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A Fuzzy Probabilistic Neural Network for Student's Academic Performance Prediction

Nidhi Arora [1], JatinderKumar R. Saini [2]

Asst. Prof., M.C.A. Department, U.V. Patel College of Engineering, Ganpat University, Kherva, India[1]

Assoc. Prof., M.C.A. Department, Narmada College of Computer Application, Bharuch, Gujarat, India [2]

Abstract: The paper presents a Neural Network model for modeling academic profile of students. The proposed model allows prediction of students' academic performance based on some of their qualitative observations. Classifying and predicting students' academic performance using arithmetical and statistical techniques may not necessarily offer the best way to evaluate human acquisition of knowledge and skills, but a hybridized fuzzy neural network model successfully handles reasoning with imprecise information, and enables representation of student modeling in the linguistic form - the same way the human teachers do. The model is designed, developed and tested in MATLAB and JAVA which considers factors like age, gender, education, past performance, work status, study environment etc. for performance prediction of students.

A Fuzzy Probabilistic Neural Network model has been proposed which enables the design of an easy-to-use, personalized student performance prediction component. The results of experiments show that the model outperforms traditional back-propagation neural networks as well as statistical models. It is also found to be a useful tool in predicting the performance of students belonging to any stream. The model may provide dual advantage to the educational institutions; first by helping teachers to amend their teaching methodology based on the level of students thereby improving students' performances and secondly classifying the likely successful and unsuccessful students.

Keywords: Education, Fuzziness, Prediction, Retention, Student Academic Performance, Probabilistic Neural Network

I. INTRODUCTION

Over a period of years, researchers have proposed various methods for predicting the academic performance of students. An act of assigning a qualitative or quantitative merit or worth to students' achievements is defined as the academic assessment. When the assessment is done before students actually perform in the curriculum, it is termed as performance prediction. An early prediction of the students' academic performance is an important practice for many reasons: to obtain an idea of the students' level of learning, to get a hold of information on the level of teaching, to decide on success or failure of students in the course enrolled, to inform low performance students to put in more effort in the course to overcome their weaknesses. Increasing students' retention or persistence is a long term goal of all academic institutes. Typically, the first-year students are at greatest risk of dropping out from the study. Students' early experience in course satisfaction plays an important role in keeping a high retention rate. One of the intrinsic goals of the model is to retain students in the course by finding the effect of the family activities, work activities and classroom environment on their performance. Two factors have a direct influence on students' performance: the students' aptitude and the amount of effort student puts forth in the course. It is indicated that the amount of effort put forth by a student depends on his grade history, motivation, extra-curricular activities, work responsibilities and family responsibilities [42].

Different educational institutes consider diverse factors while giving admission to students. Some institutes consider cognitive ability and personality measures, while some others give admission on merit, which is basically the students' result of last class he has studied. But this may not give teachers a right idea about the level of the mass they are going to address. If they keep a high standard of instruction, students may not be able to grasp what is taught in the class. On the other hand, if the standard of teaching is kept reasonably low, students may not either take the subject seriously or the same may degrade teacher's efficiency. Hence, the institute aims at evaluating and predicting a student's academic performance to determine what percentage of students fall in intelligent, average or poor category. At the beginning of the course, the teachers need to know the levels of their students, which may provide them a guideline to decide how much effort they have to put in while teaching in the classroom. This may also guide them either to lower down or to exalt their standard of teaching in classroom for imparting adequate knowledge for satisfactory academic progress.

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The model suggests a Probabilistic Neural Network hybridized with fuzzy logic to predict students' performance and to classify them according to their similar characteristics. Probabilistic Neural Network (PNN) has been widely used for pattern recognition problems, such as texture recognition [32], image recognition [24], medical/biochemical field [41], signal processing [10], civil/geotechnical engineering [34], and so on. PNN can predict the estimation of compressive strength of concrete on the basis of concrete mix proportions; the estimation performance of PNN is improved by the iteration method [21]. The rest of the paper is organized as follows: Section 2 recollects related work in the domain of education for predicting student's performance with various techniques. Section 3 gives a brief of significance of student's academic performance prediction and Section 4 presents a review on FPNN architecture and classification capabilities. Section 5 gives a general description of data used in the study, the pre-processing steps to analyze the data and experiments performed. Section 7 summarizes the results of experiments and Section 7 concludes the paper with an outlook for future work. Finally, references are listed in Section 8.

