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AN INNOVATIVE APPROACH OF PROGRESSIVE FEEDBACK VIA ARTIFICIAL NEURAL NETWORKS

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Abstract- This paper highlights the importance of Machine Learning (ML) as an e-planning tool to enhance learning and improve student performances. The ML algorithms can be deployed to intelligently examine the interactions and the activity reports in a Learning Management System (Moodle) to diagnose each student's academic progression. In this study, we group the behavior of students of an online course using the Self Organizing Map. The ML algorithm uses data obtained from the logs of Moodle to obtain a prediction map that permits rating each student's ability to pass a course throughout the semester. Such swift e-planning mechanisms can be immensely helpful in identifying weak performances so that the coordinators, sponsors, parents and even the flagged students can take corrective measures, early in the semester. Within the scope of this work, the predictive attributes are further investigated and compared to reveal the degree of effectiveness of various activities in the online course.
Key Words- Self-organizing map, e-learning, e-planning, artificial neural network, k-means clustering, computers and education

Introduction

Machine Learning (ML), a branch of artificial intelligence, is invariably concerned with the design and development of algorithms that allow computers to evolve behaviors and generate rules based on empirical data [1-6]. The major focus of machine learning research is to automatically learn to recognize complex patterns and make intelligent decisions based on past and/or present data. Therefore, the accomplishments of the ML techniques are primarily based on its ability to derive predictive patterns from a set of features [7] and guide people in decision making.

The literature is inundated with ML techniques including: decision trees, artificial neural networks, support vector machines, logistic regression, Naïve Bayes, genetic programming, k-nearest neighbors, clustering, and inductive logic programming [2, 6]. Each has its own strengths and is more effective in some applications than in others. The ML techniques have been deployed in a wide spectrum of fields such as stock market, data mining, predictive analysis, pattern & speech recognition, e-commerce, computer vision, computer games, medical applications, bio-surveillance and adaptive control [5, 8-11].

In general, the algorithms based on artificial neural networks (ANNs) have proved to be better suited in highly complex and data intensive applications especially for behavior recognition, clustering, feature extraction, approximation and prediction, notably in higher education. Within this, the Self-Organizing Map (SOM) is one of the most popular and amaranthine neural algorithms due to its efficient visualization properties [12].

Background of ML in Education

In the recent past, there has been a significant growth in the use of the ML techniques in the area of higher education. Functionalities such as: student performances [1, 9, 13-14], student modeling [6], mediation of student e-discussions [15], student retention [2, 4-5] and other data mining applications ([16-18] and the references therein) have been established and researched into, with reference to the e-learning systems.

E-learning systems provide multiple ways of learning (self-paced, collaborative, synchronous & asynchronous, tutorial-based, homework, etc.) and incorporate numerous interactive online activities such as forums, quizzes, lessons, blogs, assignments, surveys, glossaries, wiki and workshops [19-20]. Therefore, articulating and identifying user behavior in the e-learning systems can provide new insights into and improve the understanding of how students view and undertake the web-based learning tools and activities. It can also provide guidance for better organization of the courseware and the online learning activities [13, 20-21]. Since the e-learning systems involve acquisition and storage of large volumes of data, which most of the times need to be handled simultaneously, the deployment of artificial neural network is seen as a more effective tool for the analyses. What ANNs also bring to seismic interpretation is the ability to study multiple attributes and their relationships at the same time, a problem that can be too complicated for the human brain.

Kotsiantis et al. in [2] utilized the Naïve Bayes Classifier to identify the poor performing students. However, the work could only predict whether the student will pass the course. Kalles in [4] used the decision trees to identify the poor performing students enrolled in distance education courses. The *early grades* enabled the educators to respond and assist the poor performing students in a timely manner. Baker in [9] had classified students' off-task behaviors based on association rules from Moodle log data. Oladokun et al. in [22] considered the use of ANNs in predicting performances of students considered for admission at university level. While these and other interdisciplinary mechanisms in literature address the attrition rates and the poor performances of students, predicting students' performances early in the semester can help introduce specific remedial measures for the under-performing students and also identify the specific courseware more effective in fulfilling the learning outcomes of a course and garnering optimized students' performances. These are the two seminal objectives of this paper.

