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An Estimation Model of English Abilities of Students Based on Their Affective Factors in Learning by Neural Network

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Abstract: The gap between teaching perspectives and students' differences may impact negatively on teaching and learning effectiveness. A new approach to bridge such a gap needs establishing. Artificial Neural Network as a tool capable of approximating solutions for extremely complex problems encourages us to develop an estimation model of students' English ability. The model was trained using back propagation algorithm and tested using 154 samples from two universities. The model estimation rate on students' English abilities demonstrated a high level of estimation by 91.96%, 94.19%, 93.73%, and 91.96% for Listening, Reading, Speaking, and Reading, respectively.

1 INTRODUCTION

Teaching is considered to play a vital role as the formal medium for learning competences on the part of the students [1]. Considering that effective teaching can facilitate learning, teaching is critical in the formation of knowledge, skills and attitude on part of the students. Low quality teaching that could result in unsuccessful learning. In fact, according to data in *Teaching Perspective Inventory* by Pratt and Collins [2], over ninety percent of teachers hold only one or two perspectives as their dominant view of teaching and teachers' perspectives vary in their views of knowledge, learning, and teaching. Moreover, most instructors use a "one-size-fits-all" approach when teaching [3]. This approach could be misguided when applied in teaching practices. The "one-size-fits-all" approach is not appropriate because each student is naturally different from others in their cognitive and affective characteristics. Related to the affective factor, students may have different levels of motivation, different attitudes towards teaching and learning, and different responses to a specific classroom environments and instructional practices [3]. For example, in terms of learning English, some students are highly motivated because they want to work in a foreign company.

The concept of affective factors described by Ellis [5] and Brown [4] clearly outlines the importance of affective factors in the learning of a language. These factors include, among others, motivation, attitude, inhibition, and anxiety. Notably, Williams and Burden [6] also emphasize the importance of student psychological factors for teachers to realize in language learning. More importantly, on a highly conceptual level Immordino-Yang and Damasio [7] also argue the relevance of affective and social factors to learning. They put affective factors, rather than the cognitive factors as having a primary role in the students' learning. They argue that aspects of cognition are affected by and placed under the processes of emotion, which they term as emotional thought. Affective factors play a role as "a rudder" that guides students' rationality in mobilizing their cognitive potentials to result in more rational actions. Unfortunately, thus far attempts to systematically get the most of the benefits of the affective factors in education have not been entirely successful.

Filling in the gap between teaching perspectives and student diversity by examining and estimating students' ability in their affective factors could be a guide to teaching effectiveness. Estimating students' ability can be utilized to reveal the strengths and weaknesses of a particular student. As has been suggested by Felder and Brent [3] on areas of learning, to understand students' differences is a process of "characterizing students" in their affective factors. Identifying students' characteristics in advance is a benefit for the instructor in a number of important ways, such as selecting teaching materials, applying appropriate teaching methods and strategies, and determining learning resources and teaching media best suited for the students.

Research dealing with social sciences to study students' data has been performed by a number of researchers. In the field of affective factors in language learning, an attempt to reveal which type of motivation will have an influence on the specific motivation and other factors that can increase the motivation has been carried out by Obeidat [9]. Wei [10] also studied interrelatedness between motivation and anxiety. Halpern [11] investigated linguistic and cognitive affective factors that impact English language learners' performance on a reading test. The results of the research by these researchers give an insight of the important aspects underlying the students' internal factors and the interrelatedness among each factor in language learning.

Advanced research in predicting students' performance using algorithms also has been carried out. Kumar et al., [12] applied data mining using *k*-means clustering to group data having the same features, and using decision trees as the pattern analysis. Also, a prediction method has been reported using Neural Networks to classify students' graduation outcomes in a 2-year institution, inferring which students would successfully graduate [13]. In this study 12 parameters in student profiles were used to predict graduation outcomes.

A series of tests and experiments were performed to get the best average prediction rate of 77% on test data. Also, based on a study by Ibrahim and Rusli [14], Neural Networks outperform decision trees and linear regression when predicting students' academic performance.

Neural Networks (henceforth NN) have been widely used in areas of prediction. The wide area of application of NN in many fields and sectors is due to their power to model behaviors to produce an approximation to the given outputs [8]. The present study has also been motivated by the potential use of NN in yielding estimations for producing an output based on affective factors that can be used to predict actual English learning outcomes.

Our task in the current study is different from the work by Karamouzis and Vrettos [13], in that we want to estimate students' ability in English learning based on their affective factors. As has been commonly understood, success in education is believed to be based more on the role of cognitive factors. While this might sound acceptable conceptually, empirical research of methods to estimate students' English ability using their affective parameters has not yet been fully explored.

