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Learner-Oriented Customization of E-Learning Systems

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ABSTRACT: *E-learning uses media, information and communication technology for learning. In traditional classroom teaching, a teacher motivates and adapts his/her teaching style according to the level of students/learners. In contrast, e-learning environment lacks this feature; material is presented to all types of learners in the same manner. Classification of learners is needed to mimic the behavior of classroom teaching so that material based on learners' interest can be presented. In the present work, we have used Multi-LayerPerceptron's (MLP) for learner classification. For that, three new attributes, namelyLearning Rate, Environmental Affectability and Rote Learning have been computed. We have generated data (attributes) for different levels of students, built MLP-based classifiers and reported experimental results on them.*

Keywords: *classification, learning rate, environmental affectability, rote learning, e-learning*

I. INTRODUCTION

Learning is defined as a process of permanent/potential behavioral change in internal processes such as thinking, attitudes, rote learning and emotions. E-learning is learning through an electronic interface which uses virtual learning environment (VLE)[2,3]. E-learning is also referred as internet based distance learning, virtual learning, digital multimedia learning, distributed learning, Learning Management Systems (LMS), web-centric learning etc. Fundamentally, all of the above techniques use digital and multimedia information and networking technology in the process of learning. Here the learning pattern may be asynchronous or synchronous [3].

Theories of learning are conceptual frameworks describing how information is absorbed, processed, and retained during learning [5]. Also very important is the fact that individuals differ in how they learn [14]. Learning styles encompass a series of theories suggesting systematic differences in individuals' natural or habitual pattern of acquiring and processing information in learningsituations. Learning styles are strategies that a learner applies often in a given learning environment. One of the hypothesisof this paper is that if we can directly or indirectly capture the learning style of a student through learning data-derived attributes, the same may then be used to classify learners.

This paper addresses the process of classifying learners by collecting data from some learning activities. We have specifically used the following three parameters/features: (i) Learning Rate (LR)–A measure combining the time taken to complete learning activities with the probability of committing mistakes; (ii) Environmental Affectability of learners(EA) – measures how satisfied the learner is with the learning environment (iii) Rote Learning (RL) - Based on the ability of a student to exactly reproduce what is learnt. We name the students as "applied learners" when they are able to effectively apply the concepts given for learning. If a student knows the concepts but unable to apply them he/she is termed as "rote learners".

The input dataset consists of the data generated from the activities/exercises of undergraduate engineering students (learners). After data collection, classifier is used to learn the knowledge levels (classes) of students.

II. LITERATURE REVIEW

Conventional classroom is still the predominant mode of learning in Indian undergraduate programs. There are several known shortcomings of the mode, such as large numbers of students and limited meeting times, which make it difficult to understand each student closely. Student classification is a way to solve the problem by mapping the condition of each student based on certain parameters. Many methods have been applied to classify students that are based on IF-THEN rules and pattern recognition [13]. In[10] different mining techniques are used by various researches and their mining purposes were under studied. Sixteen different learning styles were identified by Felder Silverman to classify the learners. Among these learning styles most of the learners come under the category Active/Sensor/Visual/Sequential. In[12][2][18] a group of students were analyzed using MOODLES based on various parameters that stored in the log files then these students were clustered based on their learning behavior. In [9][17]to help teachers to perceive and interpret the learner's activities in e-learning situations, by exploiting and analyzing the tracks and providing knowledge on the activities, and to automatically determine the learners' learning style in web based learning fromlearning indicators has described.

III. FEATURES

3.1 Learning rate

We have given some online exercises to different levels of students. Based on the questionnaire style and the time taken to complete the exercises, learning rate is calculated using formula(1). It gives the overall probability of learners committing mistakes in that exercise. Recommended probability of correctly answered questions and time of completion from the expert of the course is also obtained. Using them, Learners Rate is computed as follows:

$$\Delta LR = LR_A - LR_P = \frac{N - M_A}{T} - \frac{1 - \bar{M}_P}{\bar{T}_P} \quad (1)$$

Here ΔLR is the difference between learner's rate and predicted rate. $LR_p$is the predicted rate and $LR_A$is learner's rate. N is the number of exercises in this session, M_A is the number of mistakes in this session, T is time of this session, $\bar{M}_P$is mean of predicted time taken to complete the exercises in this session.