The University of the South Pacific

The University of the South Pacific (USP) was set up in the South Pacific region in 1968 by its 12 member countries - Cook Islands, Fiji Islands, Kiribati, Marshall Islands, Nauru, Niue, Samoa, Solomon Islands, Tokelau, Tonga, Tuvalu and Vanuatu. A total of 14 campuses are spread over an area of 30 million square kilometers of the Pacific Ocean. Due to this geographical separation, the university is expected to take its products and services to the doorstep of each and every household in the USP region [23]. This has resulted in a pedagogical shift from traditional face-to-face or chalk-and-talk to more flexible learning modes of delivery. While the print-based has been the preferred mode of delivery, the low pass rates have prompted the educational practitioners to shift emphasis to blended and fully online modes [20].

Contributions

While, the blended and fully online modes introduced in USP are seen as being cost-effective, scalable, innovative, student and learning centered, flexible scheduling of student activities, attracting large student enrolments and providing students an equal platform, a couple of problems they inherently face are the lack of self-motivation and the students leaving assessments until late into the semester. As a consequence, many students fail the courses offered through these delivery modes. Therefore, there is a genuine need to monitor students' performances throughout the semester, provide the *early warning grades* and identify which online activities are the most effective learning tools.

The paper utilizes SOM to address the aforementioned concerns. This unsupervised learning method was chosen since the course examined, MA101 *Mathematics for Social Science*, was offered for the first time in an online mode. Thus, there was no prior knowledge and experience of student's engagement in this online course. Also, monitoring the progress of so many students in the various online activities incorporated in the course would have been a tremendous challenge. SOM compresses information while preserving the most important topological and metric relationships of the primary data items on the display, making the abstraction more comprehendible for the data users.

Organization

We organize the remainder of the paper as follows: In Section 2, we introduce clustering and the SOM algorithm. Section 3 considers the methodology of this research and outlines the experimentation on the MA101 dataset at USP. Section 4 considers the evaluation of results, while we summarize our work and outline directions for future work in Section 5.

The Self-Organizing Map

The Role of Clustering

Clustering involves grouping data or objects into classes bases on similarity measures, using normally the Euclidean distances. Clustering aims to maximize inter-cluster similarities and intra-cluster dissimilarities. It also helps users understand the natural grouping in a dataset. The method is good if it precisely produces clusters with high intra-class and low inter-class distances [see Fig. 1]. Clustering has been commonly used in market segmentation, data mining, e-learning and bioinformatics analysis, etc.

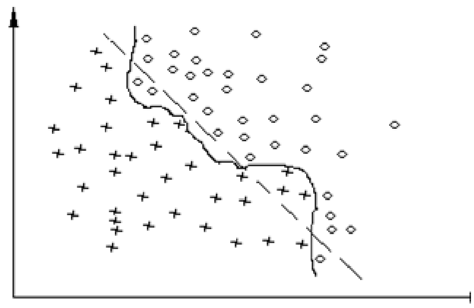

Fig. 1- Two different clusters visualized in 2D and can be separated by a straight or curved line.

In the case of e-learning, clustering algorithms could offer immense opportunities and assistance in identifying poor performers or similar learners, perform courseware evaluation and act as recommender systems (e.g., remedial activities, "study-buddies", personalized site layout, private tutoring, study clinics, etc.). Clustering is also recommended where the nature of courses (activities, assessment portfolio, and coordinator) may change from one offering to the other, and prior knowledge may neither be available nor always appropriate. Hence, SOM has been adopted for analysis and evaluation in this paper.

The SOM for Clustering

The basic SOM model is a set of code vectors with a defined neighborhood relation which could be initialized either randomly or linearly. In linear initialization, eigenvalues and eigenvectors of the training data is calculated first. Then the map is initialized along the greatest eigenvectors. The model, developed by Kohonen in 1983, projects the nonlinear statistical relationships between high-dimensional data into simple topologies such as two-dimensional grids. SOMs thus reduce information while preserving the most important topological relationships of the data elements: samples of *n* dimensions that are close to each other in the input space are also close to each other in the projected output of SOM.

