Students' Communicative Competence Prediction and Performance Analysis of Probabilistic Neural Network Model

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Abstract

The purpose of the research paper is to classify and assess the communicative competence of a class of thirty students of higher secondary school in India, before and after a well formulated training with the specially designed syllabus for the reinforcement of communicative competence. Regression statistics is applied to analyse the impact of different predictor variables for the total performance. The affecting variables or predictors are modelled applying Probabilistic Neural Network (PNN) techniques to classify the category of communicative competence performance of the learners. Learners are trained and tested in each component of communicative competence, based on the guidelines of Common European Framework of Reference for Language, Teaching and Assessment (CEFR).

Keywords: *Education Data mining, Communicative Competence, Common European Framework of Reference for Language, Teaching and Assessment (CEFR), Regression Statistics, Probabilistic Neural Network (PNN), Learning Management System (LMS)*

1. Introduction

The student's Communicative Competence plays an important role in getting their first job and further helpful in sustaining their position they hold and move successfully in their career ladder. The authors adopted Common European Framework of Reference for Language, Teaching and Assessment (CEFR) [10] for analyzing the various parameters of Communicative Competence and to evaluate the teaching learning process by applying Regression Statistics and Probabilistic Neural Network model. Michael Canale's [6] theory of Communicative Competence comprises of the four different components, Linguistic, Discourse, Socio-cultural, and Strategic. The first two sub-categories reflect the use of language itself. Thus Linguistic Competence includes "knowledge of lexical items and of rules of morphology, syntax, sentence-grammar semantics and phonology". The second sub-category is Discourse Competence the ability to connect sentences in discourse and to form a meaningful whole out of a series of utterances. While Linguistic Competence focuses on sentence-level grammar, Discourse Competence is concerned with intersentential relationships.

The last two sub-categories define the most functional aspects of communication. Socio Cultural Competence "requires an understanding of the social context in which language is used: the roles of the participants, the information they share and the function of the interaction". Strategic Competence is the way we manipulate language in order to meet communicative goals. The importance of communicative competence is discernible as it permeates virtually in all the interactional activities of human beings.

The contemporary researchers work on communicative competence and the relevant assessment techniques and how the methodologies keep changing over the years are reviewed in section 2. The detailed description of the data source and the descriptors taken for the neural network model, the independent variables and dependent variable for the statistical regression model is discussed in the section 3. The experimental results are discussed in section 4. The authors conclude the work in section 5 with future research direction.

2. Review of the Literature

Noam Chomsky [9] was the first one to coin the term 'competence' and differentiated competence as 'an idealized capacity' and performance as 'production of actual utterances'**.** Initially traditional concept of communicative competence focused only on linguistic competence. Later Dell Hymes [11] alluded to the limitations of Chomsky's and zeroed in the sociocultural factors. Further he developed the communicative competence model based on the degree of possibility, feasibility, appropriateness and occurrence focussing the heterogeneous community unlike Chomsky's homogeneous community.

Widdowson [16] distinguishes 'significant', sentences produced in isolation and 'value', the sentences used to communicate. Furthermore he develops a three-tier model of Communicative Competence of Systematic level (Linguistic Competence) Schematic level (Ability for use) and Procedural level (actual performance). Savignon [14] equates communicative competence with Language proficiency and stated that communicative competence is not static but dynamic.

Canale and Swain [5] & [6] subsumed four sub competences, Linguistic, Sociocultural, Discourse and Strategic competence to Communicative Competence. Bachman [4] further devised a comprehensive stratified model 'Communicative Language Ability' with the components of language competence, strategic competence and psycho physiological mechanism**.** It is only the expansion of Canale and Swain model. They gave more importance to language acquisition rather than communicative competence.

Celce Murcia [7] model encompasses content specification of communicative competence which ameliorates the limitations of Canale and Swain's model. Revised model of Celce Murcia [8] included Formulaic and Interactional competence along with the content specification.

Brijesh Kumar [3] states that the classification task is used to evaluate student's performance and as there are many approaches that are used now a days for data classification, the decision tree method is used here data set comprising attendance, Class test, Seminar and Assignment marks was collected from the students' management system, to predict the performance at the end of the semester. Neural networks models have been designed for the analysis and evaluation of service quality in education sector with the inputs like customer expectations, perceptions and the gaps.

Amelia Zafra [2] suggested an approach where an individual represents if-then rules that add comprehensibility to the discovered knowledge and the fitness function to evaluate the rules obtained will be Sensitivity & Specificity. These measurements allow us to consider both successes in the positive and negative class.