3.2 Environmental Affectability [6]

Environmental factors are the factors that exercise impact on learners with respect to location, ambience and convenience. Though learning environment has some impact on learners, its degree varies from learner to learner. For that, the system is designed to ask some questions regarding learners' environment. Some of the environmental effect related questions are given below:

- Temperature/humidity
- Seating/Poster comfort
- Visual comfort
- Ventilation

For each question, the learner needs to select a value between 1 and 3 indicating his/her affectability from the environment. Here, response 1 indicates that they are not comfortable, 2 implies they are partially comfortable and 3 implies that they are fully satisfied. Based on the responses, learner's environmental affectability is computed using the formula shown below:

$$\text{ENF} = \frac{\sum_{i=1}^{4} ES_{1i}}{\sum_{i=1}^{4} ES_{2i}} \; X \; \frac{\bar{T}_1 - \bar{T}_{PS1}}{\bar{T}_2 - \bar{T}_{PS2}} \; \text{X} \; \frac{\bar{F}_1 - \bar{F}_{PS1}}{\bar{F}_2 - \bar{F}_{PS2}} \quad 2)$$

ENF is the Environmental Factor.$\sum_{i=1}^{4} ES_{1i}$is the satisfaction degree for session by most satisfaction degree. $\sum_{i=1}^{4} ES_{2i}$is the satisfaction degree for session by least satisfaction degree. $\bar{T}_1$and $\bar{T}_2$ are average times of doing exercises by learner, $\bar{T}_{PS1}$and $\bar{T}_{PS2}$ are average of predicted time, $\bar{F}_1$and $\bar{F}_2$ are average of mistakes for learner, $\bar{F}_{PS1}$and $\bar{F}_{PS2}$ are average of predicted mistake probability related to sessions 1 and 2.and $\bar{T}_2$are average times of doing exercises by learner, $\bar{T}_{PS1}$and $\bar{T}_{PS2}$are average of predicted time, $\bar{F}_1$and$\bar{F}_2$ are average of mistakes for learner, $\bar{F}_{PS1}$and $\bar{F}_{PS2}$ are average of predicted mistake probability related to sessions 1 and 2.

3.3 Rote Learning

Rote learning technique forgoes understanding or analyzing the concept and emphasizes only on blind memorization. This is many times used where a learner needs to recollect certain information quickly like standard formulae in physics. This technique is generally followed in school level where the students or learners need to remember the basic knowledge like atomic number, symbol and names of elements in chemistry, syntax of a particular language in computer programming language etc.,

In rote learning the student will mug up the concepts without any understanding. This leads to failure in situations where his/her knowledge is tested by changing the questions or questions emphasizing application of that concept. With rote learning the learner lacks creativity which becomes hindrance for further development in that area.

Rote learning also lacks in correlation among different concepts that the learner come across in the process of learning. In rote learning, sometimes the syntax of the concept is correct but semantically it may convey an inappropriate meaning. Studies show that learners who understand the concepts will excel in problem-solving or in applying the knowledge when compared to rote learners

It is strongly discouraged by many new curriculum standards. For example, science and mathematical practices in the United States specifically emphasize the importance of deep understanding over the mere recall of facts. In some instances of learning of math and science, rote methods are used by students to memorize formulas etc. But there would be greater understanding if students commit a formula to memory through practical exercises. Newer standards often recommend that students derive formulas themselves to achieve proper understanding. It shows that students who learn with understanding are able to utilize their knowledge in problem-solving better than those who learn only by rote.

IV. CLASSIFICATION OF LEARNERS

We have used WEKA tool for our classification task. WEKA is a collection of machine learning algorithms for data mining tasks. It contains techniques/methods for data pre-processing, classification, regression, clustering, association rules and visualization [11].

