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Artificial Neural Networks: Applications In Management

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Abstract: *With the advancement of computer and communication technology, the tools used for management decisions have undergone a gigantic change. Finding the more effective solution and tools for managerial problems is one of the most important topics in the management studies today. Artificial Neural Networks (ANNs) are one of these tools that have become a critical component for business intelligence. The purpose of this article is to describe the basic behavior of neural networks as well as the works done in application of the same in management sciences and stimulate further research interests and efforts in the identified topics.*
Key words: *Artificial Neural Networks, Management Applications, Management, Marketing*

I. Introduction

CLASSIFICATION is one of the most frequently encountered decision making tasks of human activity. A classification problem occurs when an object needs to be assigned into a predefined group or class based on a number of observed attributes related to that object. Many problems in business, science, industry, and medicine can be treated as classification problems. Examples include bankruptcy prediction, credit scoring, medical diagnosis, quality control, handwritten character recognition, and speech recognition. Neural networks have emerged as an important tool for classification. Neural networks have seen an explosion of interest over a last few years and are being successfully applied across an extraordinary range of problem domains. The excitement stems from the fact that these networks are attempts to mimic the capabilities of the human brain.

Artificial neural networks are distributed information processing systems composed of many simple computational elements interacting across weighted connections. ANNs can identify and learn correlated patterns between input data sets and corresponding target values. After training, ANNs can be used to predict the outcome of new independent input data. ANNs seek to simulate the human brain structure, human thinking and human learning in a machine. Thus they are ideally suited for the modeling of agricultural data which are often complex and non linear.

These networks are "neural" in the sense that they have been inspired by neuroscience but not necessarily because they are faithful models of biological cognitive phenomena. The majority of the networks are closely related to traditional mathematical and statistical models such as clustering algorithms, non linear filters etc.

An ANN consists of many single processors, which interact through a dense web of interconnections. A neuron or processing element has primarily two things to do. One is that it computes output which is sent to another neuron which determines its output value by applying a transfer function. Two, it updates the local memory, i.e. weights and other data types called data variables. These processing elements are organized into two layers. The first layer is known as the input layer and the last layer is referred to as the output layer. The one or more inner layers are known as hidden layers. The input neurons receive values from outside the neural networks' environment, whereas the output neurons send the values to this outside environment.

II. Characterictics Of Neural Networks

- The NNs exhibit mapping capabilities hence they can map their input patterns to the associated output patterns.
- Since the NNs learn by examples, the NN architecture can be trained with known examples of a problem before they are tested for their inference capability on unknown instances of the problem.
- They possess the capability to generalize.
- They are robust systems and fault tolerant and hence they can recall full patterns from incomplete, partial or noisy patterns.
- They can process information in parallel at high speed and in a distributed manner.
- They can be used to cluster the training data into natural groups based on the similarity of characteristics in the training data.

III. Neural Networks: Basics

The terminology of artificial neural networks has developed from a biological model of the brain. A neural network consists of a set of connected cells: The neurons. The neurons receive impulses from either input cells or other neurons and perform some kind of transformation of the input and transmit the outcome to other neurons or to output cells. The neural networks are built from layers of neurons connected so that one layer receives input from the preceding layer of neurons and passes the output on to the subsequent layer.

The neuron is a real function of the input vector (y_1,….., yk). The output is obtained as $f(x_j)=f(\alpha_j+\sum^{k}_{i=1} w_{ij}y_j)$, where f is a function, typically a sigmoid function. A graphical presentation of neuron in the figure below:

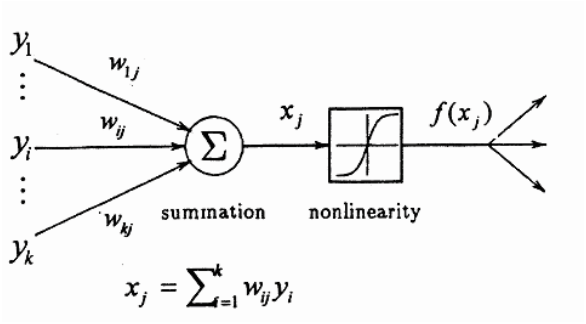


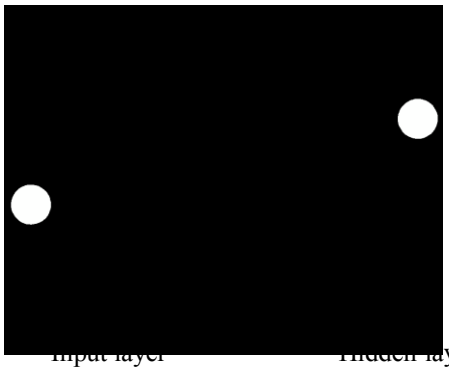
Figure 1 : a simple neuron

Neural networks architectures

An ANN is defined as a data processing system consisting of a large number of simple highly inter connected processing elements (artificial neurons) in an architecture inspired by the structure of the cerebral cortex of the brain. There are several types of architecture of NNs. However, the two most widely used NNs are discussed below:

Feed forward networks

In a feed forward network, information flows in one direction along connecting pathways, from the input layer via the hidden layers to the final output layer. There is no feedback
(Loops) i.e., the output of any layer does not affect that same or preceding layer.



