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Accuracy Driven- Financial Forecasting using MLP and SVM

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Abstract: In the face of growing role of financial sector in every form of economy across the globe the efficient allocation of resources at appropriate prices could not only significantly enhance the efficiency with which the economy functions but also put tremendous impact on the way it operates. In view of this, the fields like behavioral-economics & Computational finance have received much attention for their more flexible & detailed view regarding the forecasting of stock markets in both emerging as well as in the developed economics. Throughout this paper a sincere effort has been made to put forth a comparative prediction efficiency of Multi Layer Perceptron and Support Vector Machine in the field of financial time series analysis. For the empirical analysis the BSE sensex data of Indian Stock Market has been considered. The study proved SVM as a handy tool over MLP in various front for financial forecasting of similar natur

Key words: Multi Layer Perceptron(MLP), Support Vector Machine(SVM), Financial forecasting, Prediction efficiency.

INTRODUCTION

In the face of growing role of financial sector in every form of economy across the globe the efficient allocation of resources at appropriate prices could not only significantly enhance the efficiency with which the economy functions but also put tremendous impact on the way it operates. Probably that's the secret behind the fields like behavioral-economics & Computational finance have received much attention for their more flexible & detailed view regarding the forecasting of stock markets in both emerging as well as in the developed economics. The efficiency with which a financial market works decides, how well it directs resources to their most productive uses. In a well functioning financial market risks could be accurately priced and would be borne by those who have appetite for absorbing risks. Economic activities in real sense with higher investments, in both quantity as well as quality, would leads to economic growth with macroeconomic stability and minimize financial uncertainties. Moreover, a stable financial system facilitates efficient transmission of monetary policy initiatives. India being a developing economy has immense need to respond 'risk in financial market' quickly and effectively to minimize financial uncertainty.

Necessity of a healthy capital market in mobilizing resources is well-established. Volatility has its different degree of importance to academicians, policy makers, and financial market participants for various reasons. Volatility in the prices of stock adversely affects investors' earnings in particular and health of the economy in general. Analysis of stock market for the evaluation of the risk has given due importance in India after liberalization in 1991. Though, the confidence of investors on Indian Capital market in the early 1990's has been warned by excessive volatility, yet during the past few years it has undergone metamorphic reforms. The impact of such reforms has been realized by every segment of Indian Capital Market viz. primary and secondary markets, derivatives, institutional investment and market intermediation etc. The stock market in India has had its fair share of crisis endangered by excessive speculation resulting in excessive volatility. The wide spread concern of the exchange management, brokers and investors alike has realized the importance of being able to measure and predict stock market volatility. As volatility has direct and disproportional impact on investors' return it would be immensely useful from an investor's view point, if the future stock return volatility could be predicted from the past data. Such types of forecasting capabilities are of much use for pricing of sophisticated financial instruments e.g. futures and options by studding different dependent and independent parameters relating to it.

LITERATURE REVIEW

Since the 1960's there have emerged numerous studies, questioning the degree of stock market efficiency. During the last decade a large number of researchers across the globe had contributed to the field of application of MLP and SVM for financial forecasting. Some of these pioneer works has been reviewed for understanding of current trend and the gray area in this filed which needs more insight.

With the dawn of 21^{st} century a pioneering work on implementation of Neural Network Regression (NNR) as an alternative technique in financial forecasting was come in to being by Ch. L. Dunis and J.Jalilov in the year 2002. This paper examines the use of NNR as an alternative forecasting technique in financial forecasting models and financial trading models. In both types of applications, NNR models results are benchmarked against simpler alternative approaches. They developed financial trading models for four major stock market indices (S&P500, FTSE100, EUROSTOXX50 and NIKKEI225) using daily data from 31^{st} January 1994 through 4^{th} May 1999 for in-sample estimation and leaving the period 5^{th} May 1999 through 6^{th} June 2000 for out-of-sample testing and proved that the NNR models do indeed add value in the forecasting process. In the year 2004 a paper from Jae Kim Kyoung, Boo Lee compares a feature transformation method using a genetic algorithm

(GA) with two conventional methods for artificial neural networks (ANNs). They incorporated GA to improve the learning and generalizability of ANNs for stock market prediction. On comparison of results achieved by the feature transformation method using GA (i.e. the proposed model) to other two feature transformation methods, it was proved that the proposed model outperform the other two conventional methods in most of the fronts. Experimental results show that the proposed approach reduces the dimensionality of the feature space and decreases irrelevant factors for stock market prediction.

The application of SVM to forecast financial market is a new concept and not much explored. For the first time, H. Yang has successfully applied support vector regression (SVR) to financial time series prediction. He has noticed that upside margin and downside margin do not necessary be the same, and further he has observed that the choice would affect the upside risk, downside risk and as well as the overall prediction result. In his paper, he had introduced a novel approach to adapt the asymmetrical margins using momentum and compared this method to predict the Hang Seng Index and Dow Jones Industrial Average.

