the manual method and the proposed method. The experiment provided promising results. **Novelty/Improvement**: Personalized E-learning systems are used to maximize the learning in terms of providing the learning objects as per the students' requirements. The BN technique is used to replace the KLSI to detect the learners' learning styles on LMS automatically.

Keywords: Learning Styles, Student Modelling, Bayesian Networks, E-Learning

1. Introduction

When it is required to understand the students' learning requirements in terms of learning preferences, the learning styles theories are used[1-3]. Incorporating learning styles in personalized E-learning systems are found prolific for enhancing the learning of students[4]. Many learning style theories are given by various educationists and researchers[5-7]. But the Felder Silverman learning style theory[8] is largely used by researchers on LMS for learning styles' identification on LMS[9]. E-learning is the use of Information and Communication Technology (ICT) in learning prospects[10] and found as rapidly growing mode of education these days[11]. However, E-learning is abundant of advantages but on the other hand E-learners suffer from lack of supervision and assistance of the teacher/e-teacher[12,13]. Therefore, personalized E-learning systems provide the learning objects and support as per the students' requirements and needs[14].In this regard learning styles are incorporated in personalized E-learning systems[15]. For incorporating the learning styles on LMS it is important to map the class room learning style theory on LMS using any related attributes, i.e., synchronous and asynchronous activities of e-learners.

For the present study, Kolb's learning styles model (KLSM)[16] is selected which categorizes the learners into four unalike categories of learning styles. This model is used in class room system to improve learning by numerous researchers[17,18] and found significance with auspicious results. In class rooms the KLSI is used to classify the stu-

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dents into the classes identified by KLSM, i.e., Diverger, Assimilator, Converger and Accommodator. The present study will use Data Mining Technique; Bayesian Network to automatically detect the learning styles on web based education systems.

2. Materials and Methods

2.1 Survey Design

To find the mapping between the class room learning styles and the E-learner's activities on LMS, it was required to conduct a survey from the E-learners. Therefore, the sample population was chosen from an online university of Pakistan where the E-learners were registered in various courses of computer science. This survey helped to get the first hand initial data to attain the objectives.

2.2 Questionnaire Design

The questionnaire was designed using the necessary deliberations, i.e., question contents, phrasing/terminology, formation of responses, sequence of all questions, whole layout, revision and final version of questionnaire. The questionnaire was consists of 9 questions to inquire about the E-learning activities of students. However, the standard KLSI[19] was used first from the sample population to identify their learning styles.

2.3 Data Collection

In this survey, 863 students participated who were registered in computer science courses. The same participants were inquired using another questionnaire about their activities on LMS, i.e., login time on LMS, immediate contact person in case of difficulty, frequently used tool to contact their preferred person in case of difficulty, participation activities on Discussion Board (DB), reading behaviour, participation in chat, assignments submission etc. The data was collected using online survey from the sample population when they login for their daily activities of online courses.

2.4 Classification using BN

A Bayesian Network (BN)[20] is acyclic graph and can be used the representation of uncertain facts graphically for imprecise solutions. Following is the basic equation of BN.

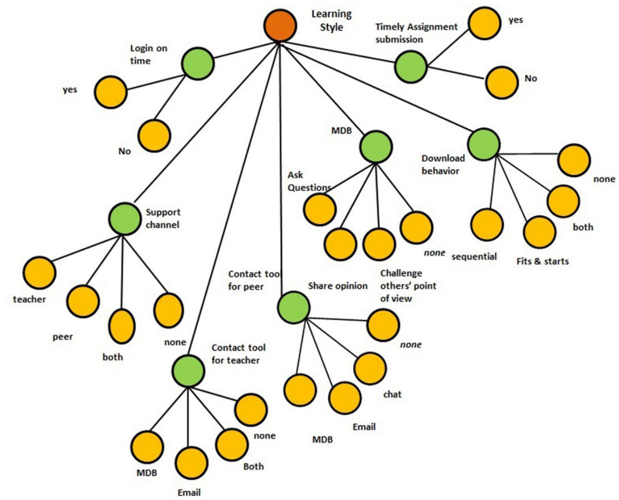

Figure 1. Bayesian network structure for learning styles' detection.

$$p(Cj \mid d) = \frac{p(d \mid Cj)\, p(Cj)}{p(d)} \quad (1)$$

Where
$p(Cj \mid d)$ = probability of instance 'd' being in class 'Cj'
$p(Cj)$ = probability of class 'Cj' occurrence
$p(d)$ = probability of occurrence of instance 'd'.