II. Related Work

Various researchers have applied data mining in different areas of education, such as enrolment management ([2], [21]), graduation ([4], [30]), academic performance ([23], [28], [35]). The use of data mining techniques in this field is relatively new. There are many data mining techniques used in this field, such as neural networks, decision tree, Bayesian network, k-means clustering and so on [31]. Academic researchers have developed several conventional models based on statistics like discriminant analysis, multiple regression and stepwise regression to predict an applicant's success in the MBA program. In the statistical methods used so far in this domain, different scores from each assessment criterions are added based on some pre-determined weights to compute a single score for an individual student's performance. However, such prediction schemes are found to be deficient in the formal mechanisms which consider some of the cognitive factors for an exact prediction of performance of the student. A data mining case study [27] identified the behaviour of failing students so that they can be warned to be at risk before the final exams. In their study, Chamorro-Premusic & Furnham [7] concluded that openness and conscientiousness together with measurable approaches to learning mediate the effects between ability and academic performance in the predominantly female college students. According to them, gender is also one of the moderating factors influencing the relationships between personality traits and academic performance. All statistical methods for assessing or predicting student's academic performance have reported satisfactory results but a common aspect where all these methods lack is dealing with dynamically changing environment and vagueness in reality. Neural networks come up with adaptability as the solution of dynamic environment whereas hybridization of fuzzy logic with neural networks can handle vagueness also.

In recent past, PNN models have been used by [33] to distinguish cancer patients from healthy persons according to the levels of nucleosides in human urine and by [25] for handwritten digit recognition. For more information on other motivating applications of the PNN, the reader is referred to [1], [4], [12], [18] and [20]. The crucial problem in these applications is the choice of the smoothing parameter. Deniz & Ersan [14] presented several ways in which student's performance data can be analyzed and presented for an academic decision making and academic decision support system. Lassibille & Gomez [23] presented an integrated fuzzy set approach to assess the outcomes of a student learning. They exploited fuzzy set principles to represent the imprecise concepts for subjective judgment and applied a fuzzy set method to determine the assessment criteria and their corresponding weights. Reasoning based on fuzzy approaches has been successfully applied for inference of multiple attributes containing imprecise data. Biswas [5] proposed an application of fuzzy sets to student academic evaluation. The reasons behind the use of the fuzzy approach are that an educational grading system involves substantial amounts of fuzziness and that fuzzy theory can provide a model of subjective judgments. Chen and Lee [9] proposed a method for the evaluation of student answer scripts. The purpose of their study was to counter some drawbacks of the method proposed by Biswas. The method proposed by [9] is similar to the method of [17] which applies fuzzy membership function values and probability theory.

It is known that Expert Fuzzy scoring systems [26] help teachers to make assessment in less time and with a level of accuracy that compares favorably to the best examiner. Tinto's model [38] is the predominant theoretical framework for considering factors in academic success. He considered the process of student attrition as a socio-psychological interplay between the characteristics of the student entering university and the experience at the institute. Many studies included a wide range of variables, including personality factors, intelligence and aptitude tests, academic achievement, previous college achievements, demographic data etc. [8], [14], [21] for assessing academic performance of students.

III. Academic Performance Prediction

Academic performance prediction of students involves the measurement of ability, competence and skills. Ability, competence and skills are fuzzy concepts and can be approximately captured in fuzzy terms. This usually involves

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awarding numerical merit to the students which represents their achievement by reasoning with arithmetical or statistical methods. A variety of criteria are used in mathematical methods for the evaluation purpose. For example, different scores from each criterion are added to obtain a single score. Simple statistical methods such as calculating the average or complex statistical methods such as calculating the mean, median, mode, range, standard deviation, variance and standard z-score can also be used.

