STOCK INDEX FORECASTING USING RADIAL BASIS FUNCTION NETWORK AND SUPPORT VECTOR MACHINE

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ABSTRACT

In this paper, we present application of two very well-known techniques: radial basis function network (RBFN) and support vector machine (SVM) in financial time series forecasting using various algorithm specific parameters. The main objective of this study is to test the short-term and long-term predictability of both the techniques on the Dow30 index. The experimental analysis on short-term predictions shows that the RBFN system provides more precise forecast results as compared to the results of the SVM. On the other hand, SVM performs better than RBFN for long-term forecasting in terms of decreasing error rate.

Keywords: Radial Basis Function Network, Support Vector Machine.

INTRODUCTION

Financial forecasting, especially in the stock market, is difficult due to micro and macro-economic variables and causes financial losses to individuals and financial institutions quite often. Researchers endeavor to improve the reliability and predictability of variables that affect financial forecasts by developing improved systems. Various techniques like the traditional statistical methods and expert systems have been used to predict stock price movements. However, these models require some basic assumptions and continued review and refinement as economic condition changes; they have not proved to be very reliable (Trippi & Turban, 1996).

In recent times, interest in using artificial neural networks (ANNs) for forecasting has received considerable attention. Its unique advantage makes it well suited to deal with unstructured problems, inconsistent information and real-time output (Trippi & Turban, 1996). Studies show that ANNs provide a promising alternative approach to time series forecasting (Trippi & Turban, 1996; Sharda & Patil, 1990). However, in the stock market, ANN suffers from a number of weaknesses which include the need for a large number of controlling parameters, difficulty in obtaining a stable solution and the danger of over fitting (Tay & Cao, 2001). Several authors reported that support vector machine (SVM) provides a promising alternative approach to time series forecasting. SVM is a robust classification and regression technique (Mitra & Acharya, 2004) that maximizes the predictive accuracy of a model without over fitting the training data. In the literature, many authors have applied SVM in financial time-series forecasting (Bao et al., 2004; Kim, 2003; Tay & Cao, 2001).

In this study, we propose RBFN and SVM techniques for long term and short-term stock index forecasting. All models are tested on the DOW30 index. The results obtained after simulation show that RBFN is better for short-term forecasting while SVM is better for long term forecasting with less accuracy compared to RBFN.

METHODOLOGY

The following two techniques are used to compare their performance in the stock market prediction for long-term and short-term:

Support Vector Machine (SVM)

SVM is a robust classification and regression technique (Mitra & Acharya, 2004) that maximizes the predictive accuracy of a model without over fitting the training data. SVM is particularly suited to analyzing data with very large numbers of predictor fields. SVM works by mapping data to a high-dimensional feature space so that data points can be categorized, even when the data are not otherwise linearly separable. A separator between the categories is found, and then the data are transformed in such a way that the separator could be drawn as a hyper plane. Following these characteristics new data can be used to predict the group to which a new record should belong. The support vector machines (SVMs) are a general class of learning architectures, inspired by the statistical learning theory that performs structural risk minimization on a nested set structure of separating hyper planes. Given a training data, the SVM learning algorithm generates the optimal separating hyper plane in terms of generalization error. Various kernel types like polynomial, radial basis and sigmoidal can be used to tune the network.

Radial Basis Function Network (RBFN)

Radial basis function networks (RBFN) (Shivanandan & Deepa, 2011) are feed-forward networks trained using a supervised training algorithm. It has single hidden layer generally with a special type of activation function sigmoidal and Gaussian kernel function, one can use a suitable function as per suitability of data pattern. In comparison to back propagation in many respects, radial basis function networks have several advantages. They usually train much faster than back propagation networks. They are less susceptible to problems with non-stationary inputs because of the behavior of the radial basis function in hidden units (Amiri, 2008). The popularity of this network (Cios et. al, 2007) arises from the two basic facts. The first one is that unlike most supervised learning neural network algorithms, it is able to find a global optimum. For comparison, using a feed-forward neural network with the back-propagation learning rule usually finds only the local optimum. The second fact is that training time for RBF network is short compared with the other NNs, most notably when using the back-propagation rule for adjustment of the weights. In addition, the topology of the RBF network is very simple to set up, and requires no guessing as with back-propagation.