In Bayes Theorem the conditional/marginal probabilities are correlated. These can produce the conditional probabilities of random variables. If U be the universe of variables then the chain rule is used. Therefore if U = $\{A_1, \ldots, A_n\}$ then the joint distribution of U can be found by.

$$P(U) = \prod_i P(A_i \mid P(A_i)) \quad (2)$$

Using the attributes mentioned in section 2.4, the BN graph is represented by Figure 1.

The data mining software was used to process the data results of survey. The BN produced the Conditional Probability Tables (CPT) for each learning style using each attribute. These probabilities will unceasingly be updated with the interaction of the students with LMS when he /she will perform any activities on LMS. The BN inference mechanism will continuously update the values to identify the students' learning styles. Figure 2 is used to represent the CPT for students' behaviour to attend the online lecture.

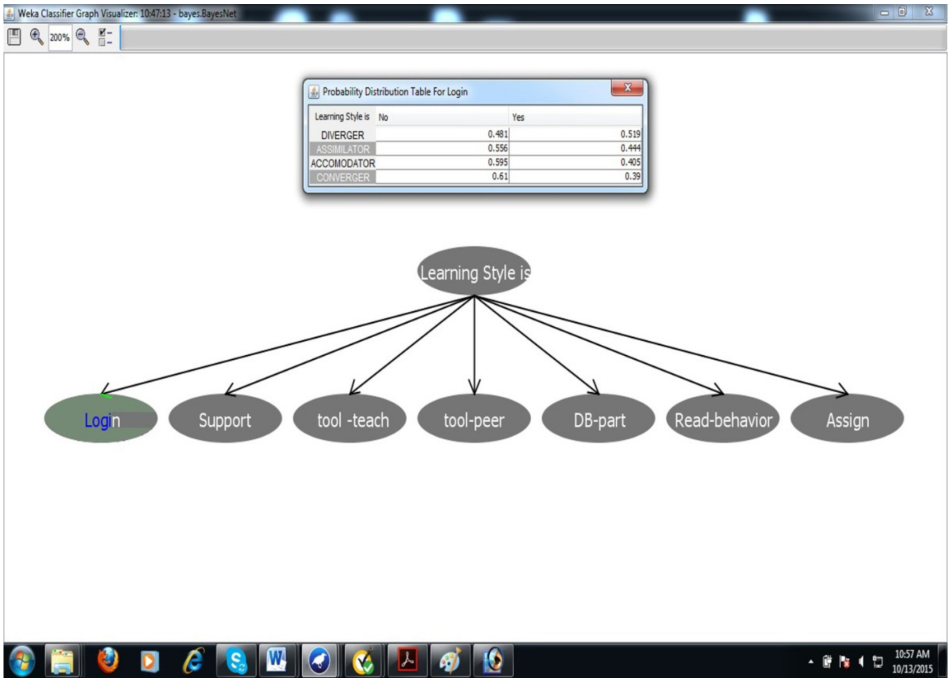

Figure 2. Represents the CPT for students' behaviour for online lecture.

3. Results and Discussions

The results obtained from the processed data using data mining software will be discussed in this section. The participants were 863 in number which were registered in different courses mentioned above. The survey data obtained from the students was pre-processed and then processed using Data Mining software. Then BN classifier was used to obtain the CPTs for each learning style. Figure 3 is used to show the processing of data using Data Mining Software.

The BN classification provided the learning styles from the survey data are mentioned in Table 1. This is