Nguyen Thai Nghe1 [13] suggests that Predictions of student performance can be useful in many contexts. For admissions, it is important to be able to identify excellent students for allocating scholarships and fellowships. Amela, J.-Land Díez, M. Vallés [1] state that learning management system captures Students' interaction with the course activities or resources produces a series of reports or records**.** By analyzing this information the system sets the students progress. The progress can be split in achievement or success that will affect the student motivation and knowledge level.

The authors adopted the research frame work

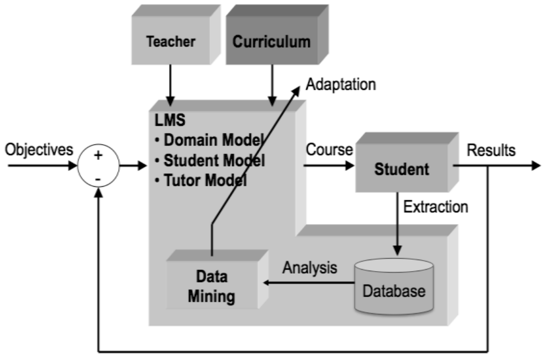

Fig. 1: Source (V. Amela and J.-L. Díez, M.Vallés, 2011)

Shown in the Fig. 1 proposed initially by Amelia and Diez[1] and later customized as per the requirements of Learning Management System.

3. Data and Methodology

A set of 30 Indian students who have completed their Secondary School Education in a private school located in the city Madurai of the State Tamilnadu, are the sample taken for this study. A diagnostic test was conducted in the beginning of the first year of the Higher Secondary School Education and the data was captured in an excel file. A newly designed syllabus based on the guidelines of Common European Framework and Reference for Language, Teaching and Assessment (CEFR) was adopted in the training for two years.

3.1 Proposed model for Performance Evaluation of Learning Management System (LMS)

The data collected for 30 students comprises of 54 variables of formative assessment and summative assessment. The students are assessed in all the above mentioned components of Communicative Competence periodically by internal tests, assignments and mini projects. The input dataset comprises of all descriptors given in the Common European Framework and Reference for Language, Teaching and Assessment (CEFR), the students are tested with three formative assessments and three summative assessments along with the progress achievement Test – I during the Ist year of the course. Also the students are tested with another set of three formative assessments and three summative assessments along with the progress achievement Test – II during the second of the course. Final Achievement Test results reveal the overall progress of communicative competence for the entire course. The authors adopted a new research framework to assess the communicative competence with content specification to analyze the correlation of depending variables with the independent variable or target vector. The effectiveness of the exclusively designed course on the students' communicative competence is assessed using Computational intelligence model of Probabilistic Neural Network (PNN) and statistical regression techniques.

3.2 Performance Evaluation of LMS using Multiple Linear Regression model

The target vector is the dependent variable namely final achievement test result of the 30 students in our study of learning management system. The various other independent descriptors numbering 54 are explanatory variables which influence the dependent variable. The general form of a multiple linear regression with 'k' independent variables for a target Vector Y is given by

$$Y = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + \ldots\ldots + b_kx_k + \varepsilon \qquad (1)$$

[15]. The result analysis of this model is discussed in section 4.1

3.3 Performance Evaluation of LMS using Probabilistic Neural Network model

Probabilistic neural networks perform classification where the target variable is categorical, whereas general regression neural networks perform regression where the target variable is continuous. Probabilistic neural networks are conceptually similar to K-Nearest Neighbour (k-NN) models. [17] A probabilistic neural network builds on this foundation and generalizes it to consider all of the other points. The distance is computed from the point being evaluated to each of the other points, and a radial basis function (RBF) is applied to the distance to compute the weight for each point. The radius distance is the argument to the function. The primary work of training a PNN or GRNN network is selecting the optimal sigma values to control the spread of the RBF functions [17]. The data mining research tool, DTREG uses the conjugate gradient algorithm to compute the optimal sigma values. The decision layer is different for PNN and GRNN networks. For PNN networks, the decision layer compares the weighted votes for each target category accumulated in the pattern layer and uses the largest vote to predict the target category.

3.4 Implementation

The excel data analysis park takes the input range of the data set for Y and X values and the results are interpreted in section 4. The Probabilistic Neural Network model was implemented using a Data mining Tool (DTREG) [17]. The classification problem is optimized with 54 variables as input data with 30 instances (i.e.) Student's records. The total weight for all 30 rows is 2206 as mentioned in the Table 4.

DTREG measures the residual error of the model using the weight values for each iteration. If the error does not improve consecutive iteration, DTREG assumes the weights have converged to the optimal values, and it stops the conjugate gradient process [17]. Training and validation data interpretations are discussed in detail in section 4.

4. Experimental Results and Discussion

4.1 Result analysis of Multiple Linear Regression model

R square is 0.99 which is about 99% of final achievement marks in terms of diagnostic test, formative assessment and summative assessment variables. The overall regression statistics are summarised in the table. In the ANOVA, F test of significance also reveals that regression is significant and not an occurrence by chance (F <0.05) Table 2 shows the test of significance and the analysis of variance.

