Analysis of Learner Strategies Obtained in IDEL Using Classification & Clustering Techniques

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Abstract: In eLearning environment learning contents are precious source of information. The contents vary from simple written text embedded with images, visuals, graphs, tables, charts to audios/videos. Personalized eLearning systems deliver learning objects to according to certain need and objective of personalization. An interactive Dynamic eLearning Framework for Visual and Verbal Learners (IDEL) is a personalized learning object delivery and recommender system that address the learning strategies in terms of visual, verbal, listening and reading [1]. This paper aims to analyze and validate the nine learning strategy groups created in IDEL using classification and clustering techniques like Naïve Bayes, J48 and K-Means.

Keywords – Clustering Techniques, Classification, Naïve Bayes, K-Means.

I. INTRODUCTION

IDEL is a web based eLearning system that utilizes a multimodal approach to detect the learning strategies of visual and verbal learners. The approach uses visual/verbal dimension of Felder Silverman Learning Style model and aural/read-write dimension of VARK model. In IDEL a preference identification method detects the learning strategies of visual and verbal learners. Upon signup profile of a learner is created and learning strategy is stored in learner profile database [1].

Data mining allows to analyze and visualize raw data for better understanding easily. The aim of educational data mining (EDM) is to find meaningful information that is useful for various stakeholders in education [2]. The data mining techniques available in literature are divided into three categories as classification, clustering and association rule mining. Data mining has several applications in intelligent tutoring systems. It is used to group students according to a certain data pattern, evaluate student performance and predict student performance, provide feedback to instructors, providing recommendation to students etc. Data mining algorithms such as K-Means, Fuzzy C-Means, Apriori, FP Growth are frequently used by researchers to mine the educational data. Review of various educational data mining techniques and their applications in eLearning are discussed [2], [3], [4]. R Koppisetty has provided an extensive review of applications of data mining in adaptive and intelligent tutoring system [5].

II. LITERATURE SURVEY

Classification is a supervised data mining technique used to predict categorical data. The method or classifier assigns a data item from feature space to a target class or a label. Generally, it predicts the class labels from a given set of known class categories to an unknown set of similar data items where predictor class label is missing.

Liyanage, M. P. P., KS, L. G., & Hirakawa, M. (2016) proposed an automated system to predict learning styles using data mining techniques such as J48, Naive Bayes, Bayesian Network and random forest by integrating Weka tool with Moodle LMS for log analysis. The learning styles of newly registered students are found using ILS Questionnaire. The authors evaluated learning logs of 80 students and found that J48 decision tree algorithm to be best suitable for classification [6].

Mesaric, J., & Sebalj, D. (2016) used decision tree classifiers to classify the students in two classes as per the success rate in academic exams conducted at the end of year. The authors implemented REPTree and J48 algorithms for classification and performed an analysis to find the factors that affects the academic success. REPTree has achieved highest rate in classification up to 79% as compare to J48 but could not able to generate the tree for both classes [7].

Y. Helmy., A. Abdo., R. Abdallah (2016) proposed a hybrid framework that uses ILS questionnaire for learning style

 DOI : 10.18231/2454-9150.2017.0004

ISSN : 2454-9150 Vol-03, Issue-05, Aug 2017

detection and Decision Tree, Naive Bayes, Neural Networks and Support Vector Machine for classification [8].

Abdullah, M., Daffa, W. H., Bashmail, R. M., Alzahrani, M., & Sadik, M. (2015) conducted a study to evaluate learner style impact on performance of learners in eLearning environment for providing recommendations to learners and instructors. The data collected through Blackboard LMS is analyzed using classification techniques in Weka tool. The NB Tree classifier provided the highest accuracy value of 69.697% the author suggest that the model is applicable for Felder Silverman Learning Style Model and the 12% increase is observed in performance of students with the proposed approach [9].

