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AN IMPACT OF LEARNING BEHAVIOR AND CREATIVITY QUOTIENT IN LEARNING ENVIRONMENT

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Abstract: Data Mining (DM) is the process of searching through collecting and analyzing a huge amount of data in a database, which detects patterns or relationships. DM techniques are used to find an association between the Learning behavior and Creative Quotient (CQ) Level of students. Expectation Maximization (EM) is used to determine the similarity of students' creativity and learning behavior. Each cluster reveals the learning behavior of the student and Creativity. Multilayer Perceptron (MLP) predicts the learning behavior of students and their CQ Level. It reveals that there is a positive correlation between student CQ Level and Learning behavior. This analysis could help the staff members to provide the right training to the students for their improvement of CQ Level.

Keywords: Multilayer Perceptron, Criterion Reference Model, Learning Behavior, DAPLB Approach, Expectation Maximization Clustering.

I. INTRODUCTION

Educational data mining (EDM) is a research area that deals the various methods to explore data in an educational system [13]. EDM uses computational approaches to evaluate educational data in order to study educational questions. These methods are used for better understanding of students in the learning environment. Criterion – Reference Model is used to categorize the student performance (Marks) based on the criterion. The theory and practical marks are considered for prediction, which can be viewed as a performance. This paper deals with educational objectives, which determine the student's creative quotient level in educational setting and student's performance with respect to their Creative Quotient Level. The EM clustering technique is used for categorizing the student objects based on their creative quotient level into classes of similar students 'objects **[1]**. Similarly the student performances are classified as Level 1, Level 2, Level 3 and Level 4. MLP is a network model that combines sets of input data onto a set of appropriate outputs [14]. MLP is used for classifying subcategory in the students' dataset. It is one of the approaches for discriminating the pattern of subcategories. The results reveal useful information through mining and determine interesting patterns of the specific category. Experimental unit variables are used for finding patterns in the students' dataset. An observational unit variable finds the subcategory of the creative quotient level. Similarly it classifies the performance of students. This paper finds the association between the Creative quotient level of the students and their performance based on supervised and unsupervised learning process.

II. MOTIVATION

A. Learning Behavior

The learning style or behavior is defined as "the way each person absorbs and retains information and skills". Each learner possesses an individual learning style, which is a preferential mode of learning. Learning style in college education varies among individual students and groups of students. The patterns of repetitive and consistent learning behavior in the classrooms are observed. Such patterned behaviors or characteristics of the styles of learning. The learning style characteristics are 1) Serious, Analytical learners 2) Observation-Centered Learner 3) Active, Practical learners 4) Nonadaptive Struggling learner 5) Passive Accepting Learner and 6) Concrete, Detail, Fact Oriented Learner [2].

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The problem of discrimination and learning behavior classification is mainly concerned with differentiating between g (g>=2) mutually exclusive students and with classifying learning behavior on the basis Multivariate observations [3,4]. The sub category problem is a mutually exclusive population according to their attributes and classifying an unseen instance into its sub categories using multiple features. In this study, the subcategories are experimental unit variables and observed features are observational unit variables.

Learning styles are characterized based on abstractness and correctness in learning style or motivation and responsibility. The proposed model determines the learning style and is able to characterize, how the mind functions are while learning.

B. Criterion –Reference Model

A criterion – reference model is a model used for assessing the level to which student has attained the goal of course. The assessment is carried out with specific criteria. The results are expressed in terms of relations that match the students' performance with the given criteria. The result is assigned on the basis of the standard that the student ha achieved on the criteria [5,6].

C. Expectation Maximization (EM) Clustering

The EM algorithm is an iterative refinement algorithm that can be used to find the parameter estimation. It assigns an object to the cluster that is similar to the cluster mean. Instead of assigning each object to a dedicated cluster, which assigns the data objects in a cluster based on the weight using membership probability. There are no restricted boundaries between the clusters. The mean values are calculated and computed based on the weight [9].

D. Multilayer Perceptron

In this technique, the data objects are classified based on the weights. It is a network of simple neurons call perceptrons. The various real world inputs are weighted and computed based on the nature of data. The inputs are processed in the input layer and outputs are determined using nonlinear activation function [8].

III DAPLB APPROACH

This approach is divided into four phases which is depicted in Fig 1. In Phase I, the research questions are designed by the expert based on (learning behavior and Performance) and pretest the questionnaire. After pretesting a questionnaire, the learning behavior and performance test have been conducted in Under Graduate Course.

