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Identifying Patterns in Financial Markets

New Approach Combining Rules Between PIPs and SAX

Springer

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To Ana, Marta, José Luis e Manel
João Leitão

To Susana and Tiago
Rui Ferreira Neves

To Carla, João and Tiago
Nuno C.G. Horta

Preface

Financial markets have received an increasing interest from financial people and computational intelligence researchers over the past years because it is an area with vast amounts of money, and it is becoming easier for everyone to access and operate. One of the main challenges is to predict the future trend of prices, in order to obtain the highest profit with the lowest risk. To achieve that, it is necessary to define investment strategies that are able to process large amounts of data and consequently generate appropriate buy/sell signals. The data can be obtained from several sources: fundamental analysis, technical analysis, and time series. To solve this complex problem, the computational intelligence area is very useful. One way used by traders to predict the behavior of the markets is studying and analyzing chart patterns in the historical prices of the financial assets.

The visual identification of chart patterns is very complicated because the patterns in time series are not clear and perfect as the ones in the books. So, in order to identify patterns, automatic systems from computational intelligence must be used. In this work, a new approach to pattern discovery is presented, which is built on rules between Perceptually Important Points (PIPs), the Symbolic Aggregate approXimation (SAX) representation, optimized by Genetic Algorithm (GA). The identification of PIPs allows a huge dimensional reduction in the time series and, at the same time, maintains the main characteristics of its data. The definition of rules between near or adjacent PIPs allows the explicit definition of relationships between time series points. The mapping between rules and characters allowed the distinction of the different types of trends between the PIPs of time series and also allowed the representation of time series by a sequence of characters, which facilitated the identification of patterns. The GA is used to optimize the type of pattern to be identified and the investment rules used in the trading simulation. This new approach is called Symbolic Important Rules (SIR). The proposed approach was tested with real data from S&P500 index, and all the results obtained outperform the Buy&Hold strategy. Three different case studies that test SIR/GA approach are presented. With this approach, it was possible to obtain in the period 2011–2014 a total return of 76.7%, which outperformed the Buy&Hold strategy (61.9%).

Chapter 1 describes the problem addressed by this book, the portfolio optimization using GA. The main goals for the work are presented in this chapter and the document's structure.

Chapter 2 presents background information and reviews the existing literature that is relevant to the development of this project. In the first part of the chapter, a brief description of the existing approaches to invest is presented, and Sect. 2.1 will describe in detail the fundamental and the technical analysis. The optimization technique, named Genetic Algorithms, is presented in Sect. 2.2. A review of the existing literature about pattern recognition/detection and its techniques to invest in the market is detailed in Sect. 2.3.

Chapter 3 will explain in detail the new approach, SIR/GA methodology, for pattern discovery, and also the architecture of the proposed solution.

Chapter 4 will demonstrate the experiences done with the SIR/GA approach and will show the results and explain the conclusion taken from the experiences.

Chapter 5 presents the conclusions and the future work.

Lisbon, Portugal

João Leitão
Rui Ferreira Neves
Nuno C.G. Horta

Contents

Abbreviations

ASCII	American Standard Code for Information Interchange
B&H	Buy-and-Hold
ED	Euclidean Distance
GA	Genetic Algorithm
JGAP	Java Genetic Algorithms Package
NYSE	New York Stock Exchange
OBV	On-Balance Volume
PAA	Piecewise Aggregate Approximation
PD	Perpendicular Distance
PIP	Perceptually Important Point
ROI	Return On Investment
RSI	Relative Strength Index
S&P500	Standard and Poor's 500 index
SAX	Symbolic Aggregate approXimation
SIR	Symbolic Important Rules
SMA	Simple Moving Average
VD	Vertical Distance

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Chapter 1
Introduction

Abstract This chapter presents an overview of the work and its structure. In Sect. 1.1 the goals are described, in Sect. 1.2 the main improvements in the work's subject area and in Sect. 1.3 the structure of this book is detailed.

1.1 Work's Purpose

The aim of this work is to create an application of pattern discovery and based on that predict the stock market behavior. A new methodology, named SIR/GA, to identify patterns in the historical prices of stocks will be developed. After identify patterns, the goal is to create investment rules based on the pattern discovered. In order to achieve this goal, the GA will be used to find a set of patterns and investment rules that allows finding the best investment strategy.

The last goal is to outperform, in terms of total return, the Buy and Hold strategy with the new SIR/GA approach. The application must be able to make automatic investment decisions based on the detection of patterns in the historical prices of stocks.

1.2 Main Contributions

The main contributions made in this work are:

- The creation of the new methodology to identify patterns that combines rules between PIPs with the mapping between those rules and different characters in the SAX representation.
- The combination of multiple exit/sell methods namely time, price, and pattern.
- The use of a GA adaptive approach able to automatically identify multiple patterns and generate trading rules.

