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Neural Network Approach for Stock Forecasting

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ABSTRACT

Data mining techniques is use for prediction of stock price which is the most important issue in finance across the globe. Data Mining, also popularly known as Knowledge Discovery in Databases, refers to the nontrivial extraction of implicit, previously unknown and potentially useful information from data in databases. While data mining and knowledge discovery in databases are frequently treated as synonyms, data mining is actually part of the knowledge discovery process. An artificial neural network (ANN) is a system that is based on operations of biological neural networks, and hence can be defined as an emulation of biological neural systems ANN's are at the forefront of computational systems designed to produce, or at least mimic, intelligent behavior. Unlike classical Artificial Intelligence (AI) systems that are designed to directly emulate rational, logical reasoning, neural networks aim at reproducing the underlying processing mechanisms that give rise to intelligence as an emergent property of complex, adaptive systems. Neural network systems have been developed for fields such as pattern recognition, capacity planning, business intelligence, robotics, or even for some form of intuitive problem solving. In computer science, neural networks gained a lot of steam over the last few years in areas such forecasting, data analytics, as well as data mining.

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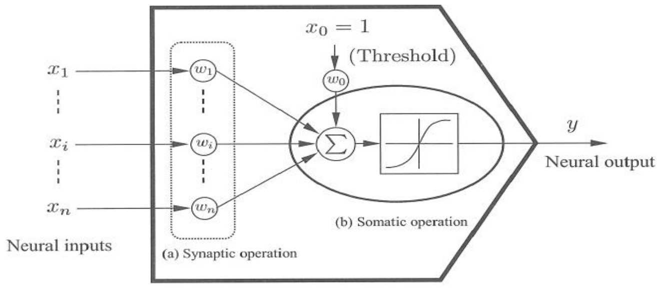
I. INTRODUCTION

Work on artificial neural networks commonly referred to as "neural networks" (NN) has been motivated right from its origin by the recognition that the human brain computes in an entirely different way then the conventional computer. The brain is a highly complex, nonlinear and parallel computer (information processing system). It has the capability to organize its structural constituents, known as neurons, so as to perform certain computations (e.g. pattern recognition, perception, and motor control) many times faster than the fastest digital computer in existence today. Consider for example, human vision, which is an information-processing task. It is the function of the visual system to provide a representation of the environment around us and, more important, to supply the information we need to interact with the environment. To be specific, the brain routinely accomplish perceptual recognition task (e.g. recognizing a familiar face embedded in an un-familiar scene) in approximately 100-200 ms, where as tasks of much lesser complexity may take days on a conventional computer. How, then, does a human brain do it? At birth, a brain has great structure and the ability to built-up its own rules through what we usually refer to as "experience". Indeed, experience is built up over time, with the most dramatic development (i.e. hard wiring) of the human brain taking place during the first two years from birth: but the development continues well beyond that stage.

A "developing" neuron is synonymous with a plastic brain: Plasticity permits the developing nervous system to adapt to its surrounding environment. Just as plasticity appears to be essential to the functioning of neurons as information-processing units in the human brain, so it is with neural networks made up of artificial neurons. In its most general form, a neural network is a machine that is designed to model the way in which the brain performs a particular task or function of interest; the network is usually implemented by electronic components or is simulated in software on a digital computer. The interest is confined to an important class of neural networks that perform useful computations through a process of learning. To achieve good performance, neural networks employ a massive interconnection of simple computing definition of a neural network viewed as an adaptive machine.A neural network is a massively equivalent distributed process or made up of simple processing units, which has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two respects:

- Knowledge is acquired by the network from its environment through a learning process.
- Inter neuron connection strengths, known as synaptic weights, are used to store the acquired knowledge.

