

# Evaluation of a Supervised Learning Approach for Stock Market Operations

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## 1 Introduction

Stock markets play a fundamental role in the countries' economies, since they allow companies to raise funds for their investments in technology, expansion or infra-structure by selling stocks to the public. At the same time, stocks are, for the stockholders, important assets that can help to maintain or increase the investor's wealth for future use, like retirement, education, etc. On the other hand, stock prices are volatile and depend on several factors like companies' performances, economic activity, etc. Hence, investors and funds managers usually must constantly monitor the behavior of stock prices, in order to take correct trading decisions and to avoid excessive exposition to risky stocks.

Data mining techniques have been widely proposed for stock market analysis in order to identify some patterns in price time series. A common premise is that such underlying patterns may be suitably used for price forecasting, for operation strategies advices or even for automatic trading. In these approaches, usually the attribute vectors consist of traditional technical indicators, computed from prices and volumes time series.

The objective of this work is to perform an empirical evaluation of *Random Forests* for the task of advising trade operations in the BM&F/BOVESPA stock market. We propose a supervised learning approach, in which the features are standard technical indicators and the classes correspond to three possible actions: *Buy-Sell*, *Sell-Buy* or *No action*. The evaluation is conducted through a cross validation procedure adapted for time series (Hyndman and Athanasopoulos, 2012). Three main performance indices are analysed: percentage of opportunities seized by the classifier, percentage of successful operations advised by the classifier and average return per operation.

## 2 Material and Methods

Our case study is based on daily data provided by BM&F Bovespa Exchange<sup>1</sup>. Raw data is constituted by date, stock identification, prices (opening, minimum, average, maximum, closing), number of trades with the asset and trading value. The study is concentrated on data from January/2010 to October/2012.

In this preliminary study, we focused on the 68 stocks that integrate the Ibovespa index (BM&F BOVESPA, 2012), due to their high liquidity and volumes of trading.

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<sup>1</sup><http://www.bmfbovespa.com.br/shared/iframe.aspx?idioma=pt-br&url=http://www.bmfbovespa.com.br/pt-br/cotacoes-historicas/FormSeriesHistoricas.asp>

The data processing and tests routines outlined in the next subsections were implemented in the R environment (R Development Core Team, 2011).

## 2.1 Random forests

Random forests, introduced by Breiman (2001), are aggregated classifiers composed by *ensembles* of trees independently induced. The classification of a new instance is made by a voting system, where the instance is classified by each individual tree and the class “votes” are counted. Although in most cases the majority criterion is used (the most voted class is assigned), it is possible to set up lower thresholds such that one class is assigned only if achieves a minimum percentage of votes among the trees.

For the random forest construction, each tree is induced as follows. We denote by  $N$  the number of examples and by  $M$  the number of attributes in the original training set.

1. A bootstrap resample of size  $N$  is drawn from the original data, and is used to induce the new tree.
2. At each node split,  $m \ll M$  attributes are selected at random of the  $M$  original attributes, and the best split on these  $m$  attributes is used to split the node. The value of  $m$  is fixed during the forest construction and may be calibrated by the user. The *randomForest* Package (Liaw and Wiener, 2002), used in this work, sets  $m = \sqrt{M}$  as default.
3. Each tree is grown to the largest extent possible. There is no pruning.

Breiman (2001) shows that the forest error rates increase with the correlation among trees and decrease with the strength of each individual tree in the forest. The random sampling of examples and of attributes aim to decrease the trees correlation.

## 2.2 Technical indicators

The attribute vectors are constituted by 22 standard technical indicators (Puga et al., 2010), computed through the *TTR* Package (Ulrich, 2012):

- Simple moving average (SMA) of 3, 13 and 21 days;
- Exponential moving average (EMA) of 5, 13 and 21 days;
- Rate of change (ROC) of 13 and 21 days;
- Stochastic oscillator %K, slow %D and fast %D of 7, 14 and 21 days;
- Moving average convergence divergence (MACD) and respective histogram, with short term moving average of 12 days and long term moving average of 26 days;
- Relative strength index (RSI) of 9, 14 and 21 days;

### 2.3 Operation strategies and data classification

A market operation strategy is a predefined set of rules determining an operator’s action in the market. We consider two operations strategies types, parameterized as follows:  $t$  denotes the start day of the strategy,  $g$  is the maximum expected gain (stop-gain),  $l$  is the maximum tolerated loss (stop-loss) and  $d$  is the maximum duration (in days) of the operation.