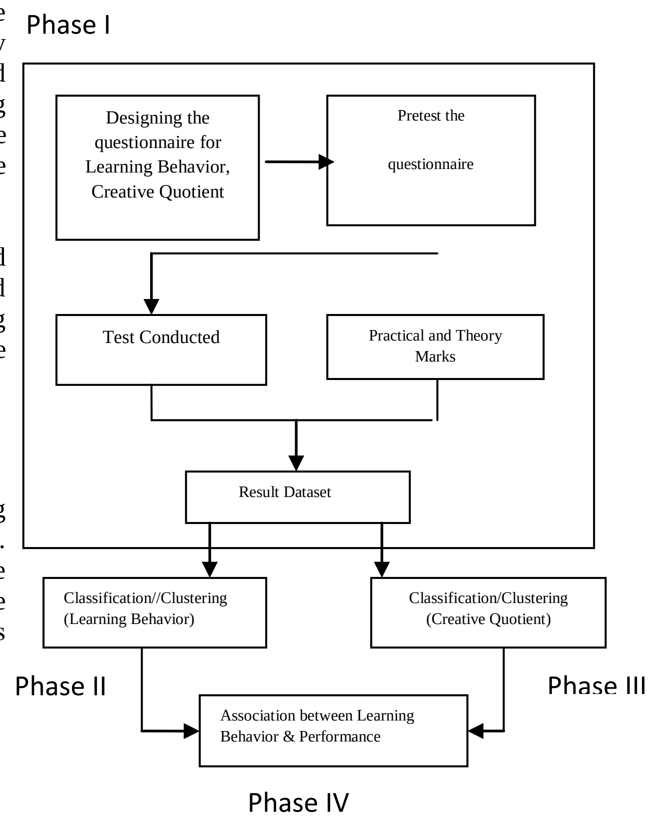

Fig 1: DAPLB Approach

The theory and practical marks are obtained from the semester exam, which is viewed as CQ Level 1 (Marks >=80), Level 2 (>=60), Level 3(>=40) and Level4 (<=39). [5, 6, 10, 11] based on Criterion-Referenced Model.The students' dataset contains the test results of Learning Behavior and performance of the students in the written and practical test in CQ Level.

In Phase II and III, EM clustering and Multi Layer Perceptron techniques are employed to find the association between the Learning Behavior and CQ. Each Cluster group the students according to the Creative Quotient Level designate the cluster as 'Level 1, Level 2, Level 3 and Level 4' based on their performance.

EM clustering reveals the identity of the students' Learning behavior and designates the cluster as 1) Serious, Analytical learners 2) Observation-Centered Learner 3) Active, Practical learners 4) Nonadaptive Struggling learner 5)

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Passive Accepting Learner and 6) Concrete, Detail, Fact Oriented Learner.
The MLP technique is used to classify the learning behavior of the students. The six sigmoid nodes are used as experimental variables, the weights are described to each node, and the data objects are classified based on the category of learning behavior. Similarly the skill-based classification can be carried out based on the CQ Level.

In Phase IV Association rule mining is used for finding the relationship between creative quotient levels with performance and Learning Behavior of students.

IV RESULTS AND DISCUSSION

The association between the Creative Quotient level with Performance and Learning Behavior of the students have been analyzed with the dataset containing 320 students.

Table 1: Cluster assignments on CQ Performance

C0	C1
242	78

Table 1 depicts the various clusters and corresponding CQ Levels are identified. It reveals that Level 2 students are grouped in cluster 0. Level 3 students are grouped in cluster 1.

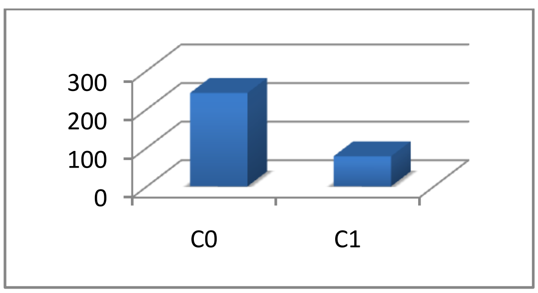

Fig 2. Comparison of CQ Level

Fig 2 reveals Comparison of CQ Level in C0 and C1. It depicts that Level 2 students are grouped in Cluster 0. Level 3 students are grouped in Cluster 1.
Table 2 reveals the various clusters and corresponding learning behavior are categorized. It reveals that Active and practical learner objects are silhouetted in cluster 0, Concrete detail, fact oriented
learner objects centered learner objects are silhouetted in cluster 2 and cluster 3, Passive accepting learner objects are silhouetted in cluster 1 and cluster 4,Observation are silhouetted in cluster 4 and Non-passive struggling learner objects are silhouetted in cluster 1.

