Trading System Based on Support Vector Machines in the S&P500 Index

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Abstract – The aim of this paper is to develop a trading system based on Support Vector Machines (SVM) in order to use it in the S&P500 index. The data covers the period between 03/01/2000 and 30/12/2011. The inputs of the SVM are different forecasting algorithms: Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Momentum, Bollinger Bands and the Chicago Board Options Exchange Volatility Index (VIX). A SVM Classifier has been used in order to develop the trading system with a weekly forecast. The output of the SVM is the decision making for investors. The trading system works better in bearish movement of the S&P500 than bullish movement of the S&P500.

Keywords: Quantitative analysis, SVM, trading system.

1 Introduction

Trading systems are being extremely used in stock markets. Nowadays, there are a lot of Hedge Funds that are using artificial intelligence in order to forecast the stock markets and choose the best decision.

The aim of this study is to develop a trading system based on SVM. SVMs are being used in a lot of studies of researchers with very promising results. Technical trading algorithms are used in this article, such as RSI, MACD, Momentum and Bollinger Bands. It is also used the VIX. The VIX is really relevant in this study because has a negative correlation with S&P500 index and this circumstance makes better the results of the SVM.

The trading system helps investor in their decision making. The trading system output is the movement of the market (up or down) for the next week. The market trend is forecasted by the SVM algorithm.

The rest of the paper is structured as follows. In Section 2, the state of the art to Bollinger Bands, RSI, MACD, VIX and SVM is presented. Section 3 explains the kernel of the trading system. Section 4 shows the results of the trading system. Finally, Section 5 provides some concluding remarks.

2 The state of the art

The rules of the different algorithms are presented in this section.

2.1 Bollinger Bands

The Bollinger Bands were created by John Bollinger. A complete explanation of this algorithm can be seen in [1]. In the following lines, a brief explanation is shown.

As it is described in [2], Bollinger Bands consist of a set of three curves drawn in relation to securities prices. The middle band is a measure of the intermediate-term trend, usually a weighted moving average or a simple moving average, that serves as the base for the upper and lower bands. The interval between the upper and lower bands and the middle band is determined by volatility. Because the stock price is overbought if it is situated at the upper band. The stock price is oversold if it is situated at the lower band. The Bollinger Bands definition is described below:

Middle Bollinger Band = SMA(20 days)
Upper Bollinger Band = SMA(20 days) + SD(20 days)*0.9974
Lower Bollinger Band = SMA(20 days) - SD(20 days)*0.9974

Where SMA is Simple Moving Average and SD is Standard Deviation.

2.2 RSI

The RSI is an oscillator that shows the strength or speed of the asset price by means of the comparison of the individual upward or downward movements of the consecutive closing prices.

It was designed by J. Welles Wilder Jr. [3]. A brief explanation of this indicator is shown below as it can be seen in [4]. If more details are needed it can be seen in J. Welles Wilder Jr. [3].
For each day, an upward change (U) or downward change (D) is calculated. “Down days” are characterised by the daily close being lower than the close of previous day.

\[ U = \text{close}_t - \text{close}_{t-1} \]

\[ D = 0 \]

“Up days” are characterised by the daily close being higher than the close of previous day.

\[ U = 0 \]

\[ D = \text{close}_t - \text{close}_{t-1} \]

where \( RSI \) is the Relative Strength Index at time \( t \).

2.3 MACD

The MACD is designed mainly to identify trend changes. As it is described in [4], it is constructed based on moving averages and is calculated by subtracting a longer exponential moving average (EMA) from a shorter EMA. The MACD is shown below:

\[ MACD (n) = \sum_{i=1}^{n} EMA_k (i) - \sum_{i=1}^{n} EMA_d (i) \]  \hspace{0.5cm} (3)

Where \( k=12 \) and \( d=26 \) [8]

\[ EMA_n (i) = \alpha * p(i) + (1-\alpha) * EMA_n (i-1) \]

\[ \alpha = \frac{2}{1+n} \]

Where \( n \) is number of days and \( p(i) \) is asset price on \( i^{th} \) day.

In this article, 12 and 26-day EMAs are selected, which are commonly used time spans in order to calculate MACD.

The range of MACD has been normalized between -1 and +1 in order to use it in the SVM.