Teachers are considered to be most responsible observers who not only engage class but also monitor the behaviour and understanding of students. Foreseeing their performance may have the potential to impact student achievement. Prediction results may prove to be fruitful to teachers for balancing the effort to improve performance of the students. Probabilistic neural network (PNN) is a feed-forward neural network, and its structure is neural network implementation of Parzen nonparametric probability density function (PDF) estimation and Bayes classification rule [30]. PNN is effective choice for prediction problems because it needs less time to determine the networks' architecture and to train the network. Moreover, PNN provides probabilistic viewpoints as well as deterministic classification results. FNNs do not require mathematical models and have the ability to approximate nonlinear and uncertain systems [11], [15], [18].

IV. FUZZY PROBABILISTIC NEURAL NETWORK

The Probabilistic Neural Network, introduced by Donald Specht, is a 4-layer, feed-forward, one pass training algorithm used for classification and mapping of data [35]. Unlike other Artificial Neural Networks such as back-propagation network, it is based on well-established statistical principles derived from Bayes' decision strategy and non-parametric kernel based estimators of probability density functions. A Probabilistic Neural Network (PNN), which is a type of Radial Basis Function (RBF) Network [40], is predominantly a classifier which maps any input pattern to a number of classes. It can be forced into a more general function approximator. Probabilistic Neural Networks possess the simplicity, speed and transparency of traditional statistical classification models along with much of the computational power and flexibility of back-propagated neural networks [36]. PNN has proven to be more time efficient than conventional back-propagation based networks and has been recognized as an alternative in real-time classification problems. The traditional neural networks use some learning rule to initialize and update the value of connection weights between various layers and subsequently to train the network. Unlike these networks, no learning rule is required to train a PNN and no predefined convergence criteria are needed. The drawback of the PNN in prediction problems is that it can be used only if the desired output is expressed as one of several pre-defined classes [13].

Probabilistic Neural Networks use radial basis functions as activation functions in the hidden layer to make a local decision function centred on a subset of the input space [39]. The global decision function is constructed by summing all local functions [16], [22]. PNNs are found to be the best neural classifiers due to their design architecture [3]. For this reason PNNs have the advantage over other multi-layer networks. The problem of local minimums does not affect the decision of a PNN. When the amount of available data is limited and the allotted time for classification is constrained by some restrictions, PNNs represent an excellent and reliable approach. PNNs have several advantages over other neural networks. The training process of PNN is orders of magnitude faster than back-propagation [37]. With an inherently parallel structure, PNN guarantees to converge to an optimal classifier as the size of the representative training set increases.

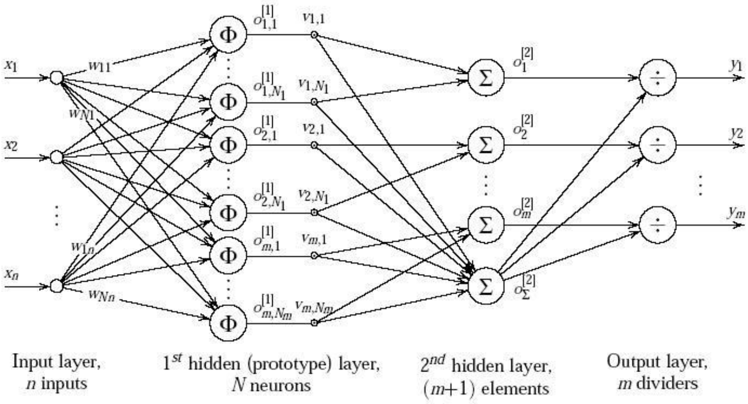

Fig. 1 Fuzzy Probabilistic Neural Network Architecture

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One of the characteristic features of PNN that strongly favours it to be a choice of prediction is that it never gets stuck into local minima and the training samples can be added or removed from the network without the need of additional training. A PNN is an implementation of a statistical algorithm called kernel discriminant analysis in which the operations are organized into a multilayered feed-forward network. The PNN is composed of many interconnected neurons organized in successive layers. Fuzzy Probabilistic Neural Network (FPNN) [6] as shown in figure 1 is a four-layered structure consisting of Input layer, Prototype/Pattern layer, Summation layer and Output layer.

