Differentiated Instructional Content Classification Using Student Modelling Approach

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***Abstract*—The student model plays a main role in planning the training path, supplying feedback information to the pedagogical module of the system in an Intelligent Tutoring System. Student model is the preliminary component, which stores the information about the specific individual learner. In this study, neural network and psychometric analysis captured the student capabilities in a Physics domain in a technology– enabled active learning environment to create a rich interactive learning experience. 415 training sessions from 105 Pre-University Students were tested in this Student Modelling System, to capture their input via Multiple Choice Questions where the student's results were subjected to neural network and psychometric interventions. This is because neural networks can bring psychometric and econometric approaches to the measurement of attitudes and perceptions. Added to it, the differentiated instructional content classification lets the students to ponder upon the learning content based on their ability, rather than tumbling upon the content, which are far beyond their ability and learning reach. The result of this research showed a positive classification of students based on their capability. Looking at the overall percentage of misclassificaiton and that of the correctly predicted group members, the discriminating function gives the acuracy of the model to be presisely at 79.8%. Thus, this research seems to pave way to all the Physics facilitators, who wish to adopt differentiated instruction using student-modelling approach.**

***Index Terms*—multiple choice question, neural network, psychometric analysis, MOOCs**

I. Introduction

To overcome the challenges faced by the teachers and to cater to the needs of their students, e-learning experts in recent times have focused in Intelligent Tutoring System (ITS). In Gheorghiu and Vanlehn paper, they suggested that meaningful, constructive and adaptive feedback is the essential feature of ITSs, and it is such feedback that helps students achieve strong learning [1], gains. Multiple-Choice Questions (MCQs) are one such feature that provides students with feedback [2]. In this study an attempt is made to classify the students based on their capabilities using Neural Network and Psychometric interventions via a Multiple Choice Questions based, Technology-enabled, active learning environment. The result showed the positive classification of students based on their capability.

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II. Background

Many researchers for predictions of students' results used concepts from Artificial intelligence, such as, neural networks. For example, Cooper presents a neural networkbased decision support system that identifies students who are "at-risk" of not retaining their second year of study [3]. The system correctly predicted retention for approximately 70% of the students. Halachev presents a neural network used for the prediction of the outcome indicators of e learning, based on a Balanced Scorecard [4]. Neural networks can bring psychometric and econometric approaches to the measurement of attitudes and perceptions

[5]. Many researchers tried to predict the students' results based on various data. They also used different statistical methods like multivariate regression, path analysis or discriminant analysis. None of these methods has the power of discovering potential data patterns as neural networks. As such, Feed forward neural networks are applied in many fields like financial forecasting, medical diagnosis, bankruptcy prediction and OCR for regression or classification purposes because they are one of the best functional mappers. The good results of applying neural networks in classification problems lead to their usage for predicting students' results in higher education [6]. Thus, in this study, neural network and psychometric analysis are used to classify the students and store the student's knowledge in the form of a student profile or log file. This process of classification of students makes this study a unique one.

Added to the above significance of this study, to overcome the lack of the presence of a teacher, intelligent tutoring systems attempt to simulate a teacher, who can guide the student's study based on the student's level of knowledge by giving intelligent instructional feedback [7]. In addition, in Gheorghiu's and Van Lehn's paper, they have also suggested that meaningful, constructive and adaptive feedback is the essential feature of ITSs and it is such feedback that helps students achieve strong learning gains [8]. Thus, we see that learning activities rely on a feeback mechanism, which is an essential feature of ITSs'. Further, researchers investigating the effect of different types of feedback in web-based assessments showed positive results using MCQs in online test for formative assessment [eg. [2], [9]-[11]]. Hence, this study is also an attempt to prove knew

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knowledge to all those who intend to build a MCQ based Technology-enabled active learning system for classifying their student's capabilities for identifying the readiness of completing a lesson in a Physics domain.

