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Neural Networks: Business Applications

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Abstract:
Though inspired by biological learning systems, artificial neural networks (ANNs) have moved steadily towards the field of statistics, established themselves as a complete alternative to traditional statistical models. The recent rise in research activities into ANNs has established that neural networks have powerful prediction and pattern classification capabilities. With these promising capabilities, ANN have reached into a wide range of financial and business related applications as an important quantitative modeling tool in the ambit of financial markets, operations research and marketing. The aim of this paper is to provide brief description of neural networks especially their architecture, benefits and limitations over traditional forecasting models as well as main areas of application in business.

Key words: *Neural Network, Machine Learning, SVM, SOM*

1. Introduction
Artificial neural network (ANN) has been the most popularly used machine learning algorithm. It is inspired by biological learning systems even though it does not mimic it fully. During the last few years, neural networks have established themselves as a complete alternative to traditional statistical models. An ANN is an information processing paradigm that is inspired by the way biological nervous system, like brain processes information. This section presents an overview of the different types of neural network models which are applicable in solving business problems.

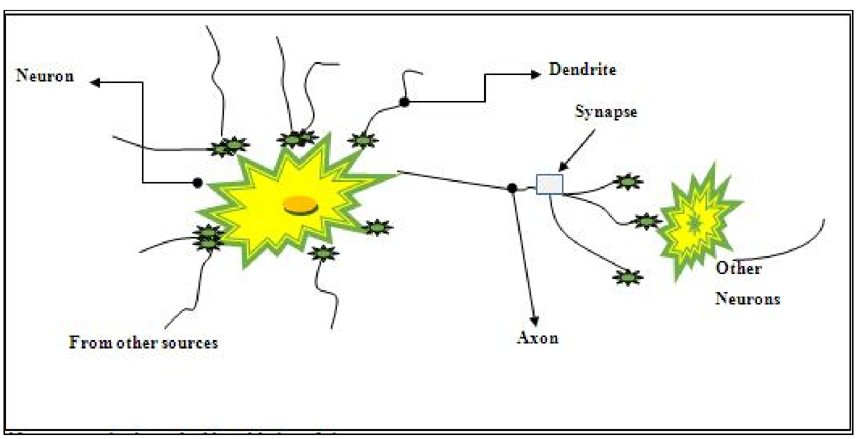

Figure 1: Neuron

Neurons are the basic building blocks of the nervous system (see fig. 1). A typical neuron of the human brain collects signals from other neurons through a host of fine structures called *dendrites*. The neuron sends out spikes of electric signals through a long, thin stand called as an *axon*. Each axon splits into thousands of branches and at the end of each branch, a structure called a *synapse* transforms the signals from the axon into electrical effects that inhibit or excite activity in the connected neurons. When a neuron receives excitatory input that is sufficiently large compared with its inhibitory input, it sends a spike of electrical signal down its axon. In a neuron, learning occurs by altering the value of the synapses so that the effect of one neuron on another changes.
The complexity of real neurons is highly abstracted when modeling artificial neurons. Artificial neurons basically consist of *inputs* (like synapses), which are multiplied by *weights* (strength of the respective signals), and then computed by a mathematical function which determines the *activation* of the neuron. Another function computes the *output* of the artificial neuron. Every neuron has two methods of operation; the training mode and the using mode. In the training mode, the neuron can be trained for particular input patterns to fire (or not) while in the using mode, when a trained input pattern is identified at the input, its

associated output becomes the current output. In case, the input pattern does not belong in the trained list of input patterns, the firing rule is used to decide whether to fire or not.In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase[1].

2. Neural Networks Architecture

The architecture of a neural network describes how their neurons are connected to each other[2]. There are many types of neural networks, for example multi-layer perceptron(MLP) or feed-forward neural networks, functional link neural networks, product unit neural networks, recurrent neural networks, time-delay neural networks and lattice structures [3]; [2]. Various other types of neural networks exist in the literature, like, Hopefield Neural Network, Radial Basis Function Neural Network (RBFNN), Self-Organizing Maps (SOM), Support Vector Machine (SVM) etc.

Generally neural network can be divided into several layers, where the layer can be one of the three different types that are listed below.

- **Input layer**: Contains source nodes that gathers information from the outside world and passes it onto the rest of the neural network [2]; [4].
- **Hidden layer**: Contains neurons (i.e. computational nodes) and is located between the input and output Layers of the neural network [4].
- **Output layer**: In addition to having neurons, the output layer also provides the response of the neural network to the outside world [2]; [4].

