Forecasting Alcohol Consumption Trends Among College Students Using Artificial Neural Network (ANN)

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Abstract

Problems with alcohol are a major concern on college campuses today. Efforts to influence the rate of student alcohol problems are increasingly seen to be urgent priorities. Forecasting alcohol consumption trends amongst students on college campuses would facilitate accurate remedial strategies. Previous forecasting techniques based on multiple regression analysis have been helpful, but were not very accurate. A quantitative neural network model is developed that predicts drinking behaviors across the campus. This forecast is made be examining demographics, student status, family drinking history, ethnicity, and involvement in athletics etc.

Introduction

The number of American people who drink is constantly on the rise and has reached epidemic proportions. National surveys have reported that the majority of the college students drink, and that approximately fifteen percent of these could be classified as problem drinkers. Efforts to influence the rate of student alcohol problems are increasingly seen to be urgent priorities. Many colleges have launched alcohol prevention and intervention programs for college students. Unfortunately, most such programs are either not validated or are plainly based on models exhibiting poor efficiency.

In recent years, several instruments have been designed to measure alcohol consumption trends among college students both using ad hoc and statistical methods. Typically, these instruments have examined negative consequences as a global index, ignoring possible sub factors. Typical approaches to the development of an alcohol problem index involve

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targeting exhaustive list of possible problems that college students face without assessing the underlying factor structure. This decreases the sensitivity of the instrument and treats all problems equally.

Laimer, Anderson, Baer and Marlatt[1] have studied and identified predictors of alcohol use and drinking problems among Greek and residence hall students. In their study, members of college fraternities and sororities were compared to students living in residence halls in terms of their current drinking rates and alcohol-related problems, as well as family history of alcohol consumption, alcohol outcome expectancies, and high school drinking rates. Regression analyses were utilized to evaluate the relative contribution of residence type, to the prediction of current drinking rates and problems after accounting for family history, outcome expectancies, and prior drinking patterns.

Kypri, Gallagher and Smith[2] developed an Internet-based survey method for college student drinking research to characterize the alcohol consumption of college students. Lied and Marlatt[3] have modeled sex and prior drinking history as a determinant of alcohol consumption. Park[4] in his paper, has examined, the nature and frequency of positive and negative alcohol-related consequences, the relationship of these consequences to alcohol consumption patterns, and the impact of these consequences on subsequent drinking intentions. Borsari and Carey[5] in their research studied that perceived social norms could make excessive alcohol use appear common and acceptable to the student. Maddocka, Laforgeb, Rossib, and O'Harec[6] have developed a short, reliable two-factor instrument measuring drinking-related negative consequences from a previous measure using two samples of college students. These forecasting techniques mostly based on multiple regression analysis have been helpful, but were not very accurate.

In our paper surveys are administered to the student body at Texas A&M University-Kingsville and a quantitative Artificial Neural Network model is developed that models and forecasts drinking behaviors across the campus. On a campus of six thousand students, two hundred and seventy students were surveyed. Of these two hundred and seventy students, one hundred and nineteen were female (just under half of the students surveyed). Twenty-seven were part time (registered 1-11 hours), one hundred and sixty five were involved in athletics, of which, seventy-six were involved in a NCAA recognized sport.

This paper is organized as follows. Section two deals with alcohol consumption model and indicators, Section three discusses Neural Networks modeling and training, Section four deals with simulation results and Section five concludes the paper.

Alcohol Consumption Model

In order to predict vulnerability of a student towards drinking during college years, several factors had to be taken into account.

Input1: Gender

Male or Female

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Input2: Age
17 to 20, 21 to 23, 24 to 26, and other (all in years)
Input3: *Hours*
College hours - 0 to 30, 31 to 60, 61 to 90, over 90
Input4: *Status*
Student status - full time (12+hours) or part time (1-11 hours)
Input5: *Ethnicity*
Ethnicity - Asian, African American, Caucasian, Hispanic, Other
Input6: *Reasonable*
Students' Perception of Reasonable Drinking Habits.
Inpu7: *Athletics*
Students' involvement in University athletics
Input8: *Level*
Level of Athletics involvement
Input9: *Precollege*
Whether Students' ever drank alcohol before your first year of college
Input10: Start
If they drank before first year of college, the age they had their first drink.