III. Methodology

The data for this study were collected from 105 students who used the Student Modelling online portal for taking their respective MCQ tests. The test data were all Physics MCQ questions, targeting the pre-university students at a private college in Malaysia. The data collected from the 105 students in 3 practice test and one real test, which amounts to 4 x 105 = 420 data sets. These data were collected and stored in the database from October 16th, 2015 through December 4th, 2015.

IV. Data Collection Procedure

Data for this study was gathered from 3 sources. The primary data was from the first year final scores of the students in the physics subject, collected from the Exam department. This data will allow to classify the students based on their general background knowledge in physics domain. This followed a (Phase 1) pre-test, to measure, differences between the students before the intervention to neural network. In the Phase 1, the students were exposed to 3 practice tests in which, first practice test was of Low level category, second test was in Medium level of difficulty and the Third and final practice test in the category of High level.

The secondary data (Phase 2), were gathered from the developed system after the students are exposed to the purposed system intervention by neural network. This way we substantially reduced the threat of selection bias, since the pre-test revealed whether and to which extent the groups differed on the dependent variable (i.e., knowledge level of the subject domain) prior to the intervention [12]. The research design of the study is as shown in the Fig. 1.

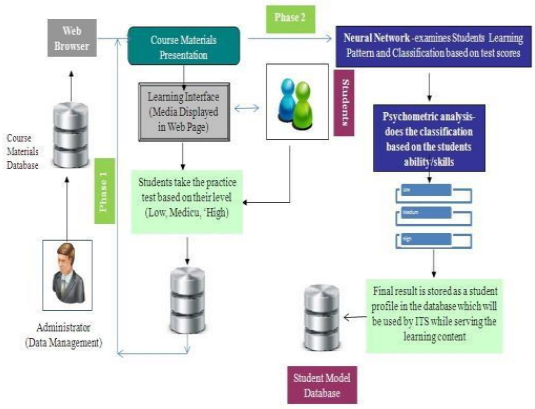

Figure 1. Research design

V. Design of User-interfaces for Various Modules in the Student Model

The Student Model user-interfaces consist of Admin user-interface for the admin (Tutors) to upload the Multiple Choice Questions. This user-interface also includes provision for the tutors to assign the correct answers for each of the uploaded MCQ's which will be categorized based on the different levels of the test being assigned to the students. The next user-interface that will be discussed is the Student Module user-interface that allows students to take their tests based on different levels. The third user interface that will be discussed is the neural network userinterface that is provides the admin to set the learning rules, such as, the weights and range of each category used in the MCQ's. The final module will contain user interface for displaying all the reports that are generated from the student's intervention in the MCQ's and the final results after their Neural Network intervention.

VI. Proposed Student Model

Stage-1 of the Proposed Student Model consists of a Tutor admin where the tutors upload their learning content together with the set of MCQ's for the students to take their MCQ tests. The MCQ's thus uploaded by the tutors are rated as Low, Medium and High level based on the difficulty level of the MCQ questions by the tutors while uploading them to the database server. Such uploaded questions are used both in practice test and as well as real test in the development of Student Model.

VII. Practice Test for Student in Three Levels (LOW, MEDIUM, HIGH)

After the tutors upload the multiple choice questions, students are asked to take online MCQ practice tests that allows them to answer three compulsory set of questions with three test levels. The test are set with low level category, medium level category and high level category. All these MCQ questions are categorized during the tutors upload stage. These three tests are mentioned as practice test and the real test is one which will be taken by the students after the neural network interception. The data obtained from the practice tests are then subjected to Psychometric analysis to determine the classification of students with respect to their capabilities to complete the Online Learning Courses.

VIII. The Background Process During the Practice Test

During the process of the students taking the three practice test, under Low, Medium and High category, the data are stored in the database and at the same time the neural network is trained. In the training phase, the correct class for each record is known (this is termed supervised training), and the output nodes can therefore be assigned "correct" values -- "1" for the node corresponding to the correct class, and "0" for the others. It is thus possible to compare the network's calculated values for the output nodes to these "correct" values, and calculate an error term for each node. These error terms are then used to decide the weights.