ARTIFICIAL NEURON



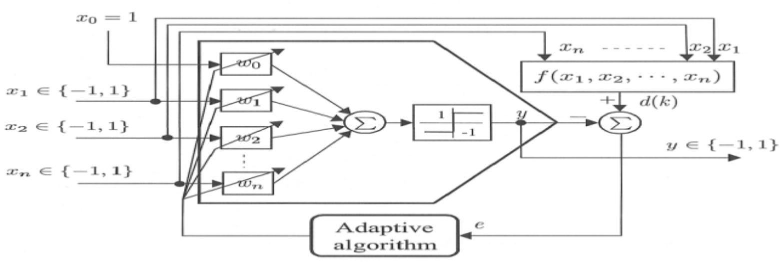
Artificial Neuron

In artificial neural networks, the synaptic and somatic operations are emulated as follows:

- Synaptic Operation: The input weights act as storage for knowledge (and therefore, as memory for previous experiences).
- Somatic Operation: The somatic operation is provided by various mathematical operations such as aggregation, thresholding, nonlinear activation and dynamic processing to the synaptic inputs.

ADAPTATION IN NN'S

The procedure that is used to perform the learning process is called a learning algorithm (fig. 3), the function of which is to modify the synaptic weights of the network in an orderly fashion to attain a desired design objective.

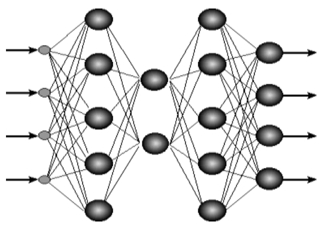


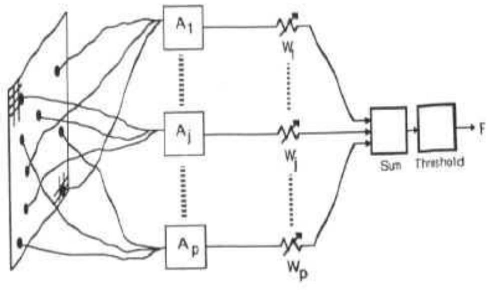
Adaptation in NN's

The modification of synaptic weights provides the traditional method for the design of neural networks. Such an approach is the closest to linear adaptive filter theory, which is already well established and successfully applied in many diverse fields. However, it is also possible for a neural network to modify its own topology, which is motivated by the fact that neurons in the human brain can die and then new synaptic connections can grow.

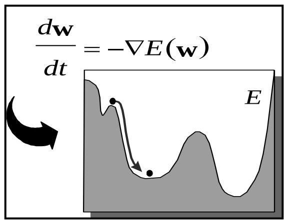
II. PERCEPTIONS

The most influential work on neural nets in the 60's went under the heading of 'perceptrons' a term coined by Frank Rosenblatt. The perceptron turns out to be an MCP model (neuron with weighted inputs) with some additional, fixed, pre--processing. Units labeled A1, A2, Aj, Ap are called association units and their task is to extract specific, localized featured from the input images. Perceptrons mimic the basic idea behind the mammalian visual system. They were mainly used in pattern recognition even though their capabilities extended a lot more.





In 1969 Minsky and Papert wrote a book in which they described the limitations of single layer Perceptrons. The impact that the book had was tremendous and caused a lot of neural network researchers to loose their interest. The book was very well written and showed mathematically that *single layer* perceptrons could not do some basic pattern recognition operations like determining the parity of a shape or determining whether a shape is connected or not. What they did not realize, until the 80's, is that given the appropriate training, multilevel perceptrons can do these operations.



$$E(\mathbf{w}) = E\left\{\mathbf{x}^{\alpha}, \mathbf{y}^{\alpha}, \mathbf{y}\left(\mathbf{x}^{\alpha}, \mathbf{w}\right)\right\}$$

III. THE LEARNING PROCESS

Types of learning

All learning methods used for adaptive neural networks can be classified into two major categories:

Supervised learning which incorporates an external teacher, so that each output unit is told what its desired response to input signals ought to be. During the learning process global information may be required. Paradigms of supervised learning include error-correction learning, reinforcement learning and stochastic learning.An important issue concerning supervised learning is the problem of error convergence, i.e. the minimization of error between the desired and computed unit values. The aim is to determine a set of weights which minimizes the error. One well-known method, which is common to many learning paradigms, is the least mean square (LMS) convergence.

Unsupervised learning uses no external teacher and is based upon only local information. It is also referred to as self-organization, in the sense that it self-organizes data presented to the network and detects their emergent collective properties. Paradigms of unsupervised learning are Hebbian learning and competitive learning. from Human Neurones to Artificial Neuron Esther aspect of learning concerns the distinction or not of a separate phase, during which the network is trained, and a subsequent operation phase. We say that a neural network learns off-line if the learning phase and the operation phase are distinct. A neural network learns on-line if it learns and operates at the same time. Usually, supervised learning is performed off-line, whereas unsupervised learning is performed on-line.