MODEL IMPLEMENTATION

Evaluation process of the two models explained above and to be used for long term, and short-term stock index forecasting is shown in figure 1. This process contains two steps. First, it requires data processing and second is model processing. Each of its component and subcomponents are explained below in more detail:

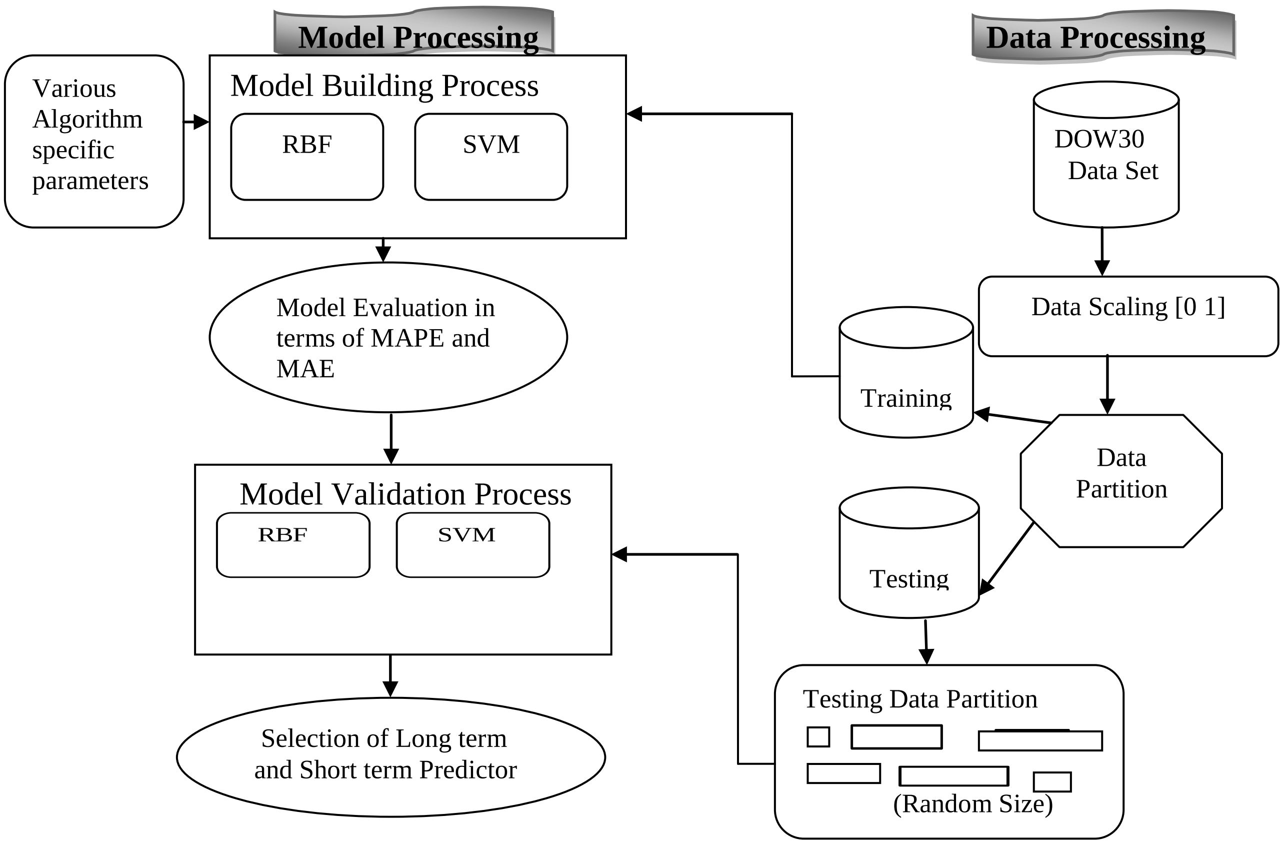


Figure 1: Model Implementation Process

Data Processing: In order to feed data to the model, it must be processed and scaled for better performance of the model. This is the reason why DOW30 data set is scaled in between 0 and 1 using simple normalization formula as written in equation 1:

$$D(Norm) = \frac{D(i)}{\max(D)} \tag{1}$$

Where, *D(i)* is the i^{th} instance and max(*D*) is the maximum value of a particular feature.

The data were downloaded (www.yahoofinance.com) and partitioned into two subsets: training and testing, the data sets consists of 3000 instances of daily index price value, covers the period from March 01, 2000 to Feb 02, 2012, out of this 3000 daily stock training set consists 75% data while testing set consists of latest 25% data. Training data are used to build the model while testing data are further divided into several parts of random size in order to evaluate the model for long term and short term forecasting, these random sizes are fixed according to the number of samples of DOW30 and divided into various partitions which consists 15,30,40,75,150,200 and 300 samples of the latest date. Partitions are categorized into long term and short-term as per the requirement, forecasting up to 30 days are considered here under short term category while more than 30 days forecasting is considered under long term category.

