A Project Report

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"Question Difficulty Analyzing System"

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ABSTRACT

Computerized Adaptive Testing (CAT) is a growing mode of assessment in many educational as well as non-educational institutions around the world. A distinct feature of CAT is its ability to tailor the test to the ability level of a test taker based on the observed responses to previously administered items. Hence, shorter tests can be administered and yet more accurate estimates can be attained. In the literature, several approaches have been proposed for making CAT systems based on Item Response Theory (IRT) and Bayesian Belief Networks (BBNs). Along with other detriments, these approaches rely on strict assumptions and require a large amount of probability data. In this thesis, we survey the state-of-the-art of computerized adaptive testing. Then, we explore the application of several static neural network models in designing traditional tests. After that, we propose a novel approach for making CAT systems using Neural Networks (NNs).As a form of neural networks, NN is data-driven and self-adaptive classifier. Moreover, being recurrent, it captures the system dynamics by remembering the time-varying pattern of examinee's responses to previously administered items. The results of the proposed approach are found to be promising as compared to some existing techniques.

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1.1 INTRODUCTION

Examination is a vital unit in the process of education. The accurate evaluation of examinees' knowledge is undeniably a very important aspect in examinations. Two of the most commonly used assessment methods in exams are oral and written. Along with the other advantages of oral exams over written exams, one important benefit of oral exam is that it is adaptive and hence more accurate. In an oral exam, an intelligent examiner tends to adapt to each examinee based on his/her responses to the previous question/item that has been asked. Although a traditional written test has several other advantages, this adaptation cannot be achieved whether it is conducted on paper or on computer.

Computerized adaptive testing (CAT) is a mode of administering exams in which a computer replaces the mind of an intelligent examiner to estimate the ability and provide the best weights to the questions.

The CAT system is designed in such a way that adapts to each examinee based on his responses to the previous items or questions that have been administered. As test takers respond to items, CAT successively selects questions in order to maximize the precision of the test.

The concept of computerized adaptive testing was initially proliferated by Lord in 1970. His basic argument was that "The abilities of an examinee are measured effectively if the test is neither too difficult nor too easy for him". This means that the selection of items for an examinee should be tailored to the level of his abilities. These abilities of a person are fuzzy and cannot be measured directly like height and weight; hence called latent. Thus the goal of education testing systems (including CAT) is the determination of how much of such latent abilities a person possesses based on observed responses to test items.

Since in a CAT system every examinee's ability state or proficiency level is estimated after receiving his response to the presented item, the ability state is a function of not only the response of the last item but also of the responses of all items previously administered to the test-taker. Hence, the pattern of item response and the ability computed after each item is a time-varying pattern. Time-varying or dynamic patterns cannot be classified using feed-forward neural networks since they require the network to have memory.

Neural Networks (NNs) possess the capability of learning such patterns. They have feedback connections with delays among the nodes that provide the network with memory to remember past inputs.

It has been proved to be very effective in remembering and generalizing on dynamic data. One of the interesting things about an NN is that it tends to mimic the human brain. Human brain learns time-varying patterns by adjusting weights to the biological neurons present inside the brain. Thus, using NNs a CAT system will tend to provide better result. In this research, we came up with a new approach for designing CAT systems based on recurrent neural networks.

1.2 MOTIVATION

The primary advantage of a CAT to test developers and administrators is its promise of efficient testing. This is the reason that CAT is becoming a vital unit of many educational and non-educational institutions. In the educational context, usually the admission test in colleges and universities are based on CAT systems; popular examples include SAT, GRE and TOEFL. Many researchers have recently conducted investigations related to adaptive exams. Similarly, in non-educational domain, CAT based patients' diagnostic systems, marketing research strategies, efficient health outcomes assessments in clinical settings are some recent and prominent examples of CAT systems. The importance of CAT is apparent from the growing number of its applications in many domains.

The approach used in CAT system is very different from the traditional paper and pencil test in which the same sets of questions are presented to all the examinees regardless of their responses or abilities. Each item in the test provides some information about the tested ability. To achieve high precision in the ability estimation, a large number of items are required. The more the items, the more information gained about the examinee and the greater the precision. On the other hand, the CAT system provides more precise classification of the examinees with less number of items. Also with CAT, the ability estimation is independent of the questions asked; his ability estimate on the average will be the same. This is known as the item invariance principle. This principle is very important and critical in testing especially in coordinated courses where two examinees are presented with two different exams; the relative measures of their abilities should remain the same.

CHAPTER 2

NEURAL NETWORKS

We will describe in this section the part concerning to Artificial Neural Networks and the Backpropagation algorithm which will serve as a background for our proposal. Most of the material in this section is well described in the literature available, but we have based most of this part by considering the approach that Tom Mitchell states in its book of Machine Learning [22]. Artificial neural networks have their basis on the biological model, where we have a set of neurons that are connected one thru another to build a neural net. In the artificial model the neurons are also connected as a set of nodes that are influenced by a set of weights; each neuron has an activation function that allows the information to pass from one node to another. The simplest model was a single layer neural network, ie. having only one input, a neuron or set of neurons and an output; this model was known as the Perceptron model. The inability of this model to handle nonlinear separable problems arise the need of the use of connection of neurons in a multilayer fashion and this model is known as the multilayer Perceptron model.