The method does not utilize class information during the training phase, which essentially involves two processes: vector quantization and vector projection [24]. Vector quantization creates a representative set of vectors, classified as the output vectors or code vectors from the input vectors. This significantly reduces the map size to be processed, hence, the computation load decreases considerably thereby making clustering of large datasets feasible. Vector projection basically projects output vectors onto a SOM of lower dimension; projections of two or three dimensions are particularly useful for data visualization *[see Fig. 2].*

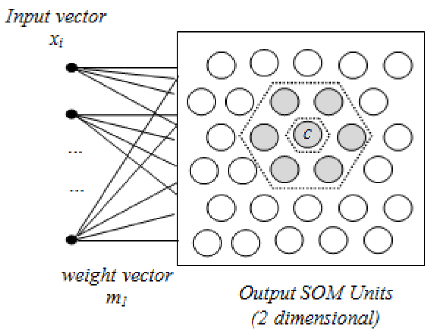

Fig. 2- A graphical representation of the SOM architecture with a 2D hexagonal grid

The Methodology

The SOM Algorithm

The SOMs are trained through a competitive learning process *[Fig. 3].* The winning unit is identified by choosing the neuron which minimizes the Euclidean distance between data samples *x* and the map units *m*. This unit is described as the best matching unit (BMU), signified by the subscript *c*:

$$\|x - m_c\| = \min\{\|x - m_i\|\} \text{ or } c = \arg\min\{\|x - m_i\|\} \quad (1)$$

Where ||.|| is the Euclidean distance measure

Then the map units are updated in the topological neighborhood of the winner unit, which is defined by the neighborhood function. The update can be performed by:

$$m_i(t+1) = m_i + h_{ci}(r(t))[x(t) - m_i(t)], \quad (2)$$

Where t denotes time, and $h_{ci}(r(t))$ the neighborhood function around the winner unit *c* with a neighborhood radius *r(t)* (known as *region of influence*). Gaussian is the commonly used neighborhood function in the SOM network. The region of influence is determined around the winner unit in terms of co-ordinates *r* in the lattice of neurons [25-26].

$$h_{ci}r(t) = \alpha(t)\exp\left(-\frac{\|r_i - r_c\|^2}{2\sigma(t)^2}\right) \quad (3)$$

The learning rate $\alpha(t) \in [0,1]$ must be a decreasing function over time and $h_{ci}(r(t))$ a non-increasing function around the winner unit defined by the topological lattice of map units. The neighborhood has to be large enough in the beginning and during training the neighborhood radius may shrink to 1 unit in order to converge. This way the map self-organizes large neighborhood radius and then fine-tunes with small radius. Hence, the map learns the position of the data cloud. The training process continues until convergence is reached.

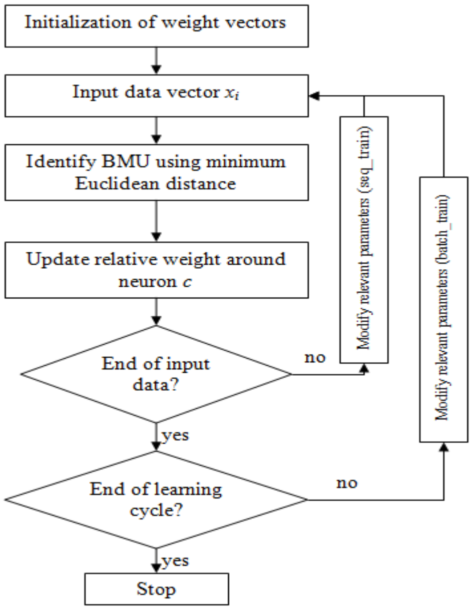

Fig. 3- SOM learning algorithm (sequential training / batch training mode)

Next, we consider the SOM analysis process carried out on the MA101 dataset. The SOM toolbox for Matlab has been used for SOM analysis and visualization. The process is illustrated in Fig.(**4**) and discussed in the following subsections.

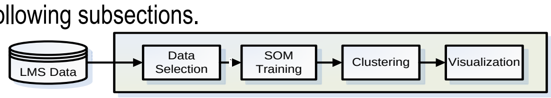

Fig. 4- Phases of the self-organizing map analysis process.

A. Data Selection

MA101 was delivered online via Moodle in semester 2, 2010. The course had 84 students enrolled and had incorporated many online activities such as weekly discussion forums, glossary, lessons, quizzes, chat, blog and surveys, etc. Moodle logs every click that students make for navigational purposes and has a log viewing system built into it [Fig. 5-].

The log reports show summarized student statistics; however, there is still provision for these data to be further evaluated to ascertain knowledge. Activity reports for all students are available and details about each module (last access, number of times read, etc.) as well as the detailed involvement are clearly highlighted. Table 1 lists the attributes extracted/aggregated for each student in the online course.