We prepared a data set of 134 undergraduate engineering students. From this data set 100 samples are used for training and 34 students for testing, based on the 3 parameters described above. The learners are classified by human experts based on the above parameters as follows.

If LR>=6 and EF>=6 and RL<=5 then LT =rapid

If LR<6 and LR>=4 and EF<6 and EF>=4 and RL>5 and RL < =7 then LT =medium

If LR<4 and EF<4 and RL>7 then LT =slow

This data is converted to the ARFF format as required by WEKA[1][7][8]. We processed this data on compatible classifiers present in WEKA and the Kappa statistic, Mean Absolute Error(MAE) and Root Mean Squared Error(RMSE) are noted. We compared the performance of different model building algorithms to identify the outperforming classifiers.

Kappa statistic

Cohen's Kappa statistic [15] measures, for each classifier applied, the agreement between ground truth labeling and the labeling provided by the classifier. Simple method for calculating Kappa statistic from confusion matrices can also be seen in Wikipedia [16]. Kappa statistic varies between 0 and 1. Higher the Kappa, stronger the agreement between the classifier and ground truth. If Kappa = 1, then there is perfect agreement. If Kappa = 0, then there is no agreement. Values of Kappa from 0.40 to 0.59 are considered moderate, 0.60 to 0.79 substantial, and above 0.80 outstanding [8].

Mean Absolute Error (MAE)

Mean absolute error can be defined as sum of absolute errors divided by number of predictions. It measures how close a predicted model is to the actual model.

$$\text{MAE}(y, \hat{y}) = \frac{1}{n_{\text{samples}}} \sum_{i=0}^{n_{\text{samples}}-1} |y_i - \hat{y}_i| .$$

A lowvalue of MAE suggests that prediction and accuracy of the model is better.

Root Mean Square Error (RMSE)

Root mean square error is defined as square root of sum of squares error divided number of predictions. It measures the differences between values predicted by a model and the values actually observed.

$$RMS = \left(\frac{1}{n} \sum_{i=1}^{n} (\text{model}_i - \text{observed}_i)^2 \right)^{\frac{1}{2}}$$

Small value of RMS Error means better accuracy of the model.

Results obtained from Classifiers w.r.t Kappa Statistics, MAE and RMSE

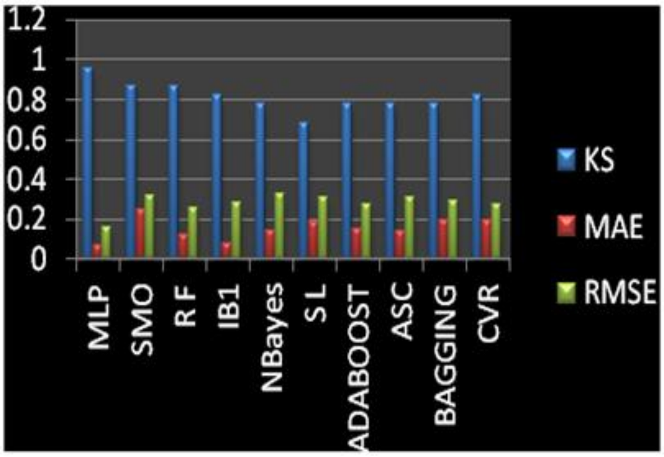

Fig: 1 Graph shows the comparisons of different error rates using table 1.

S.no	Algorithm	Kappa statistic	MAE	RMSE
1	MLP	0.9547	0.067	0.1612
2	SMO	0.866	0.2484	0.3166
3	Random Forest	0.8649	0.1196	0.2593
4	IB1	0.8187	0.0784	0.2801
5	N Bayes	0.773	0.1445	0.325
6	Simple Logistic	0.6779	0.1814	0.3078
7	ADABOOST	0.7736	0.151	0.2771
8	ASC	0.7766	0.137	0.3074
9	BAGGING	0.7748	0.1946	0.2935
10	CVR	0.8177	0.191	0.2691

From the above results we observed that Multi Layer Perception (MLP) outperformed the other classifiers with respect to Prediction and Accuracy to our test data. Hence we use MLP to classify our Learners.