J. Leitão et al., *Identifying Patterns in Financial Markets*, SpringerBriefs in Computational Intelligence, https://doi.org/10.1007/978-3-319-70160-8_1

1.3 Document Structure

This document is organized as follows:

- Chapter 2 addresses the theory behind the developed work, including technical analysis, technical indicators, and soft computing methodologies. Also, in this chapter, are presented and analyzed several and different methodologies regarding the identification of patterns.
- Chapter 3 describes the new approach SIR/GA methodology for pattern discovery and also the architecture of the proposed solution.
- Chapter 4 describes first the metrics used to evaluate the developed solution and second three case studies where the solution was tested.
- Chapter 5 summarizes the provided report and supplies the respective conclusion and future work.

Chapter 2
Related Work

Abstract This chapter presents background information and reviews the existing literature that is relevant to the development of this project. The first part of this chapter presents a brief description of the two existing approaches to analyze the market, in Sect. 2.1 will be described in detail the fundamental and the technical analysis and its tools. A formal definition of an optimization methodology is given in Sect. 2.2. A review of the existence literature about pattern recognition/detection and its techniques to invest in the market is detailed in Sect. 2.3.

2.1 Market Analysis

The aim of financial market analysis is to predict the behavior of the prices in the market in order to make a better decision (buy/sell) over a financial asset. There are two distinct types of market analysis: Fundamental Analysis and Technical Analysis. The core study of these two distinct types of analysis is different which do not invalidate the fact that the two types can be used simultaneously in order to make the best decision in a financial market. In this work the identification of patterns in the financial markets and the investment rules based on that appeal to the application of technical analysis.

2.1.1 Fundamental Analysis

The Fundamental Analysis [1] is based on a set of financial and economic indicators with the goal of finding the intrinsic value of a company and consequently its stock price. The fundamental analysis studies all the factors, internal or external, that can influence the value of a company. After finding the intrinsic value of a company it is possible to understand if the company is overvalued or undervalued and based on that make a better investment decision. In the case where the stock price of a company is higher than its intrinsic value (overvalued), the better decision is to sell

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and in the opposite case, where the stock price is lower than its intrinsic value the better decision is to buy because the company is undervalued.

2.1.2 Technical Analysis

The Technical Analysis [2, 3] is based on past market data, such as price and volume, with the goal of predict its behavior. The analysts believe that the stock price in the market already reflects in itself all the fundamental factors that can affect its price, so it is unnecessary to proceed to the Fundamental Analysis [3].

The advantages of this type of analysis are: the data used (price and volume) are easily accessible to anyone and exist in huge quantity, which is very useful to the pattern detection methodologies that will be presented after.

In technical analysis in order to predict correctly the future movement of the financial markets several technical indicators are used [2, 3], which are built based on the price and volume. In addition to technical indicators the analysts also study the formation of chart patterns [3, 4] in the historical prices of financial assets. Some of the most well known and most utilized technical indicators and chart patterns are presented next.

I. **Technical indicators**

A technical indicator is a metric whose value is calculated from the price or the volume of an asset. Its objective is to help predicting the future price, or simply to indicate a general price trend. Some of the most popular technical indicators are presented next. Other technical indicators can be found in [2, 5].

(a) **Simple Moving Average**

This indicator is one of the oldest indicators used by the analysts and represents the mean value of the prices over a certain amount of time (days). Normally, the closing price of each day is used to calculate the value of this indicator.

The Simple Moving Average (SMA) can be calculated for different lengths of time, where the most common are 200, 100, 50, 30, 20, and 10 days. Smaller moving averages are usually used for short-term investments and longer moving averages are used for long-term investments. Naturally, long-term Simple Moving Averages have fewer fluctuations than long-term Simple Moving Averages.

In Fig. 2.1 it is represented the price chart of Apple with a Simple Moving Average of 10 days and other of 20 days for the period 06/06/2014–07/05/2015. It is possible to observe that the line that represents the 10 days average (SMA10) reacts better and faster to the several short-term changes in the price comparing with the line that represents the 20 days average (SMA20).

This indicator can be used by traders to buy a financial asset when the average is in an upward trend and to sell it when the average is in a downward trend. Several

Fig. 2.1 Apple's price chart with 10 and 20 days SMA

and different moving averages can be used simultaneously to determine intersection points between them which originate buy or sell signals.

There are other indicators based on the SMA, like the Exponential Moving Average which attributes more importance (more weight) to the most recent days when calculating the average, in the attempt to better react to sudden changes of price.

(b) **Relative Strength Index (RSI)**

This indicator is one of the most used indicators of the category momentum, which compares the magnitude between the recent profits and losses, with the aim to determine if a financial asset is overbought or oversold. This indicator oscillates between 0 and 100 and it is often calculated for a period of 14 days. In Eq. (2.1) is described the formula to calculate this indicator.

$$\begin{aligned} \text{RSI} &= 100 - \frac{100}{1 + \text{RS}} \\ \text{RS} &= \frac{\text{Average of } x \text{ days' up closes}}{\text{Average of } x \text{ days' down closes}} \end{aligned} \tag{2.1}$$

In Fig. 2.2 it is possible to observe an example with the price chart of Apple and its RSI of 14 days for the period 31/12/2014–07/05/2015. The RSI has several characteristics that can generate different signals:

- If the RSI value of an asset is higher than 50 it means an upward movement of prices and so the asset should be bought. If the RSI value is lower than 50 it means a downward movement of prices and consequently the asset should be sold.