The diagram of a neuron with *d* inputs and one output is presented in Fig. 2. Each input has associated a synaptic weight, noted with *w*.

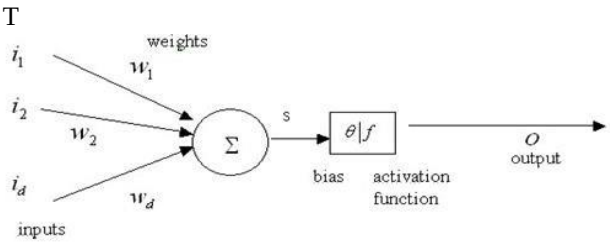

Figure 2. Neuron with d inputs and one output

This weight determines the effect of a certain input on the activation level of the neuron. Before the neural network intervention for student classification, the dataset from the three students practice tests are used as data to train network. Single layer feed-forward network was used for classification. Feedforward Neural Network has a single layer of weights where the inputs are directly connected to the outputs. In this network, all the neurons are directed towards the front. Each neuron on the layer is connected to another neuron on the next layer without feedback connection [13]. The input to the nodes are feed to the feed forward neural network (FNN), which can classify nonlinear separable patterns and approximate an arbitrary continuous function. The reason FNN was chosen is that it has been widely used in pattern classification [14].

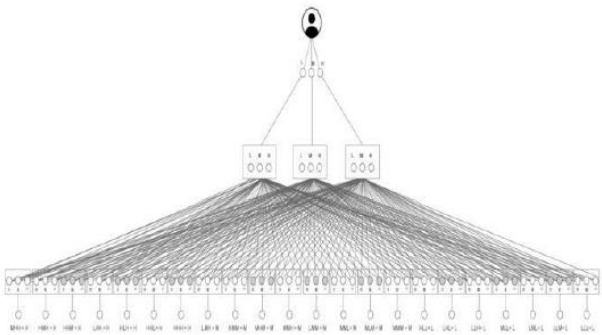

Figure 3. Neural network algorithm diagram

The output vector is of dimension three, which represents the three practice test scores classified into (Low, Medium, High). Training data were used to train the network to perform classification into desired groups using the following weights as shown in Table I.

TABLE I. TRAINING WEIGHTS FOR EACH CATEGORY

Input, x	Weight, w
X_1 – Low	.6
X_2- Medium	.8
X_3- High	1

Output, $y = X_1 * W_1 + X_2 * W_2 + X_3 * W_3$

IX. DATA ANALYSIS AND FINDINGS

The quality of a student model is measured by a model's fit of the observed data, or its ability to predict student performance on a held out dataset [15]. Further, student model clusters students in groups according to their common characteristics [16]. Thus effectiveness of a student model relies on how effectively the model classifies the students' performance and provides information that are essential for the ITS in serving appropriate learning content for the students. In this study, there has been an attempt to develop a student model that does best classification of students by subjecting them to an aptitude test based online learning environment. Therefore, one of the primary focus of this research would be to check, "*How far the student's classification ideally fit into the final students predicted level and obtained level during the process of differentiating them using the student mode approach"?*

In order to proceed with this research question, the discrimination function analysis tests were employed. The various justifications and conditions to proceed with the discrimination functional analysis and the respective statistical test inferences are explained accordingly in this section.

TABLE II. TESTS OF EQUALITY OF GROUP MEANS

	Wilks' Lambda	F	df1	df2	Sig.
Test 1	.788	13.613	2	101	.000
Test 2	.471	56.663	2	101	.000
Test 3	.569	38.227	2	101	.000
Real Test	.952	2.559	2	101	.082
Final Marks	.753	16.556	2	101	.000

The p-values for all the predictor variables except for Real test are less than 0.05, which means, 4 out of 5 are significant predictors. That is, smaller the Wilks's lambda, the more important is the independent variable to the discriminant function. Also, Wilks's lambda is significant by the F test for all the 4 independent variables. Which means, all 4 predictor variables are significant predictors as shown in Table II.

