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FORECASTING STOCK MARKET USING SVM

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Abstract: Prediction of stock market is a long-time attractive topic to researchers from different fields. In particular, numerous studies have been conducted to predict the movement of stock market using machine learning algorithms such as support vector machine (SVM) and reinforcement learning. In this project, we propose a new prediction algorithm that exploits the temporal correlation among global stock markets and various financial products to predict the next-day stock trend with the aid of SVM. Recent studies introduce particular strategies that overcome these problems. Support Vector Machine (SVM) is a relatively new learning algorithm that has the desirable characteristics of the control of the decision function, the use of the kernel method, and the sparsity of the we implement an algorithm witch support to the SVM and predict the stock marketing value.

Keywords: Stock Classification; Data Mining; Support Vector Machine; Forecasting; Multivariate Classification

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INTRODUCTION

The macroeconomic environment and the financial market are complex, evolutionary, and non-linear dynamical systems. The field of financial forecasting is characterized by data intensity, noise, non-stationarity, unstructured nature, and hidden relationships. Predicting financial indicators is therefore a difficult task. However, forecasting is important in the sense that it provides concrete data

for investment decisions. How can we predict whether the price of a particular stock will go up or down in the upcoming year? In the modern techniques, one way is to develop a predictor based on the information in the historical data. First of all, we should select some major factors that may

influence the performance of the stocks, we can further discover an interesting model from our dataset to predict the future performance of any stocks. That is to say, we need to learn a model that can map those factors into the class attribute which indicates the whole performance of stocks. Support vector machine (SVM) is a machine learning technique that can be used for this purpose of classification.

Established on the unique theory of the structural risk minimization principle to estimate a function by minimizing an upper bound of the generalization error, SVM is shown to be very resistant to the over-fitting problem, eventually it is to our belief that data of overseas stock and other financial markets, especially those having strong temporal correlation with the upcoming US trading day, should be useful to machine learning based predictor, and our speculation is verified by numerical results, achieving a high generalization performance. Another key property of SVM is that training SVM is equivalent to solving a linearly constrained quadratic programming problem so that the solution of SVM is always unique and globally optimal, unlike neural networks training, which requires nonlinear optimization with the danger of getting stuck at local minima.

First of all, we should select some major factors that may influence the performance of the stocks, that can be divided into two major groups: Company Specific and Mnemonics. We can further discover an interesting model from our dataset to predict the future performance of any stocks. For increasing the profit we consider the following values :

Net Revenue

Revenue is income that a company receives from its normal business activities, usually from the sale of goods and services to customers.

Net Income

Net Income is a company's total earnings (or profit), calculated by taking revenues and adjusting for the cost of doing business, depreciation, interest, taxes, and other expenses

Price per earnings ratio of stock

A valuation ratio of a company's current share price compared to its per-share earnings. Calculated as: Market Value per Share/Earnings per Share (EPS).

Diluted earnings per share

A performance metric used to gauge the quality of a company's earnings per share (EPS) if all convertible securities were exercised.

Consumer spending

It is also known as personal consumption expenditure. It is the largest part of aggregate demand or effective demand at the macroeconomic level.

Consumer investment

In economics, investment represents capital expenditure by companies in an economic model, which is distinct from consumer expenditure, government expenditure, and net exports.

Unemployment rate

The percentage of the total labor force that is unemployed but actively seeking employment and willing to work

Inflation rate

The percentage increase in the price of goods and services, usually annually

Federal funds rate

In the United States, the federal funds rate is the interest rate at which private depository institutions (mostly banks) lend balances (federal funds) at the Federal Reserve to other depository institutions, usually overnight. It is the interest rate banks charge each other for loans.