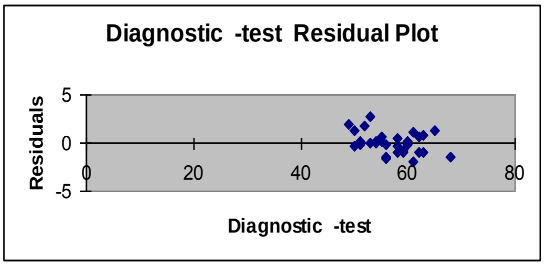

Fig 2

Table 1: Summary Output

Regression Statistics	
Multiple R	0.999887
R Square	0.999774
Adjusted R Square	0.932896
Standard Error	1.56758
Observations	30

The difference between the actual and predicted value of target vector in a given model is tabulated in the Table 3. The residual plots are also graphically presented in the Fig 2-5. As the residuals are close to zero the model is a good fit. The final step in our study demonstrates the use of sensitivity analysis of the best model to identify the deficient items suggested by all stakeholders for providing guidelines to the policy makers. [12]

Table 2: Anova

Significance	*df*	*SS*	*MS*	*F*	*F*
Regression	15	162889.1	10859.27603	4419.179	4.5773E-23
Resi	15	36.85959	2.457306145		
Total	30	162926			

Table 3: Residual Output

No.	*Predicted Achievement - Test*	*Residuals*	*Standard Residuals*
1	66.15369	1.846307	1.665671522
2	75.09764	-0.09764	-0.088083376
3	76.2237	0.776305	0.700353969
4	77.29189	0.70811	0.638831194
5	75.37319	-0.37319	-0.336679342
6	72.81982	-0.81982	-0.739611806
7	72.3136	0.686391	0.619237058
8	70.18052	-0.18052	-0.162857248
9	82.90336	-0.90336	-0.814975726
10	78.79774	0.202255	0.182467328
11	72.86608	0.133924	0.120821261
12	64.27966	2.720336	2.454188067
13	78.83048	1.169518	1.055096379
14	78.00175	-1.00175	-0.90374512
15	80.69865	1.301351	1.17403144
16	73.50971	-1.50971	-1.36200870
17	67.05738	-0.05738	-0.05177021
18	68.06463	1.935373	1.746023474
19	64.7659	1.234099	1.113359747
20	69.77066	0.229337	0.206899495
21	71.11782	-0.11782	0.106295939
22	80.82288	0.177124	0.15979492
23	73.42404	-1.42404	1.284720708
24	77.61557	-1.61557	1.457512076
25	82.03312	-1.03312	-0.93204475
26	70.06526	-0.06526	-0.05887691
27	68.54697	0.453035	0.40871141
28	75.0427	-1.0427	-0.94068547
29	75.97042	-1.97042	-1.77763745
30	65.38536	-0.38536	-0.34765624

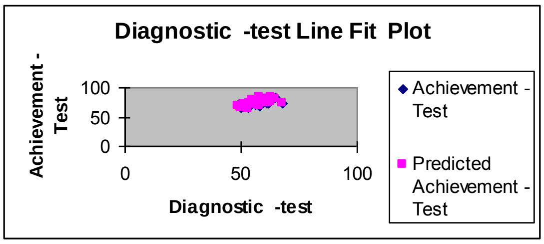

Fig. 3

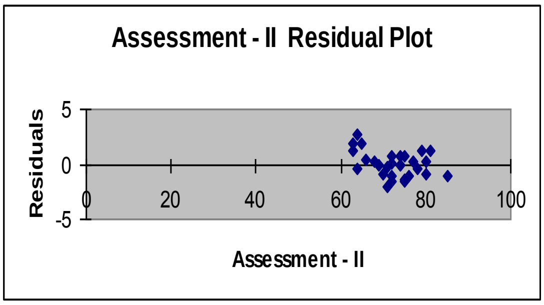

Fig. 4

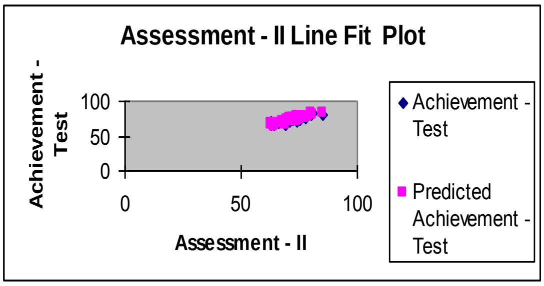

Fig. 5

4.2. Result analysis of Probabilistic Neural Network model

DTREG uses confusion matrix as a specific table layout that allows visualization of the performance of conjugate gradient algorithm. Each column of the matrix represents the instances in an actual class. Sensitivity and specificity are statistical measures of the performance of classification function Sensitivity measures the proportion of actual positives which are correctly identified. Specificity measures the proportion of negatives which are correctly identified these two measures are closely related to the concepts of type I and type II errors. True positive: Sick people correctly diagnosed as sick, False positive: Healthy people incorrectly identified as sick, True negative: Healthy people correctly identified as healthy, False negative: Sick people incorrectly identified as healthy. Confusion matrix as shown in Table 6 & Table 7 reveal that the test results are converged and validated with better prediction accuracy performance.