The objective was to incorporate a mixture of active (forum posting, assignment submissions, quiz attempts, etc.)

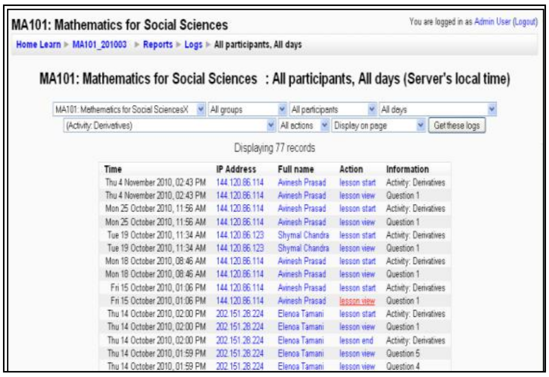

Fig. 5- A screenshot of the Moodle log report of MA101

Table 1- Selected/Aggregated Attributes in MA101

Name	Description
LoginFreq	no. of times student logged in
BlogView	total blogs viewed
BookView	total book pages viewed
ChatView	total time chat module accessed
AssignmentView	no. of time assignments viewed
DistAssignmentView	unique assignments viewed
DistAssignmntUpload	distinct assignments uploaded
CourseView	total forum posting done
FeedbackSubmit	no. of distinct forum postings
ResourceView	total resource material accessed
ChoiceChoose	total choice activity participated in
ForumDiscView	no. of times forums viewed
DistForumView	total unique forum viewed
ForumAddPost	no. of posting to forum
DistForumAddPost	no. of distinct forum participation
glossaryView	no. of times glossary viewed
GlossAddComm	no. of comments posted on glossary
DistGlossAddComm	total distinct glossary posting
LessonStarted	no. of lessons participated
DistLessonAttmtd	no. of different lesson attempted
NumLessonCompleted	no. of lessons completed
NumLessonPassed	no. of lessons passed
LessonAvgScore	average lesson score
QuizStarted	total quiz attempted
DistQuizAttemptd	distinct quiz attempts
NumQuizCompleted	no. of quiz completed
NumQuizPassed	total quiz passed
QuizAvgScore	average quiz score
OnlineCW	interactive cw (quiz & lessons)
ContinuousAssmnt	progressive cw (gradebook)
CourseOutcome	pass or fail

and passive (glossary views, discussions views, resources viewed, etc.) activities. Furthermore, it was ensured that some attributes selected were quantitative while the others reflected the qualitative facets (average quiz score, average lesson score, etc.) of students' performances.

B. SOM Training

After the desired dataset is selected, the data is preprocessed for training. Data preprocessing is a very crucial step when extracting patterns as there are always some aggregated values in the dataset which may contribute to relatively higher range. This has to be scaled to avoid attributes having any initial biasness during training. The histogram equalization based normalization method is applied on the data in order to obtain invariance with respect to the scales of the variables. For our research, we chose 48 map units with topology size of 4x12 for the training.

C. Clustering

The clustering process aims to partition the data in *natural groups*, each describing the different class of performers. In SOM, the grouping is based on similarity measure (Euclidean distance) and carried out on the map units of SOM. We have used the k-means clustering algorithm with k=2 (the number of clusters in which the data is divided) to investigate if the student usage log is successful in identifying the satisfactory and unsatisfactory performers.

D. Visual Inspection

The most widely used methods for visualizing the cluster structure of the SOM are especially the unified distance matrix (U-Matrix) and the distance matrix (D-Matrix) techniques [19]. Fig. 6 shows these two techniques.

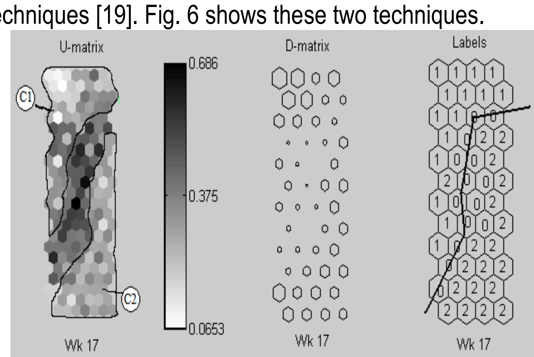

Fig. 6- U-Matrix and D-Matrix techniques for MA101 data

C1 and C2 represents the two clusters formed based strictly on user behavior online and online assessment status. The distances between the code vectors are represented by darker shades. The shaded scale in the middle shows the distance measurement. We note the darker the shades, the greater the distance between the code vectors. Hence, darker shades represent cluster boundaries and lighter region indicates clusters, as visible in the distance matrix (D-Matrix) shown. With the auto labeling feature of the SOM Toolbox, two distinct clusters are identified and labeled as 1 and 2 respectively. Those map units that did not have any hits are labeled as 0.

