International Journal of Future Generation Communication and Networking
Vol. 14, No. 1, (2021), pp. 355–358

Choice of Methods in Predicting Index Return Returns Using Artificial Neural Network for National Stock Exchange of India

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Abstract

This study uses artificial neural network (ANN) in forecasting the NIFTY. The paper trains several ANN by using back propagation algorithm and they were assessed. The study uses long range data for a period of 1st April 2005 to 31st closing daily return. A total of 2485 data points were trained. The study shows that algorithm provides 99 percentage accuracy. The study is taken as an alternative to the liner models that are mostly used in prediction of the returns. The best prediction was found through OSS-TANSIG which had a validity of 0.9407. With respect to its usability as given by the weighted totals most of the models are of same worth. Hence, the choice of model in real life, especially for very long period data is insignificant and not of high order. This scanty difference in method may have arise due to very long duration data, since BPNN works best in very short and tick data format.

Keywords: *Neural Network, Indian Stock Market, NIFTY returns.*

INTRODUCTION

There had been several studies which try to predict the return of the index in Indian Study. Most of the model either follows an OLS model or ARIMA structure for linear return prediction. However, linear models have their own short coming. In this paper we use Artificial Neural Network (ANN) which had been widely used in economic research. The objective of the study is to investigate the ability of ANN in forecasting the daily NIFTY return.

Study by Guresen et al (2011) shows that the performance of ANN helps in forecasting the market values perfectly. In a different study by Chen et al (2003) by using probabilistic neural network to predict the Taiwan Stock Market values. Moghaddam et al (2016) confirms that if trained properly through series of weights, index return is best predicts the market return by ANN. They use NASDAQ's six months data of 2015 and saw that the data trained results in 99.99 percent accuracy in prediction. Qin et al (2012) used C-fuzzy decision tree to predict index stock exchange and observe between various predictive models, the best fit is ANN. By developing an adaptive neuro-fuzzy inference controller to forecast next day stock price trend. Atsalkis and Valavanis (2009) saw that the best prediction is ANN model.

Artificial Neural Network

Artificial Neural Network (ANN) is a machine learning mechanism. It has gained predominance in stock trading in recent times. This technique replicates the human brain and nervous system by using backward propagating algorithm. Usually neural network are organized in layers and layers are made of multiple nodes which connect an activities function. Therefore input-output parameters with weight associated with it. During the learning phase the neural network learn by adjustment of the weight so as to correctly predict the value. In this study we use Multilayer perception model perception model used by Tong-SenQuah (2008) to predict stock return.

Methodology

The study uses Multi layer perception (MLP) which is a common regression approach. MLP networks usually has three layers, input layer, output layer and a hidden layer. Neuron takes value of inputs parameters, sum them up according to weights assigned and adds a bias. Thereafter the transfer function is applied to determine the output.

In mathematical terms, the performance of a neuron P can be described as

$$UP = \Sigma^{n}_{i=1} WP_i \; X_i \qquad \ldots\ldots\ldots\ldots\ldots\ldots (1)$$

$$Y_p = \varphi\,(UP + bp) \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

ISSN: 2233-7857 IJFGCN

Where;

X1 ……. Xn are the input parameters,

Wp i ……..are the connection weights of neuron P

UP – The input combination

bp- the Bias

φ is the activation function

Y_p is the output of the neuron

For this study feed forward artificial neural network were trained by the Back Propagation Algorithm also known as Back Propagation Neural Network (BPNN). Several learning techniques such as Scale Conjoint Gradation (SCG), Levenberg-Marquardt (LM), One Step Secant (OSS), Gradient descent with adoptive learning rate (GDA) and Gradient descent with momentum (GDM) are used to train and predict the BPNN. This study uses LM, OSS and GDA learning methods to understand the extent of predictability.

Data Specification

The data was taken from public domain of NIFTY end day return for the period 1st April 2005 to 31st March 2015. A total of 7374 data points of end of the day return were extracted for one period lag. This was divided into three equal sets for equal length of time randomly. One set was used for training set (50%), Validation Set (30%) and Testing Set (20%). On the basis the preliminary study the training method and transfer function were OSS (One Step Secant), TANGISIC (Hyperbolic Tangent Sigmoid transfer function) and LOGISIG (Log-Sigmoid Transfer Function).

Model Specification

The study uses Index return. The general specification is

Y(k) = *f* (y (k-1),y(k-2),y(k-3)….y(k-n) …………………………….. (3)

Where;

Y(k) is the index return at time k, n is the number of historical days. The performance of the ANN was evaluated using the determination coefficient (R^2).

$$R = 1 - \frac{\Sigma (Y\,exp - Ypred)^2}{\Sigma (Y\,exp - \bar{Y})^2} \qquad \ldots\ldots (4)$$

For constructing the model, training and testing procedure MATLAB software was used.

RESULTS AND DISCUSSION

The NIFTY returns were predicted for two input data set as discussed earlier and were developed and validated. The optimized network structure for both type of data set was selected based on their ability i.e; to predict.

Table 1 shows the value of R^2 for different training algorithm and transfer function of Back Propagation Neural Network (BPNN) with 20-40-20 neurons in hidden layers. Total ten experiments were carried out of which three did not yield desired training and validation and hence dropped from the study. Seven experiments results were used. Experiment one with GDA (LOSIG), Experiment 2 through 4 with OSS (LOGSIC, PURELIN and TANSIG) and experiment 5 through 7 with LM (TANSIG, PURELIN, LOGSIG).

Table 1 Prediction ability of Back Propagation Neural Network with different training and transfer function

No of Experiment	Training Function	Transfer Function	R^2			
			Train	Test	Validation	Total

ISSN: 2233-7857 IJFGCN

1	GDA	LOGSIC	0.9162	0.8326	0.8362	0.8649
2	OSS	LOGSIC	0.9166	0.9133	0.8631	0.9069
3	OSS	PURELIN	0.7016	0.8821	0.8220	0.7675
4	OSS	TRANSIG	0.9386	0.8913	0.9480	0.9267
5	LM	TRANSIG	0.9925	0.9866	0.8863	0.9630
6	LM	PURELIN	0.9457	0.9676	0.9027	0.9396
7	LM	LOGSIC	0.9989	0.9698	0.7339	0.9476

Source: Computed

The findings of the experiment show that OSS-TANSIG generates the most robust training for prediction. The other methods which are good are OSS-TRANSGIG and LM-PURELIN. These analyses are done based on the best validation of the model. Models with validation of more than .90 are taken to be the better predictor. The study uses all the experiments with more than .70 validations. It is observed that most of the methods are able to predict more than 80 percent which is high in respect to any linear model prediction model. This also brings us to an general understanding about the models used in this study. With respect to its usability as given by the weighted totals most of the models are of same worth. Hence, the choice of model in real life, especially for very long period data is insignificant and not of high order. However, it has been observed in some studies earlier that ANN yield better results through very short period data and tick data of the stock and indices.

CONCLUSION

The study used NIFTY return of a period between 1st April 2005 to 31st March 2015. Using a BPNN function to test the R^2 values through various testing and validation techniques. The study shows that BPNN method is being able to predict more than 80 percent of return in all the methods applied through seven valid experiments. The best prediction was found through OSS-TANSIG which had a validity of 0.9407. With respect to its usability as given by the weighted totals most of the models are of same worth. Hence, the choice of model in real life, especially for very long period data is insignificant and not of high order. This scanty difference in method may have arise due to very long duration data, since BPNN works best in very short and tick data format.

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ISSN: 2233-7857 IJFGCN

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ISSN: 2233-7857 IJFGCN