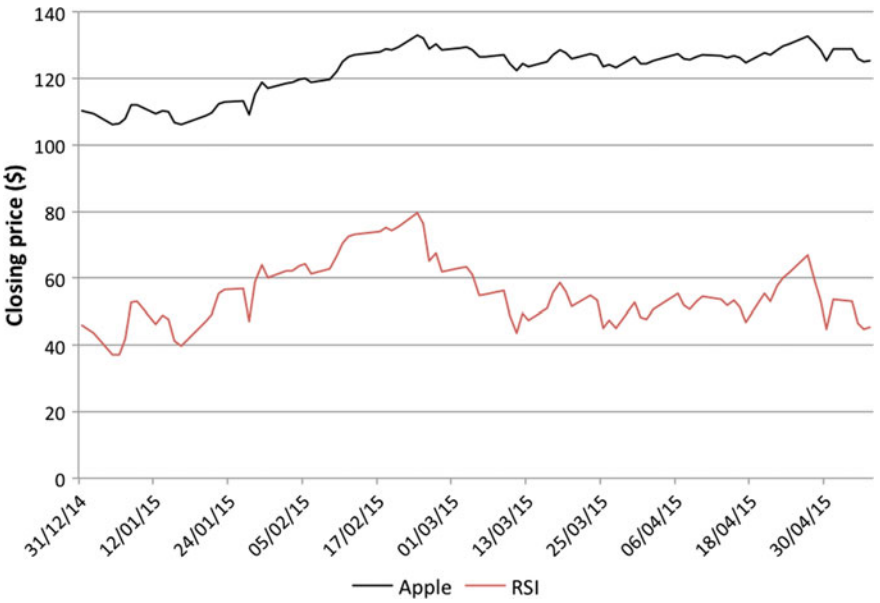


Fig. 2.2 Apple's price chart and its 14 days RSI

- If the RSI value of an asset is higher than 70 it means the asset is overbought and so the asset should be sold. If the RSI value is lower than 30 it means the asset is oversold and so the asset should be bought.

(c) **On-Balance Volume**

This indicator is the oldest and the most well-known volume indicator. The volume and the price are used in the calculation of this indicator, which measures buying and selling pressure. The idea behind this indicator is that using volume to analyze the price chart of an asset, it is possible to predict its behavior or simply confirm its trend. The formula to calculate the OBV is represented in Eq. (2.2).

$$\begin{aligned}
&\text{OBV}\,(x) = \text{OBV}\,(x-1) + \text{Volume}\,(x)\,, \quad \text{if Price}\,(x) > \text{Price}\,(x-1)\\
&\text{OBV}\,(x) = \text{OBV}\,(x-1) - \text{Volume}\,(x)\,, \quad \text{if Price}\,(x) < \text{Price}\,(x-1)\\
&\text{OBV}\,(x) = \text{OBV}\,(x-1)\,, \quad \text{if Price}\,(x) = \text{Price}\,(x-1)
\end{aligned} \tag{2.2}$$

In Fig. 2.3 it is represented as an example of the application of this indicator in the price chart of Apple over the period 09/06/2014–07/05/2015. This indicator has several characteristics that can generate different signals like:

- When the OBV has an upward movement it means that the financial market will start to increase and become a bullish market even if the prices are not rising yet. The performance of a financial market starts to decrease (bearish market) when the OBV has a downward movement even if the prices are not falling.

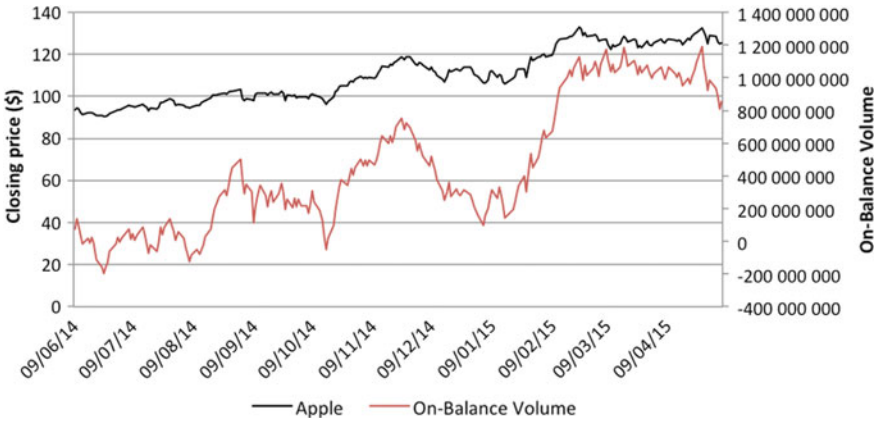


Fig. 2.3 Price chart of Apple with the OBV

- In the case where the OBV and the prices are following an upward movement this means that this trend will be maintained in the future. The same applies to the opposite case.