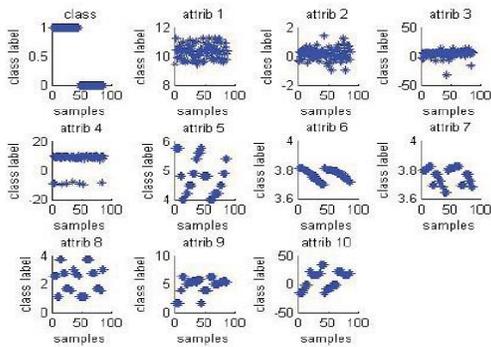


Figure1. Scatterplots of the dataset

Dow Jones industrial average

It is an index that shows how 30 large, publicly owned companies based in the United States have traded during a standard trading session in the stock market.

	True Poor	Group	True Good	Group
Poor	37		2	
Good	1		38	
Total	38		40	
N correct	37		38	
Proportion	97.36%		95%	
N=78	N CORRECT=75	Proposition correct=96.15%		

Table I. The results of the SVM model’s classification on training samples

That is to say, we need to learn a model that can map those factors into the class attribute which indicates the whole performance of stocks. Support vector machine (SVM) is a machine learning technique that can be used for this purpose of classification. Established on the unique

theory of the structural risk minimization principle to estimate a function by minimizing an upper bound of the generalization error, SVM is shown to be very resistant to the over-fitting problem, eventually achieving a high generalization performance. Another key property of SVM is that training SVM is equivalent to solving a linearly constrained quadratic programming problem so that the solution of SVM is always unique and globally optimal, unlike neural networks training, which requires nonlinear optimization with the danger of getting stuck at local minima.

Observation	Stock	Predicted Group	Actual Group
1	Computer Associate 2002	Good	Poor
2	Computer Associate 2001	Poor	Good
3	Ford 2002	Poor	Poor
4	Ford 2001	Good	Good
5	Intel 2002	Good	Good
6	Kellogg 2002	Good	Good
7	Ups2002	Good	Good
8	JCpenny	Good	Good

	2002		
9	Microsoft 2002	Good	Good
10	Tyson 2002	Good	Poor

Table II. Classification of test samples by SVM classifier

The rest of this article is organized as follows. we will give brief theoretical overviews of SVM. In we focus on the application of SVM on the stocks market. introduction of these variables. Also, we label each stock in a specific year in our dataset as a good or a poor investment. Although there is no definitive method for defining a market investment as “good” or “poor”, we use a method that is simple and objective: if the price of a company’s stock over a given year rose, it is classified as a good investment, otherwise it is classified as a poor investment. Our training sample was based on a random selection of 15 companies, for all years from 1995-2002, where data was provided in their annual reports. This made a sample size of 88 distinct company-year observations. To create a test sample, we randomly selected totally 10 stocks out of the data set, and the remaining 78 entries were used as the training samples.

From the elementary analysis of the dataset shown in Figure 1 and Figure 2, we can easily see the value distribution of each attribute. The value range of each attribute has their own pattern, so it seems that linear classification is very hard to build a correct relation from all the attributes to the class label in this case. However, the SVM is good at non-linear classification and can be tried to develop a strong connection from the input attributes to the class label by supervised learning.

	SVM Classification accuracy rate
Training Data Set	97.435% (76/78)
Testing	70% (7/10)

Data Set	
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TABLE III. ACCURACY RATES

II. LITERATURE REVIEW

1. Stock Market Value Prediction Using Neural Networks

The idea of neural networks was first inspired by human beings nervous system which consists of a number of simple processing units called neuron . Each neuron receives some signals from outside or from other neurons and then by processing them in activation function produces its output and sends it to other neurons. Each input impact is different from other inputs. For example in figure two the impact of the i th neuron on j th neuron is shown with w_{ij} , the weight of the connection between neuron i and j .