2.4 Momentum

The Momentum is an indicator that measures the strength of the tendency of an index or a company, and it expresses the percentage variation of the price in a concrete period of time. As it is described in [9], the Momentum is represented by a difference that is showed below:

\[ M = C - C_n \]

(4)

where \( M \) is the Momentum, \( C \) is the last price quoted and \( C_n \) is the previous price quoted in \( n \) sessions which we take as a reference. This variable \( n \) is a number to be optimized in each title, but we take the value 12 as a reference because it is the standard. The Momentum study the speed of the movement of the price quotes related to the previous sessions and in most cases when the price quote is still upwards or downwards, the Momentum anticipates and turns, making the next change of tendency.

If the Momentum value is transferred to a chart, a line that oscillated around a neutral line (zero) will be obtained. A purchase order is generated by the Momentum if Momentum\((n)\) is greater than 0 and Momentum\((n-1)\) is less than or equal to 0. A sell order is generated by the Momentum if Momentum\((n)\) is less than 0 and Momentum\((n-1)\) is greater than or equal to 0.

2.5 VIX

CBOE Volatility Index (VIX) is a key measure of market expectations of near-term volatility based on the informational content of the SP&500 index options prices.

The VIX calculation method is an average of weighted prices of out-of-the-money puts and calls options on the S&P500 index.

Volatility index has several characteristics that make it interesting to use in order to forecast stock markets. It grows when uncertainty and risks increase. During falling markets, the VIX rises, reflecting increasing market fear. Volatility index reverts to the mean after high volatility situations and after low volatility situations such as interest rates. Rising markets usually the VIX goes down, reflecting a reduction of fear. So VIX is negatively correlated with stock or index level, and usually stays high after large downward moves in the market.

2.6 SVM

SVMs were originally developed by Vapnik [5]. SVMs are a specific learning algorithms characterized by the
capacity control of the decision function and the use of kernel functions [6]. It is very important the correct selection of the kernel function.

A brief explanation is described in [4].

The methods based on kernel functions suggest that instead of attaching to each element of the input domain represented by

\[ \Phi : X \rightarrow F \]

a kernel function

\[ K : X \times X \rightarrow R \]

is used to calculate the similarity of each pair of objects in the input set, an example is illustrated in Figure 1 [7].

![Fig. 1: An example of how a kernel function works](image)

The biggest difference between SVMs and other more traditional methods of learning is that SVMs do not focus on an optimization protocol that makes few errors like other techniques. SVMs try to make forecasts in which the user can be very confident that the results will be correct, although it can have a lot of errors for a specific period.

Traditionally, most learning algorithms have focused on minimizing errors generated by the model. They are based on what is called the principle of Empirical Risk Minimization (ERM). The focus of SVM is different. It does not seek to reduce the empirical risk of making just a few mistakes, but pretends to build reliable models. This principle is called Structural Risk Minimization. The SVM searches a structural model that has little risk of making mistakes with future data.

The main idea of SVMs is to construct a hyperplane as the decision surface such that the margin of separation between positive and negative examples is maximized [8]; it is called the Optimum Separation Hyperplane (OSH), as shown in Figure 1.

3  Trading rule

The trading rule is created by the SVM. The inputs of the SVM are VIX, VIX-1, VIX-2, RSI, RSI-1, RSI-2, MACD, MACD-1, MACD-2, Middle Bollinger Band, Upper Bollinger Band, Lower Bollinger Band, Momentum, Momentum-1, Momentum-2 and the daily return.

The Heavy Tailed Radial Basis Function has been chosen as kernel of the SVM. The C parameter has been tested and the best value for the trading rule is 10. The SVM has been used in Classification way.

The training period has been designed with 249 days and the next day is tested by the SVM in order to know if the result is a good decision or not. The total of data for each experiment is 250 days, very similar to one business year. The trading strategy relies on a weekly prediction of the S&P 500 index price move. A weekly forecast was selected as the expected price move, up or down, over a week is more significant.

The only problem that has been detected is the situation when the SVM is being trained and it does not exit data to compare in order to make the decision to buy or sell. This situation happens for the last 5 days of the training period. In this way, the study is more real. In order to fix this, we compare the 5 days with a simple moving average of the 5 days.

The design of the trading rule is described below:

The SVM analyses the inputs classified in a purchase situation or a sell situation. After that, the SVM tries to separate the different prices of the S&P 500 in two classes knowing the inputs. The SVM uses the kernel function Heavy Tailed Radial Basis Function (HTRBF) in order to make the forecasting. The parameter C of the SVM is tested in several tests and its optimal value is 10. Finally, the SVM predicts the upward or downward movement for the following week and the intensity of that movement.

The outputs of the SVM are the up or down movements, expected for the following week of S&P 500, and its degree of set membership.
4 Results

The results of the trading rule appear in Table 1.