A Naive Bayes classifier is implemented by Kozierkiewicz Hetmanska, A., & Bernacki, J. (2015) for classification of students in terms of the learning outcomes in an intelligent tutoring system [10]. Levashenko, V., Zaitseva, E., Kostolny, J., & Kvassay, M. (2015) used fuzzy classifiers and fuzzy decision trees for solving the classification problem in an educational web portal [11]. For predicting the outcome Ribeiro, B., & Cardoso, A. (2008) used neural network and support vector machine based classification system that works on learning logs taken from a Moodle based and adaptive eLearning environment [2]. Chellatamilan, T., Ravichandran, M., Suresh, R. M., & Kulanthaivel, G. (2011). proposed a system to predict learning styles in eLearning environment using the data mining techniques ID3, J48 Decision trees and K Means Clustering [13].

Clustering is an unsupervised learning technique. In clustering grouping of objects is done based on similarity characteristics. Similarity measures varies according to application and requirement. Like classification clustering techniques are also used to group the known data items and usually they are applied on to predict clusters upon a set of data items with various distance / dimension measures.

Yang, J et al., (2014) has proposed an approach to dynamically find the learner style using information patterns. The authors implemented a method that predicts the learning style by observing critical learning behavior. The system creates clusters of learner according to learning style. To verify the system predicts and creates the desired clusters 30 students were asked to complete the ILS questionnaire and results were compared. The author's claim that the learning style predication accuracy of approach is high as compare to previous studies [14].

Sajjadi, S., Shapiro, B., McKinlay, C., Sarkisyan, A., Shubin, C., & Osoba, E. (2017) used grade data to obtain the predictive clusters for early detection of success or failure. The authors used K-means data mining technique with fivefold cross validated dataset [15]. Murugananthan, V., & Shivakumar, B. L. (2014) has developed a framework "eLearn" to group and classify the contents using K-Means method. The authors claim to achieve 89.998% system performance accuracy [16].

Mirabedini, S. (2013). has proposed a new clustering algorithm that automatically finds the number of clusters. This approach was developed to overcome the problem of specifying number of clusters prior to apply a clustering technique like K-Means algorithm which iteratively finds the specified number of clusters using the data set [17].

Varghese, B. M., Unnikrishnan, A., Sciencist, G., Kochi, N. P. O. L., & Kochi, C. U. S. A. T. (2010). has used two clustering algorithms K-Means and Fuzzy C-Means to reveal the hidden patterns from a digital educational database that contains over 8000 records. In this study, the internal assessment and university assessment results were correlated with attends and numbers of sessions attended [18].

Manish Joshi et al., analyzed learning content access / visits behavior of 176 students using Crisp Fuzzy C-Means and Rough K-Means clustering algorithm in Moodle LMS to detect learning styles. The authors discussed the concept of overlapping cluster and demonstrated how to identify learning styles using the non-crisp clustering techniques for creating three clusters named as studious, crammers, workers according to their study patterns [19]. Despotovic Zrakic et al., implemented a tool for creating clusters using K-Means algorithm based on the learning behaviors in one-week duration using LMS. All the three clusters represent the learning styles in FSLSM [20]. Kock, M., & Paramythis, A. (2010) introduced multi-level clustering technique to identify the problem-solving styles using the learning activity sequence behavioral data in an intelligent tutoring system [22]. Rodrigo, M. M. T., Anglo, E. A., Sugay, J. O., & Baker, R. (2008) proposed a method to characterize the learning behavior and affective states of learners using K-means clustering algorithm in Weka [23].

III. DATA ANALYSIS USING DATA MINING TECHNIQUES

In IDEL, the learning strategies are identified using the explicit approach of learning style detection. 62 Learners have participated into experiment conducted in IDEL. Table The data obtained through these tests is stored into database. The relation strategy stores the identified learning strategy of each learner. The data in strategy table is used for analysis. The analysis is carried out to suggest the classification and clustering methods that provides best results on the data set obtained using the proposed approach. Data mining tool Weka is used to perform the data mining and analysis. The figure below shows the snapshot of the input database relation used for data mining and analysis in Weka tool. As shown in figure there are 62 instances that stores the learning strategy of

 DOI : 10.18231/2454-9150.2017.0004

individual learner based on learning style preference and listening-reading preference. The relation strategy has four attributes LID, FLSP, FLRP, FLST.