This paper presents a Neural Network model for estimating English abilities of students based on their affective factors in learning. First, a brief overview on affective factors is presented and the three major factors of motivation, attitude and personality are defined for application in our study. Next, data collection on the students' affective factors and reduction of dimensions of the data by Factor Analysis are described and the estimation model is proposed. Finally, our experiment results and conclusion, including directions for future works, are presented.

2 AFFECTIVE FACTORS

Bloom [17] classifies human learning potentials that explorable within education contexts, cognitive, affective, and psychomotor domains. These three domains ideally are put into account when a study on their roles is set to examine one student's success in learning.

In the area of language learning, affective factors are factors that are related to the learners' emotional state and their attitude towards the target language. In the affective issue there has been extensive research. Most researchers have the common basic understanding that affective factors play an important role in language learning. However, these researchers have different opinions about factors underlying affective factors. Brown [4], for example, has a view that affective factors are those factors that come from learners themselves. Meanwhile, Ellis [5] has different ideas on affective factors in second language acquisition. Ellis says these affective factors are influenced by personality factors, such as anxiety and how the anxiety affects the learning will depending on learning conditions. The classification by researchers generally falls into categories as follows: self-esteem, inhibition, risk-taking, anxiety, empathy, extroversion, and motivation.

Based on the various classification on the affective factors described previously, we propose three major factors that are put under the general heading of 'affective factors'. These three major factors are motivation, attitude, and personality. The components of each of these factors are identified by exploring each factor conceptually. The result is that the motivation factor can be identified as integrative, instrumental, resultative, intrinsic, extrinsic, global, and situational. Three kinds of attitude can be categorized as attitudes toward the community, English, and learning. Meanwhile, the components in the factor of personality can be identified as introversion, extroversion, anxiety, self-esteem, and inhibition. In this study, these three major factors and their corresponding components are utilized as the basis for exploring the students' success in learning English. The choice of affective factors as the main factors is based on work by Immordino-Yang and Damasio [7] defining the primary role of affective factors in one's learning.

3 ESTIMATION MODELS OF ENGLISH ABILITIES BY NN

3.1 Data Collection on Students' Affective Factors and its Validation

A questionnaire method is used to quantify students' affective factors as knowledge suitable for NN inputs. The questionnaire has been developed using Likert's five scale with the response ranging 5 to 1, indicating strongly agreement to strongly disagreement, respectively. A literature review was conducted to select parameters for affective factors. We have summarized and arranged the factors into three major factors, motivation, attitude, and personality. Each major factor has sub-factors reflected in motivation, attitude, and personality, as shown in Fig. 1. The questionnaire is a modified version of questions in the instruments developed by Horwitz et al. [15].

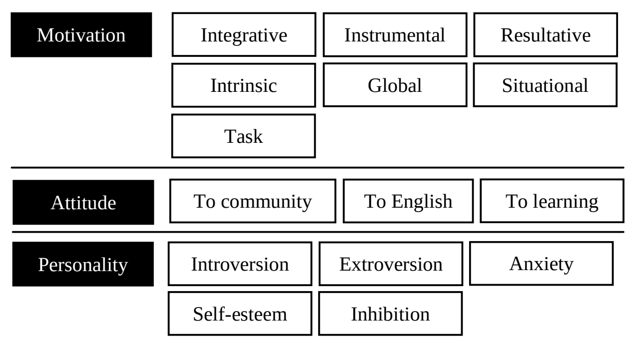

Figure 1. Questionnaire construct

The questionnaires developed were validated by English experts who could evaluate critically the logic and the formulation of the questionnaires to be presented to the students. The objective of this questionnaire validation by an English expert is to check and to confirm that the questionnaires are well constructed in terms of content accuracy and language expression. The next step taken on the developed questionnaires is that the questionnaires were checked for internal consistency of each question. Reliability analysis of the questionnaires using Coefficient Alpha is employed to measure the internal consistency of psychometric scores for sample examinees. The coefficient alpha is given as:

$$\alpha = \frac{N \cdot \bar{c}}{\bar{v} + (N-1) \cdot \bar{c}} \qquad (1)$$

Where N is the number of items, $\bar{c}$ is the average inter-item-covariance among items, and $\bar{v}$ is average variance. Prior checking the internal consistency of the questionnaire, trial data were gathered. In total, 69 responses were collected for each student. Regarding the ability of the students in learning English, we also obtained each English ability score for listening, reading, speaking, and writing. In total, there were 86 variables, comprising 82 variables as the questionnaire and 4 variables as the students' scores in learning English.