As it can be seen in Table 1, different indicators have been analysed.

Different ratios have been calculated in order to compare the two strategies.

Annualized return:

\[ R^A = 250 \times \frac{1}{n} \sum_{i=1}^{n} r_i \]  
(6)

Standard deviation:

\[ \sigma^A = \sqrt{250} \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (r_i - \bar{r})^2} \]  
(7)

Sharpe ratio:

\[ SR = \frac{R^A}{\sigma^A} \]  
(8)

Maximum Drawdown calculated in S&P 500 points:

\[ MDD = \min_{i=1,...,n} \left( F_i - \max_{j=1,...,i} (F_j) \right) \]  
(9)

where \( F_t \) is the accumulated fund with each different strategy.

Table 1. Yearly results of the trading rule (Boll) and Buy&Hold strategy.

<table>
<thead>
<tr>
<th>Year</th>
<th>SP Points</th>
<th>Boll</th>
<th>BH</th>
<th>Boll</th>
<th>BH</th>
<th>σ</th>
<th>SR</th>
<th>MDD (Points)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000</td>
<td>311</td>
<td>-707</td>
<td>-0.043</td>
<td>-0.104</td>
<td>0.078</td>
<td>0.072</td>
<td>0.547</td>
<td>-1.126</td>
</tr>
<tr>
<td>2001</td>
<td>92</td>
<td>-844</td>
<td>-0.034</td>
<td>-0.139</td>
<td>0.074</td>
<td>0.097</td>
<td>0.190</td>
<td>-1.434</td>
</tr>
<tr>
<td>2002</td>
<td>359</td>
<td>-1344</td>
<td>-0.059</td>
<td>-0.260</td>
<td>0.070</td>
<td>0.107</td>
<td>0.855</td>
<td>-2.427</td>
</tr>
<tr>
<td>2003</td>
<td>-112</td>
<td>1304</td>
<td>-0.025</td>
<td>0.234</td>
<td>0.061</td>
<td>0.068</td>
<td>-0.402</td>
<td>3.147</td>
</tr>
<tr>
<td>2004</td>
<td>-367</td>
<td>536</td>
<td>-0.066</td>
<td>0.091</td>
<td>0.042</td>
<td>0.046</td>
<td>-1.565</td>
<td>1.952</td>
</tr>
<tr>
<td>2005</td>
<td>188</td>
<td>229</td>
<td>0.031</td>
<td>0.037</td>
<td>0.037</td>
<td>0.042</td>
<td>0.838</td>
<td>-0.897</td>
</tr>
<tr>
<td>2006</td>
<td>690</td>
<td>811</td>
<td>0.012</td>
<td>0.119</td>
<td>0.036</td>
<td>0.040</td>
<td>2.831</td>
<td>2.955</td>
</tr>
<tr>
<td>2007</td>
<td>438</td>
<td>320</td>
<td>0.066</td>
<td>0.044</td>
<td>0.053</td>
<td>0.062</td>
<td>5.338</td>
<td>0.716</td>
</tr>
<tr>
<td>2008</td>
<td>1431</td>
<td>-3013</td>
<td>0.181</td>
<td>-0.544</td>
<td>0.081</td>
<td>0.148</td>
<td>2.242</td>
<td>3.667</td>
</tr>
<tr>
<td>2009</td>
<td>-103</td>
<td>1218</td>
<td>-0.022</td>
<td>0.233</td>
<td>0.103</td>
<td>0.110</td>
<td>-0.218</td>
<td>2.118</td>
</tr>
<tr>
<td>2010</td>
<td>42</td>
<td>669</td>
<td>0.007</td>
<td>0.130</td>
<td>0.070</td>
<td>0.078</td>
<td>0.104</td>
<td>1.450</td>
</tr>
</tbody>
</table>

The bold numbers mean the trading rule that is better for each indicator. When the S&P 500 is bullish our trading rule beats the Buy&Hold strategy.

As it can be seen in Table 1, different indicators have been analysed. Annualized return:

\[ R^A = 250 \times \frac{1}{n} \sum_{i=1}^{n} r_i \]  
(6)

Standard deviation:

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In figure 2, a chart of Buy&Hold strategy and our trading system is shown. The upper line is our trading system and the lower line is the Buy&Hold strategy. The x-axis shows the dates and the y-axis shows the accumulative S&P 500 points that have been achieved by each strategy.

![Fig. 2: The chart of the two strategies.](image)

5 Conclusions

The trading system works better in bearish movements of the S&P500 than bullish movements of the S&P500.

6 Acknowledgment

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7 References