II. Chart Patterns

Analyzing the historical prices of a financial asset it is possible to observe some similar geometric shapes over the time. Those geometric figures represent the behavior of the traders in the market. Knowing that history repeats, the identification of geometric figures allow the analysts to predict with some confidence the behavior of the traders and consequently the future trend of prices.

The chart patterns, according to [3], can be divided in 2 types: Continuation Patterns and Reversal Patterns. The continuation patterns generally are faster to form than the reversal patterns. In order to be more certain of the future direction of prices, the volume indicator can be used to confirm the formation of chart patterns. In the next sections some of the most used and famous continuation and reversal patterns will be presented. For more information on others chart patterns [4].

(a) Continuation Patterns

This type of chart patterns is characterized by confirming the uptrend or downtrend of the market, despite of the trend of prices become a sideways movement temporarily. When this type of pattern occurs, it can indicate the trend is likely to resume after the pattern completes.

(1) Triangles

There are three types of Triangles: (a) Symmetrical Triangle, (b) Ascending Triangle and (c) Descending Triangle. These patterns have a typical duration of 3 months. In case (a) the prices after breakout the triangle follow the direction of the previous

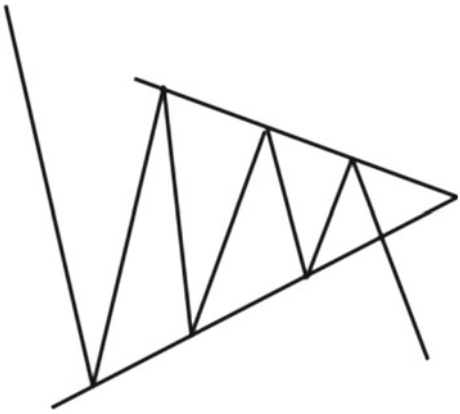


Fig. 2.4 Bullish Symmetrical Triangle (left) and Bearish Symmetrical Triangle (right)

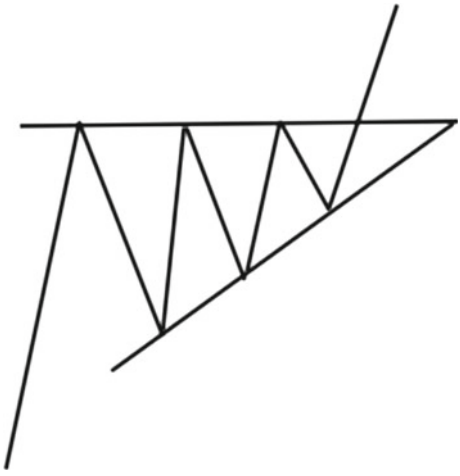


Fig. 2.5 Ascending Triangle

trend. This case applies to bull markets and bear markets as illustrated in Fig. 2.4, respectively.

The case (b) is often a bullish chart pattern, as illustrated in Fig. 2.5, where the prices breakout the triangle with an upward direction thereby confirming the previous trend.

The case (c) is often a bearish chart pattern, where the prices breakout the triangle with a downward direction that confirms the previous trend. This pattern is illustrated in Fig. 2.6.

(2) **Flags and Pennants**

These two types of patterns are very similar due to the fact that they are preceded by a strong increase or decrease movement that is followed by a consolidation period that marks the reset of the initial movement (strong increase or decrease). These patters have a typical duration of one to 4 weeks. In Fig. 2.7 are illustrated the two types

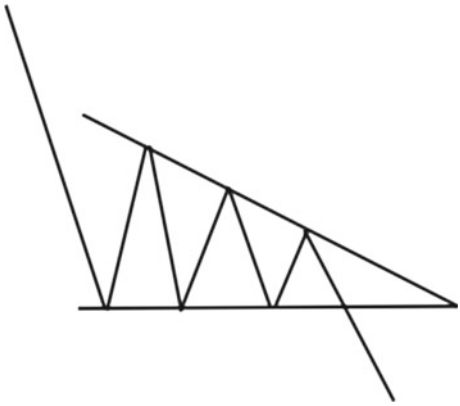


Fig. 2.6 Descending Triangle

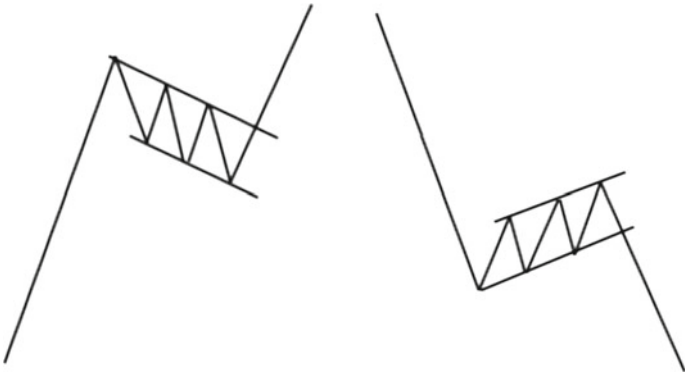


Fig. 2.7 Bull Flag (left) and Bear Flag (right)

of the Flag Pattern: the Bull Flag and the Bear Flag. The two cases of the Pennant Pattern: the Bull Pennant and the Bear Pennant are illustrated in Fig. 2.8.