There is only one input layer and one output layer, while the number of hidden layers may vary (including no hidden layer). Since no computation takes place in the input nodes, the input layer is ignored when determining the total number of layers in a neural network e.g. A two layered network has one input, one hidden and one output layer [5].

According to a recent study, approximately 95% of reported neural network business application studies utilize multi-layered feed forward neural networks (MFNNs) with the back propagation learning rule [6]. This type of neural network is appropriate for solving problems that involve learning the relationships between a set of inputs and known outputs. They are a supervised learning technique in the sense that they require a set of training data in order to learn the relationships and consist of two or more layers of neurons connected by weights.

Feed Forward Neural Network or Perceptron is of two types, the Single Layer Perceptron (SLP) and the Multilayer Perceptron (MLP).

2.1. Single Layer Perceptron (SLP)

Figure 2 shows the structure of SLP. Where input x = $\{x_i\}$, for i = 1… n, and the network weights w = $\{w_i\}$, for i = 1… n, and y is the network output. W_0 is the bias. The function expressed by this network is

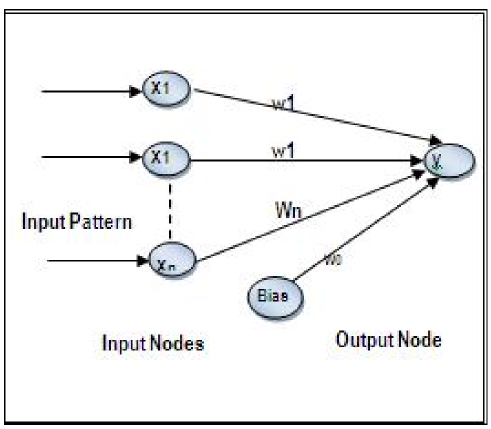

Figure 2: Neural Network

$$y = \left(\sum_{i=1}^{n} w_i x_i + w_0 \right) \text{----------------------------Eq.1}$$

SLP optimizes the weight by minimizing a cost function, which is often chosen to be the mean square error.

2.2. Multilayer Perceptron (MLP)

Multi-Layer perceptron (MLP) is a feed forward neural network with one or more layers between input and output layer. Feed forward means that data flows in one direction from input to output layer (forward). MLPs are widely used for pattern classification, recognition, prediction and approximation. Multi-Layer Perceptron can solve problems which are not linearly separable. Figure 3 shows a two-layer MLP. The nodes in the second layer are called the hidden nodes, which receive inputs from the Input nodes and forwards signals to the upper one.

The function expressed by this two-layer network has the form

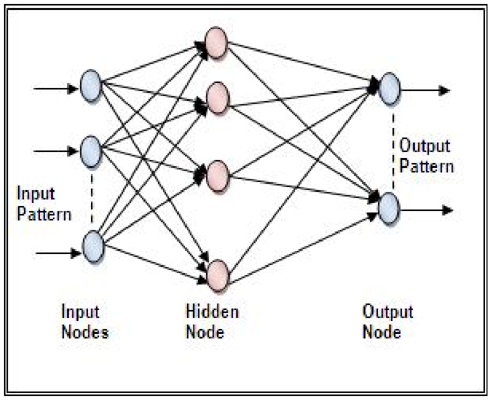

Figure 3:Multi-Layer Perceptron

$$n_i = \left(\sum_{i=1}^{n} w_i x_i + w_0 \right)$$ --------------------------------Eq. 2

Where n_i (for i = 1, …, n,) is the calculated output value of neuron in a hidden layer and input x = {x_i}, for i = 1, …, n, and the network weights w = {w_i}, for i = 1, …, n. w_0 is the bias. The output of this network y is

$$y = \left(\sum_{i=1}^{n} w_i n_i + w_0 \right)$$ -------------------------Eq. 3

Where {n_i}, for i = 1, …, n, is input to output layer from hidden neurons and the w = {w_i}, for i = 1, …, n are weights. w_0 is the bias.

Each hidden unit is a function of the weighted sum of the inputs. The function is called as activation function, and the values of the weights are determined by the estimation algorithm. If the neural network has a second hidden layer, each hidden unit in the second layer is a function of the weighted sum of the units in the first hidden layer. The activation function remains same in both layers.

The activation function links the weighted sums of units in a layer to the values of units in the succeeding layer. There are a number of activation functions but two widely used functions are as:

Hyperbolic: This function has the form:

$$f(y) = \tanh(y) = \frac{e^{(y)} - e^{(y)}}{e^{(y)} + e^{(y)}}$$ ----------------Eq. 4

It takes real-valued arguments and transforms them to the range (–1, 1).

