

Intelligent Tutoring System: Predicting Students Results Using Neural Networks

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Abstract

In this paper we propose methods to utilize Artificial Neural Networks to obtain knowledge for the management of educational resources. The final evaluations provide us a model that allows prediction of student details. Intelligent Tutoring System (ITS) is a system that uses Feed forward Backpropagation and it has been trained with a group of student data to predict student results. Various tests have been conducted to examine adherence to real time data. The accuracy of prediction is high and hence states that the Neural Network is capable of making proper predictions.

Keywords

ITS, feed forward, neural network

1. Introduction

Intelligent Tutoring Systems (ITS) differ from classic computer-aided instruction (CAI) in the way they adapt to users' individual needs. This is accomplished by modeling what the student does or does not understand.

The basis of this student model is a domain model, which is a detailed description of the subject being taught. In order to be truly adaptive, ITS need to use information in the student modeling to guide all instructional decision making. There has been much research in the field of student models that can accurately predict the student performance to examine themselves. Intelligent Tutoring system was trained in Neural Network using feed forward backpropagation

technique for predicting the student results for attentive of Examination.

We have predicted the upcoming results of Students with the previous results. This paper presents a new approach for developing an intelligent problem selection agent, based on Artificial Neural Networks. We will train a neural network on data from previous studies. It was decided to test the predictive capabilities of neural networks in a simplified setting. This paper presents the results of this preliminary work.

Our approach was to develop the prediction of student performance which was followed by the description of ITS and Artificial Neural Networks (ANN's) and System Architecture for ITS in section 2 and 3. How a neural network was trained to predicting student performance in section 4, and then the predicted accuracy in was discussed in next section. The final section presents conclusion and plans for future work.

2. Process description of ITSs and Artificial Neural Networks

2.1 ITS

The purposes of design and conceptualization, ITS's are described as having four major components [7]:

(1)The domain knowledge, which is aimed to store, manipulate and reason with knowledge of the domain being taught.

(2)The pedagogical module, which provides information about the teaching strategy that, must be used to a specific student.

(3)The student model, that stores and analyzes information of student's current state of knowledge and predict their performance academically.

(4)The interface, which handles the form of communication between the ITS and the student.

Since one of the most important features an ITS should provide is, the capability to adapt its behavior to the specific **traits** of the student. Student model seems to be the most important component and student modeling (also Called learner modeling) focuses the interest of researchers from the areas of cognitive psychology, artificial intelligence and computer science.

ITS compares it to the correct solution, using domain knowledge represented in the form of more than 120 constraints. It uses Constraint-Based Modeling [4] to model knowledge of its students.

2.2 Artificial Neural Networks

Artificial Neural Networks (ANN), are algorithms influenced by the behavior of the human brain [5]. Their operation is based on the interconnection of simple elements of processing that operate in parallel [3]. An ANN tries to imitate the process of storing and using information in the human brain in order to use it to solve problems by means of computers [7]. There are several important characteristics [5] in the construction of a neural network. On one hand, the number of neurons and the layout determines their structure. On the other hand, since the neurons are interconnected, it has sense to talk of the propagation of signals with the purpose of processing information. This processing will be made by means of the change of state of the neurons. The state of all neurons of the net is denominated state of the network and its variation in the time is made in agreement with a certain way of operation. The networks of neurons have demonstrated to be useful in problems of prediction and classification [1].

3. System Architecture for ITS

3.1 ITS Model

1. Inputs(Internal Test Marks) are used for training the Neural Networks and the Desired output is got from the External Mark(Last 2 Years Results are collected)
2. To implement the backpropagation Network based on the inputs,
 - 2.1Set the Number of input nodes in the Input layer
 - 2.2 Set the Number of hidden nodes in the Hidden Layer
 - 2.3 Set the Weight Value

3. Training is done in the Feed forward pass in the Backpropagation Algorithm
4. Testing is done in the BPN and the Output Vector was found.
5. Comparison was made between the Actual Output (Exam Result) and NN Output.

3.2 An Intelligent Problem-Selection Agent

We have previously encountered problems with a probabilistic student model, due to a large number of prior probabilities needed, and the heuristics necessary to select the problem out of a set of candidates. We decided to explore the capabilities of artificial neural networks (ANN) for this kind of instructional decision making.

The first phase includes the development of a neural network of suitable architecture and training the network to produce satisfactory predictions of student's results. The second phase will include the development of a mechanics for deciding upon the best problem to present to the student, based on predictions generated by the neural network. We present our experiences during a preliminary investigation of predictive capabilities of ANN's in educational settings.

3.3 System Architecture

The overall architecture of this ITS used in Feed forward Neural Network is shown below.