(3) **Rectangles**

The rectangles represent a period of time where the prices follow a sideways movement delimited by two parallel horizontal lines (resistance and support). During the geometric formation the supply and demand is balanced. In Fig. 2.9 it is possible to observe the Bullish Rectangle and also the Bearish Rectangle.

(b) **Reversal Patterns**

This type of chart patterns, as the name implies, is characterized by a change in the direction of a price trend. An uptrend reverses to a downtrend and a downtrend reverses to an uptrend in this type of patterns. So, in this type of patterns the previous trend is inverted which marks the beginning of the new trend.

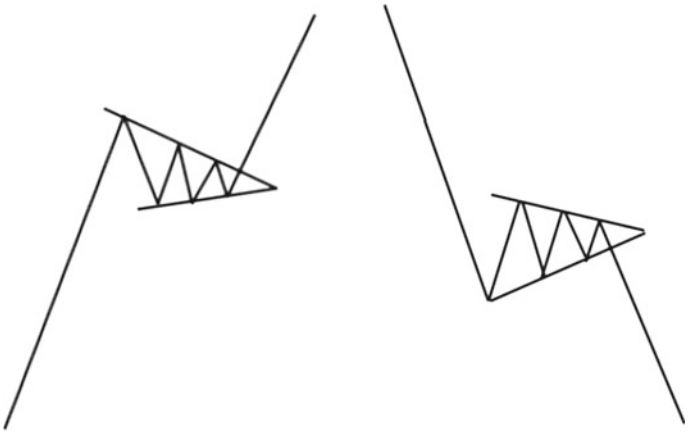


Fig. 2.8 Bull Pennant (left) and Bear Pennant (right)

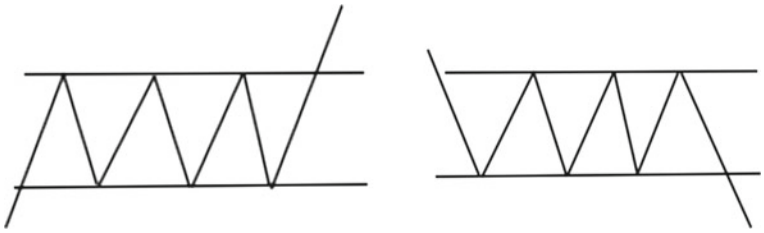


Fig. 2.9 Bullish Rectangle (left) and Bearish Rectangle (right)

Fig. 2.10 Head-and-Shoulders (left) and inverse Head-and-Shoulders (right)

(1) **Head-and-Shoulders**

This pattern is the most reliable and well-known reversal pattern and represents a reversal in the trend, generally the uptrend, where the confirmation of the reversal occurs when the prices breakout the support or the resistance line, named neckline. The two possibilities of this pattern are illustrated in Fig. 2.10.

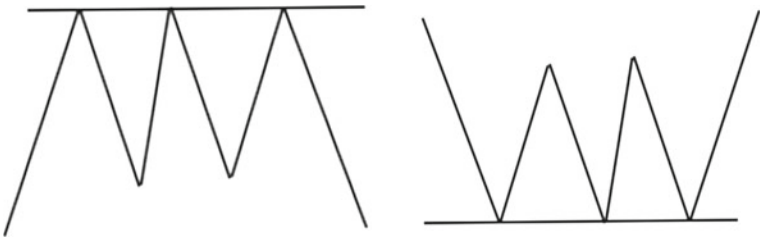


Fig. 2.11 Triple Top (left) and Triple Bottom (right)

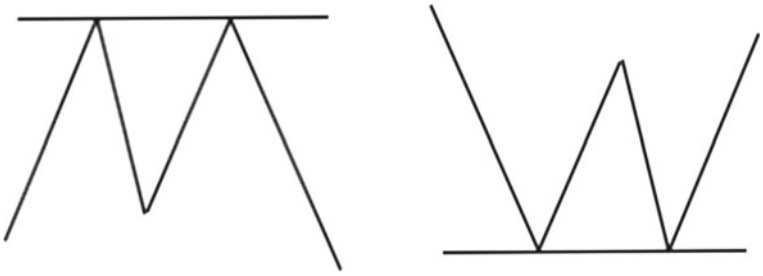


Fig. 2.12 Double Top (left) and Double Bottom (right)

(2) **Triple Top and Triple Bottom**

These patterns, as the name implies, are defined by three peaks (Triple Top) or by three bottoms (Triple Bottom). These patterns are similar to the Head-and-Shoulders pattern except the fact that the three peaks or bottoms, in this case are all at the same amplitude as can be seen in Fig. 2.11.

(3) **Double Top and Double Bottom**

These patterns are frequently seen in price charts and are very similar to the two previous patterns (point 2). The Double Top pattern is represented by 2 peaks with the same amplitude and the Double Bottom pattern is represented by 2 bottoms at the same amplitude too. As can be seen in Fig. 2.12, the Double Top and Double Bottom are often described by the character "M" and the character "W" respectively.