However, visual inspection can be a tedious process and sometimes may be impossible to isolate clearly the classification boundary. Therefore, we reaffirm the results using a second technique known as the automatic clustering algorithm. Fig. 7 shows the results obtained by the agglomerative hierarchical clustering algorithm included as part of the SOM Toolbox.

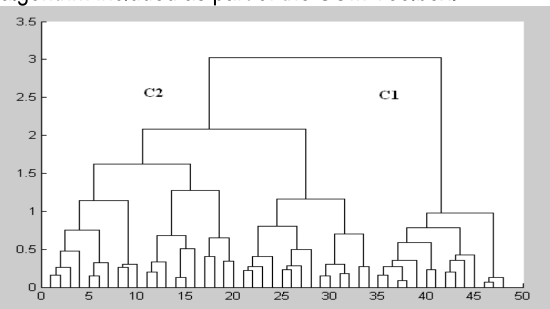

Fig. 7- Hierarchical clustering tree indicating existence of two clusters

Since SOM is an unsupervised learning algorithm, it is difficult to identify what the clusters represented except to deduce from the component planes that C1 represented relatively lower level of user activity compared to C2 (Fig.(**7**)). Replacing the auto labels (Fig.(**8**)) with actual class label obtained at the end of the course indicated that students falling in C1 belonged to the 'fail' class and C2 represented the 'pass' class.

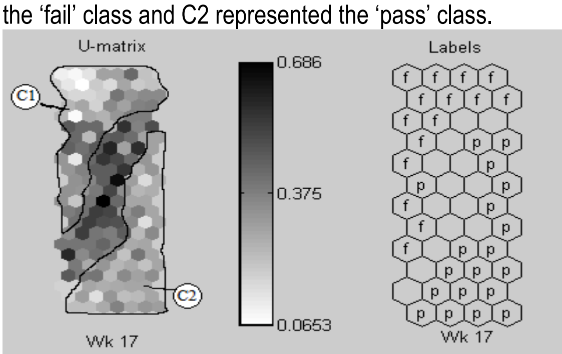

Fig. 8- U-Matrix with class labels of "f" for fail and "p" for a pass in the online course.

Fig. 8 clearly shows the accurate grouping of the data samples by the SOM algorithm. The usefulness of this discovery would be of high significance if the detection of these natural groups could be identified early in the semester. Fig.(**9**) reveals the map using data extracted at different stages during the semester. The progressive visualization and the corresponding U-matrix are outlined with the emerging clusters demonstrated.

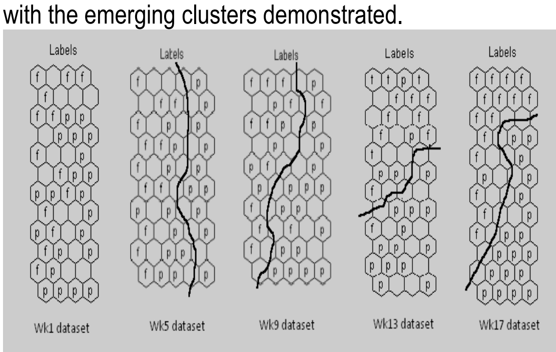

Fig. 9- U-Matrix with class labels at different points during the semester.

Code vectors clearly show the formation of clusters as the course progress during the semester. The clusters start to form from around week 5. However the quality/accuracy seems to be rather low initially. Nevertheless, as visually evident, it shows huge prospect to be able to identify and classify poor performers early in the semester. In the next section we discuss the cluster quality and investigate the attribute contribution towards the early emerging clusters.

Evaluation of Results

In this section, we evaluate the results obtained in the paper. We also discuss the reliability measure of the knowledge extracted via the SOM clustering.

