

Stock Price Forecasting using Support Vector Machines and Improved Particle Swarm Optimization

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Abstract—The present paper employs an Particle Swarm Optimization (PSO) Improved via Genetic Algorithm (IPSO) based on Support Vector Machines (SVM) for efficient prediction of various stock indices. The main difference between PSO and IPSO is shown in a graph. Different indicators from the technical analysis field of study are used as input features. To forecast the price of a stock, the correlation between stock prices of different companies has been used. It is in general observed that the proposed model is computationally more efficient, prediction wise more accurate and more robust against other researches done by standard PSOSVM based model.

Index Terms—Particle Swarm Optimization, Support Vector Machines, Stock Market forecasting, IPSOSVM, PSOSVM, Intelligent Algorithms

I. INTRODUCTION

The process of making assumptions of future Changes based on existing data is Forecasting. The more accurate the forecasting, the more it could be helpful to make decisions for future. Empowering the managers in all businesses to modify current situation in order to achieve the favorable results in future is the key use of forecasting. Forecasting stock price has always been a serious issue in financial fields. Stock market prediction is regarded as a challenging task in financial time-series forecasting because of the fact that stock market indices are essentially dynamic, nonlinear, complicated, nonparametric, and chaotic in nature [1]. Stock market forecasters focus on developing approaches to successfully forecast/predict index values or stock prices, aiming at high profits using well defined trading strategies. The central idea to successful stock market prediction is achieving best results using minimum required input data and the least complex stock market model [2]. In the recent years lots of attentions have been devoted to the analysis and prediction of future values and trends of the financial markets. Due to volatility and non-stationary characteristics of stock indices data it is difficult to build an accurate forecasting model. But even then different financial forecasting methods have been proposed in the literature each of which has its own

merits and limitations. Studies done during previous years, indicates that intelligent forecasting models outperform traditional models, especially in short-term forecast. Traditional statistical models have shortcomings in data processing, and sometimes have to rely on hypotheses, hence affect the forecasting accuracy. Artificial intelligence techniques such as artificial neural networks (ANNs), fuzzy logic, and genetic algorithms (GAs) are popular research subjects, since they can deal with complex engineering problems which are difficult to solve by classical methods. Kim and Han (2000) [3] utilized genetic algorithms (GAs) to discredited features and determine the connection weights of artificial neural networks (ANNs) [4] Brain inspired genetic complimentary learning for stock market prediction [5]. Bhattacharya, Pictet and Zumbach have developed a GP based trading model for efficient prediction of exchange rates recently [6]. The support vector machine (SVM) which was first suggested by Vapnik , has recently been used in a range of applications, including financial stock market prediction. As Chen and Shih improved, the SVM technique, in general, is widely regarded as the state of art classifier. Previous researches indicated that SVM prediction approaches are superior to neural networks approaches.

II. SUPPORT VECTOR MACHINES

Because SVMs are learning algorithms developed to efficiently train linear learning machines in kernel-induced feature spaces by applying the generalization theory of Vapnik and co-workers, SVM applies the maximized margin criterion to optimize separating hyperplane between binary classes. A hyperplane can be applied to linear separable data which separates the binary decision classes in the two attribute cases as are shown in the following equation [7]:

$$y = w_0 + w_1x_1 + w_2x_2 \quad (1)$$

y : outcome

x_i : the attribute values

w_i : Weights determined by the learning algorithm

The following equation to represent the maximum margin hyperplane.

$$y = b + \sum_{i=1}^n \alpha_i y_i x(i).x \quad (2)$$

where y is the class value of training example $x(i)$, the vector x represents a test example, the vectors $x(i)$ are the support vectors and represents the dot product. In this equation, b and α_i are parameters that determine the hyperplane. In order to find the support vectors a linearly constrained quadratic programming problem is solved and the parameters b and α_i are determined. In this case, the data does not fit in a linearly separable relationship. So SVM uses a Kernel function to transform the inputs into the high-dimensional feature space.

$$y = b + \sum_{i=1}^n \alpha_i y_i k(x(i).x) \quad (3)$$

There are many different kernels for generating the inner products to construct machines with different types of nonlinear decision surfaces in the input space. SVMs are always exposed to over-fitting problem. This is because the risk minimization principle which is implemented by SVMs is structural while most of traditional neural network models follow the empirical principles. The difference is between their attitudes toward the error minimization. The former applies methods to minimize the misclassification error or deviation from the correct solution of the training data, but the latter seeks to minimize the upper bound of generalization error.

III. PROPOSED METHOD

A. Correlation between Stock

Recent Studies have been claimed that the stock prices move integrated. As shown in Fig. 1, there is statistically significant correlation between prices of certain stocks and thus, price movements in one stock can often be used to predict the movement of other stocks [8], [9]. Although each of them (Nasdaq, Dow Jones, S&P 500) evaluates the stock changes through different methods, the movements still are not irrelevant Letters X and Y are assigned to two stocks which are meant to find the correlation between them.



Figure 1. Dow Jones Industrial, S&P 500 and Nasdaq 100 Indices

The given Formula is as below:

$$Cor(X,Y) = ((X(ci) - X)(Y(ci) - Y)) / \delta_x \delta_y n \quad (4)$$

where $X (ci) \& Y (ci)$ are closing prices of the stock on the i th day, $X \& Y$ are the mean prices of the stocks, σX and σY are the standard deviations, and n is the number of days over which the correlation is to be found, Fig. 2.