Input layer Hidden layer Output layer

Figure 2: A multi-layer feed forward neural network

Recurrent networks

These networks differ from feed forward network architectures in the sense that there is at least one feedback loop. Thus, in these networks, for example, there could exist one layer with feedback connections as shown in figure below. There could also be neurons with self- feedback links, i.e. the output of a neuron is fed back into itself as input.

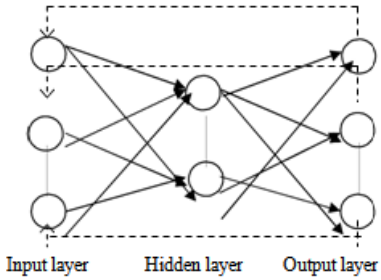


Figure 3: A recurrent neural network

Learning/Training methods

Learning methods in neural networks can be broadly classified into three basic types: supervised, unsupervised and reinforced.

Supervised learning

In this, every input pattern that is used to train the network is associated with an output pattern, which is the target or the desired pattern. A teacher is assumed to be present during the learning process, when a comparison is made between the network's computed output and the correct expected output, to determine the error. The error can then be used to change network parameters, which result in an improvement in performance.

Unsupervised learning

In this learning method, the target output is not presented to the network. It is as if there is no teacher to present the desired patterns and hence, the system learns of its own by discovering and adapting to structural features in the input patterns.

Reinforced learning

In this method, a teacher though available, does not present the expected answer but only indicates if the computed output is correct or incorrect. The information provided helps the network in its learning process. A reward is given for a correct answer computed and a penalty for a wrong answer. But, reinforced learning is not one of the popular forms of learning.

Types of neural networks

The most important class of neural networks for real world problems solving includes

- Multilayer Perceptron
- Radial Basis Function Networks
- Kohonen Self Organizing Feature Maps

Multilayer Perceptrons

The most popular form of neural network architecture is the multilayer perceptron (MLP). A multilayer perceptron:

- has any number of inputs.
- has one or more hidden layers with any number of units.
- uses linear combination functions in the input layers.
- uses generally sigmoid activation functions in the hidden layers.
- has any number of outputs with any activation function.
- has connections between the input layer and the first hidden layer, between the hidden layers, and between the last hidden layer and the output layer.

Given enough data, enough hidden units, and enough training time, an MLP with just one hidden layer can learn to approximate virtually any function to any degree of accuracy. (A statistical analogy is approximating a function with *n*th order polynomials.) For this reason MLPs are known as universal approximators and can be used when you have little prior knowledge of the relationship between inputs and targets. Although one hidden layer is always sufficient provided you have enough data, there are situations where a network with two or more hidden layers may require fewer hidden units and weights than a network with one hidden layer, so using extra hidden layers sometimes can improve generalization.

Radial Basis Function Networks

Radial basis functions (RBF) networks are also feed forward, but have only *one* hidden layer. A RBF network:

- has any number of inputs.
- typically has only one hidden layer with any number of units.
- uses radial combination functions in the hidden layer, based on the squared Euclidean distance between the input vector and the weight vector.
- typically uses exponential or softmax activation functions in the hidden layer, in which case the network is a Gaussian RBF network.
- has any number of outputs with any activation function.
- has connections between the input layer and the hidden layer, and between the hidden layer and the output layer.

MLPs are said to be distributed-processing networks because the effect of a hidden unit can be distributed over the entire input space. On the other hand, Gaussian RBF networks are said to be local-processing networks because the effect of a hidden unit is usually concentrated in a local area centered at the weight vector.

Kohonen Neural Network

Self Organizing Feature Map (SOFM, or Kohonen) networks are used quite differently to the other networks. Whereas all the other networks are designed for supervised learning tasks, SOFM networks are designed primarily for unsupervised learning (Patterson, 1996).

At first glance this may seem strange. Without outputs, what can the network learn? The answer is that the SOFM network attempts to learn the structure of the data. One possible use is therefore in exploratory data analysis. A second possible use is in novelty detection. SOFM networks can learn to recognize clusters in the training data, and respond to it. If new data, unlike previous cases, is encountered, the network fails to recognize it and this indicates novelty. A SOFM network has only two layers: the input layer, and an output layer of radial units (also known as the *topological map* layer).