2.2 Optimization Methodologies—Genetic Algorithms

A Genetic Algorithm (GA) [6, 7] is a search heuristic that mimics the process of natural selection. The Genetic Algorithms belong to the class of the evolutionary algorithms, which are used to generate solutions to optimization problems through techniques based on natural evolution. The GA's are widely used in financial markets to find the best combination of parameters of an investment strategy [6, 8].

In the GA a population of potential solutions is used to find the best solution for a problem. Each potential solution is represented by a one-dimensional vector, named chromosome that represents the several parameters to optimize. Each parameter of the chromosome is called gene and for each is assigned a value. For example, some parameters that can be defined as genes can be the Simple Moving Average, the RSI, etc.

The process of the GA is an iterative process, where the population in each iteration is named generation. In each generation the solutions are evaluated according to a fitness function, i.e. an objective function like maximize profit, and the ones with higher fit value are selected to the next generation. After that, the genetic operators are used in the solutions to create better solutions and to create the next generation. These genetic operators are:

- Crossover—this operation is similar to the human reproduction, where a new solution (children) is created through a combination between the characteristics (parameters) of two solutions (parents).
- Mutation—this operation represents the biologic mutation and it is used to maintain the genetic diversity of populations in the next generations by changing some genes of the chromosomes.

This iterative process is terminated when the stop criteria is reached, that can be defined like: a solution is found that satisfies the minimum criteria, maximum number of generations is reached, lack of improvements of solutions in successive generations, etc.

2.3 Pattern Detection Methodologies

In this section several different techniques to reduce the data dimensionality of time series and its application in the identification of patterns are presented. The first methodology presented is based on matrixes, the second in relevant points and the last in SAX representation.

2.3.1 Heuristic Based on Templates

As the name implies, this method will recognize patterns based on a template pattern approach, where the templates are represented in a matrix format. In [9, 10] is used a method, based on templates, to detect the Bull Flag pattern (Fig. 2.7 left) with the aim of predict a rise in prices in the future. In this approach the goal is to detect the pattern in the historical prices of financial assets, in order to obtain more return than the average return of the financial markets. Through this pattern detection approach were created investment rules that were tested in the NYSE index in [11].

0.5		-1	-1	-1	-1	-1	-1	-1	
1	0.5		-0.5	-1	-1	-1	-1	-0.5	
1	1	0.5		-0.5	-0.5	-0.5	-0.5		0.5
0.5	1	1	0.5		-0.5	-0.5	-0.5		1
	0.5	1	1	0.5				0.5	1
		0.5	1	1	0.5			1	1
-0.5			0.5	1	1	0.5	0.5	1	1
-0.5	-1			0.5	1	1	1	1	
-1	-1	-1	-0.5		0.5	1	1		-2
-1	-1	-1	-1	-0.5		0.5	0.5	-2	-2.5

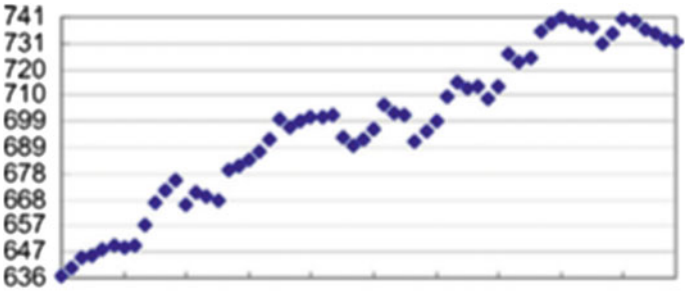
Fig. 2.13 Bull Flag matrix pattern template

This approach aims to detect the Bull Flag pattern based on a template represented by the matrix in Fig. 2.13, which comprises a consolidation area (first seven columns), where prices fluctuate within a channel similar to a parallelogram, which is followed by a strong rise (3 last columns), named breakout, where prices start to increase.

This template illustrated in Fig. 2.13 is represented by a 10×10 matrix named "*T*", where each cell can have a value between -2.5 and $+1.0$ and the cells without value are assigned to 0. Also, the sum of all the values of each column in matrix "*T*", is always equal to 0. Then 10×10 matrixes, named "*I*" are created to represent each time series of the historical prices. The time series that are represented in matrixes "*I*" have a variable number of days (ex: 120, 60, etc.) allowing the identification of patterns with different time lengths. This concept is called sliding window.

In each time series the noise of its data is reduced by replacing the closing prices that exceed a boundary, defined by two standard deviations related to the mean of the time series prices, by its value (boundary value). Then the time series are divided in 10 identical groups, where each group will be mapped in a column of matrix "*I*". As an example, if the time series has a length of 60 days each column of its matrix "*I*" represents 6 days. Using this technique it is possible to represent in matrix "*I*" time series of any length.