Model Building: In recent years, the usage of RBFN and SVM have been extended to a much wider range of application involving dynamic application systems, pattern classification, prediction and classification (Karray & De Silva, 2011), in this study, RBFN and SVM are used for stock index forecasting and both models are tuned with various algorithm specific parameters. A simple architecture of 4-4-1 of RBFN is constructed for stock index forecasting as there are four inputs (open, close, low and high index price) and one output (Next day close price) in the data set. Network is trained with different learning rate α =0.2,0.3 and 0.4 with one hidden layer and radial basis function as activation function with default value of other parameters like center and width. Similarly, SVM is also trained with same data set with different kernel type like Polynomial function, Radial basis function and Sigmoidal function.

Model Evaluation: With the help of various algorithms specific parameters as explained above, trained models are obtained. Models are evaluated (Wang et al., 2011) in terms of mean absolute error (MAE) and Mean absolute percentage error (MAPE) according to the following formulae:

$$MAE = \frac{1}{N}\left[\sum_{i=1}^{N}\left|AV_i - PV_i\right|\right] \tag{2}$$

$$MAPE = \frac{1}{N}\left[\sum_{i=1}^{N}\frac{\left|AV_i - PV_i\right|}{AV_i}\times 100\right] \tag{3}$$

Where AV_i and PV_i are actual value and predicted value respectively for i^{th} instance and N is the total number of instances.

Results obtained in case of model evaluation for various algorithm specific parameters with the calculated value of MAE and MAPE are shown in table 1.

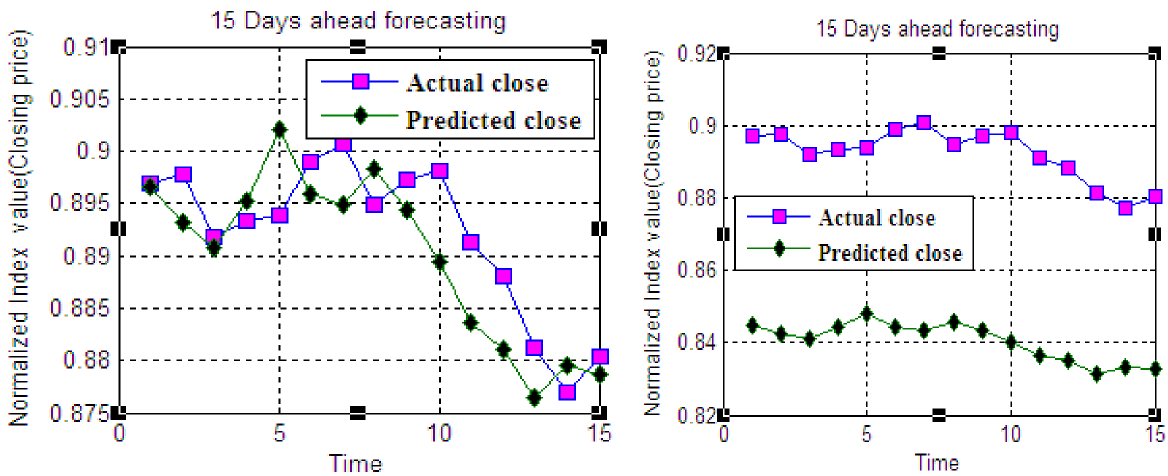
Table 1: Model accuracy with different algorithm specific parameters in the training phase

Model	Algorithm specific Parameters	MAE	MAPE
RBF	Learning rate =0.2	0.0067	0.9135
	Learning rate =0.3	0.0068	0.9284
	Learning rate =0.4	0.0067	0.9182
SVM	Kernel type: Polynomial	0.048	3.78
	Kernel type :Radial Basis	0.036	3.48
	Kernel type : Sigmoidal	0.050	4.01

Model Validation: After an evaluation process, best RBFN and SVM model with lowest MAPE is selected. From table 1, it is clear that RBFN model with learning rate =0.2 is producing better result than others while SVM model with kernel type: radial basis function is producing better result. It can be observed from table 1 that accuracy of the model is affected due to various algorithm specific parameters. Validation of the models is carried out with the help of testing data samples of different partitions. Finally, models are analyzed as short-term and long term predictor.

EXPERIMENTATION AND RESULTS

Robustness of the models (Samarasinghe, 2007) in multistep ahead forecasting is examined here with different fragmented data of random size prepared for testing. These are 15, 30, 40, 75, 150, 200 and 300 days ahead. Sample graph of simulated results along with actual and predicted output is shown in figure 2 (a) and 2(b) respectively for RBFN and SVM model for 15 days ahead forecasting. N-days ahead forecasting results for both models are shown in table 2. As per our expectation, forecasting accuracy is decreasing (error is increasing) as the forecasting period increases in case of RBFN while the trend is just opposite in case of SVM where accuracy is increasing (error is decreasing) as the forecasting period increases but for 200 step ahead forecasting, accuracy of RBFN model is increasing (error decreases) and for the same SVM forecasting accuracy is decreasing (error increases) also for 300 steps ahead forecasting trend is again opposite.