Focusing on the affective ability on developing the parameter, the developed parameter reached 82 variables. Accordingly, the dimensionality of the input data is very high. We utilized Factor Analysis to reduce the number of parameters. Since we were measuring the same factor that underlies affective factors, it is possible that the variables belonging to motivation factors have a correlation to the other factors. The Factor Analysis was carried out in two steps. First, we use KMO and Bartlett's test of sphericity to measure whether the correlation matrix is an identity matrix, which indicates that the factor model is inappropriate. Values in the identity matrix below 0.5 were eliminated. In the second step we performed maximum likelihood method and varimax rotation in extraction to sharpen the value of the correlation resulted from the reduced variables from the first step. The result of the analysis showed that 38 variables belonging to the predicted factors were confirmed empirically. This empirically validates the three major factors that are originally constructed to include a number of corresponding variables relevant to these three factors. As suggested by Bishop [16] one of the most important aspects of pre-processing involves reduction in the dimensionality of the input data. Variables that have high standard deviation were then eliminated as this variable is considered outliers that would potentially reduce the internal consistency. Consequently, 30 input variables were selected from the questionnaires and four output variables are included the data set.

Having selected variables reduced to a lower number, we recalculated the reliability of the questionnaires and showed that the questionnaires have good internal consistency for a data collection by alpha .845, .820, and .656 for motivation, attitude, and personality respectively.

3.2 Subjects

The subjects responding to the questionnaires were 154 students of two state universities: Brawijaya University and the State University of Malang, Indonesia. The subjects' major is English. During data collection the students were on their second year of study. 59% of whom were randomly selected from the students of the English Department, Faculty of Letters, the State University of Malang and 41% of whom were from the students of the English Literature Study Program, Faculty of Culture Sciences, Brawijaya University, Malang, East Java, Indonesia.

3.3 Estimation Models by NN

A three-layered multilayer perceptron was developed to estimate the students' abilities, due to the capability of this strategy to get the approximate solution for extremely complex problems. We construct four network models to estimate each English ability, listening, reading, speaking, and writing, as shown in Fig. 2. The first layer of each network, which is input layer, consists of 30 neurons for each question variable based on the affective level. The second layer consists of 60 neurons. The number of hidden neurons is chosen heuristically because 60 neurons in hidden layer showed the least error during training of the data set. The third layer, the output layer, consists of 1 neuron denoting the inferred ability of the student in the given English skill (listening, reading, speaking, or writing).

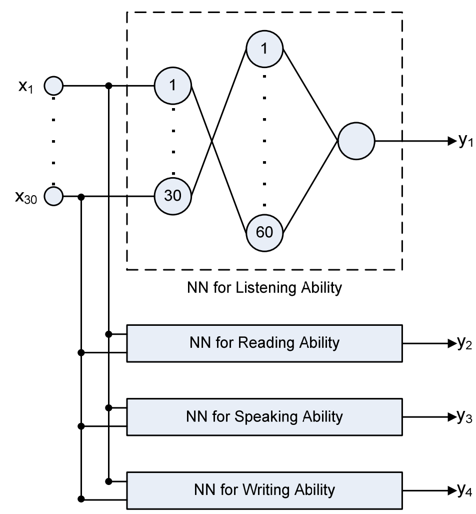

Figure 2. Estimation models of English abilities by NN

For each network model, each of the neurons is fully connected to the neuron in the upper level layer. The second layer receives accumulated input from the previous layer (input layer) and provides output to the next layer (output layer). The total output produced by the neuron can be summarized in Equation 2.

$$y_k = g(a_k) \quad (2)$$

$$k = 1,\ldots,4$$

Where g is activation function of the output units and a_k is the total weight from the previous layer as shown in Equation 3.

$$a_k = g\left(\sum_{j=1}^{n=60} w_{kj} F\left(\sum_{i=1}^{m=30} w_{ji} x_i\right)\right) \quad (3)$$

In our network model, the activation function for both g in the second layer and F in the first layer is a sigmoid function which restrains the range of neuron between 0 and 1.

3.4 Training of NNs

Training of NNs was done by Back Propagation (BP) [18] with learning rate 0.1 and more than 10000 iterations. The data used in the training was 138 of 154 data sets.

4 ESTIMATION RESULTS

We give the system accuracy by 10-fold cross validation. Each of network models was run ten times and average of the error was calculated. Each run comprised of randomly selected cases into training set and test set. The training set and test set is specified with the portion 138:16. System accuracy is given by:

$$Accuracy = 1 - average\_err_{system} \quad (4)$$

The accuracy for each ability show high values of 91.96%, 94.19%, 93.73%, and 91.96% for Listening, Reading, Speaking, and Reading skills, respectively as shown in Table 1. The average of the error system resulted in 0.0703 and the average accuracy was 92.96%.