**Buy-Sell**( $t, g, l, d$ ): Buy the stock at day  $t$  and sell it when the first of the following conditions occurs:

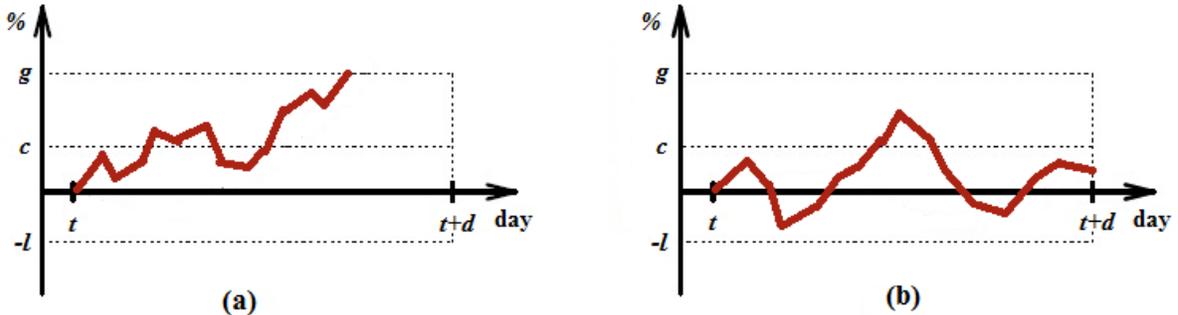
1. Its closing price raises above  $g\%$  with respect to the price at day  $t$ ;
2. Its closing price falls below  $l\%$  with respect to the price at day  $t$ ;
3. After  $d$  days, if none of the above cases have occurred in the period  $t+1, t+2, \dots t+d$ .

**Sell-Buy**( $t, g, l, d$ ): At day  $t$ , rent a share of the stock, sell it and re-buy an equivalent share of the stock when the first of the following conditions occurs:

1. Its closing price falls below  $g\%$  with respect to the price at day  $t$ ;
2. Its closing price raises above  $l\%$  with respect to the price at day  $t$ ;
3. After  $d$  days, if none of the above cases have occurred in the period  $t+1, t+2, \dots t+d$ .

Notice that in Buy-Sell and Sell-Buy types strategies, return is computed by the difference between the sell and buy prices, discounted of the trade costs (e.g. brokerage fees). In Sell-Buy strategy, there is an additional rental fee that must be considered.

An operation strategy is classified as successful if its net return is positive, and unsuccessful otherwise. Figure 1 shows two hypothetical examples of applications of Buy-Sell strategy. In case (a), the price variation (red line) reaches the expected gain ( $g$ ) and the strategy ends successfully (with positive net return) before day  $t + d$ . In case (b), the price variation oscillates between  $-l$  and  $g$  until the day  $t + d$ , when the strategy ends. Since the net return is negative (the price variation is lower than the operation cost), the strategy is unsuccessful.



**Figure 1:** Buy-Sell strategy application examples (adapted from Stern et al, 2008).

The dataset classification is performed in the following way. For fixed parameters  $g, l$  and  $d$ , we verify the success/failure of strategies Buy-Sell( $t, g, l, d$ ) and Sell-Buy( $t, g, l,$

$d$ ) for each day  $t$  in the historical data. If some of these strategies is successful, assign it to day  $t$ . If none of them is successful, a *No action* class is assigned. For convenience, we adopt the following class notation:  $1 = \text{Buy-Sell}$ ,  $0 = \text{No action}$  and  $-1 = \text{Sell-Buy}$ .