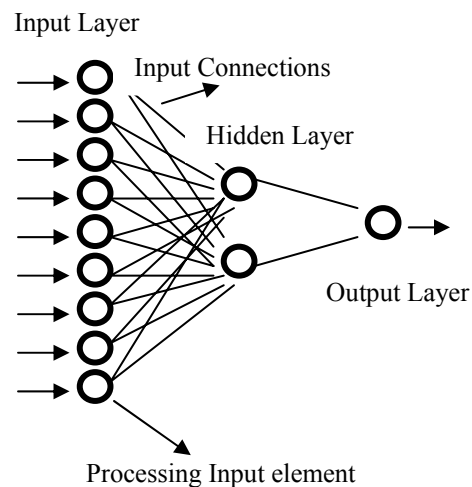


Figure 1. NN System Architecture

3.4 BPN Learning Algorithm

This algorithm consists of two pass.

3.4.1 Forward pass:

For each pattern, the activation is propagated from the input to the output. Here the input to hidden and the output was found out.

3.4.2 Backward pass:

- (i) The error was calculated at the output
- (ii) The error was then propagated backwards through the network to estimate the contribution to the error from each unit.
- (iii) Each weight value was changed by a small amount so as to reduce the total error.

3.5 Training Phase:

- (i) The inputs (Results) are got from the previous results.
- (ii) Apply them to the input vector.
 $X_p = X_{p1}, X_{p2}, X_{p3}, \dots, X_{pm}$ to the input units.
- (iii) Calculate the net input values to the hidden layer units.
 $net = (x_{pm} w_{in})$
- (iv) Calculate the outputs from hidden layer,
 $h = F(net)$
 $F(net) = out = 1 / (1 + e^{-net})$
- (v) Then the desired output is subtracted from the actual output to find the error and its propagated backwards to minimize the error by adjusting weights.
- (vi) Move to the Output layer; calculate the net input values to each unit.
 $net = (h_p w_{2n})$
- (vii) Calculate Output
 $O = F(net)$
- (viii) Calculate the error terms for Output units.
 $d = (t - O) \cdot O(1 - O)$

Where, t-target O-Output

- (ix) Calculate error terms for hidden units.
 $e = h(1 - h) \cdot d \cdot w_2$

The error terms on the hidden units are calculated before the connection weights to the output layer units have been updated. This training is called deterministic training since all training algorithm has a target, since output and methodology is fixed.

- (x) Update weights on Output layer

$$\Delta w_{2t} = \eta dh + \Delta \theta w_{2(t-1)}$$

η - Learning rate

Learning rate – Positive and less than 1

θ - Momentum factor

- (xi) Update weights on hidden layer

$$w_1^{new} = w_1^{old} + \Delta w_1$$

$$\Delta w_{1t} = \eta e x_{pm} + \Delta \theta w_{1(t-1)}$$

By choosing the weight value randomly, the input to hidden layer and then the output was calculated.

Then the error between target and output was calculated.

Now (adjust) update the weights and train the dataset to minimize the error.

4. Testing and training a neural network

As stated earlier, the purpose of the preliminary experiment was to determine whether predictive abilities of ANN's are satisfactory for usage in instructional decision making. To do experiment with neural networks, we used feed forward Backpropagation, which provides the facility to implement and test various configurations of neural networks and learning algorithms. Our neural network is a feed-forward network, with Single input layer (five inputs), a single hidden layer (3 inputs) and a single Output layer (1 Output).

The inputs and target results are collected from OOPS test marks of previous 2 years results. It contains 150 students Marks. The inputs to the network correspond to five test results. On the basis of these inputs the network predicts the number of errors. The prediction is considered to be incorrect if the predicted number of errors differs from the actual number of errors by more than 0.5. The network was trained with all the data from 2004-05 and 2005-06, to produce a population student model. 30 epochs with MSE of 0.000107 were needed to achieve 98.06% accuracy. The correlation r for the network was 0.99.

The implementation was done using Backpropagation network based on the following inputs,

$$\text{Total Internal Marks} = A + B + C$$

$$= ((\sum_{s=1}^3 X_s) / 15) + B + X_m / 20$$

Where, A is Internal tests ($\sum_{s=1}^3 X_s / 15$)

B is Attendance

C is Model Exam ($X_m / 20$)

Table 1. Training the Test marks with Desired Output

	Test Marks of OOPS(Input)					Expected Output (I)	Expected Output (II)
	Test1 (0.50)	Test2 (0.50)	Test3 (0.50)	Test4 (0.50)	Model Test (1)	Internal(0.20) $((\sum_{s=1}^3 X_s)/15)+B+X_m/20$	External (0.80)
Stud 1	0.27	0.34	0.42	0.34	0.45	0.0017	0.63
Stud 2	0.37	0.24	0.32	0.26	0.68	0.0017	0.65
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.							
Stud n	0.31	0.32	0.13	0.28	0.41	0.0015	0.55