Table2. Cluster assignments on Learning Behavior.

C0	C1	C2	C3	C4	LB
112	0	0	0	0	AP
0	0	75	86	0	CF
0	13	0	0	6	PA
0	0	0	0	18	OB
0	10	0	0	0	NPA

Table3. Confusion Matrix for Learning Behavior

Cross Validation		Predicted					
		a	b	c	d	e	Learning Behavior
Actual	a	112	0	0	0	0	AP
	b	0	161	0	0	0	CF
	c	0	0	18	0	1	PA
	d	0	0	0	18	0	OB
	e	0	0	0	0	10	NPA

Table 3 represents that the categorization of various objects related to the Creative Quotient level by using supervised learning (Multi Layer Perceptron). In this technique, the accuracy measures are used to group the objects perfectly without any misclassification. The table value denotes that Active students' objects are grouped. It shows that the accuracy of the model which is good for classification for the unknown test data.
Table 4 clearly indicates that the general ways of learning, which majority of Under Graduate Students preferred. Approximately 35% of the students have viewed themselves as Active Learners. 7% of the students are Concrete Detailed learners, 23% of the students are Passive learners, 27% of the students are Observation learners, 8% of the students are Non-Passive Learners, who agreed with the preferred learning styles.

Table 4. Learning Style Preferences

Learning Style Characteristic	Response	Agreement %
Active and Practical Learner	112	35
Concrete Detail, Fact Oriented	23	7
Passive Learner	75	23
Observation	86	27

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Non-Passive Learner	24	8

Table 5.a reveals that the correctly and incorrectly classified instances show the percentage of test instances that were correctly and incorrectly classified. The raw numbers are shown in the confusion matrix, with a, b, c, d and e representing the class labels.

Table 5.a: Stratified Cross Validation

Correctly Classified Instances	319	99.6875 %
Incorrectly Classified Instances	1	0.3125%

Fig 3.a. represents that the correctly classified Instances and Incorrectly classified Instances .It is evident that the correctly classified Instances are 99% and incorrectly classified Instances are 1%.

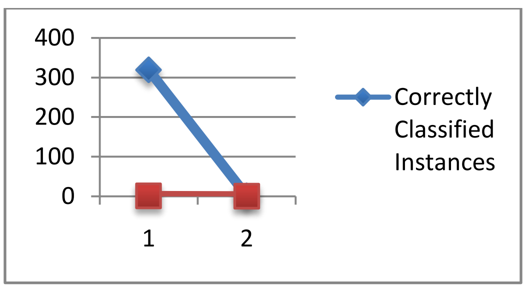

Fig 3.a Stratified Cross Validation

Table 5.b. Error Rate

Types of Error	Values
Mean Absolute Error	0.009
Root Mean Squared Error	0.0398
Relative Absolute Error	3.6399
Root Relative Squared Error	11.3355

Table 5.b shows error rate of the dataset in predictive modeling. It reveals that the various types of errors are measured, which is Mean Absolute Error ,Root Mean Square Error, Relative Absolute Error and Root Relative Square Error. The Mean Absolute Error rate value is low relatively the Root Mean Squared Error value is also low. It indicates that the classification model is good.

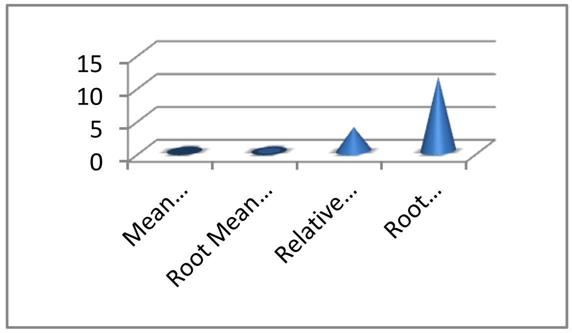

Fig 3.b Error Rate in DALP Dataset

Fig 3.b. depicts the Error rate of the dataset. It reveals that the various types of errors are measured, which is Mean Absolute Error ,Root Mean Square Error, Relative Absolute Error and Root Relative Square Error. The Mean Absolute Error rate value is low (0.009) relatively the Root Mean Squared Error value is low (0.0398). The Root Relative Squared Error is high (11.3355) relatively the Relative Absolute Error is high (3.6399).