Sigmoid:This function has the form: $f(y) = \frac{1}{1+e^{(y)}}$ -------------------------------------Eq. 5

It takes real-valued arguments and transforms them to the range (0, 1).

- **Back Propagation Neural Network**
  Back propagation or propagation of error is a common method of teaching artificial neural networks how to perform a given task. It is a type of supervised learning, which means that the algorithm is provided with examples of the inputs and desired outputs and then the error (difference between actual and expected results) is calculated. The back propagation algorithm is used in multi-layered feed forward ANNs (see fig. 4). This means that the artificial neurons are organized in layers, and send their signals forward. The value of output is compared to the desired value and then the errors are propagated backwards. The weights of the network are then adjusted to correct or to reduce the error and the next input pattern is presented. The weights are repeatedly modified in this manner until the total error across all training patterns is reduced below some pre-defined tolerance. The idea of the back propagation algorithm is to reduce this error, until the ANN learns from the training data.
- **Other neural network models**
  There are many other different types of neural network models like Hopefield NN, Radial Bias function NN and many more. Most of these are extensions of the main models discussed above.

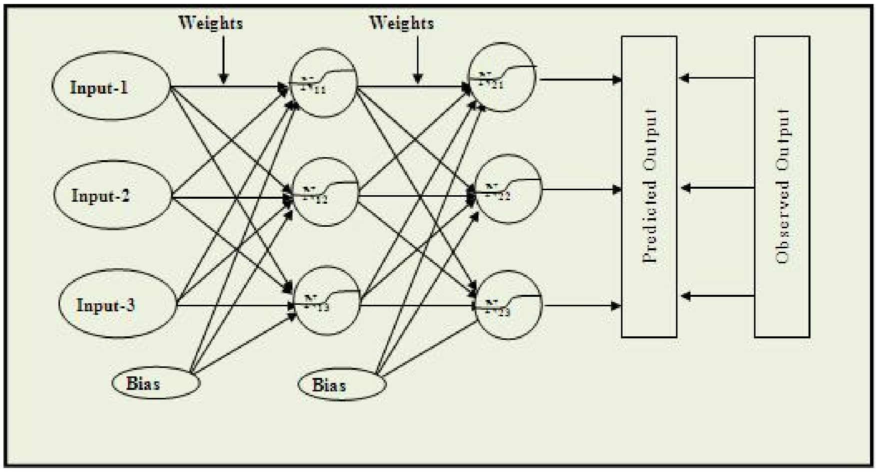

Figure 4: Architecture of Multi-Layer NN

3. Benefits of Neural Networks

- In neural networks data processing starts without any preconceived hypothesis. It starts randomly by assigning weights to various input variables. Adjustments are made based on the difference between predicted and actual output. Thus allowing for unbiased and better understanding of data.
- Neural networks can be retained using additional input variables and number of individuals. Once trained they are very fast and can be called on to predict in a new patient.
- For a particular problem, several numbers of neural networks are available to choose from.
- Increase in efficiency reduces the processing cost.
- Neural networks are able to represent any functions. Therefore they are called 'Universal Approximates'.
- Neural networks are able to learn representative examples by back propagating errors.

4. Limitations of Neural Networks

- **Low Learning Rate:** For the problems which are large and more complex in network architecture or having a large number of training examples, the time needed to train the network can become excessively long.
- **Forgetfulness**: The network tends to forget old training examples as it is updated with new ones. A previously trained neural network that must be updated with new information must be trained using the old and new examples there is currently no known way to incrementally train the network.
- **Imprecision:** Neural networks do not provide precise numerical answer, but rather relate an input pattern to the most probable output state.
- **Black box approach:** Neural networks can be trained to transform an input pattern to output but it does not provide any insight to the physics behind the transformation.
- **Limited Flexibility:** The ANNS is system specific as it is designed and implemented for only one particular system. It is not applicable to another system.

5. Application of Neural Networks

Since last decade, neural networks have found their applications in wide areas of business, commerce and industry. Such neural networks are used according to the situations and problems to which a particular network suits. Thus neural networks find their application in;

5.1. Marketing

The main aim of the present day marketing process is to identify customers who are likely to respond positively to a product, and to target any advertising towards these customers. Target marketing involves market segmentation, wherein the market is divided into different groups of customers with very different consumer behavior. Market segmentation can be achieved using neural networks by segmenting customers according to basic characteristics including demographics, socio-economic status, geographic location, purchase patterns, and attitude towards a product [7]. Unsupervised neural networks can be used as a clustering technique to automatically group the customers into segments based on the similarity of their characteristics [8]. Alternatively, supervised neural networks can be trained to learn the boundaries between customer segments based on a group of customers with known segment labels, i.e. frequent buyer, occasional buyer, or rare buyer [9]. Once market segmentation has been done, direct marketing can be used to sell a product to customers without the need for intermediate action such as advertising or sales promotion. Customers who are contacted are already likely to respond to the product since they exhibit similar consumer behavior as others who have responded in the past. In this way, marketers can save both time and money by avoiding contacting customers who are unlikely to respond.