TABLE III. LOG DETERMINANTS AND TEST RESULTS SHOWING SIGNIFICANCE

Log Determinants			Test Results		
Category	Rank	Log Determinant	Box's M		51.285
Low	5	-8.602	F	Approx.	1.503
Medium	5	-7.050		df1	30
High	5	-8.433		df2	3599.160
Pooled within groups	5	-7.246			Sig 0.039

Box's M test can be used to check if there are equal covariance matrices among groups. From the Table III,

the value of Box's M is 51.285, the F-value is 1.503 and the pvalue is 0.039 which is larger than 0.01. We should not reject the null hypothesis and it can be concluded that there are equal covariance matrices among groups. That is, since the value of Box's was significant, indicating that the dependent variable covariance matrices are equal across the levels of the independent variables, this allows the discriminant function analysis to be assessed by Wilks' lambda and Chi-square for multivariate effects. Therefore, we can look into the Wilks' lambda in Table IV for more information on discriminating functions.

TABLE IV. WILKS' LAMBDA SHOWING THE TEST OF FUNCTIONS(S) FOR TWO

Wilks' Lambda				
Test of Function(s)	Wilks 'Lambda	Chi-square	df	Sig.
1 through 2	.302	118.508	10	.000
2	.893	11.155	4	.025

The result reveals Chi-square value of 118.508, which is in fact significant ($\chi2(3)= 140.530$, $p<.05$) in the first row (1 through 2). In the second row (2), which is also significant ($\chi2(3)= 11.155$, $p<.05$). However, comparing the values of p, we can conclude that over and above the first function, the second function does not contribute much. Also, the larger the eigenvalue, the more of the variance in the dependent variable is explained by that function. This means, from the Table V, the eigenvalue is less in the function 2 compared to function 1. Therefore, more of the variance in the dependent variable is explained by function1 than function 2.

TABLE V. TABLE SHOWING THE CANONICAL CORRELATION AND EIGENVALUE FOR TWO FUNCTIONS

	EIGENVALUES*			
	Eigenvalue Variance	% of Cumulative %	Canonical Correlation	Function %
1	1.958*	94.3	94.3	.814
2	119*	5.	100.0	.326

*First 2 canonical discriminant functions were used in the analysis.

The eigenvalues are sorted in descending order of importance. So, the first one always explains that majority of variance in the relationship. Thus, they allow comparing variables measured on different scales. Coefficients with large absolute values correspond to variables with greater discriminating ability. This can be seen in the Table VI and 1.7.

TABLE VI. STANDARDIZED CANONICAL DISCRIMINANT FUNCTION COEFFICIENTS (FUNCTION 1 & 2)

	Function	
	1	2
Test 1	.315	.102
Test 2	.728	.028
Test 3	.497	-.561
Real Test	-.251	-.282
Final Marks	.185	.903

Further, the table of Standardized Canonical Discriminant Function Coefficients shows the coefficients for those independent variables. If the coefficient of a variable is larger, the variable is more important for the discriminant analysis, vice versa. The positive or negative sign of the coefficient shows the relationship (Table VII). Some researchers recommend interpreting the functions in terms of these coefficients. However for greater efficacy we use Canonical Discriminant Function Coefficients to calculate the two Discriminant function (DF1 & DF2). This is because, Standardized Canonical Discriminant Function Coefficients are unstandardized coefficients. It is more common to interpret the structured coefficients, which is well within cell correlation of the variables with the Function value [17].