When one neuron receives an input, and according to its activation function, propagates the information to other neurons is named as the Forward Propagation Algorithm. Drawbacks of this model, as the impossibility of update the weights that influence each network gave birth to what is knows as the Backpropagation algorithm. In this latter model after performing a Forward Propagation algorithm the weights are updated by making a reverse traversal thru the nodes of the Neural Network, by diminishing the error that is obtained by comparing the actual output to the needed output in the learning process phase. In our proposal we have used a model of Multilayer Perceptron and by using the Backpropagation algorithm for training and make predictions with our neural network model.

CHAPTER 3

3.1 METHODOLOGY

In this I have implemented a neural network to set and modify weights of questions which were asked in the computerized adaptive test so that the weights will be balanced.

To do such task I have used unsupervised learning algorithm called Restricted Boltzmann Machine algorithm.

3.2 What are Boltzmann Machines?

Boltzmann machines are stochastic and generative neural networks capable of learning internal representations and are able to represent and (given sufficient time) solve difficult combinatoric problems.

They are named after the Boltzmann Distribution (also known as Gibbs Distribution) which is an integral part of Statistical Mechanics and helps us to understand the impact of parameters like Entropy and Temperature on the Quantum States in Thermodynamics. That's why they are called Energy-Based Models (EBM). They were invented in 1985 by Geoffrey Hinton, then a Professor at Carnegie Mellon University, and Terry Sejnowski, then a Professor at Johns Hopkins University.

3.3 How do Boltzmann Machines work?

A Boltzmann Machine looks like this:

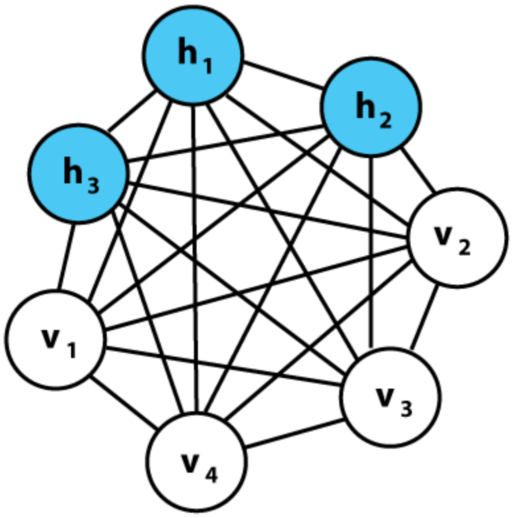


Fig. 3.1

Boltzmann machines are non-deterministic (or stochastic) generative Deep Learning models with only two types of nodes — `hidden` and `visible` nodes. There are no output nodes! This may seem strange but this is what gives them this non-deterministic feature. They don't have the typical 1 or 0 type output through which patterns are learned and optimized using Stochastic Gradient Descent. They learn patterns without that capability and this is what makes them so special!

One difference to note here is that unlike the other traditional networks (A/C/R) which don't have any connections between the input nodes, a Boltzmann Machine has connections among the input nodes. We can see from the image that all the nodes are connected to all other nodes irrespective of whether they are input or hidden nodes. This allows them to share information among themselves and self-generate subsequent data. We only measure what's on the visible nodes and not what's on the hidden nodes. When the input is provided, they are able to capture all the parameters, patterns and correlations among the data. This is why they are called `Deep Generative Models` and fall into the class of `Unsupervised Deep Learning`.

3.4 What are Restricted Boltzmann Machines?

RBMs are a two-layered artificial neural network with generative capabilities. They have the ability to learn a probability distribution over its set of input. RBMs were invented by Geoffrey Hinton and can be used for dimensionality reduction, classification, regression, collaborative filtering, feature learning, and topic modeling.

RBMs are a special class of Boltzmann Machines and they are restricted in terms of the connections between the visible and the hidden units. This makes it easy to implement them when compared to Boltzmann Machines. As stated earlier, they are a two-layered neural network (one being the visible layer and the other one being the hidden layer) and these two layers are connected by a fully bipartite graph. This means that every node in the visible layer is connected to every node in the hidden layer but no two nodes in the same group are connected to each other. This restriction allows for more efficient training algorithms than what is available for the general class of Boltzmann machines, in particular, the gradient-based contrastive divergence algorithm.