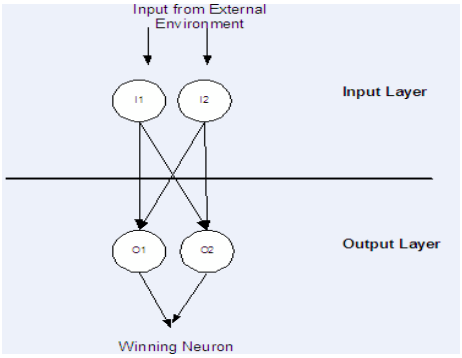


Figure 4: A Kohonen Neural Network Applications

Applications In The Field Of Marketing:

ANN can be applied to many marketing decision problems which could previously be tackled only by multivariate statistical analysis. Typical problems are market segmentation tasks and market response modeling, consumer spending patterns, new product analysis, identification of customer characteristics; targeted marketing etc. the most crucial point for research activities in the field of marketing is the lack of applications on the individual level data.

These kinds of problems are encountered in the context of purchase behavior in the tradition of stochastic models of consumer behavior.

Applications In The Field Of Finance:

Artificial neural networks are frequently used in many modeling and forecasting problems, mainly due to the chances of use of computer intensive methods. Recently, they have been increasingly applied in the financial time series analysis. The main advantage of the same is the ability to approximate almost any non-linear function arbitrarily close. ANNs can provide a better fit particularly in financial time series with complex non linear dynamic relationships. However, it is usually difficult to interpret the meaning of the parameters and the neural networks are seen as “black box” models constructed for the pattern recognition and prediction. The essential topics in finance are the forecasts of changes in the value of financial assets under the form of stocks, currencies, analysis of strength of historical financial statements.

Applications In The Field Of Manufacturing And Production:

Forecasting i.e. production costs, delivery dates etc., quality control and optimization dominates the production problems. As quality control problems correspond to classification thus the appropriateness of the application of artificial neural networks is supposed to be as good as those in the fields of finance and marketing.

Applications In The Field Of Strategic Mangement And Business Policy:

The research in strategic planning systems is focused on two areas namely the impact of strategic planning on firm performance and the role of strategic planning in strategic decision making. ANN as efficient tool have been utilized for determining and clarifying the relationship between strategic planning and performance and also assessing decision making.

Table: Reported Applications of Artificial Neural Networks

Business Area	Problem type	reference
Marketing and Sales	Forecasting costumer respond	[10-12]
	Market development forecasting	[13]
	Sales forecasting	[14-19]
	Price elasticity modeling	[20]
	Target marketing	[15, 21-22]
	Customer satisfaction assessment	[23]
	Customer loyalty and retention	[24-26]
	Market segmentation	[27-30]
	Customer behavior analysis	[31-32]
	Brand analysis	[27, 33]
	Market basket analysis	[34]
	Storage layout	[35]
	Customer gender analysis	[36]
	Market orientation and performance	[6]
	Marketing strategies, strategic planning and performance	[3, 37-39]
	Marketing data mining	[40]
	Marketing margin estimation	[41]
	New product acceptance research	[42]
	Consumer choice prediction	[43]
	Market share forecasting	[44]

Business Area	Problem type	Reference
Finance and Accounting	Financial health prediction	[3, 47-49]
	Compensation assessment	[50-51]
	Bankruptcy classification	[52-57]
	Analytical review process	[58-59]
	Credit scoring	[60-62]
	Signature verification	[48, 63]
	Risk assessment	[64]
	Forecasting	[65-66]
	Stock trend classification	[67-69]
	Bond rating	[70-71]
	Interest rate structure analysis	[72]
	Mutual found selection	[73]
	Compensation assessment	[50-51]
	Credit evaluation	[74-79]

Business Area	Problem type	Reference
Manufacturing and production	Engineering design	[80-84]
	Quality control	[85-89]
	Storage design	[35]
	Inventory control	[90-92]
	Supply chain management	[93-95]
	Demand forecasting	[96-100]
	Monitoring and diagnosis	[101-105]
	Process selection	[80,106-109]

Business Area	Problem type	Reference
Strategic management and business policy	Strategic planning and performance Assessing decision making	[3, 37, 39, 111-114] [114-120]

IV. Conclusion

Here in this paper we have tried to survey the reported works in the area of applications of ANN to different problems of management. Neural networks are shown to have matured to the point of offering practical solutions in many of their applications. However there is a clear deficit of more complete work describing neural network models.

The various advantages and disadvantages of using the artificial neural networks can be summarized as follows:

Advantages:

- The ANN models can provide highly accurate results in comparison with regression models.
- The significance and accuracy of these models can be assessed using the traditional statistical measures of mean squared error.
- These models automatically handle variable interactions.
- ANN models can be easily updated and hence are suitable for dynamic environment.
- Artificial neural networks have associative ability i.e. once developed; an ANN is generally robust to missing or inaccurate data.
- ANN is a reliable tool for predicting the determinants of relationship quality.

Disadvantages:

- No method has yet been devised to determine the significance of independent inputs in a neural network directly.
- It is difficult to state the results in simple precise analytical model statement.
- ANN learning process can be very time consuming.
- If the environment changes, the network must be reconstructed.

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