After that, the difference between the highest and the lowest price of each time series, which defines the maximum amplitude, is divided by 10 in order to identify the price range of each row in matrix "*I*". As an example if the highest and the lowest price in a time series are 100$ and 50$ respectively, so the first row corresponds to the price range between 95$ and 100$, the second row to the price range 90$–95$ and so on. Then, each cell of matrix "*I*" will have a value between 0.0 and 1.0 dependent on the number of days that are mapped on it. In Fig. 2.14 it is possible to observe an example of a 60 days time series without noise and its matrix "*I*".



0.	0.	0.	0.	0.	0.	0.	0.33	0.83	1.
0.	0.	0.	0.	0.	0.	0.	0.5	0.17	0.
0.	0.	0.	0.	0.	0.	0.5	0.17	0.	0.
0.	0.	0.	0.17	0.5	0.5	0.5	0.	0.	0.
0.	0.	0.	0.5	0.5	0.5	0.	0.	0.	0.
0.	0.	0.33	0.33	0.	0.	0.	0.	0.	0.
0.	0.33	0.33	0.	0.	0.	0.	0.	0.	0.
0.	0.17	0.33	0.	0.	0.	0.	0.	0.	0.
0.33	0.5	0.	0.	0.	0.	0.	0.	0.	0.
0.67	0.	0.	0.	0.	0.	0.	0.	0.	0.

Fig. 2.14 60 days time series and its matrix "*I*". *Source* Ref. [11]

After obtaining the two matrixes, "*I*" and "*T*", it is used a fit function (2.3) that multiplies the two matrixes, the pattern's matrix "*T*" and the time series matrix "*I*" in order to obtain a value which indicates the level of similarity between them and in this case if the matrix of the time series is similar to the Bull Flag matrix pattern template. Thus, highest values will occur when the matrix "*I*" is in highest conformance with matrix "*T*".

$$\text{Fit}_k = \sum_{i=1}^{10} \sum_{j=1}^{10} (T\,(i,\,j) \cdot I_k\,(i,\,j)) \tag{2.3}$$

Then it is calculated, through the Eq. (2.4), the amplitude of the time series where range is the difference between the highest and the lowest price and p_k is the closing price in day k.

$$\text{Height}_k = \frac{\text{range}_k}{p_k} \tag{2.4}$$

The values obtained by the previous formulas Fit and Height are used to create investment rules. So, when those values are higher than a threshold it generates a buy signal, which is followed by a variable holding period (example: 5, 10, 20, 40, 60, 80,

100 days) until the sell order is generated. The results of applying these investment rules are represented in Table 2.2.

The authors of the previous studies used this pattern identification approach with neural networks and genetic algorithms as optimization methodologies with the goal of create an investment decision model in [12, 13]. The neural network contained 22 input nodes, where 20 of them correspond to the fit values of each column (10 to price and 10 to volume) and the last 2 correspond to the height of price and height of volume. The output of the neural network in one case is a prediction of the future price and in the other case are two confidence values that allow, through a "thresholding" technique, avoiding false buy signals and also reducing the number of wrong entries/exits operations in the market. The genetic algorithms are used in [12] to optimize and identify the subset of 22 input data nodes that should be used in the neural network. The results of these studies are represented in Table 2.2.

The advantages of this methodology are the representation of patterns through matrixes templates is very visually intuitive, also is very efficient to identify simple patterns and the implementation of its method do not required a great complexity.

A disadvantage of this methodology is that using this method it is not possible to represent complex patterns like the Head-and-Shoulders (Fig. 2.10) due to the lack of space in the matrix template. It would be possible to increase the size of the matrix, but the sliding window would also have to increase more. Other disadvantage is the lack of explanation about the technique used to build the template of Fig. 2.13 therefore the template building is a black box for the users. To solve this problem in [14] is described a simple technique to build the matrix template for several types of patterns, where the user only need to put values equal to 1 in each column and the rest of the values of each column are automatic generated because its sum must be equal to 0.

Other disadvantage of this method is related with the weights assigned to the cells of the matrix because, as can be seen in Fig. 2.15, the matrix on top is much more similar to the Bull Flag pattern than the matrix on the bottom, however its fit value (6.5) is lower than the fit value of the bottom matrix (7.5), which can cause the wrong identification of the pattern. To resolve this problem a new Bull Flag template was created in [15] with new weights in each cell of its matrix. The results of this study are represented in Table 2.2.

In [16] the authors used the template pattern approach to represent several patterns in order to be able to identify more and different cases in the historical prices. With the combination of different patterns it is possible to identify more entry and exit points, which creates more complete and robust investment strategies. The Genetic Algorithm was used in this study to optimize important parameters of the process like: sliding window size, noise reduction rate, FitBuy which is the minimum value to generate a buy signal and FitSell which is the minimum value to generate a sell signal. The results of this study outperformed the Buy&Hold strategy and are represented in Table 2.2.