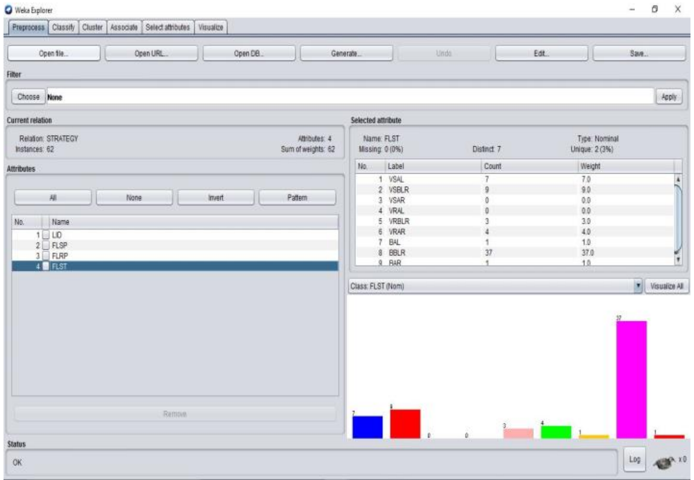

Figure 1: Input data in Weka Tool

3.1 Classification

Three different versions of Supervised Naïve Bayes Classification and J48 algorithm in Weka tool is used for analysis and evaluation on data in strategy table. Evaluation of full training data set, 10-fold cross validation and 66% split for training and remaining 34 % for testing is carried out. Table 1 shows the results and comparative analysis of both the classifiers. J48 decision tree classifier has achieved higher accuracy in 10-Fold-Cross Validation test mode on the dataset obtained by explicit approach.

Table 1: Classifier Accuracy Comparison

Classifier	Test Mode	Total Instances	Correctly Classified	Incorrectly classified	Accuracy
Naive Bayes	evaluate on training data	62	60	2	96.7742 %
Naive Bayes	10-fold cross-validation	62	59	3	95.1613 %
Naive Bayes	split 66.0% train, remainder test	21	19	2	90.4762 %
J48 pruned tree	evaluate on training data	62	60	2	96.7742 %
J48 pruned tree	10-fold cross-validation	62	60	2	96.7742 %
J48 pruned tree	split 66.0% train, remainder test	21	19	2	90.4762 %

3.1.1 Results of Naive Bayes Classifier

The results achieved using Naïve Bayes Classifier algorithm in Weka tool are shown below for all the three test modes.

3.1.1.1 Test Mode -10-Fold Cross-Validation

```
=== Run information ===
Scheme:      weka.classifiers.bayes.NaiveBayes -D
Relation:    STRATEGY
Instances:   62
Attributes:  4
             LID
             FLSP
             FLRP
             FLST
Test mode:   10-fold cross-validation

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances          59               95.1613 %
Incorrectly Classified Instances         3                4.8387 %
Kappa statistic                          0.9161
Mean absolute error                      0.0406
Root mean squared error                  0.1091
Relative absolute error                 28.3372 %
Root relative squared error             41.7496 %
Total Number of Instances               62

 a b c d e f g h i   <-- classified as
 7 0 0 0 0 0 0 0 0 | a = VSAL
 0 8 0 0 0 0 0 1 0 | b = VSBLR
 0 0 0 0 0 0 0 0 0 | c = VSAR
 0 0 0 0 0 0 0 0 0 | d = VRAL
 0 0 0 0 3 0 0 0 0 | e = VRBLR
 0 0 0 0 0 4 0 0 0 | f = VRAR
 0 0 0 0 0 0 0 1 0 | g = BAL
 0 0 0 0 0 0 0 37 0 | h = BBLR
 0 0 0 0 0 0 0 1 0 | i = BAR
```

3.1.1.3 Test Mode - Split Train and Test Mode:

```
=== Run information ===
Scheme:      weka.classifiers.bayes.NaiveBayes -D
Relation:    STRATEGY
Instances:   62
```

 DOI : 10.18231/2454-9150.2017.0004

ISSN : 2454-9150 Vol-03, Issue-05, Aug 2017

Attributes: 4
LID
FLSP
FLRP
FLST
Test mode: split 66.0% train, remainder test

=== Evaluation on test split ===

== Summary ===
Correctly Classified Instances 19 90.4762 %
Incorrectly Classified Instances 2 9.5238 %
Kappa statistic 0.764
Mean absolute error 0.0441
Root mean squared error 0.1143
Relative absolute error 30.9947 %
Root relative squared error 46.257 %
Total Number of Instances 21