INPUT VARIABLE

Following are inputs variables for stock prediction

For our approach we identified 18 input variables to train the network comprising both technical variables and fundamental analysis variables.

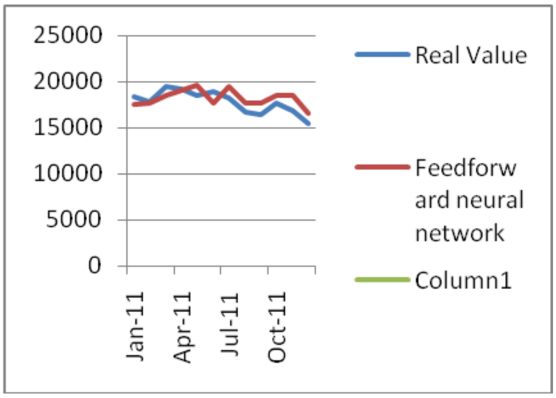
The technical analysis variables are:	The fundamental analysis variables are:
o*i-1* the opening price of day *i-1*	a*i-1* the price per annual earning of year *i-1*
o*i-2* the opening price of day *i-2*	a*i-2* the price per annual earning of year *i-2*
h*i-1* the daily high price of day *i-1*	r*i-1* the rumor or news to buy/sell of day *i-1*
h*i-2* the daily high price of day *i-2*	r*i-2* the rumor or news to buy/sell of day *i-2*
l*i-1* the daily low price of day *i-1l*	v*i-1* the book value of the trading year *i-1*

l*i-2* the daily low price of day *i-2*
c*i-1* the closing price of day *i-1*
c*i-1* the closing price of day *i-2*
t*i-1* the trading volume of day *i-1*
t*i-2* the trading volume of day *i-2*
v*i-2* the book value of the trading year *i-2*
v*i-2* the book value of the trading year *i-2*
s*i-1* the financial status of a company trading year *i-1*
f*i-2* the financial status of a company trading year i-*2*

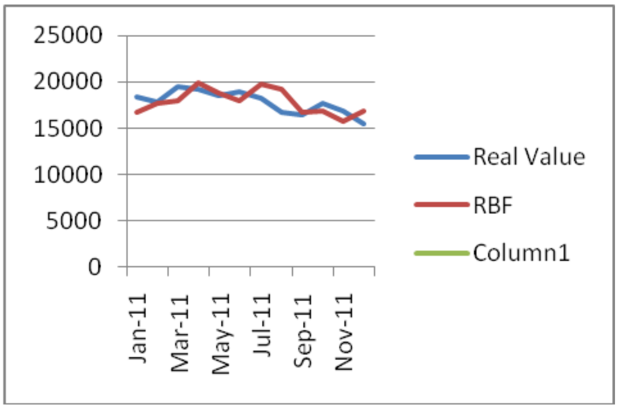
NEURAL NETWORK MODELS
A: Feedforward neural network
B: Radial basis function (RBF) network
C: Kohonen self-organizing network
D: Learning Vector Quantization
E: Recurrent neural network
F: Modular neural networks

Sample of Monthly Stock Forecasting

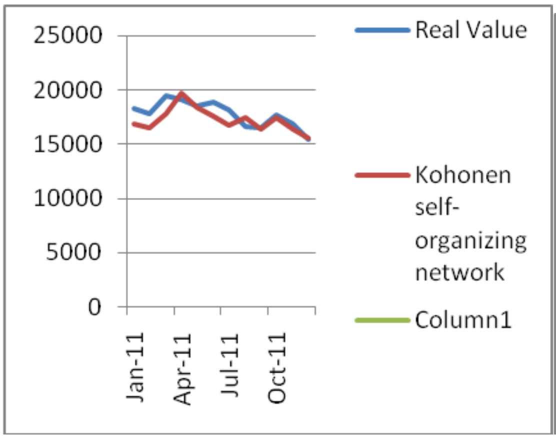
Time Period	Real Value	Forecasted Values of Different Neural Network Models					
		A	B	C	D	E	F
Jan-11	18327	17532	16795	16874	18465	19456	18465
Feb-11	17823	17630	17658	16574	17456	18450	17426
Mar-11	19445	18465	17952	17894	19465	19452	16787
Apr-11	19135	18978	19875	19746	19667	18456	17213
May-11	18503	19602	18765	18465	18462	18462	15676
June-11	18845	17654	17961	17561	18462	17412	16644
July-11	18197	19465	19785	16751	17546	18652	16452
Aug-11	16676	17682	19235	17514	17452	16478	17456
Sep-11	16453	17684	16764	16457	16452	16952	16546
Oct-11	17705	18465	16846	17456	17456	17923	17845
Nov-11	16805	18468	15789	16458	17458	17852	16484
Dec-11	15455	16486	16875	15576	15468	16459	17465