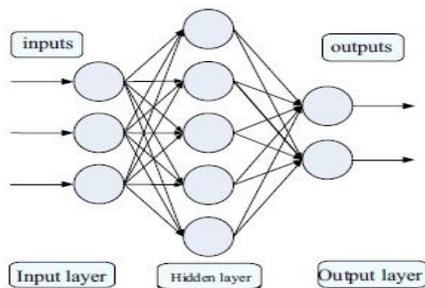


Figure2: Stock market prediction by using ANN

2. Stock Market Value Prediction Using Support Vector Machines

Recently, a new technique within the field of computational intelligence, that of Support Vector Machines (SVM), has been applied to financial markets. In the current literature, these have in some cases shown to be more effective than ANN's (Kim, 2003; Thissen et al., 2003; Liu and Wang, 2008). This section starts with introducing the underlying theory behind the SVM, in which the bare basics are briefly introduced, necessary to effectively apply SVMs in financial forecasting. Subsequently, the application of SVMs in financial forecasting is investigated.

Support vector machines (SVMs) are very popular linear discrimination methods that build on a simple yet powerful idea. Samples are mapped from the original input space into a high-dimensional feature space, in which a „best“ separating hyperplane can be found. A separating hyper plane H is best if its margin is largest. The margin is defined as the largest distance between two hyper planes parallel to H on both sides that do not contain sample points

between them (we will see later a refinement to this definition) . It follows from the risk minimization principle (an assessment of the expected loss or error, i.e., the misclassification of samples) that the generalization error of the classifier is better if the margin is larger. The separating hyper plane that are the closest points for different classes at maximum distance from it is preferred, as the two groups of samples are separated from each other by a largest margin, and thus least sensitive to minor errors in the hyper plane"s direction .

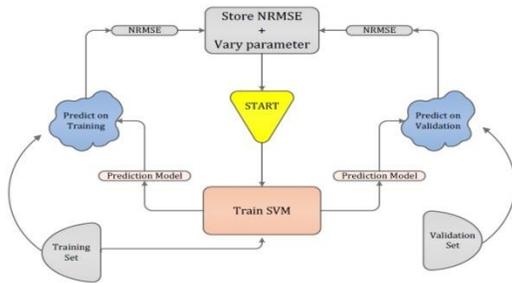


Figure 3: Iterative process Varying SVM Parameter

About the Work:

The above figure show that the actual implementation of the stock market prediction by using Support Vector Machine. Here we actually done the collection of data by using the CVS file common value also we collect the value from the web and send to the processing after that probabilistic approach it will send to the SVM Classifiers and after that we generated the out put of the predicted value.

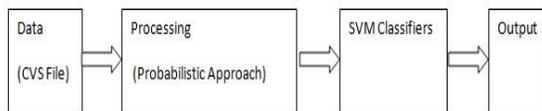


Figure4:Proposed work for SVM Parameter

Future Research

This research has shown that SVMs offer some advantages in comparison to ANNs in financial forecasting. Future research may explore the possibility of refining the SVM in order to achieve a higher generalization performance.

Refining the SVM may lie in finding a better structure in terms of the kernel function, which might be a combination of various kernels. It might also lie in how the free parameters for the SVM are selected, perhaps by an alternative computational intelligence method. This would require further research on the topic that points to the direction of genetic algorithms in combination with SVM. By imitating the biological evolution process, genetic algorithms try to find optimal or new optimal solutions with relatively modest computational requirements.

Alternatively, future research may be conducted on combining different inputs from various data sources to an SVM prediction model. One could thereby think of inputs from various macroeconomic indicators that might have an effect on the exchange rate.

CONCLUSION: In the project, we proposed the use of data collected from different global financial markets with machine learning algorithms to predict the stock index movements. Our findings can be summarized into three aspects:

1. Correlation analysis indicates strong interconnection between the Market stock index and global markets that close right before or at the very beginning of trading time.
2. Various machine learning based models are proposed for predicting daily trend of Market stocks. Numerical results suggests high accuracy
3. A practical trading model is built upon our well trained predictor. The model generates higher profit compared to selected benchmarks.

There are a number of further directions can be investigated starting from this project. The first one is to explore other creative and effective methods that might yield even better performance on stock market forecasting. Second, models can be modified to take care of the tax and fees in the trading process. Finally, we can investigate the mechanism of short sale and maximize our profit even when the market is bullish.

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