The item pertaining to age of a student was used, when comparing information with other surveys. Some questions were used to gather information on how much the students who drank consumed regularly. In order to completely understand factors that influenced students who drink, questions about the parents' drinking status were also considered but not included in the survey. Two questions were used to determine the effect the parents may have had on the student. The final factor included in the survey was the students' involvement in athletics and the level that they were involved.

Neural Networks

Neural Networks (NN) are massively parallel, distributed processing systems that can continuously improve their performance via dynamic learning. NN have more recently begun to emerge as an entirely new approach for the modeling of adaptive, distributed, and mostly nonlinear systems. NN are suited for applications involving complex systems. When applied correctly, a neural or adaptive system can outperform other methods[7]. Neural computers have opened the door to many applications that are difficult for conventional computers to carry out. An artificial NN model emulates a biological NN based on the human brain. The NN resembles the human brain in two ways. It acquires knowledge through learning. This knowledge is stored within inter-neuron connection strengths known as synaptic weights. The biological NN is composed of special cells called neurons that are partitioned into groups called networks. By way of comparison, the artificial NN is composed of Processing Elements, which contains the transfer function, and weights (which express relative strength of the input data or transfer data from layer to layer and to the output). The artificial NN can appear in many configurations called architectures. These architectures may have many different transfer functions, different

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number of Input Processing Elements (PE's), Output PE's, Hidden PE's and Hidden Layers. Key advantages of the NN are its ability of learning, recognition, generalization, classification and interpretation of incomplete and noisy inputs (data) and its ability to represent both linear and nonlinear relationships.

Training is the process of teaching the network what one wants it to learn. Neural networks are characterized by the pattern and strength of connections between the various network layers, the number of neurons in each layer, the dynamic learning algorithm, and the neuron activation functions. Generally speaking, a neural network is a set of connected input and output units in which each connection has a weight associated with it. During the learning phase, the network learns by adjusting the weights so as to be able to correctly predict or classify the output target of a given set of input samples. With supervised learning, the network is able to learn from the input and the error (the difference between the output and the desired response). Given the numerous types of neural network architectures that have been developed in the literature, three important types of neural networks often used for classification problems were implemented.

Multilayer Perceptrons (MLPs):

MLPs are layered feedforward networks typically trained with back propagation (learning algorithm). Their main advantage is that they are easy to use, and that they can approximate any input/output map. The key disadvantages are: they train slowly, and require a large amount of training data (typically three times more training samples than network weights) [8].

Generalized Feedforward Networks (GFN):

GFNs are a generalization of the MLP, which contains connections that can jump over one or more layers. In practice, generalized feedforward networks can often solve the problem much more efficiently [8].

Radial Basis Function (RBF):

RBF networks are nonlinear hybrid networks typically containing a single hidden layer of processing elements (PEs). This layer uses Gaussian transfer functions, rather than the standard sigmoid functions employed by MLPs. These networks tend to learn much faster than MLPs [7].

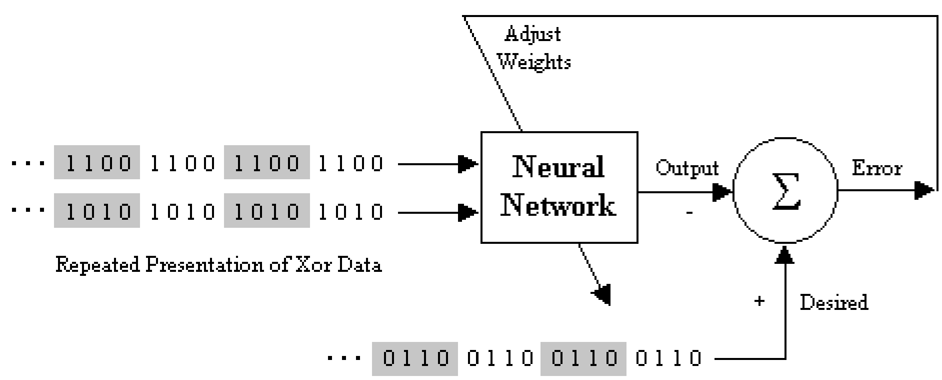

Figure 1: Demonstration of a neural network-learning model.