In the year 2005 Yu Zhao comes up with an improved one-class SVM and tested on the wireless industry customer churn data set. His method has been shown to perform very well compared with other traditional methods, ANN, Decision Tree, and Naïve Bays. In the year 2009 N.I. Sapankevych provides a survey of time series prediction applications using SVM. His ultimate goal is to provide the reader with insight into the applications using SVM for time series prediction along with a brief tutorial on SVMs for time series prediction. Further he had outlined some of the advantages and challenges in using SVMs for time series prediction.

OBJECTIVES AND METHODOLOGY

In a liberal economy volatility in equity market has become a matter of growing concern for investors, brokers, policy makers and other stack holders directly or indirectly related to it. The impact of stock return volatility may adversely affect economic performance through consumer and business investment spending. Further the extreme volatility could derail the financial system and lead to structural or regulatory changes. That's why, forecasting of market behavior assumes so much importance.

On the other hand, due to inherently noisy, non stationary and deterministically chaotic nature of financial time series it is too difficult, if not impossible to predict complete information about the future price out of the past behavior of financial markets. Hence, the objective is to find out a suitable model which have capabilities of managing all (most of) the above mentioned nature of a financial time series and predict better than other available models. Out of 'N' number of methods; here two well known nonparametric, nonlinear, noise-tolerant and multivariate models e.g. MLP and SVM are treated with.

For comparison, the functional characteristics of SVM and MLP model in financial forecasting accuracy have been discussed. Further, their efficiency has been evaluated with certain real world data and the results are analyzed for concluding remarks.

To serve the purpose, the daily basis data of BSE Sensex from 2008 -2012 has been taken. These empirical data runs through MS-Excel and Neuro-intelligence software. The results obtained during training and validation has been compared and analyzed to get the comparative edge of one over another.

NEURAL NETWORK AND MULTILAYER PERCEPTRON

Artificial Neural Network (ANN) is a concept which processes information in the way the biological nervous systems, such as the brain, process information. The strength of the model is its structure and its working process. It is a composition of large number of highly interconnected processing elements, known as artificial neurons working in unison to solve specific problems. ANNs are learned by example as human beings. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning of ANN is similar as in other biological systems. It is nothing but certain adjustments to the synaptic connections that exist between the neurons. The concept of ANN, for the first time, was developed in 1943 by the neurophysiologist Warren McCulloch and the logician Walter Pits. But due to technological constraints of the time did not permit them to do too much. Following an initial period of enthusiasm, the field survived a period of frustration and disrepute. In 1969 a book published by Minsky and Papert summed up a general feeling of frustration against neural networks among researchers, and was thus accepted by most without further analysis. But subsequently, some pioneers were able to develop convincing technology which not only surpassed the limitations identified by Minsky and Papert but also put the neural network field in to height where it enjoys a resurgence of interest.

WHY USE NEURAL NETWORKS?

Being a non-parametric, non-linear, non-assumable, noise-tolerant and adaptive model, neural network has remarkable ability to derive meaning from complicated or imprecise data to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can work as an "expert" in the category of information it has been given to analyze. This expert can then be used to provide projections over given new situations of interest and answer "what if" questions. Apart from it, the fault tolerant nature via Redundant Information Coding made ANN a full proof model to rely on.

MULTILAYER PERCEPTRON

The architecture of a multilayer perceptron is consists of neurons arranged into an input layer, an output layer and one or more hidden layers. The fig-1 shows a simple architecture of multilayer perceptron.

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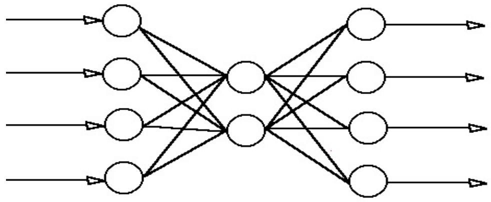

Fig. 1: Architecture of Multilayer Perceptron

SUPPORT VECTOR MACHINE

Support Vector Machine (SVM) was introduced by Boser, Guyon, and Vapnik in COLT-92. In simple terms, SVMs are a set of related supervised learning methods used for classification and regression. They belong to a family of generalized linear classifiers. To be defined, 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. Support Vector machines can otherwise be defined as systems which use hypothesis space of a linear functions in a high dimensional feature space, trained with a learning algorithm from optimization theory that implements a learning bias derived from statistical learning theory.

The Support Vector Machines developed by Vapnik gained popularity due to many promising features such as

- Use of the Structural Risk Minimization (SRM) principle, against traditional Empirical Risk Minimization (ERM) principle, used by conventional neural networks in formulation. SRM minimizes an upper bound on the expected risk, where as ERM minimizes the error on the training data. The superiority of SRM over ERM is proven.
- Better empirical performance.