A Restricted Boltzmann Machine looks like this:

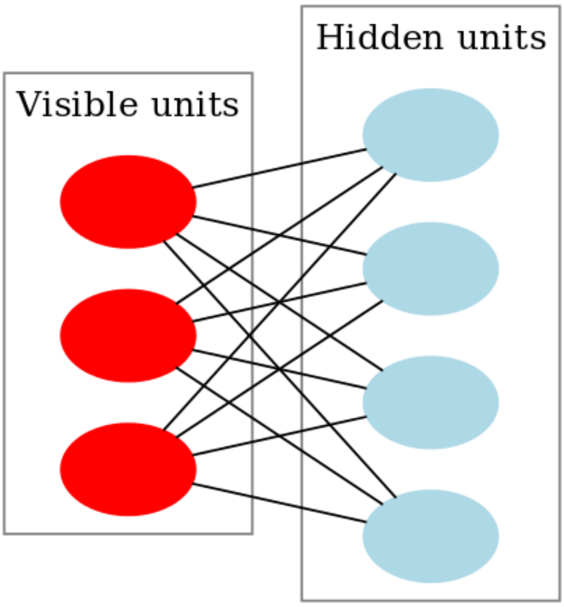
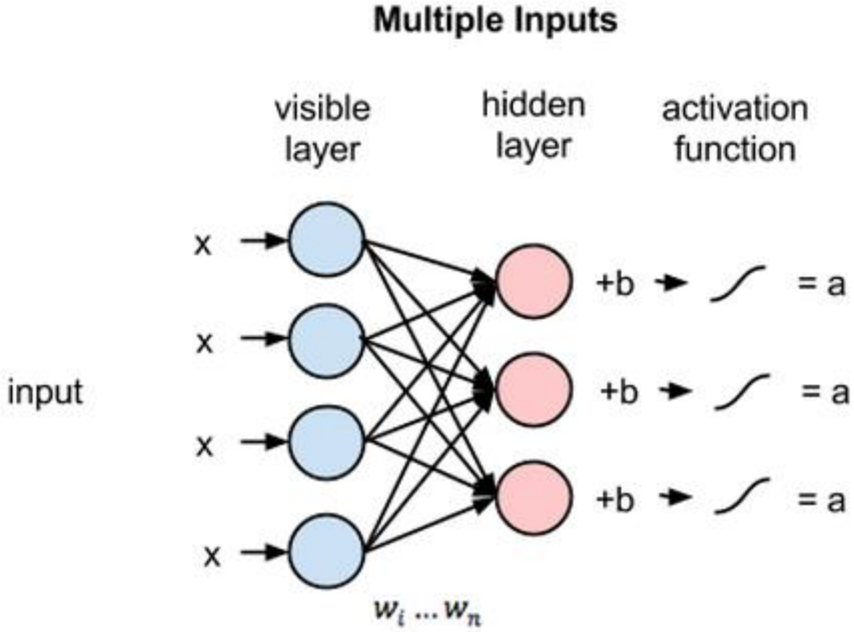


Fig. 3.2

3.5 How do Restricted Boltzmann Machines work?

In an RBM, we have a symmetric bipartite graph where no two units within the same group are connected. Multiple RBMs can also be `stacked` and can be fine-tuned through the process of gradient descent and back-propagation. Such a network is called a Deep Belief Network. Although RBMs are occasionally used, most people in the deep-learning community have started replacing their use with General Adversarial Networks or Variational Autoencoders.

RBM is a Stochastic Neural Network which means that each neuron will have some random behavior when activated. There are two other layers of bias units (hidden bias and visible bias) in an RBM. This is what makes RBMs different from autoencoders. The hidden bias RBM produce the activation on the forward pass and the visible bias helps RBM to reconstruct the input during a backward pass. The reconstructed input is always different from the actual input as there are no connections among the visible units and therefore, no way of transferring information among themselves.



The above image shows the first step in training an RBM with multiple inputs. The inputs are multiplied by the weights and then added to the bias. The result is then passed through a sigmoid activation function and the output determines if the hidden state gets activated or not. Weights will be a matrix with the number of input nodes as the number of rows and the number of hidden nodes as the number of columns. The first hidden node will receive the vector multiplication of the inputs multiplied by the first column of weights before the corresponding bias term is added to it.

And if you are wondering what a sigmoid function is, here is the formula:

$$S(x) = \frac{1}{1 + e^{-x}} = \frac{e^x}{1 + e^x}$$

So the equation that we get in this step would be,

$$\mathbf{h}^{(1)} = S(\mathbf{v}^{(0)T} W + \mathbf{a})$$

where **h(1)** and **v(0)** are the corresponding vectors (column matrices) for the hidden and the visible layers with the superscript as the iteration (v(0) means the input that we provide to the network) and **a** is the hidden layer bias vector.

So, the inputs will be the responses of the students on the questions, this machine will do its work and output the Excel sheet of questions with its proper weight.

CONCLUSION:

Implemented a Neural Network to analyze response accuracy per question and modify the weights to hence obtain a new weighting for the question set, which will better suit the current demographic.