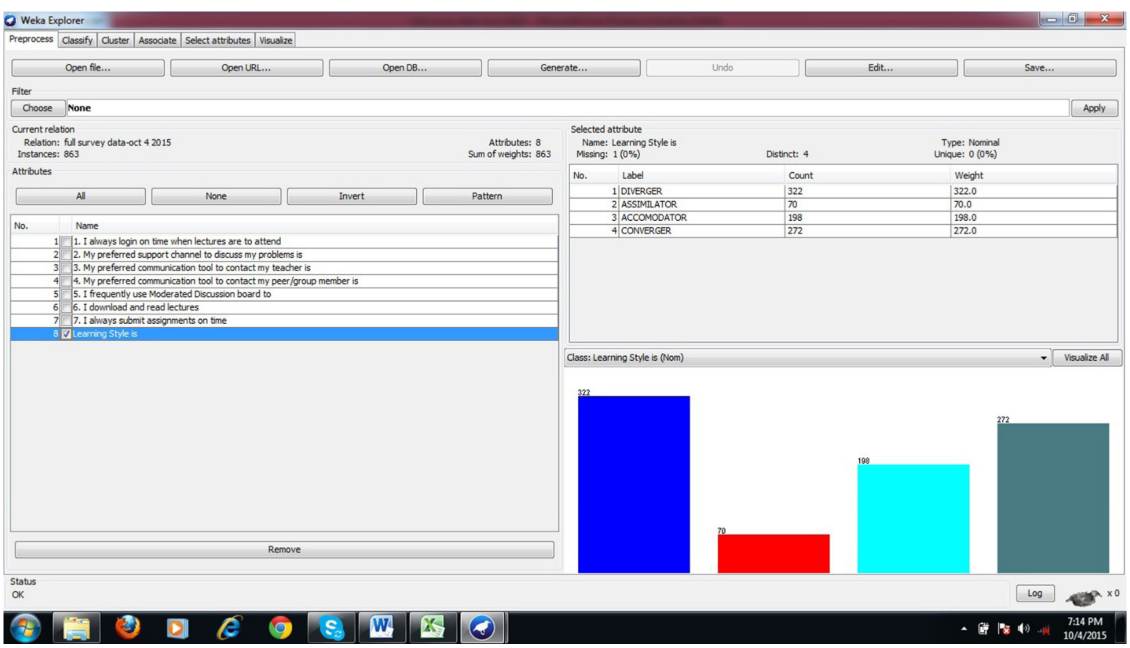

Figure 3. Shows the results of number of students fall into the learning style as per the given data.

Table 1. Represents the number of students fall in each class as per the survey data

Sr#	Learning Style	Number of Students
1.	Diverger	322
2.	Assimilator	70
3.	Accomodator	198
4.	Converger	272

the actual identification of learning styles found from the sample population. However, Table 2 is used to represent the probability values obtained using BN for each learning styles different activities on LMS. Table 2 is depicting only Divergers' activities threshold values.

The attained probabilistic values in form of CPT were stated. These values were evaluated with 20 users of a public University of Pakistan using a course of BS-Education, named "Child Development (CD)". The students were chosen from the conventional class room system to record their first experience with learning management system. Students' log records were averaged and

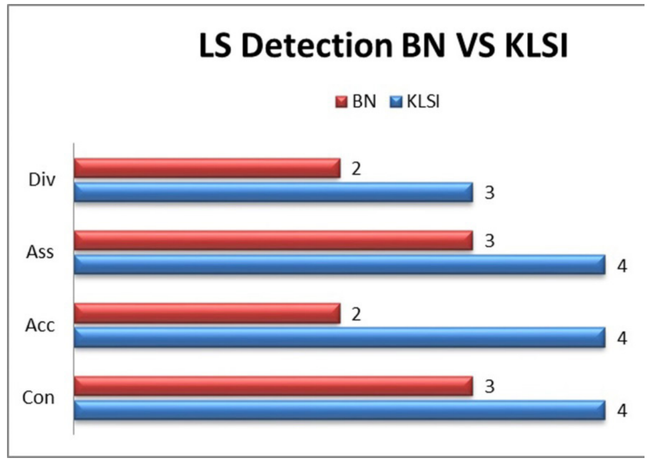

Figure 4. Learning styles detection using KLSI vs. BN.

then matched with known values for each learning styles. Eventually, when the system collected log information about the student's interaction behaviour, the probabilities acquired for each learning style were matched with already known values from BN called threshold values. These values helped us to know the learning style

Table 2. Represents the CPT for learning style (Diverger)

Attributes	Class DIVERGER: P(C) = 0.37297921			
Login on time	**No**	**Yes**		
	0.48148148	0.51851852		
Contact person in difficulty	**other**	**Both a and b**	**Peers**	**Teacher**
	0.11349693	0.4202454	0.32515337	0.14110429
Contact tool for teacher	**other**	**Both a and b**	**Emails**	**Discussion Board**
	0.1595092	0.32822086	0.28527607	0.22699387
Contact tool for friends	**Chat**	**Discussion Board**	**Emails**	**None of these**
	0.50613497	0.1809816	0.20552147	0.10736196
Discussion board	**No participation**	**Ask Questions**	**Challenge other**	**Share point of view**
	0.32208589	0.38343558	0.09509202	0.1993865
Download Material	**Fits and starts**	**Both a and b**	**Sequential**	**No download**
	0.21165644	0.39570552	0.30674847	0.08588957
Assignment Submission	**On time**	**Not on time**		
	0.82407407	0.17592593		

automatically on LMS. Figure 4 is used to demonstrate the results. The students' learning styles were already identified by using KLSI then they were selected to participate in this online course. After using BN techniques, the 66.67% of Divergers were found positive on LMS. Similarly, 75% of Assimilator identified automatically, 50% of Accommodators and 75% of Convergers were found accurate.

4. Conclusion

The present study has used a data mining technique BN for detection of learning styles on LMS, the acquired CPT values were evaluated using an experiment and found promising results. However, the results can be better in future by improving the technique. The technique used can be incorporated in personalized E-learning systems to know about the students' learning preferences to teach them accordingly.

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