PREDICTION PERFORMANCE ANALYSIS

Financial time series forecasting is one of the most challenging applications of modern time series forecasting. Financial time series are inherently noisy, non stationary and deterministically chaotic. These characteristic suggest that there is no complete information that could be obtained from the past behaviour of financial markets to fully capture the dependency between the future price and that of the past.

Financial time series forecasting can be done through univariate analysis and multivariate analysis. In multivariate analysis, any indicator, whether it is related to the output directly or not, can be incorporate as the input variable, while in univariate analysis, the input variables are restricted to the time series being forecasted. A general univariate model that is commonly used is based on the Auto Regressive Integrated Moving Average (ARIMA) method. This method is outperformed due to its parametric behaviour and some inconsistent assumptions like, time series being forecasted are linear and stationary.

The prediction performance is greatly improved by the use of a neural network both in terms of prediction metrics and trading metrics. Multivariate models can rely on greater information, where not only the lagged time series being forecasted, but also technical indicators, fundamental indicators or inter-market indicators are combined to act as predicators. Moreover, a neural network is more effective in describing the dynamics of non-stationary time series due to its unique non-parametric, non-assumable, noise-tolerant and adaptive properties. Neural networks are universal function approximators that can map any nonlinear function without priori assumptions about the data.

The issue of generalization has long been a concern to researchers, who have explored a variety of procedures for enhancing the generalization ability of neural networks. Recently, SVMs developed by Vapnik have provided another novel approach to improve the generalization property of neural networks. Unlike most of the traditional learning machines that adopt the Empirical Risk Minimization Principle, SVMs implement the Structural Risk Minimization Principle, which seeks to minimize an upper bound of the generalization error rather than minimize the training error. This will result in better generalization than that with conventional techniques.

EMPIRICAL ANALYSIS

The empirical analysis of outputs is based on values obtained by running both SVM and MLP techniques over the data. The table 1 through table 5 are designed to have a quick look and grasp of comparative efficiencies towards forecasting on the basis of data under consideration. Obtained value of some of the parameters run through MLP and SVM which can explain the comparative strength and weaknesses of a model to deal with empirical data, are put side by side, year wise.

The prediction performance is evaluated using the statistical metrics: The R-squared and the Mean Square Error (MSE). The R-squared value represents the proportion of variation in the dependent variable that is explained by the independent variables. The better the model explains variation in the dependent variable, the higher the R-squared values. The Mean Square Error (MSE) is a measure of deviation between actual and predicted values. The smaller the values of MSE are; the closer the predicted time series values to that the actual values.

Table 1: Outputs of SVM and MLP for the year 2008

		Training		Validation	
	Parameters	SVM	MLP	SVM	MLP
20	R-square	0.8586	0.8372	0.83638	0.8260
	Coefficient	3.4790	-3.7326	3.74267	-3.8586
	NMSE	0.1413	0.1627	0.16362	0.1739
	RMSE	1.0767	1.1552	1.15830	1.1942
	MSE	1.1592	1.3345	1.34167	1.4261
	MAE	0.7979	0.8679	0.87981	0.8889

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The R-square values of table 1 clearly indicate the ability of SVM is comparatively better than its counterpart to explain variation in the dependent variable i.e. the R-square value is higher for SVM than MLP in both training and validation. Regarding the measure of deviation between actual and predicted values it can be shown that the MSE values in SVM is less than MLP in training and validation, indicating the relative strength of SVM over MLP.

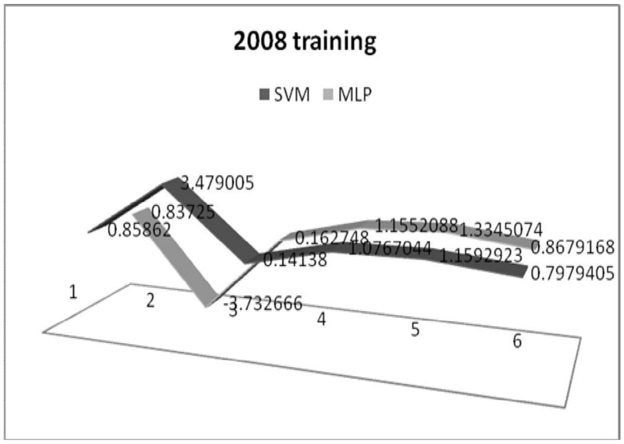

Fig 2: Training for the year 2008

For a better and easy understanding graphical representation of training and validation of the year 2008 is given on fig 2 & 3. In fig 2 the line representing SVM can be seen to explain training data in better way than its counterpart. Similarly, SVM line drawn in fig 3 shows the capabilities of SVM to analyse the validation data against MLP.