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Figure 1, represents the demonstration of a neural network-learning model. The data is repeatedly presented to the neural network. With each presentation, the error between the network output and the desired output is computed and fed back to the neural network. The neural network uses this error to adjust its weights such that the error will be decreased. This sequence of events is usually repeated until an acceptable error has been reached or until the network no longer appears to be learning.

Simulation Results

This model used the above-mentioned three NN models and ten inputs in predicting alcohol consumption trends. All three neural network models were run under varied training cycles and number of hidden layers.

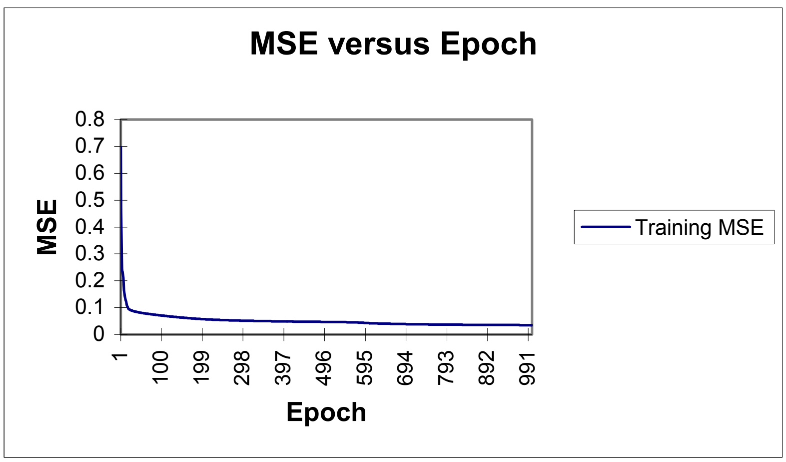

Figure 2: Training

Ultimately, the GFN neural network with two hidden layers and a training cycle of 1000 epochs was chosen based on the quality of output. Figure 2 shows Neural Network training. It is observed that the Mean Square Error (MSE) becomes constant after 900 training cycles. Figure 3 represents the ability of the neural model to predict alcohol consumption effectively.

After having determined the suitable neural network model and number of training cycles, the relative contribution of each input for a particular neural network model was evaluated through sensitivity analysis. Figures four through six represent few inputs and their relative towards predicting alcohol consumption trends (interested parties can contact the author for more information on the sensitivity of other inputs).

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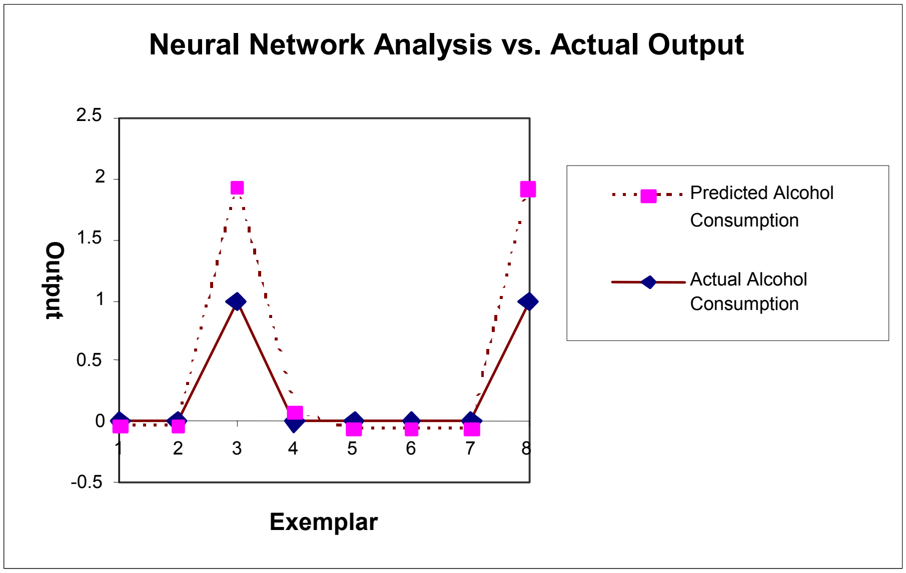