Measuring Cluster Quality

The cluster boundaries seem to be visually distinguishable from the U-matrix representation of the course. However, visual inspection does not guarantee consistency. Hence we used a simple k-means partition-clustering algorithm to automatically distinguish the cluster boundary. K-means is one of the simplest algorithms that employs square-error criterion to minimize with-cluster scatter and maximizes inter-cluster scatter. With SOM already having performed vector quantization, k-means can easily utilize the SOM code vectors to construct k partitions of the data. Fig.(**10**) illustrates the cluster boundary derived by k-means algorithm from dataset extracted towards the end of the semester. The measurement of cluster quality is shown in Table 2.

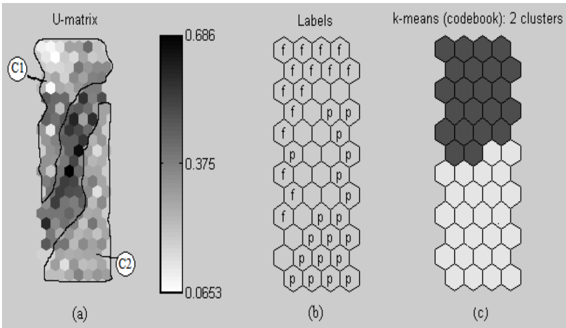

Fig. 10- (a) shows the graphical view if the U-Matrix, (b) shows the labels of the code vectors and (c) shows two clearly separated clusters.

Table 2- Cluster Quality of MA101 at different data extraction points in the semester using the k-means algorithm.

	C1	C2	Total Code Vectors	Accuracy	Mis-classification
1. Dataset extracted at Week 1					
C1 (f)	5	5	10	50.0%	50.0%
C2 (p)	13	12	25	48.0%	52.0%
Average				**48.6%**	**51.4%**
2. Dataset extracted at Week 5					
C1 (f)	8	4	12	66.7%	33.3%
C2 (p)	9	10	19	52.6%	47.4%
Average				**58.1%**	**41.9%**
3. Dataset extracted at Week 9					
C1 (f)	8	4	12	66.7%	33.3%
C2 (p)	8	13	21	61.9%	38.1%
Average				**63.6%**	**36.3%**
4. Dataset extracted at Week 13					

C1 (f)	11	2	13	84.6%	15.4%
C2 (p)	5	12	17	70.6%	29.4%
Average				**76.7%**	**23.3%**
5. Dataset extracted at Week 17					
C1 (f)	12	3	15	80.0%	20%
C2 (p)	4	15	19	78.9%	21.1%
Average				**79.4%**	**20.6%**

Experiments on the dataset indicate progressive improvement to cluster quality as the course progresses in the semester. This measure is an indication of how reliably a particular student can be distinguished into a respective cluster grouping. The results formulated as a graph are demonstrated in Fig. (11). It shows the time-zone from when the under performers in the course could be reliably identified. This is a favorable result and demonstrates the power of clustering and its potential application as a learning tool.

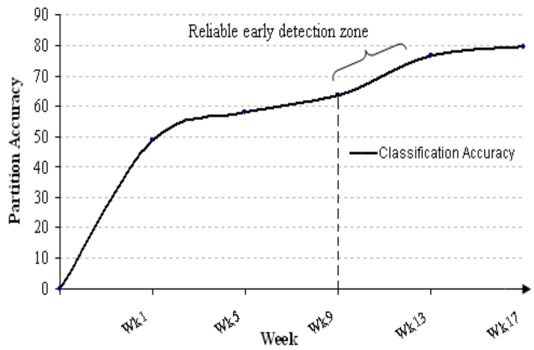

Fig. 11- Graph showing the early detection time-zone for underperformers in MA101

Considering the 17 week semester, having feedback on the underperformers by Week 9 provides sufficient time for course coordinators and students to take corrective and remedial actions. While this study shows significant accuracy in identifying under-performers in week 9 (63.3%), it does indicate by week 5 (58.1%) that there are under-performers in the course. This can be further refined using supervised data to enhance accuracy much earlier in the semester. This will be undertaken in the sequel.

The predictive models in literature have used background information of students and their performances from past courses in predicting current performances; however, *warning signals* progressively in the semester are better placed for early commitment to corrective measures. This helps improve student's performances and subsequently improving the pass rates. In addition, helping under-performing students early in the semester motivates them also and encourages them to do better in the course, hence, also reducing the attrition rate. This innovative approach potentially plays a proactive and pivotal role in improving students' performances in the course.