(a) (b)

Figure 2: 15-days ahead Forecasting of DOW30 Index (a) Using RBFN (b) Using SVM

Variations of accuracy for N-step ahead forecasting can also be seen in figure 3 in the form of bar chart. These results indicate that RBFN is performing well for short term forecasting. However, SVM can be used for long term forecasting with high error rate.

Table 2: Comparison of two models with different testing partitions

N-Days	RBF		SVM	
	MAE	MAPE	MAE	MAPE
15	0.004	0.4729	0.0516	5.8
30	0.005	0.5679	0.0484	5.5
40	0.006	0.6429	0.0444	5.0
75	0.009	1.0518	0.0388	4.5
150	0.011	1.2576	0.0336	4.0
200	0.010	1.1535	0.0362	4.2
300	0.008	1.232	0.0355	4.1

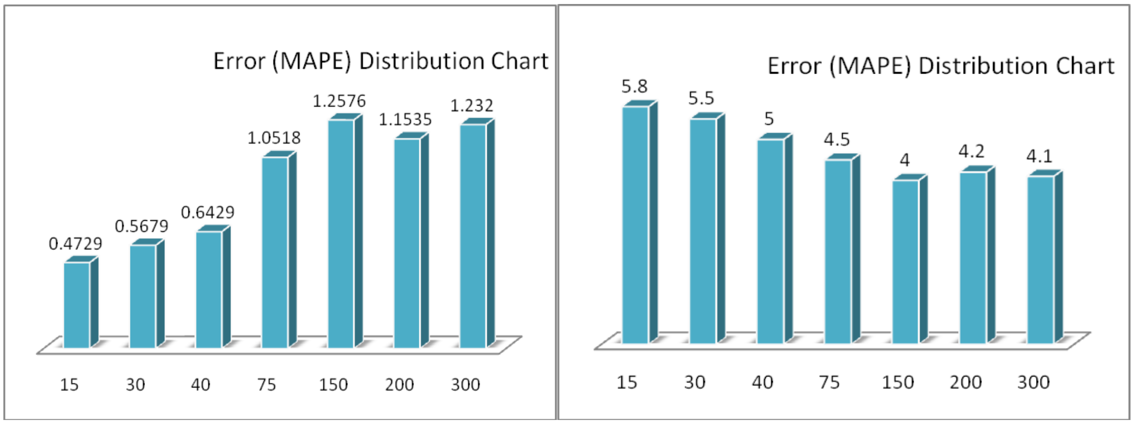


Figure 3: Forecasted error (MAPE) distribution on different test data partitions (Left) RBF (Right) SVM

CONCLUSIONS

Short-term and Long-term forecasting may be the requirement of any individual or organization for their future planning. Some investors may be interested in short-term forecasting while others may take an interest in the long term. This research work is confined on two well-known models: RBFN and SVM to predict the future direction of the index price. In this study, various algorithm specific parameters of RBFN and SVM are investigated. Experiments showed that these parameters are sensitive in terms of accuracy of the model, so it necessary to find out and optimize these parameters before model validation process.

In addition, this research work also focused on the accuracy of the two models in terms of long term and short-term prediction. Experimental results showed that RBFN is better for short-term forecasting while SVM is better for long term forecasting. An opposite trend in the case of both models has been observed here for the future value forecasting. Two models are compared and it is found that RBFN has outperformed SVM in terms of accuracy. Many authors claimed that the SVM is better than the RBFN and error back propagation network for stock index forecasting. This may be possible due to the nature and trends of data pattern and better tuning of other algorithm specific parameters.

REFERENCES

Sharda, R., & Patil, R. B. (1990). Neural networks as forecasting experts: an empirical test, *in Proceeding of the International Joint Conference on Neural Networks*, 2, 491-494.

Shivanandam, S.N. & Deepa, S.N. (2011).*Principals of Soft Computing*, Second Edition Wiley India publication.

Trippi, R., & Turban, E. (1996).*Neural networks in finance and investing*. Chicago: Probus Publishing Company.

Yahoo Finance (2012). Web Source http://www.finance.yahoo.com last accessed on March 2012.

(A complete list of references is available upon request from Dinesh Sharma at dksharma@umes.edu)