Figure 3: Testing

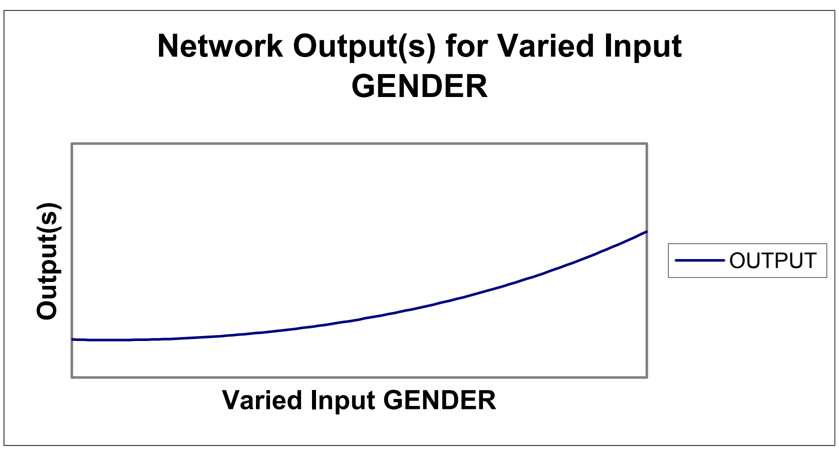

Figure 4: Sensitivity of Gender.

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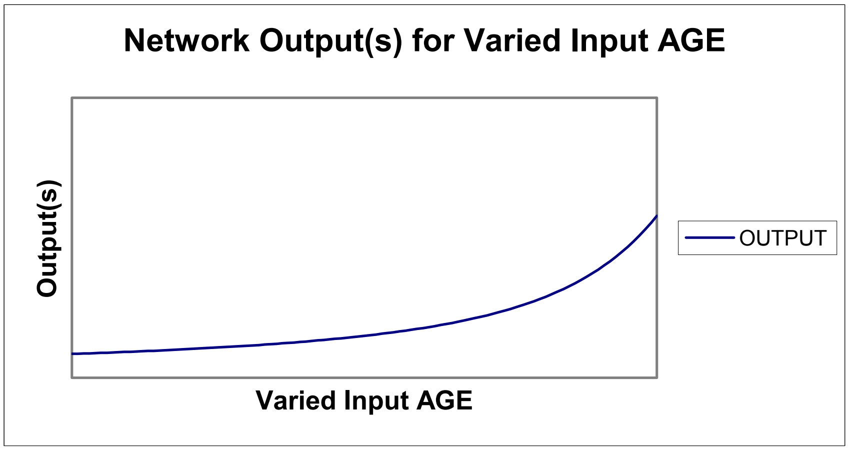

Figure 5: Sensitivity of Age.

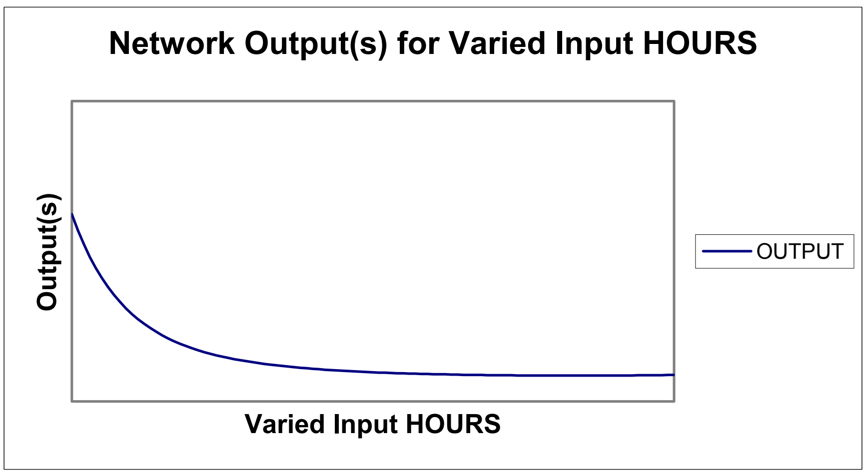

Figure 6: Sensitivity of College Hours.

Conclusions and Future Work

The survey was overall very well put together and the output produced results that were significantly closer to expected outcomes. Overall two hundred and seventy students were surveyed. It was observed that the neural network model selected, performed well with satisfactory results in predicting whether a student would drink in college or not. It was much easier to determine which of the inputs contributed significantly towards the required output by performing the sensitivity analysis on all the inputs. Some modifications could possibly enhance the accuracy of the model by incorporating

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additional factors such as effects of religious beliefs, peer interaction, Greek organizations, and living on or off campus. This would be a scope of further research.

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