The input layer receives an n-dimensional vector x(k) for classification. It does not perform any computation and simply distribute the input to the neurons in next layer. The first hidden layer called prototype layer, contains neurons identical to the number of the training samples with the gbell activation functions and their synaptic weights in input-to-prototype connections are determined by the components of the training patterns, i.e.

$$w_{ji} = x_i(j) \qquad i = 1,2,\ldots n \textit{ and } 1 \le j \le M \tag{1}$$

Where, $x_i(j)$ denotes the i^{th} node input of j^{th} sample in the input layer. The neurons in the prototype layer are divided into m groups with N_t nodes in each, corresponding to its cluster. The vector of weights of the p^{th} neuron in t^{th} group is denoted by

$$w_{t,p} = w_{t+p-1} \qquad t = 1,2,\ldots m \textit{ and } p = 1,2,\ldots N_t \tag{2}$$

When vector *x(k)* is given as input to the network, the classification of input vectors is initiated by computing net input to the pattern layer as follows:

$$n_j^{[1]} = \left\| x(k) - w_{t,p} \right\|^2 \tag{3}$$

Accordingly, the neurons in this layer performs calculations

$$o_{t,p}^{[1]}(k) = \exp\left(-\frac{n_j^{[1]}}{2\sigma_t^2} \right) \qquad t = 1,2,\ldots m \text{ and } p = 1,2,\ldots N_t \tag{4}$$

Where, σ is a smoothing parameter corresponding to the standard deviation of the Gaussian distribution.

At this point, it is also possible to determine the diameters of clusters formed by training data to roughly estimate how much they overlap as:

$$0 \le D_t = \max \left\| w_{t,p} - w_{t,q} \right\|^2 \le 2 \tag{5}$$

The second hidden layer called summation layer, consists of m+1 elementary summing nodes with each of first m nodes representing an individual class. All these m nodes receive outputs of the prototype layer so that

$$o_t^{[2]}(k) = \sum_{p=1}^{N_t} v_{t,p} o_{t,p}^{[1]}(k) \tag{6}$$

Where, $v_{l,p} \ge 1$ is a prototype-to-summation layer connection synaptic weight used to determine the shape of cluster. These weights are initialized to $v_{l,p} = 1$. The last $m+1^{th}$ node calculates the total sum

$$o_\Sigma^{[2]}(k) = \sum_{t=1}^{m} \sum_{p=1}^{N_t} v_{t,p} o_{t,p}^{[1]}(k) \tag{7}$$

It is worth to note that the sums in equation (6) are Parzen approximations of unknown data distributions in the clusters. The last layer called output normalization layer is formed by m dividers. It calculates the vector of degrees of membership *y(k)* as

$$0 \le y_t(k) = \frac{o_t^{[2]}(k)}{o_\Sigma^{[2]}(k)} \le 1 \qquad \textit{and} \qquad \sum_{t=1}^{m} y_t(k) = 1 \tag{8}$$

The network is a combination of probabilistic and generalized regression neural networks, and is capable of data classification on the basis of fuzzy decision on the membership of a particular observation to a certain class.

V. EXPERIMENTS CONDUCTED

Traditional Probabilistic Neural Networks solve the prediction/classification problems considering the standard crisp inputs. In contrast, in real problems, the inputs cannot have pure separating boundaries. The problem of overlapped clusters is common while considering the input parameters as they may belong to more than one class simultaneously with certain degrees of membership. As discussed above, a Fuzzy PNN has been used to deal with such inputs rather than the conventional PNN. For every input vector x, the degree of membership is found for each factor belonging to a particular class. For examples, we have considered the bell-shaped membership function with 3 membership classes for input viz. Good, Average and Poor for Merit in the last exam, Less, Moderate and Keen for Interest in the course etc. Different assessment components reflect different modes of evaluation used to assess students' academic performance. As such there are a variety of factors which may be considered as criteria to predict the students' performance, but the factors which have been considered for performance prediction in the proposed model are as shown in the table I.