TABLE 1. ACCURACIES OF ENGLISH ABILITY ESTIMATION BY THE SYSTEM

English Skills	Error	Accuracy
Listening	0.080360083	91.96%
Reading	0.058071803	94.19%
Speaking	0.062673028	93.73%
Writing	0.08038915	91.96%
Average	**0.070373516**	**92.96%**

5 CONCLUSION AND FUTURE WORK

Neural Network models constructed by three-layered perceptron were trained using BP algorithm to learn the presented problem. The accuracies of the models to infer each student's ability in English showed high scores of 91.96%, 94.19%, 93.73%, and 91.96% for Listening, Reading, Speaking, and Reading skills, respectively. This result shows that NN can make accurate estimation of student ability using their affective factors as the parameters of the study.

More development of research by expanding the parameters not only limited to affective factors is required since the factors affecting students in learning does not come from affective factors only. Choosing the right parameters to estimate students' abilities is also crucial. Therefore, we must pay more attention to the selection of the best parameters for estimating students' abilities.

In this research we have been trying to estimate student ability in English. Estimating student ability in English in the earlier stage could provide another perspective that would help the both educators and the student to improve learning and teaching processes and activities. Seen from the student's side, recognition of weaknesses and strengths in the specific ability may encourage the student to study harder to improve weaker abilities. Seen from the educator's point of view, knowing the student's affective levels in terms of their motivation, attitude, and personality will help the educators choose the teaching methods and teaching materials best suited to the students. The educators could also focus in selecting methods and materials that would best suit the students and make the class more interesting and favorable while reducing the stress of the students taking the class.

REFERENCES

[1] Perkins, D.N., Salomon, G: *Transfer of Learning. International Encyclopedia of Education, Second Edition*. Oxford, England: Pergamon Press, 1992.

[2] Pratt, D.D. and Collins, J.B: *The Teaching Perspectives Inventory, Proceedings of the 41st Adult Education Research Conference*, Vancouver, B.C, 2000.

[3] Felder, R.M. and, Brent, R: Understanding Student Differences. *Journal of Engineering Education* 94(1), pp. 57-72, 2005.

[4] Brown, H.D: *Principles of Language Learning and Teaching 5th Edition*. New York: Pearson Education Inc, 2007.

[5] Ellis, R: *Understanding Second Language Acquisition*. New York: Oxford University Press, 1995.

[6] Williams, M., and Burden, R.L: *Psychology for Language Teachers: A Social Constructivist Approach*. Cambridge: Cambridge University Press, 1997.

[7] Immordino-Yang, M.H., Damasio, A: We feel, therefore we learn: The relevance of affective and social neuroscience to education. *Journal Compilation*, Vol.1 No. 1, pp. 3-10, 2007.

[8] Lippman, R: An introduction to computing with neural nets, IEEE Trans. ASSP Magazine, 4, pp. 4 – 22, 1987.

[9] Obeidat. M.M: Attitudes and Motivation in Second Language Learning. *Journal of Faculty Education* UAEU Year 18- Issue No. 22, 2005.

[10] Wei, M: The Interrelatedness of Affective Factors in EFL Learning: An Examination of Motivational Patterns in Relation to Anxiety in China. *TESL-EJ*, 2007.

[11] Halpern., Carnie S. Strebel: An Investigation of Linguistic, Cognitive, and Affective Factors That Impact English Language Learners' Performance on A State Standarized reading Achievement Test. A dissertation for doctoral degree in the college of education at the University of Central Florida, 2009.

[12] Kumar., N.V.Anand, Uma., G.V: Improving Academic performance of Student by Applying Data mining Technique. European Journal of Scientific Research. ISSN 1450-216X Vol.34 No.4, pp. 256-534, 2009.

[13] Karamouzis, S.T. and, Vrettos, A: An Artificial Neural Network for Predicting Student Graduation Outcome. Proceeding of the World Congress on Engineering and Computer Science 2008. WCECS 2008, October 22 – 24, 2008, San Fransisco, USA, 2008.

[14] Ibrahim, Z., and Rusli, D: Predicting Students' Academic Performance: Compaaring Artificial neural network, Decision Tree and Linear Regression. 21st Annual SAS Malaysia Forum, 5th September 2007, Kuala Lumpur, 2007.

[15] Horwitz, E.K, Horwitz, M.B., & Cope, J: Foreign Language Classroom Anxiety. *The Modern Language Journal*, 70(2), 125-132, . 1986.

[16] Bishop, C.M. Neural Network for Pattern Recognition. : Oxford University Press. 1995.

[17] Bloom, B.S., Krathwohl, D.R., Masia, B.B: *Taxonomy of Eductional Objectives, Handbook II*: The Affective Domain, 1964.

[18] D.E, Rumelhart, J.L McClelland and PDP Research Group: Parallel Distributed Processing. Vol 1 and 2. MIT Press, 1986.