Table 2. Testing with NN Output

	Test Marks of OOPS (Input)					Actual Output	NN Output	Actual Output	NN Output
	Test1 (0.50)	Test2 (0.50)	Test3 (0.50)	Test4 (0.50)	Model Test (1)	Internal (0.20)	Internal Mark	External	External Mark (0.0080)
Stud 1	0.37	0.27	0.39	0.34	0.94	0.0017	0.00172	0.0067	0.0066
Stud 2	0.16	0.41	0.39	0.41	0.85	0.0018	0.00188	0.0068	0.0067

Table 3. Comparison with NN Output

	S1	S2	S3	S4	S5	S6	S7	S8	S9
Actual Marks	9	10	15	18	19	20	18	16	19
NN Output	9	11	15	18	19	20	18	15	18

- (i)The Number of input nodes in the Input layer depending on the internal test marks was chosen.
- (ii)The Number of hidden nodes in the Hidden Layer was chosen.
- (iii)Set the Weight Value
- (iv)Training was carried out from external marks in the Feed forward pass of Backpropagation Algorithm
- (v)Testing was done with the training inputs and the Output Vector was calculated.
- (vi)Comparison was made between the Actual Output (External Mark) and NN Output and the error were calculated.
- (vii)The error was minimized by using weight updating between hidden and the output layer.

5. Prediction accuracy

Starting with the Student model discussed in the previous section, we individualized the network by using the data for a single student only. From all the available data, we selected 150 individual results for single subject (OOPS). When processing a single result, we propagated each submission through the network, and compared the predicted outcome with the actual one. The number of incorrect predictions per result ranged from 0 to 30, with an average of 1.97%.

The average prediction accuracy for all individual results was 93.22%. The network produced the total of 28 incorrect predictions, out of 120 submissions. Table 1 categorizes test marks and Desired Output for Internal and External Marks. The Table 2 Categories the Internal Test marks, Actual Output and NN Output for Internal Marks and External Marks. The Table 3 Categories the Actual Output and NN Output for 9 students.

The Fig.2 shows the comparison between the Actual Output and NN Output

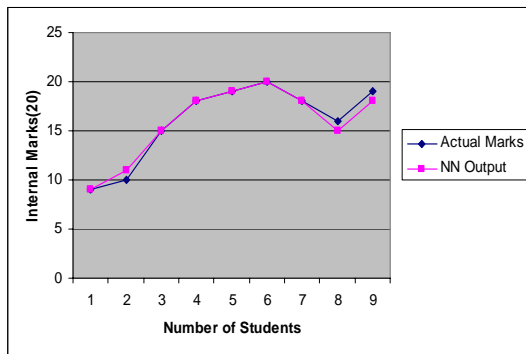


Figure 2. Comparison between Actual Output and NN Output

A further investigation of incorrect predictions reveals that the most frequent ones cover the situation when the network predicts the student's solution will be correct. We were also interested in how quickly the network adapts to the individual student. Fig.2 shows how the number of incorrect predictions varies over time. It displays the number of incorrect predictions that occur on the first submission up to the sixth submission for each individual network to adapt to each individual student. It can be seen that the corrected threshold (± 53) enables the network to predict student's behavior much better, at the same time reducing one error entry in Table 3.

6. Conclusion

In this paper, we discussed the possibility of using neural networks to predict student's results in intelligent tutoring systems. We trained a simple feedforward network using the data collected in the 2004-2005, 2005-2006 Anna university results. The network predicts the number of errors the student will make in the next exams. The student model was firstly produced using all the data, with the prediction accuracy of 78.4%, this network was then used to predict the result of each individual student. The student model can be adapted with the data from a individual tests, and it learns to predict accurately after only four tests. It was shown that the prediction accuracy is high, and can be further improved by tailoring the parameters used. The network performs better in a student results, although the discussed network predicts student's result very reliably.

The ITS is useful for the students to examine themselves and developing their skills according to their predicted output.

7. References

[1] Batchelor, B. *Practical Approach to Pattern Classification*, Plen Press, London, UK.

[2] M.Mayo, A. Mitrovic, *Using a probabilistic student model to control problem difficulty*. In: G. Gauthier, C. Frasson and K. VanLehn (eds), Proc. ITS' 2000, Springer-Verlag Berlin, 524-533, 2002

[3] McCulloch, Pits. *A logical Calculus of the Ideas Immanent in Nervous Activity*, Bull. Math. Bioph, Vol. 5.

[4] Mitrovic, A, S. Ohisson, *Evaluation of a Constraint-based Tutor for a Database Language*. Int. J. Artificial Intelligence in Education, 10(3-4), 238-256. 1999

[5] Posey, C.L, L.W. Hawkes, *neural Networks Applied to Knowledge Acquisition in the Student Model*. Information Sciences, 275-298, 1996

[6] Rinaldi, F. "Towards Answer Extraction, An application to Technical Domains" IEEE Intelligent Systems, July – August 2003.

[7] Wenger "Artificial Intelligence and Tutoring Systems". Morgan Kaufmann Publishers, Inc., 1987