TABLE VII. STRUCTURE MATRIX SHOWING LARGEST ABSOLUTE CORRELATION

Structure Matrix		
	Function	
	1	2
Test 2	.757*	-.029
Test 3	.612*	-.438
Test 1	.369*	.174
Final Marks	.363	.763*
Real Test	.155	-.172*

From the Table of Canonical Discriminant Function Coefficients we can arrive at the Discriminant function 1 and Discriminant function 2. The Table VIII shows the Canonical Discriminant Function Coefficients. That is, we use these values to construct the actual prediction equation which can be used to classify new cases.

In the table of Classification Results, the row is observed group and the column is predicted group. The percentages on the diagonal shown on the table are the percentages of correct classifications.

TABLE VIII. CANONICAL DISCRIMINANT FUNCTION COEFFICIENTS FOR FUNCTION 1 AND 2

Canonical Discriminant Function Coefficients Function		
	1	2
Test 1 (L)	.659	.214
Test 2 (M)	1.610	.063
Test 3 (H)	.898	-1.013
Real test	-.393	-.441
Final Exam	.461	2.256
(Constant)	-7.196	-4.250

Thus, the discriminant function model would be as shown below.

DF1 = -7.196+..659* Test 1 (L) + 1.610* Test 2 (M) + .898 * Test 3 (H) -.393 * Real test +.461* Final Exam. Similarly,

DF2 = -4.250+.214* Test 1(L) +.063 * Test 2 (M) 1.013* Test 4 (H) -.441 * Real test + 2.256* Final Exam.

In the Classification Results Table IX, we can see 79.8% of original grouped cases correctly classified.

TABLE IX. CLASSIFICATION RESULTS (CLASSIFICATION RESULTS*)

*Category			Predicted Group Membership			Total
			Low	Medium	High	
Original	Count	Low	9	3	0	12
		Medium	6	42	4	52
		High	0	8	32	40
	%	Low	75.0	25.0	0.0	100.0
		Medium	11.5	80.8	7.7	100.0
		High	0.0	20.0	80.0	100.0

*79.8% of original grouped cases correctly classified.

Discriminant Function Analysis requires large sample size and often a number of variables, otherwise the Function and the Structure coefficients are unstable [18]. Further [18] suggests, a ratio of N =20. In this study we had sample size N= 105 and number of variables p= 5, which gives a ratio of 21. Thus, the sample size of this study is justified. Also from the classification result Table IX, it is observed that nearly 80% (79.8) of the data was correctly classified as Low, Medium and High achievers by the discriminating function. It has also been noticed that

75% under Low category was classifed correctly, while Medium and High was placed slightly higher at 80.8 and 80.0% respectively. The percentage of wrong classification in Low category as predicted Medium was 25%, while there was no wrong classification in Low category being predicted as High. Similarly, there was very less percentage of 11.5% wrongly classified for Medium category predicated as Low, while 7.7% was wrongly classified for Medium categaory perdicted as High. In the case of High category, there was no wrong classification predicted as Low, but 20% was predicted wrongly as Medium. Looking at the overall percentage of misclassificaiton and that of the correctly predicted group members, the discriminating function gives the acuracy of the model to be presisely at 79.8%. Thus the Student Model developed in this study seems to be reasonably a good model fit for differentiating the students.

X. SUMMARY

The data collected during the Phase 1 and Phase 2 of this study were subjected to statistical analysis using SPSS version 22, Excel and OriginPro 2016 for 64-bit computer. This followed a (Phase 1) pre-test, to measure, differences between the students before the intervention to neural network. The secondary data (Phase 2), were gathered from the developed system after the students are exposed to the purposed system intervention by neural network. The findings of this research provides a clear direction of the tested model to be good enough to be used for differentiated instructional content classification. Further, the result showed that the model was also good enough to be used for group classification based on the students' ability, which was examined by MCQ based tests to capture students' knowledge and characteristic, for the teachers to use differentiated teaching mechanism in a physics domain.

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