Table 4: Training Data

	Actual		Misclassified			
Category	Count	Weight	Count	Weight	Percent	Cost
2	5	406	0	0	0.000	0.000
3	19	1398	0	0	0.000	0.000
4	6	402	0	0	0.000	0.000
Total	30	2206	0	0	0.000	0.000

Table 5: Validation Data

Category	Actual Count	Actual Weight	Misclassified Count	Misclassified Weight	Percent	Cost
2	5	406	0	0	0.000	0.000
3	19	1398	1	70	5.007	0.050
4	6	402	1	66	6.418	0.164

4.3 Confusion Matrix

Table 6: Training Data

Actual : Category:	Predicted Category 2	3	4
2:	406	0	0
3:	0	1398	0
4:	0	0	402

Table 7: Validation Data

Actual : Category:	Predicted Category 2	3	4
2:	406	0	0
3:	0	1328	70
4:	0	66	336

4.4 Sensitivity & Specificity

Table 8: Training Data

Target category of CCINDEX = 2
Accuracy = 100.00%
Sensitivity = 100.00%
Specificity = 100.00%
Geometric mean of sensitivity and specificity = 100.00%
Positive Predictive Value (PPV) = 100.00%
Negative Predictive Value (NPV) = 100.00%
Geometric mean of PPV and NPV = 100.00%
Precision = 100.00%
Recall = 100.00%
F-Measure = 1.0000

Table 9

Target category of CCINDEX = 3
Accuracy = 100.00%
Sensitivity = 100.00%
Specificity = 100.00%
Geometric mean of sensitivity and specificity = 100.00%
Positive Predictive Value (PPV) = 100.00%
Negative Predictive Value (NPV) = 100.00%
Geometric mean of PPV and NPV = 100.00%
Precision = 100.00%
Recall = 100.00%
F-Measure = 1.0000

Table 10

Target category of CCINDEX = 4
Accuracy = 100.00%
Sensitivity = 100.00%
Specificity = 100.00%
Geometric mean of sensitivity and specificity = 100.00%
Positive Predictive Value (PPV) = 100.00%
Negative Predictive Value (NPV) = 100.00%
Geometric mean of PPV and NPV = 100.00%
Precision = 100.00%
Recall = 100.00%
F-Measure = 1.0000

Table 11: Validation Data

Target category of CCINDEX = 2
Accuracy = 100.00%
Sensitivity = 100.00%
Specificity = 100.00%
Geometric mean of sensitivity and specificity = 100.00%
Positive Predictive Value (PPV) = 100.00%
Negative Predictive Value (NPV) = 100.00%
Geometric mean of PPV and NPV = 100.00%
Precision = 100.00%
Recall = 100.00%
F-Measure = 1.0000

Table 12

Target category of CCINDEX = 3
Accuracy = 93.83%
Sensitivity = 94.99%
Specificity = 91.83%
Geometric mean of sensitivity and specificity = 93.40%
Positive Predictive Value (PPV) = 95.27%
Negative Predictive Value (NPV) = 91.38%
Geometric mean of PPV and NPV = 93.30%
Precision = 95.27%
Recall = 94.99%
F-Measure = 0.9513

Table 13

Target category of CCINDEX = 4
Accuracy = 93.83%
Sensitivity = 83.58%
Specificity = 96.12%
Geometric mean of sensitivity and specificity = 89.63%
Positive Predictive Value (PPV) = 82.76%
Negative Predictive Value (NPV) = 96.33%
Geometric mean of PPV and NPV = 89.29%
Precision = 82.76%
Recall = 83.58%
F-Measure = 0.8317

5. Conclusion and Scope for further research

Implementation of the statistical regression model based on the proposed research design reveals that there is a positive correlation and a definite impact of the new course on communicative competence of the sample students. Probabilistic neural network was implemented to classify the same set of students based on the communicative competence index and target vector, which is a category variable. The results show the same accuracy level of category classification. Application of an computational intelligence model by incorporating the dynamic feedback system for a student wise performance and tutoring model is the future research work to improve the teaching learning process for better results.

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