=== Confusion Matrix ===
a b c d e f g h i <-- classified as
2 0 0 0 0 0 0 0 0 0 | a = VSAL
0 2 0 0 0 0 0 0 0 0 | b = VSBLR
0 0 0 0 0 0 0 0 0 0 | c = VSAR
0 0 0 0 0 0 0 0 0 0 | d = VRAL
0 0 0 0 0 0 0 0 2 0 | e = VRBLR
0 0 0 0 0 0 0 0 0 0 | f = VRAR
0 0 0 0 0 0 0 0 0 0 | g = BAL
0 0 0 0 0 0 0 15 0 | h = BBLR
0 0 0 0 0 0 0 0 0 0 | i = BAR

3.1.2 Results of J48 Classifier

The results achieved using J48 Classifier algorithm in Weka tool are shown below for all the three test modes.

3.1.2.1 Test Mode -10-Fold Cross-Validation:

=== Run information ===
Scheme: weka.classifiers.trees.J48 -C 0.25 -M 2
Relation: STRATEGY
Instances: 62
Attributes: 4
LID
FLSP
FLRP
FLST
Test mode: 10-fold cross-validation

J48 pruned tree

FLSP = VIS
| FLRP = AL: VSAL (7.0)
| FLRP = BLR: VSBLR (9.0)
| FLRP = AR: VSBLR (0.0)
FLSP = VER
| FLRP = AL: VRAR (0.0)
| FLRP = BLR: VRBLR (3.0)
| FLRP = AR: VRAR (4.0)
FLSP = VVB: BBLR (39.0/2.0)
Number of Leaves : 7
Size of the tree : 10

=== Stratified cross-validation ===

=== Summary ===
Correctly Classified Instances 60 96.7742 %
Incorrectly Classified Instances 2 3.2258 %
Kappa statistic 0.9448
Mean absolute error 0.0139
Root mean squared error 0.0851
Relative absolute error 9.691 %
Root relative squared error 32.5658 %
Total Number of Instances 62

=== Confusion Matrix ===
a b c d e f g h i <-- classified as
7 0 0 0 0 0 0 0 0 0 | a = VSAL
0 9 0 0 0 0 0 0 0 0 | b = VSBLR
0 0 0 0 0 0 0 0 0 0 | c = VSAR
0 0 0 0 0 0 0 0 0 0 | d = VRAL
0 0 0 0 3 0 0 0 0 0 | e = VRBLR
0 0 0 0 0 4 0 0 0 | f = VRAR
0 0 0 0 0 0 0 1 0 | g = BAL
0 0 0 0 0 0 0 37 0 | h = BBLR
0 0 0 0 0 0 0 1 0 | i = BAR

3.1.2.2 Test Mode - Split Train and Test Mode

=== Run information ===
Scheme: weka.classifiers.trees.J48 -C 0.25 -M 2
Relation: STRATEGY
Instances: 62
Attributes: 4
LID
FLSP
FLRP
FLST
Test mode: split 66.0% train, remainder test
J48 pruned tree

FLSP = VIS
| FLRP = AL: VSAL (7.0)
| FLRP = BLR: VSBLR (9.0)
| FLRP = AR: VSBLR (0.0)
FLSP = VER
| FLRP = AL: VRAR (0.0)
| FLRP = BLR: VRBLR (3.0)
| FLRP = AR: VRAR (4.0)
FLSP = VVB: BBLR (39.0/2.0)

Number of Leaves: 7
Size of the tree: 10

DOI : 10.18231/2454-9150.2017.0004

ISSN : 2454-9150 Vol-03, Issue-05, Aug 2017

=== Evaluation on test split ===
Time taken to test model on test split: 0 seconds

=== Summary ===

```
Correctly Classified Instances        19          90.4762 %
Incorrectly Classified Instances       2           9.5238 %
Kappa statistic                    0.7981
Mean absolute error                    0.0302
Root mean squared error                   0.1199
Relative absolute error              21.1738 %
Root relative squared error            48.5342 %
Total Number of Instances              21
```