Different algorithms used for model building search in different hypothesis spaces. Also, the expressibility of models differs from algorithm to algorithm. For the current data, multi layer perceptions seem to find the hypothesis closest to the actual underlying distribution.

4.1 Using Multi Layer Perception (MLP)

Multi Layer Perception (MLP) is a feed forward neural network which uses the back propagation technique. It is composed of multiple layers of nodes between input and output layers. Each node performs relatively simple operation.

Nodes in a layer (*i*) are connected to the nodes in the layers (*i-1)* or (*i+1*). The nodes in the input layer are non-computational and they use an identity function. The intermediate and the output layers use a sigmoid function. In feed forward technique data flows in forward direction from input layer to output layer. In intermediate layers the input from the previous layer is processed and the result is propagated to the next layer for further process, until the final result has been computed. The MLP is trained with the back propagation learning algorithm. Recently researchers are widely using MLPs for classification, prediction problems, patterns recognition, approximation etc.

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Table-1: Shows accuracy of different classifiers

Experimentation

The Scrutiny process consists of four steps. These steps imply the usage of the Weka Explorer application. The first step is to prepare a training dataset from learners based on the three parameters chosen for this paper. This is in the shape of an ***arff***file where all experiences of users are placed. The second step is to feed the training dataset to WEKA. The third step is to select the MLP module in WEKA and choose the proper features [4]. Once the test options are selected, the results are obtained. The final step is to have an understanding and usage of the results.

The features from the .arff file are:

@RELATION students
@ATTRIBUTE Learningrate NUMERIC
@ATTRIBUTE Environaffect NUMERIC
@ATTRIBUTE Rotelearning NUMERIC
@ATTRIBUTE class {slow, medium, rapid}

Each attribute is self-evident and is computed for each student from the activity logs and questionnaire. The last attribute represents the class where each student is placed in the input dataset. The *class* attribute has three values: s*low, medium* and *rapid*.

A sample of the data section from the *arff* file is presented below.

@DATA
6, 10, 5, rapid
4, 7,4, medium
12, 6, 5, rapid
10, 7, 4, rapid
3, 5, 4, slow
……….

Each line in the data section represents a student. The first value represents a student Learning rate, the second one represents the environmental affectability and third one is rote learning. Based on the above 3 features, we have supplied 34 instances for testing. Running the Multi Layer Perception (MLP) algorithm has been performed on this test data and the following result has been obtained.

=== Run information ===

Scheme: weka.classifiers.functions.MultilayerPerception -L 0.3 -M 0.2 -N 500 -V 0 -S 0 -E 20 -H a

Correctly Classified Instance	33 97.0588%
Incorrectly Classified Instances	1 2.9412%
Kappa statistic	0.9547
Mean absolute error	0.067
Root mean squared error	0.1612
Relative absolute error	15.3967 %
Root relative squared error	34.5512 %
Total Number of Instances	34

=== Detailed Accuracy By Class ===

TP Rate	FP Rate	Precision	Recall	F-Measure	Class
1	0.04	0.910.947slow			
1	0	1	1	1	high
0.9	0	1	0.9	0.947	Medium

=== Confusion Matrix ===

a	b	c	<-- classified as
9	0	0	a = slow
	15	0	b = rapid
1	0	9	c = medium

V. CONCLUSIONS

This paper analyses learners on three parameters, and uses MLP for classifying them. From the learner's performed activity we gather data as an input for our research/classification. The MLP classifier results were very promising and it was able to accurately classify the learners. The MLP was able to correctly classify

97 percent of the input instances. Accurate classification of learners help in designing a good e-learning environment/system. It also helps in promising/delivering the appropriate content to the learners. Once an acceptable accuracy is obtained the procedure may be integrated to work as a service along an e-learning environment. We can extend our analysis to larger/more number of parameters and classify the learners accurately.

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