Notice that there are no *a priori* optimal values for the parameters  $g$ ,  $l$  and  $d$ , since they depend, for example, on the stock price variability, and are strongly dependent each other. So, we implemented an automated procedure for setting these parameters, which is described in the next Subsection.

## 2.4 Cross validation

For time series data, the usual  $k$ -fold or leave-one-out schemes are not adequate, due to the high dependency among observations. We applied the procedure proposed by Hyndman and Athanasopoulos (2012) (Section 2/5), which is similar to the leave-one-out, except that the training set consists only of observations that occurred prior to the observation that forms the test set. Thus, no future observations can be used in constructing the classifier. This approach requires that the earliest observations are used only for training and are not considered as test sets.

Denote by  $T$  the total length of the dataset, and suppose  $k$  observations are required to produce a reliable training. Then the process works as follows.

1. Repeat the following step for  $i = 1, 2, \dots, T - k$  :
2. Build the random forest using the observations at times  $i, i + 1, i + 2, \dots, i + k - 1$ , and test it in the observation at time  $k + i$ . Account the hit/miss (by comparing the predicted and the real classes) and the corresponding return, if any operation strategy has been devised by the forest.
3. Compute the total accuracy and net returns obtained for the  $T - k$  test samples.

After the above procedure, we obtain a  $3 \times 3$  confusion matrix in the form below, where rows represent real classes and columns represent predicted classes. The cell  $n_{i,j}$  denotes the number of test examples of class  $i$  that have been classified by the random forests as class  $j$ , for  $i, j \in \{-1, 0, 1\}$ .

		Predicted class		
		-1	0	1
Real class	-1	$n_{-1,-1}$	$n_{-1,0}$	$n_{-1,1}$
	0	$n_{0,-1}$	$n_{0,0}$	$n_{0,1}$
	1	$n_{1,-1}$	$n_{1,0}$	$n_{1,1}$

Three performance indicators were considered in this work:

- *SeizOport* : Rate of seized opportunities: ratio between the number of successful operations and the number of opportunities:

$$SeizOport = \frac{n_{-1,-1} + n_{1,1}}{n_{-1,-1} + n_{-1,0} + n_{-1,1} + n_{1,-1} + n_{1,0} + n_{1,1}}$$

- *SuccOper* : Rate of successful operations: ratio between the number of successful operations and the total number of devised operations:

$$SuccOper = \frac{n_{-1,-1} + n_{1,1}}{n_{-1,-1} + n_{0,-1} + n_{1,-1} + n_{-1,1} + n_{0,1} + n_{1,1}}$$

- *AvgRetOper*: Average return per operation: ratio between the sum of net returns yielded by the devised strategies (disregarding success or failure) and the total number of devised operations.

These performance indicators are combined in a single *score*, defined by the following convex combination:

$$Score = 0.10 SeizOport + 0.85 SuccOper + 0.05 AvgRetOper$$

These weights were set in order to turn the score a conservative function, in the sense that it favors strategies with high rates of successful operations, even though achieving lower values in the other indicators.

The procedure for setting the values of parameters  $g$ ,  $l$  and  $d$  is as follows. First, we define, for each parameter, a set of candidate values. In the present study, these sets are:

- $g \in \{10\%, 15\%, 20\% \dots 35\%\}$
- $l \in \{3\%, 6\%, 9\%, \dots 15\%\}$
- $d \in \{10, 15, 20, \dots 35\}$ .

For each value in the grid above, the operations strategies are simulated on the data series and the examples are labeled with the corresponding classes. The cross validation is run and the indicators *SeizOport*, *SuccOper*, *AvgRetOper* and *Score* are computed. For each stock, we choose the values of  $g$ ,  $l$ ,  $d$  that maximize the function *Score*.

In our simulations, the operation cost is assumed as  $c = 1\%$ , and the stock rental fee is assumed as  $0.05\%$  per day.

For setting the operation strategies parameters, the cross validation procedure uses data of 2010 for training and data of 2011 for testing. After the parameters setup, a new cross validation is run for a final evaluation of the optimal parameters, taking data of 2011 for training and data of 2012 for testing.