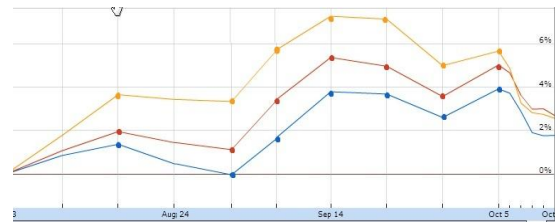


Figure 2. Close view on stock correlations

B. Input Features

TABLE I. OTHER FEATURES

Feature name	Formula
Momentum	$(C(i) / C(i - N)) * 100$
Williams %R	$(HH(n) - C(t)) / HH(n) - LL(n) * 100$
Rate of change (ROC)	$(C(t) - C(t - n)) / C(t - n)$
5 Day disparity	$(C(t) / MA(5)) * 100$
10 Day disparity	$(C(t) / MA(10)) * 100$
Stochastic %K	$(C(t) - C(t - 1)) / C(t - 1) * V$
Price volume trend (PVT)	$Fitness = (P(i) - PR) / (\sum (P(i) - PR))$

In the area of stock prediction, feature selection refers to choosing a subset of original input variables which are usually technical or fundamental indicators. Because the selected feature subset can represent better the original character of dataset, prediction with them can improve the accuracy and efficiency. According to financial experts' experiences, 35 technical indicators are being used as candidates for input features [10].

In table I other features are shown. First the n companies which exhibit the highest correlation with the stock to be predicted are found. One of these n stocks will always be the target stock itself as it will have perfect correlation with itself. Then, these 35 features are calculated for each of these n companies by using their historical prices and trading volumes. Hence, a set of $35 * n$ candidate features is obtained here.

IV. IMPROVED PSO

Particle swarm optimization (PSO) is an evolutionary computation technique, introduced by Kennedy and Eberhart. The main idea is based in the way birds travel when trying to find sources of food, or similarly the way a fish school will behave. The way this behavior is modeled, is that the "particles" inside the "swarm" (or population) are treated as solutions to a given problem .

The solution space for that problem is where the particles will be moving or traveling through ,searching for the best solutions to the problem. The particles will travel following two points in the space; a leader in the

swarm, which is chosen according to the global best solution found so far, and its memory. Every particle has a memory, which is the best solution visited by that specific particle. According to. Some experimental results show that PSO has greater "global search" ability, but the "local search" ability around the optimum is not very good. In order to enhance "local search" ability of PSO, an improved particle swarm optimization was introduced in this paper, which was PSO with mutation.. The flowchart of the method is given in Fig. 3.

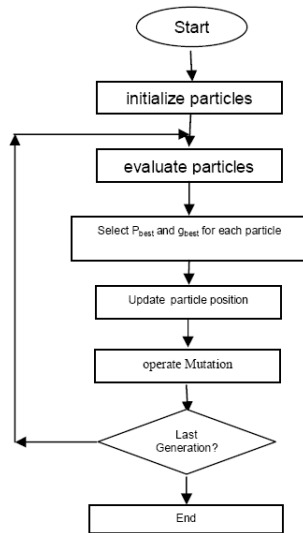


Figure 3. Flow chart of method

A. Initialize particles

- A particle by a binary vector of size 35*m is initialized. Then particles evaluation starts to select the best P and G for each particle.
- To Realize if the particles have been chosen correctly the following function is used:

$$Fitness = (P(i) - PR) / (\sum (P(i) - PR))$$

where, P(i) is the classification accuracy obtained by the SVM with the input feature set as described by particle I and PR is the accuracy of a random guess, which, in this case is 0.5.

V. EXPERIMENTAL RESULTS

The approach is done on the three most well-known stock market indices, DJI, S&P 500 and Nasdaq-100. The used data is fetched from yahoo finance, Google finance and NYSE that starts in 10.02.2008 till 9.10.2012. Not only the opening, highest, lowest and closing values of the stock price were obtained but also the volumes traded are taken in to account. 60% of the data was used for training, 20% for validation and 20% for testing the system. The calculated results have been compared with the solo SVM model which is reported by K. Kim [11]. The PSOSVM results are observed before introducing the Genetic algorithm in to PSO and been written in table II.

The final results after entering the GA is successfully more than the previous models. As it is shown in table II IPSO gives out better results in regard to PSO with at least 2%, as they were in PSOSVM 62.024, 61.794 and 61.035 for DJI,S&P 500 and NASDAQ-100, respectively.

TABLE II. HIT RATIOS %

	SVM	PSOSVM	IPSOVM
DJI	57.893	62.024	64.506
S&P 500	56.223	61.794	64.125
NASDAQ	55.273	61.035	63.407

VI. SUMMARIES

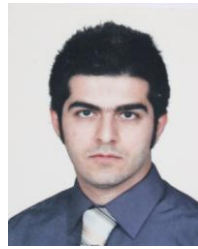
This paper proposed an improved hybrid IPSOSVM system to forecast the future movements of stock indices. A set of technical indicators, obtained from the stock to be predicted, and also from the stocks exhibiting high correlation with that stock were used as input features. Results state that mutation in particles led the accuracy being higher, since the particle always seraches the whole state space which prevents the mistakes of not finding the other best options in other possible states. By taking the political & economical factors into account even more accurate results could be observed. Note how the caption is centered in the column.

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