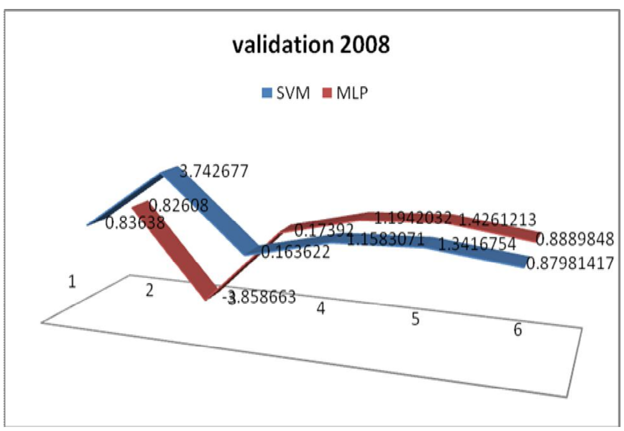

Fig 3: Validation for the year 2008

Analyzing outputs for the year 2009 in the light of statistical parameters we can also see from the table 2 that, the R-square values produced by SVM are greater and MSE and related values less than the values produced by MLP with clear indication of superiority of SVM over MLP.

Table 2: Outputs of SVM and MLP for the year 2009

		Training		Validation	
	Parameters	SVM	MLP	SVM	MLP
2009	R-square	0.8740	0.8427	0.8212	0.8175
	Coefficie	3.3191	3.7382	3.9546	3.9956
	NMSE	0.1259	0.1597	0.1787	0.1824
	RMSE	0.7769	0.8750	0.9256	0.9353
	MSE	0.6036	0.7657	0.8569	0.8747
	MAE	0.5899	0.6593	0.6590	0.6714

Values of table 3 further strengthen the advantageous edge of SVM against MLP. Here also the parameters values are favorable to the SVM model.

Table 3: Outputs of SVM and MLP for the year 2010

		Training		Validation	
	Parameters	SVM	MLP	SVM	MLP
2010	R-square	0.8122	0.7515	0.7796	0.7378
	Coefficien	7.0313	8.0891	7.6187	8.3087
	NMSE	0.1877	0.2484	0.2203	0.2621
	RMSE	0.4368	0.5025	0.4733	0.5161
	MSE	0.1908	0.2525	0.2240	0.2664
	MAE	0.3074	0.3925	0.3539	0.4046

Outputs depicted in table 4 of the year 2011 follows the same line with previous years' showing comparative efficiency of SVM over MLP to deal with similar kind of data taken for the study.

Table 4: Outputs of SVM and MLP for the year 2011

		Training		Validation	
	Parameters	SVM	MLP	SVM	MLP
2011	R-square	0.8435	0.7879	0.8167	0.7810
	Coefficie	-4.4818	-5.2177	-4.8516	-5.3024
	NMSE	0.1564	0.2120	0.1833	0.2189
	RMSE	0.5222	0.6079	0.5653	0.6178
	MSE	0.2727	0.3696	0.3195	0.3817
	MAE	0.3667	0.4559	0.4080	0.4682

The table 5 takes one step forward towards drawing conclusion in the present study. The output of the last but not the least year of empirical study indicates arrow to the superiority of SVM in comparison to MLP.

Table 5: Outputs of SVM and MLP for the year 2012

		Training		Validation	
	Parameters	SVM	MLP	SVM	MLP
2012	R-squar	0.8881	0.8160	0.8269	0.8183
	Coeffici	3.2809	4.2065	4.0801	4.1808
	NMSE	0.1119	0.1839	0.1730	0.1816
	RMSE	0.3164	0.4057	0.3935	0.4032
	MSE	0.1001	0.1646	0.1548	0.1626
	MAE	0.2389	0.3097	0.2713	0.3115

In fact we can generalize for all the years considered under empirical study, that the output of SVM outperformed MLP in most of the prediction front. To be more precise, the results obtained are much of values in regard to draw a conclusion in favour of SVM in similar situation where similar kind of data as studied here, are under consideration.

CONCLUSION AND FUTURE WORK

The stock market is a complex, nonstationary, chaotic, and nonlinear dynamic system. Therefore predicting stock market price movements is a tedious task. Here a novel type of learning machine called SVM along with MLP model is taken for analyzing the forecasting of the indices of BSE Sensex from year 2008 to 2012. The experimental results proved the supremacy of SVM model and revieled as a better choice, at least under similar circumstances studied here, for financial forcasting than MLP in overall aspects.

There is a lot of scope available for enhancemnt from many aspects viz. inclusion of GARCH -family, ARIMA model, Wavelet analysis and ID3Algorithm technics for comparative study with SVM as handy tool for prediction of Stock Market.

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