### 3 Results and Conclusions

Figure 2 presents the indicators *SeizOport*, *SuccOper*, *AvgRetOper* and *Score* for the 30 stocks with greater score values computed on 2012 data test. The proposed method yields more than 80% of successful devised operations for almost all stocks, and also yields more than 70% of seized opportunities for 22 of the 30 stocks (73%). The average returns per operation are also expressive, achieving for the majority of stocks 4% or more. These returns may be considered high, since one strategy operation lasts at most 35 trading days (see previous Section).

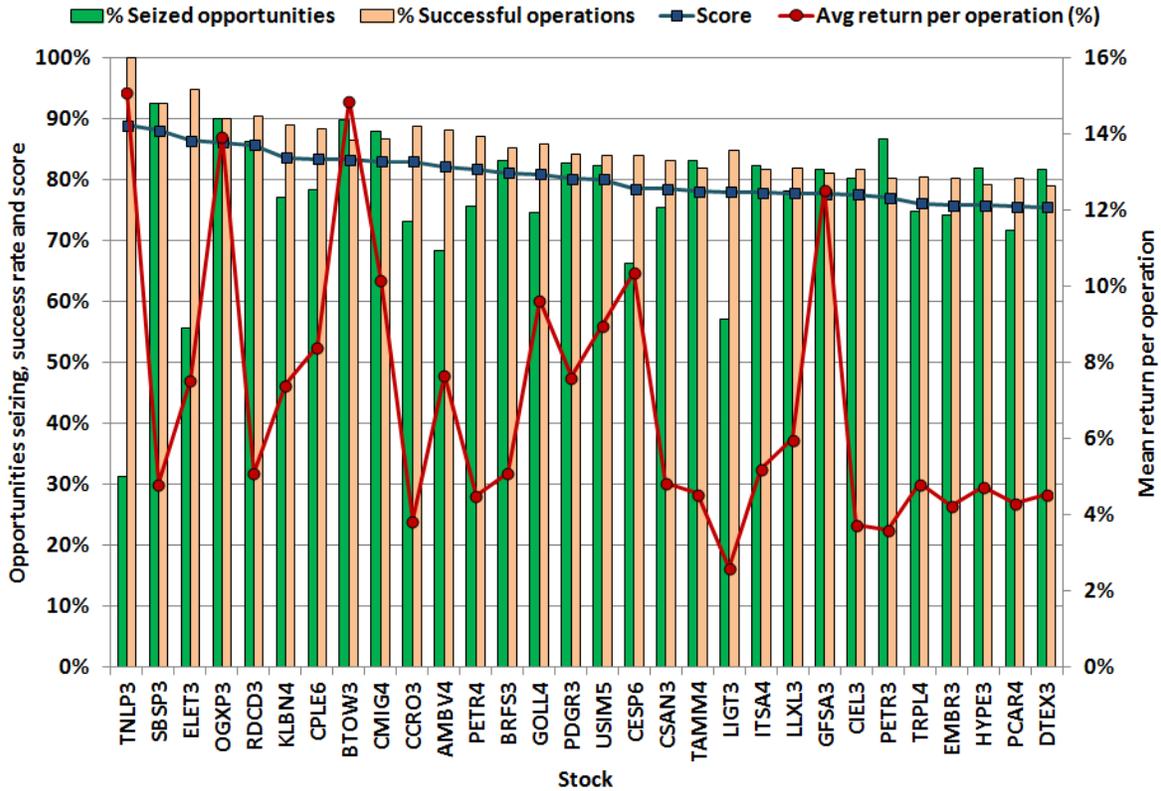


Figure 2: Performance indicators *SeizOport*, *SuccOper*, *AvgRetOper* and *Score* for the 30 stocks with maximum score values.

The preliminary results presented in this work are very promising and motivate several extensions. Some examples are the introduction of other performance indices; the inclusion of other technical indicators; performance analyses carried independently for Buy-Sell and Sell-Buy strategies; the incorporation of more than one parameter by each strategy type; comparison of the performance with other classification algorithms; the introduction of slippage in the model, and several others.

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