Another potential is that the SOM architecture can be easily integrated into the e-learning environment as one more traditional authoring tool (course creator, test creator/bank, report tools, etc.). This development can ensure that the tool will be more widely used by educators, and feedback and results obtained with ML techniques could be easily and directly applied to the e-learning environment using an iterative evaluation process.

Investigating Clusters for Courseware Evaluation

Since the SOM codebook already provides quantized vectors and the cluster boundaries, the reduced data dimensions could be further investigated for the effectiveness of various courseware activities. In our analysis we utilized visual inspection (Fig.12) to extract a fairly consistent ranking of features based on their ability to distinguish the differing learners. It is evident that the 'f' class is highly attributed to lower online coursework, less frequent logins, lower forum views and posting done by students, lesser quiz attempts and low quiz pass rate. Chat, glossary contribution and blog activities, however, do not seem to contribute much towards distinguishing the two clusters.

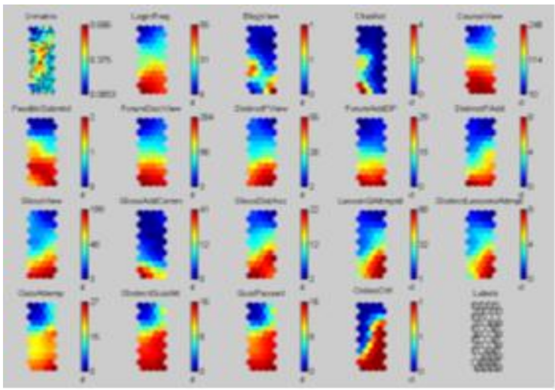

Fig. 12- Visual inspection of attributes of the dataset displayed on the component plane

Next, we use entropy and information gain ratio computation to rank the attributes contribution to the clusters. The data mining experiment was run on WEKA on the code vectors obtained from the SOM algorithm.

Table 3- Attribute relevance ranking obtained on SOM code vectors.

Rank	Attribute	Rank Coefficient
1	ContinuousAssmnt	0.833
2	ForumAddPost	0.594
3	ForumAddPost	0.594
4	DistinctForumView	0.594
5	LoginFreq	0.594
6	QuizPassed	0.581
7	QuizAttemp	0.581
8	DIstinctQuizAtt	0.581
9	CourseView	0.536
10	FeedbkSubmtd	0.536
11	GlossDistAcc	0.536
12	DistinctLessonsAttmpt	0.536
13	LessonQAttmptd	0.536
14	DistinctFAdd	0.536
15	GlossView	0.486
16	ChatAct	0.441
17	GlossAddComm	0.363
18	BlogView	0

The results in Table 3 confirmed that continuous online assessments contribute significantly towards distinguishing the 'pass' and 'fail' clusters. Of the courseware activities, the discussion forum has been found to be highly effective followed by the quizzes. This may be highly likely as the discussion forum hosted homework exercises on a weekly basis due to the very nature of the course. The lesson activity was an average performer whilst the blog activity and chat activities seemed to be ineffective for this particular online offering.
The authors herald the fact that this e-planning approach using neural networks can be particularly useful in developing the online courses. The approach is able to predict which online activities will be most effective for learning at a particular level and in a particular discipline. This will also mean that the online course development will no longer be left to chance and reflective improvements but can be based on predictive performances. Thus the planning process in course development can be much better informed for optimized delivery.

Conclusion

In this paper, we have demonstrated the ability to successfully detect under-performers with reliable accuracy using Self-Organizing Maps (SOM). The SOM was trained and tested using real student data from a first year mathematics course. The study shows the visualization abilities of SOMs to distinguish the different category of learners and investigate the effectiveness of the courseware activities. The SOM is a promising technique as it encompasses various visual representations to stimulate pattern recognition and hypothesis generation by educators and e-learning designers and yet not too complex for these users to make inferences.
The e-planning approach deployed in this paper offers interesting possibilities towards recommending effective online activities to learners, providing incremental learner diagnosis, promoting online collaboration by suggesting "study-buddies" (by grouping similar learners and providing student mentors), and evaluating effectiveness of the courseware activities. Future research could focus on providing feedback to students on preparedness before assessments and using previous data to predict students' performances very early into the semester. Probably warning grades furnished throughout the semester. Also, an in-depth study on which online courseware activities are better for courses placed at different levels in a programme.

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