Table 6: Classification accuracy by class

TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	Class
1	0	1	1	1	1	AP
1	0	1	1	1	1	CF
0.947	0	1	0.947	0.973	0.997	PA
1	0	1	1	1	1	OB
1	0.003	0.909	1	0.952	0.997	NPA
0.997	**0**	**0.997**	**0.997**	**0.997**	**1**	**WA**

Table 6 reveals that, the various measures are used for predicting class labels. Weighted Average (WA) is calculated for the all the measures, such as True Positive rate is 0.997, False Positive is 0, Precision is 0.997, Recall is 0.997, F-Measure is 0.997 and ROC Area is 1. The class labels are identified based on Learning behavior and designates the cluster as 1) Serious, Analytical learners 2) Observation-Centered Learner 3) Active, Practical learners 4) Non-Adaptive Struggling learner 5) Passive Accepting Learner and 6) Concrete, Detail, Fact Oriented Learner.

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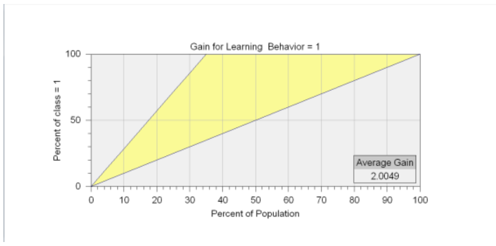

Fig 4. Gain Char for Active Practical Learner

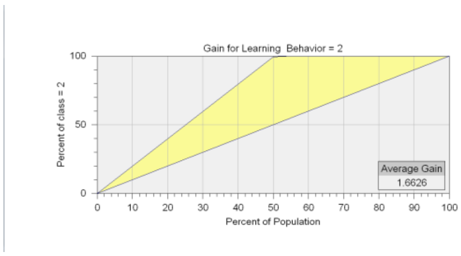

Fig 5. Gain Chart for Concrete Fact Oriented learner

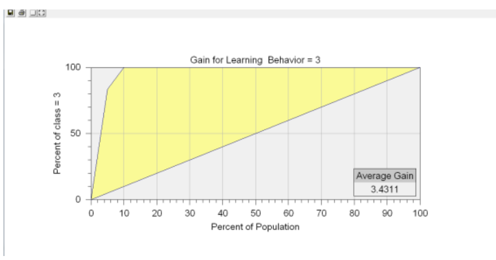

Fig 6. Gain Chart for Passive Accepting Learner

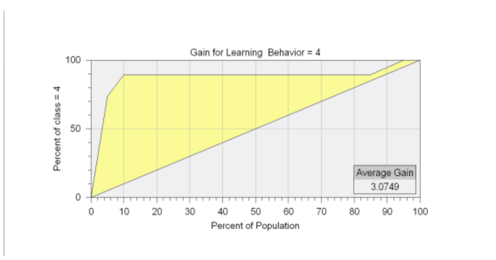

Fig 7. Gain Chart for Observation Learner

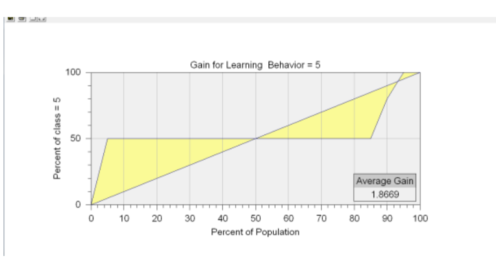

Fig 8. Gain Chart for Non-Passive Learner

Fig 4, Fig 5, Fig 6, Fig 7 and Fig 8 depicts that the gain chart is used for calculating the efficiency rate for DAPLB dataset using MLP. The gain values show how much improvement the model provides in picking out the best. Cumulative gain is the ratio of the expected class of Learning Behavior using the model to prioritize the student participants divided by the expected class of Learning Behavior. The average gain is found to be 2.0049 for Active Practical Learner, 1.6626 for Concrete Fact Oriented Learner, 3.4311 for Passive Accepting Learner, 3.0749 for Observation Learner and 1.8669 for Non Passive Learner.

V. CONCULSION

EM clustering and MLP are applied to find Creative Quotient Level among students. In EM clustering the students' objects are identified and categorized based on the creative level. It reveals that there misclassification exist in this unsupervised learning. In supervised learning, the objects are classified without any misclassification. MLP technique classifies the data objects such as Active Practical learners, Passive Accepting Learner, Observation Learner, Concrete Detail Fact Oriented Learner and Non-Passive learner and models each cluster. The classifier reveals that, each individual student's learning behavior related with CQ Level .The students having an Active practical Learner have good CQ Level, some students having Passive and Observation Learner also have good in CQ Level, Non-Passive and Concrete Fact Oriented Learner are need to improve in CQ Level. This analysis reveals that the creativity plays an important role in formal education, which enriches the creativity behaviour of students in the course of study. The educators should concentrate on the creativity characteristics of students and provide enough training to improve their creativity.

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