=== Confusion Matrix ===

```
 a  b  c  d  e  f  g  h  i   <-- classified as
 2  0  0  0  0  0  0  0  0 |  a = VSAL
 0  2  0  0  0  0  0  0  0 |  b = VSBLR
 0  0  0  0  0  0  0  0  0 |  c = VSAR
 0  0  0  0  0  0  0  0  0 |  d = VRAL
 0  0  0  0  0  2  0  0  0 |  e = VRBLR
 0  0  0  0  0  0  0  0  0 |  f = VRAR
 0  0  0  0  0  0  0  0  0 |  g = BAL
 0  0  0  0  0  0  0 15  0 |  h = BBLR
 0  0  0  0  0  0  0  0  0 |  i = BAR
```

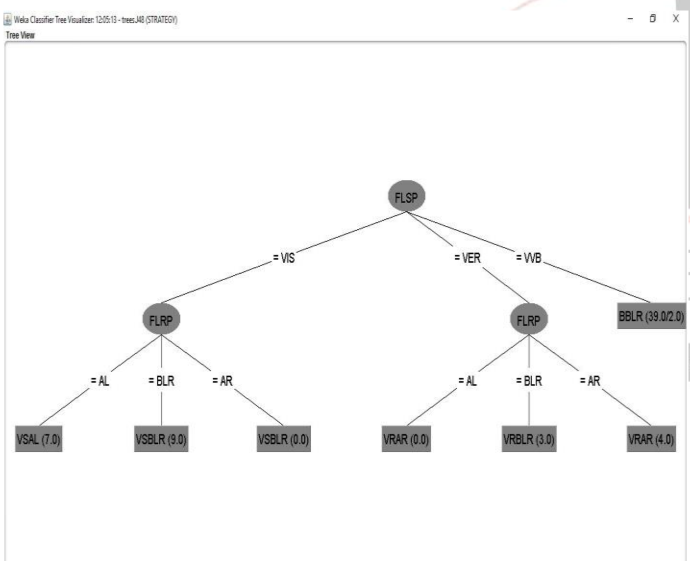

Figure 5.11 j-48 Pruned Tree

3.2 Clustering using Simple K-Means Algorithm

K-Means clustering technique is used to create the group of learners possessing similar learning strategies. For the data obtained through the proposed framework Simple K-Means algorithm is used to create the learning strategy clusters using the attribute FLST. Simple K-Means algorithm is executed in two ways for classes to clusters evaluation on training data test mode using Euclidian distance. Initially the scheme is run using random initialization point and later executed by choosing Farthest First point.

Table 2: Clustering Accuracy Comparison

Initial Starting Point	No of Instances	No of Iterations	Sum of Squared Errors	Correctly Clustered Instances	Accuracy
Random	62	5	5.79	30	48.39
Farthest First	62	6	1.22	43	69.35

5.9.3.1 Simple K-Means with Random Initialization:

=== Run information ===

Scheme: weka.clusterers.SimpleKMeans -init 0 -max-candidates 100 -periodic-pruning 10000 -min-density 2.0 -t1 -1.25 -t2 -1.0 -N 9 -A "weka.core.EuclideanDistance -R first-last" -I 500 -num-slots 1 -S 10
Relation: STRATEGY
Instances: 62
Attributes: 4
LID
FLSP
FLRP
Ignored:
FLST
Test mode: Classes to clusters evaluation on training data

kMeans
======

Number of iterations: 5
Within cluster sum of squared errors: 5.797705323283124

Initial starting points (random):

Cluster 0: 10,VIS,BLR
Cluster 1: 42,VVB,AR
Cluster 2: 34,VVB,BLR
Cluster 3: 19,VVB,BLR
Cluster 4: 1,VVB,BLR
Cluster 5: 44,VVB,BLR
Cluster 6: 14,VVB,BLR
Cluster 7: 39,VIS,AL
Cluster 8: 40,VVB,BLR

=== Model and evaluation on training set ===

Clustered Instances

```
0      9 ( 15%)
1      5 (  8%)
2      7 ( 11%)
3      8 ( 13%)
4      4 (  6%)
5     10 ( 16%)
6      3 (  5%)
7      8 ( 13%)
8      8 ( 13%)
```

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Class attribute: FLST

Classes to Clusters:

0 1 2 3 4 5 6 7 8 <-- assigned to cluster
0 0 0 0 0 0 0 7 0 | VSAL
9 0 0 0 0 0 0 0 0 | VSBLR
0 0 0 0 0 0 0 0 0 | VSAR
0 0 0 0 0 0 0 0 0 | VRAL
0 0 1 0 0 1 0 0 1 | VRBLR
0 4 0 0 0 0 0 0 0 | VRAR
0 0 0 0 0 0 0 1 0 | BAL
0 0 6 8 4 9 3 0 7 | BBLR
0 1 0 0 0 0 0 0 0 | BAR

Cluster 0 <-- VSBLR
Cluster 1 <-- VRAR
Cluster 2 <-- No class
Cluster 3 <-- No class
Cluster 4 <-- No class
Cluster 5 <-- BBLR
Cluster 6 <-- No class
Cluster 7 <-- VSAL
Cluster 8 <-- VRBLR

Incorrectly clustered instances: 32.0 51.6129 %

5.9.3.2 Simple K-Means with Farthest First Initialization

=== Run information ===

Scheme: weka.clusterers.SimpleKMeans -init 3 -max-candidates 100 -periodic-pruning 10000 -min-density 2.0 -t1 -1.25 -t2 -1.0 -N 9 -A "weka.core.EuclideanDistance -R first-last" -I 500 -num-slots 1 -S 10
Relation: STRATEGY
Instances: 62
Attributes: 4
LID
FLSP
FLRP
Ignored:
FLST
Test mode: Classes to clusters evaluation on training data

kMeans
======

Number of iterations: 6

Within cluster sum of squared errors: 1.2214535796402228

Initial starting points (farthest first):

Cluster 0: 14,VVB,BLR
Cluster 1: 52,VIS,AL
Cluster 2: 33,VER,AR
Cluster 3: 56,VER,BLR
Cluster 4: 30,VVB,AL
Cluster 5: 4,VIS,BLR
Cluster 6: 42,VVB,AR
Cluster 7: 2,VIS,AL
Cluster 8: 62,VVB,BLR

=== Model and evaluation on training set ===
Clustered Instances
0 16 (26%)
1 4 (6%)
2 4 (6%)
3 3 (5%)
4 1 (2%)
5 9 (15%)
6 1 (2%)
7 3 (5%)
8 21 (34%)

Class attribute: FLST
Classes to Clusters:
0 1 2 3 4 5 6 7 8 <-- assigned to cluster
0 4 0 0 0 0 0 3 0 | VSAL
0 0 0 0 0 9 0 0 0 | VSBLR
0 0 0 0 0 0 0 0 0 | VSAR
0 0 0 0 0 0 0 0 0 | VRAL
0 0 0 3 0 0 0 0 0 | VRBLR
0 0 4 0 0 0 0 0 0 | VRAR
0 0 0 0 1 0 0 0 0 | BAL
16 0 0 0 0 0 0 0 21 | BBLR
0 0 0 0 0 0 1 0 0 | BAR
Cluster 0 <-- No class
Cluster 1 <-- VSAL
Cluster 2 <-- VRAR
Cluster 3 <-- VRBLR
Cluster 4 <-- BAL
Cluster 5 <-- VSBLR
Cluster 6 <-- BAR
Cluster 7 <-- No class
Cluster 8 <-- BBLR

Incorrectly clustered instances: 19.0 30.6452 %

Table 3: Learner Count in each Learning Strategy

Learning Strategy	IDEL PIM APPROACH	Classification	
		Naïve Bayes	J48
VSAL	07	07	07
VSAR	00	00	00
VSBLR	09	08	09
VRAL	00	00	00
VRAR	04	04	04
VRBLR	03	03	03
BAL	01	00	00
BAR	01	37	37
BBLR	37	00	00

 DOI : 10.18231/2454-9150.2017.0004

IV. CONCLUISION

In IDEL out of nine learning strategies seven learning strategies were adopted by learners. The results of classification show that the profile data is quite accurately classified by using Naïve Bayes and J48 Decision Tree Classification techniques. The K-Means algorithm in Weka has not provided promising results on the profile data. K-Means algorithm with Farthest Initialization method has more accuracy as compare to random initialization method.

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