TABLE I
FACTORS TO PREDICT ACADEMIC STUDENT'S PERFORMANCE

Merit							
1.	Merit in the last exam	2.	Average merit				
Interest							
3.	Interest in the course	4.	Interest in the	5.	Interest in learning		
Belief							
6.	Belief in hard work	7.	Belief in learning				
Study Behavior							
8.	Study with reference	9.	Study with revision	10.	Study by practicing examples		
Class Behavior							
11.	Regularity in attendance	12.	Attention in class	13.	Taking notes during class	14.	Doing homework
Family Background							
15.	Parents' education	16.	Earning of the family	17.	Financial support	18.	Residential area

A fuzzy Probabilistic Neural Network (FPNN) has been designed using MATLAB and analyzed on a 760 samples of training dataset consisting of above 18 factors as inputs to the network. The training set for FPNN is formed as a set of 18-dimensional vector comprising all the factors in $x(1), x(2), ..., x(j)$ where each $x(j) = (x_1(j), x_2(j), ..., x_{18}(j))^T$ .The available dataset is cross-validated in a 3:1 ratio to partition it into complementary subsets, performing the analysis on one subset called training set of 570 samples, and validating the analysis on the other subset called test set of 190 samples. Cross-validation is basically used to inspect the performance of a neural network in result prediction in terms of sampling variation. This statistical technique is used here to avoid the chances of FPNN to overfit the data.

The FPNN is then trained by the membership degree matrix 570X18 formed from 570 samples of 18 factored vectors. The simulated FPNN in figure 2 depicts the 4 layered FPNN with an input vector consisting of 18 input nodes, a pattern layer, a summation layer and an output layer having 3 nodes for student's academic performance representing three classes i.e. Good, Average and Poor. As discussed in the FPNN architecture, the output of the network is a vector of degrees of membership $y(j) = (y_1(j), y_2(j), y_3(j))^T$. A student is said to belong to a class whose degree of membership function is maximum.

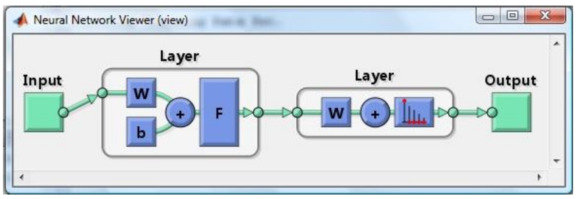

Fig. 2 Simulated Fuzzy Probabilistic Neural Network

To reduce the number of hidden nodes and to test the network on a smaller set of exemplar patterns, a data set of 400 was divided into two subsets using the same cross-validation procedure resulting in a training set of 300 and testing set of 100 samples. Figure 3 shows the dataset used to train FPNN where the dataset is equally distributed among the three classes.

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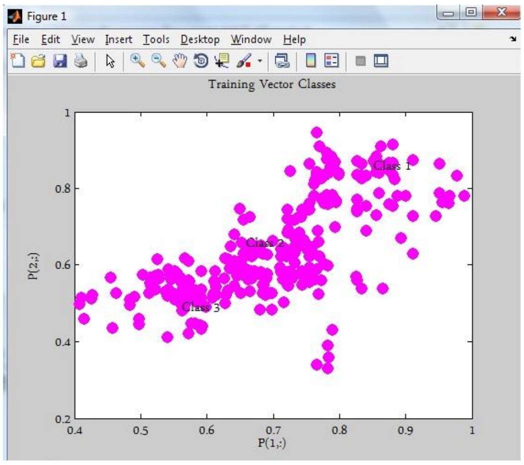

Fig. 3 Training Vector Classes

Once the network is trained, it calculates the probabilities of each training data to belong to each class as seen in Table II. This table helps in determining the likelihood of each student to belong to every class.