5.2. Banking and Finance

One of the main areas of banking and finance that has been affected by neural networks is trading and financial forecasting. Neural networks find their application in problems like derivative securities pricing and hedging [10], futures price forecasting, exchange rate forecasting and stock performance and selection prediction. There are many other areas of banking and finance that have been improved through the use of neural networks though. For many years, banks have used credit scoring techniques to determine which loan applicants they should lend money to. Traditionally, statistical techniques have driven the software. These days, however, neural networks are the underlying technique driving the Decision making [11], [12]. Hecht-Nielson Co. have developed a credit scoring systems which Increased profitability by 27% by learning to correctly identify good credit risks and poor credit risks. Neural networks have also been successful in learning to predict corporate bankruptcy [13], [14]. A recent addition to the literature on neural networks in finance is the topic of wealth creation. Neural networks have been used to model the relationships between corporate strategy, short-run financial health, and the performance of a company [15]. This appears to be a promising new area of application. Financial fraud detection is another important area of neural networks in business [11].

5.3. Telecommunications

Like other competitive retail industries, the telecommunications industries is concerned with the concepts of churn (when a customer joins a competitor) and win back (when an ex-customer returns). Neural Technologies Inc is a UK-based company which has marketed a product called DA Churn Manager. Specifically tailored to the telecommunications industry, this product uses a series of neural networks to analyze customer and call data predict if, when and why a customer is likely to churn; predict the effects of forthcoming promotional strategies; and interrogate the data to find the most profitable customers. Telecommunications companies are also concerned with product sales, since the more reliant a customer becomes on certain products, the less likely they are to churn. Market basket analysis is significant here, since if a customer has bought one product from a common market basket (such as call waiting), then enticement to purchase the others (such as caller identification) can help to reduce the likelihood that they will churn, and increases profitability through sales.

5.4. Operations Management

Important areas of operations management, particularly scheduling and planning, use neural networks to make relevant decisions. The scheduling of machinery [16], assembly lines [17], and cellular manufacturing [18]using neural networks have been popular research topics over the last decade. Other scheduling problems like timetabling [19], project scheduling [20]and multiprocessor task scheduling have also been successfully attempted. All of these approaches are based upon the Hopfield neural [21] and the realization of Hopfield and Tank [22]. That these networks could solve complex optimization problems. Recently, alternative neural network approaches like neuro-dynamic programming [23]have also been used to solve related problems. The use of neural networks in various operations plans and control activities are reviewed by and cover a broad spectrum of application from demand forecasting to shop floor scheduling and control.

5.5. Other Industries

Various other sectors apart from Business, marketing, retail, banking and finance, insurance, telecommunications, and operations management make use of neural networks in decision making. Many other industries have benefitted from neural networks over the last decade with the commercially available products that incorporate neural network technology. IBM's computer virus recognition software IBM Anti-Virus uses a neural network to detect boot sector viruses. In addition to the viruses it was trained to detect, the software has also caught approximately 75% of new boot viruses since the product was released. Sensory Inc. have used neural networks to create a speech recognition chip, which is currently being used in Fisher Price electronic learning aids, and car security systems. Companies like Siemens use neural networks to provide automation for manufacturing processes, saving operating costs and improving productivity. Handwritten character recognition software like that used in Apple Computer's Newton Message Pad uses neural network technology as well[24].

6. Conclusion

Artificial Neural Networks offer qualitative methods for business and economic systems that traditional quantitative tools in statistics and econometrics cannot quantify due to the complexity in translating the systems into precise mathematical functions. In most cases neural networks perform as well or better than the traditional statistical techniques to which they are compared. Resistance to using these “black boxes” is gradually diminishing as more researchers use them, in particular those with statistical backgrounds. Because of their proven predictive power as compared to other statistical techniques, neural networks are becoming very popular, particularly in finance and marketing. Researchers are now devising techniques for extracting rules from neural networks, and combining neural networks with other intelligent techniques like genetic algorithms, fuzzy logic and expert systems to arrive at appropriate conclusions and solutions.

In conclusion recent developments in neural networks highlight the new opportunities that it provides as an analytical tool in the area of business.

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