Comparison between SVM and MLP in Predicting Stock Index Trends

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Abstract- ***Recently, data mining and time series prediction in financial forecasting has received much research attention. Many techniques are used in prediction on stock and fund trend, volatility, etc. In this paper, two technique of neural network is compared, namely, Support Vector Machine (Support Vector Machine, SVM) and MLP for considering four years of data of Sensex.(Bombay Stock Exchange).***

Keywords: SVM, MLP, Volatility

I. INTRODUCTION

Now -a- days, Stock investment has become an important way of personal finance decisions. However, the stock market is characterized by its high-risk and high-yield property. Stock price changes has a significant impact on the daily life of people, the stability of the finance market. Therefore, stock index trend prediction has drawn much attention from the both the academic and industrial researchers.

In India the financial derivatives like options and futures have been introduced in the Bombay Stock Exchange (BSE) and National Stock Exchange (NSE) of India since June 2000.The large number of investors find the derivatives attractive due to their low price and low transaction costs as compared to the underlying financial assets in the spot market in order to derive leverage benefits, asymmetric returns and hedge the systematic risks of the portfolio of assets. Because of the large scale participation of traders in derivative markets, the informational efficiency of the spot market rises and therefore, true prices of the assets are discovered. As a result, the volatility in the spot market are expected to be moderate.

The present paper is undertaken to study the comparision between SVM and MLP for prediction of BSE Sensitive Index (Sensex) from 2008-12 .

II. LITERATURE SURVEY

F.Cruz ,Julio A Afonso-Rodr´ıguez and Javier Giner(2003) observed that GARCH models can be estimated using SVMs and that such estimations have a higher predicting ability than those obtained via common ML methods. Valeriy V. Gavrishchaka, Supriya B. Ganguli (2003) proposed Support vector machines (SVM) as a complimentary volatility model that is capable of effectively extracting information from multiscale and high-dimensional market data.

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Also Lijuan Cao(2003) derived the effectiveness of the SVMs experts model in stock market M.Sap,etl(2005) verified that application of SVM tech for forecasting is a novel approach in time series forecasting though the stock market data is a complex, nonstationary in nature. Wun-Hua Chen (2006) and etl. Used techniques such as Support-Vector Machines (SVMs) and Back Propagation (BP) neural networks for six Asian stock markets and their experimental results showed the superiority of both models, compared to the early researches.

III. EXPERIMENTAL SETTINGS

The most useful and successful applications of neural networks to data analysis is the multilayer perceptron model (MLP). Multilayer perceptron models are non-linear neural network models that can be used to approximate almost any function with a high degree of accuracy (white 1992). AN MLP contains a hidden layer of neurons that uses non-linear activation functions, such as a logistic function. Figure 1 offers a representation of an MLP with one hidden layer and a single input and output. The MLP in figure 1 represents a simple non-linear regression.

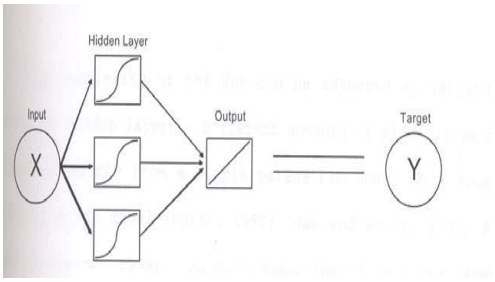

Fig-1

The another new technique for this is Support Vector Machine (SVM). SVM is introduced by Boser, Guyon, and Vapnik in COLT-92. Support vector machines are a set of related supervised learning methods used for classification and regression. They belong to a family of generalized linear classifiers. In another terms, Support Vector Machine (SVM) is a classification and regression prediction tool that uses machine learning theory to maximize predictive accuracy while automatically avoiding over-fit to the data.
The formulation for SVM classification is

SV classification:

$$\min_{f,\xi_i} \|f\|_K^2 + C\sum_{i=1}^{l}\xi_i$$

$y_i f(\mathbf{x}_i) \geq 1 - \xi_i$, for all i $\xi_i \geq 0$

SVM classification, Dual formulation:

$$\min_{\alpha_i} \sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} \alpha_i \alpha_j y_i y_j K(\mathbf{x}_i, \mathbf{x}_j)$$

$0 \le \alpha_i \le C$, for all i;

$$\sum_{i=1}^{l} \alpha_i y_i = 0$$

Variables ξ_i are called slack variables and they measure the error made at point $(\mathbf{x}_i, y_i)$. Training SVM becomes quite challenging when the number of training points is large.

IV. EXPERIMENTAL RESULTS

The present paper analyzed the Sensex daily data from Jan 2008- Dec.12 using MLP and SVM models.

The MSE and NMSE values in both for training and validation data of each year from 2008 to 2012 are shown in Table-1 and Table-2 respectively.

Table-1

Year	MSE training		MSE validation	
	SVM	MLP	SVM	MLP
2008	1.1292923	1.3345074	1.1292923	1.3345074
2009	0.60363	0.7657106	0.60363	0.7657106
2010	0.1908253	0.2525603	0.1908253	0.2525603
2011	0.2727183	0.3696291	0.2727183	0.3696291
2012	0.1001534	0.164633	0.1001534	0.164633

Table-2

Year	NMSE training		NMSE validation	
	SVM	MLP	SVM	MLP
2008	0.14138	0.162748	0.163622	0.17392
2009	0.125916	0.159726	0.17875	0.18248
2010	0.187717	0.248446	0.220391	0.262115
2011	0.156428	0.212015	0.183303	0.218954
2012	0.111901	0.183944	0.173051	0.181695

The prediction performance is evaluated using the statistical metrics: Mean Square Error (MSE). It is a measure of deviation between actual and predicted values. The smaller the values of MSE are the predicted time series values to that the actual values.

Table-3

Year	R-squared value training		R-squared value validation	
	SVM	MLP	SVM	MLP
2008	0.85862	0.83725	0.83638	0.82608
2009	0.87408	0.8427	0.82125	0.81752
2010	0.81228	0.75155	0.77961	0.73789
2011	0.84357	0.78798	0.8167	0.78105
2012	0.8881	0.81606	0.82695	0.81831

The R-squared value (in Table -3) represents the proportion of variation in the dependent variable that is explained by the independence variables. The better the model explains variation in the dependent variable, the higher the R-squared value.

V. CONCLUSION

The use of MLP and SVM in capital market forecasting is studied in this paper. This study has concluded that SVMs provide a promising alternative to time series forecasting as it provides smaller MSE. For future research the family of GARCH models, ARIMA model and other Mathematical models may be taken with SVM for showing the better accuracy exhibiting volatilities of Stock Market.

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