TABLE III
CLASS PROBABILITIES OF SAMPLE TRAINING DATA

Sample#	Class1-Good	Class2-Average	Class3-Poor	Sample#	Class1-Good	Class2-Average	Class3-Poor
1	1.0000	0.0000	0.0000	:	:	:	:
2	1.0000	0.0000	0.0000	561	0.0804	0.3916	0.5280
3	0.6776	0.0136	0.3088	562	0.2816	0.1442	0.5742
4	0.6482	0.0216	0.3302	563	0.4621	0.0556	0.4823
5	0.5927	0.0210	0.3863	564	0.1737	0.2336	0.5927
6	0.5982	0.0216	0.3803	565	0.1317	0.2922	0.5761
7	0.6700	0.0202	0.3098	566	0.3157	0.1285	0.5559
8	0.6181	0.0297	0.3522	567	0.0927	0.3954	0.5119
9	0.6944	0.0098	0.2958	568	0.2785	0.0985	0.6230
10	0.6038	0.0298	0.3664	569	0.0909	0.3585	0.5506
11	0.6124	0.0294	0.3582	570	0.3806	0.1051	0.5143

The neural network was tested on different sets of training and testing samples to monitor its performance. After considering many possible values, the smoothing parameter was fixed at 0.1 as it was found to minimize the classification error.

VI. RESULTS AND DISCUSSION

The results of experiment conducted demonstrate that the overall training error is 2.6667 and the root mean square error is 0.0265. With 18 neurons in the input layer and neurons equal to the number of training exemplar patterns in the hidden layer, the network is found to achieve a near expected correct detection. Table III shows a comparison of results of FPNN predictions with two different data set sizes. With the increase in the size of data set, the number of neurons in the hidden layer increases with no significant improvement in the prediction results. Hence, a total data set of 400 (300+100) was finally used for training the network.

The basic reason behind misclassification is observed due to the presence of noise in the test data. The cross-validation method improves the generalization capability of the network. Separate experiments were conducted with and without cross-validation method for training the FPNN.

TABLE IIIII
COMPARISON OF FPNN PREDICTION RESULT

	Data Set Size – 300	Data Set Size – 570
Class	**Correct Prediction Percentage**	**Correct Prediction Percentage**
Class 1	99 %	90 %
Class 2	100 %	96 %
Class 3	96.7 %	87.5 %

Network trained without cross-validation converge in 90 mins approximately, while when cross-validation method is applied, it is found to converge in 47 mins, which is almost less than half the time in contrast to a typical back propagation network which takes about 120 mins to be trained. This indicates that convergence of network is significantly affected by the use of a cross- validation method.

VII. CONCLUSION

Several reasons for predicting the academic performance of students' are studied and a prediction model has been proposed using Fuzzy Probabilistic Neural Network. The model may prove to play a significant role in academics by predicting the level of students in the class and by providing an insight to the teacher to better plan the lectures depending on student's level. As a result, the teacher can also maintain a balance between the quality and quantity of knowledge to be imparted in class. From the institution's viewpoint, an early prediction lends a hand in identifying inabilities of the students, taking timely measures to improve them, thereby locking in the students.

Statistical and other methods for predicting students' academic performance lack in the consideration of various relevant determinant factors. The reason for ignorance of such factors is due to their vagueness, to which the proposed method using Fuzzy Probabilistic Neural Network is found to give improved results. Experiments and results reveal that FPNN takes less time to be trained and the test results are near to the expected ones. This adds to the capability of network in performing prediction more correctly. The results indicate that the proposed network shows an average of 98.56% classification accuracy. Further work can be performed for improving the classification accuracies by the usage of different ANN architectures.

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BIOGRAPHY

Nidhi Arora has more than 11 years of teaching experience at post graduate level. She is associated with many research and technical organizations and is an active member of reviewer board of international journals from India and abroad. Her research work appears in national and international journals including IEEE and Springer Verlag London Ltd. Her areas of interest are Artificial Intelligence, Soft Computing, Simulation & Modeling, Hybrid Systems and Expert and Decision Support Systems.

Dr. Jatinderkumar R. Saini is Ph.D. from VNSGU, Surat. He is IBM Certified Database Associate (DB2) as well as IBM Certified Associate Developer (RAD). Associated with nearly 25 countries, he has been the Member of Program Committee for 40 International Conferences (including those by IEEE) and Editorial Board Member or Reviewer for 25 International Journals (including those with impact factor). He has 33 research paper publications and 16 presentations in reputed International and National Conferences and Journals. He is member of ISTE, IETE, ISG and CSI.