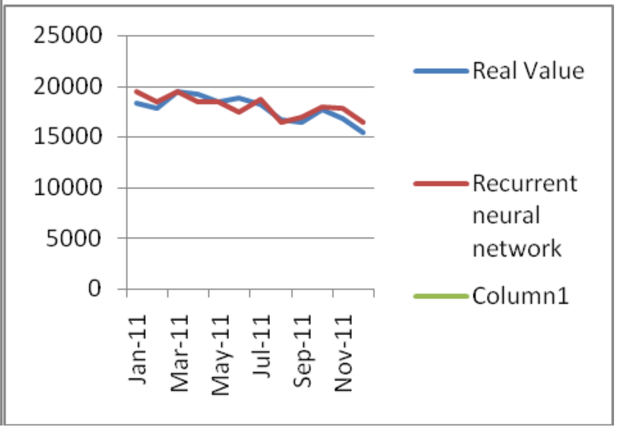


Neural Network Feedforward neural network

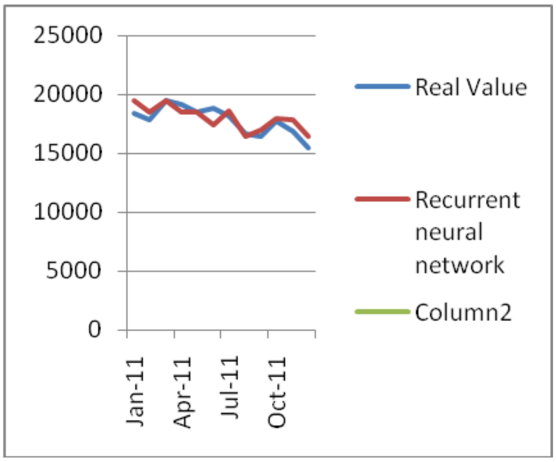


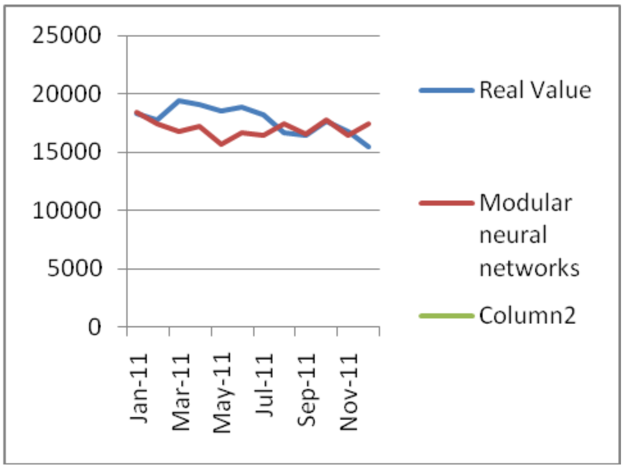
Neural Network RBF





Neural Network Kohonen self-organizing network   Neural Network Learning Vector Quantization





Neural Network Recurrent neural network   Neural Network Modular neural networks

IV. CONCLUSION

This paper presents the various combinations of neural network techniques to forecast the sensex stock exchange. To determine the performance of our model the stock data collected from Internet. The result obtained showed high level of accuracy for monthly stock price forecasted with various approach performing better than technical analysis approach. Therefore it enhance the quality of decision making of investor in the stock market by offering more accurate stock prediction compared to existing technical analysis based approach. In future work, we intend to determine the critical impact of specific fundamental analysis variables on quality of stock price prediction.

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