In a recently approach, described in [17], the creation of the Bull Flag template followed a new methodology in order to mitigate the problem identified in Fig. 2.15. Unlike the previous studies [9, 10, 14, 16] that defined the Bull Flag pattern through

0.5	0	-1	-1	-1	-1	-1	-1	-1	0
1	0.5	0	-0.5	-1	-1	-1	-1	-0.5	0
1	1	0.5	0	-0.5	-0.5	-0.5	-0.5	0	0.5
0.5	1	1	0.5	0	-0.5	-0.5	-0.5	0	1
0	0.5	1	1	0.5	0	0	0	0.5	1
0	0	0.5	1	1	0.5	0	0	1	1
-0.5	0	0	0.5	1	1	0.5	0.5	1	1
-0.5	-1	0	0	0.5	1	1	1	1	0
-1	-1	-1	-0.5	0	0.5	1	1	0	-2
-1	-1	-1	-1	-0.5	0	0.5	0.5	-2	-2.5

0.5	0	-1	-1	-1	-1	-1	-1	-1	0
1	0.5	0	-0.5	-1	-1	-1	-1	-0.5	0
1	1	0.5	0	-0.5	-0.5	-0.5	-0.5	0	0.5
0.5	1	1	0.5	0	-0.5	-0.5	-0.5	0	1
0	0.5	1	1	0.5	0	0	0	0.5	1
0	0	0.5	1	1	0.5	0	0	1	1
-0.5	0	0	0.5	1	1	0.5	0.5	1	1
-0.5	-1	0	0	0.5	1	1	1	1	0
-1	-1	-1	-0.5	0	0.5	1	1	0	-2
-1	-1	-1	-1	-0.5	0	0.5	0.5	-2	-2.5

Fig. 2.15 Matrix with fit value of 6.5 (top) and matrix with fit value of 7.5 (bottom)

a consolidation period followed by a strong rise, this approach defines the Bull Flag pattern as a strong rise (first four columns) followed by a consolidation period, illustrated in Fig. 2.16.

Also the values assignment to the matrix is completely different in this case, because there is only one cell with a positive value (first column, last row), which ensures that in order to obtain a positive fit value it is necessary that the prices of a time series pass through this cell. Cells with negative values are areas where prices should not pass through and cells with value equal to 0 are areas where prices can pass because do not affect the fit value.

This method is similar to an if-then rule because, as an example, *if* only the time series with fit value equal or higher than 4 are considered as Bull Flag pattern *then* the prices of the time series have to pass mandatorily through the cell with value 5 and can only pass through one cell with value -1, thereby constraining the values of the eight remaining columns, that must be 0.

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	-1	-1	-1	-1	-1	-1
0	0	0	-1	-2	-2	-2	-2	-2	-2
0	0	-1	-3	-3	-3	-3	-3	-3	-3
0	-1	-3	-5	-5	-5	-5	-5	-5	-5
0	-1	-5	-5	-5	-5	-5	-5	-5	-5
0	-1	-5	-5	-5	-5	-5	-5	-5	-5
5	-1	-5	-5	-5	-5	-5	-5	-5	-5

Fig. 2.16 New Bull Flag matrix pattern template

In this study, in order to evaluate the return of each operation in the investment strategies, a different sell/exit method was adopted instead of defining a holding period of time to generate the sell order. The sell/exit method is a dynamic method, where the exit point is defined by the evolution of the price and not by time. To do that two variables were defined, *take profit* and *stop loss*, which are related with the maximum amplitude of the time series identified as a pattern that limit the profit and the loss of each operation, respectively. Thus, whenever the price reaches the *take profit* value or the *stop loss* value the operation is closed. The gain at the take profit level is often greater than the loss at the stop loss level so that the total profit of a strategy depends on the success rate of operations. The results of this study are represented in Table 2.2.

2.3.2 Perceptually Important Points (PIPs)

In this approach, as the name implies, the time series are represented by a set of Perceptually Important Points (PIPs) which are the most relevant points because are the ones who characterize the time series and the patterns. Patterns are characterized by a set of critical points, as an example the Head-and-Shoulders pattern can be defined by a head point, two points for the shoulders and two more points for the neckline. These points are the most relevant points because are the ones that define the shape of this pattern. So, in order to identify PIPs in time series, a technique based on distance measures was used in [18]. The algorithm to identify PIPs is described as:

- The sequence P is the set of time series data points. The first and the last point of the sequence P are the first two PIPs identified. The next PIP is the point of sequence P with maximum distance to the first two PIPs. Then, the fourth PIP will then be the point in P with maximum distance to its two adjacent PIPs, i.e., in between the first and the second PIPs or the second and the last PIPs. This process ends when the number of PIPs identified is equal to the number of PIPs of the pattern.

To measure the maximum distance between one point and its two adjacent PIPs, in [18] are presented 3 methods:

1. **Euclidean distance (ED)**

Calculates the sum of the ED (2.5) of the test point p_3 to its adjacent PIPs p_1 e p_2

$$\text{ED}\,(p_3,\, p_2,\, p_1) = \sqrt{(x_2 - x_3)^2 + (y_2 - y_3)^2} + \sqrt{(x_1 - x_3)^2 + (y_1 - y_3)^2} \tag{2.5}$$

2. **Perpendicular Distance (PD)**

Calculates the PD (2.9) between the test point p_3 and the line connecting the two adjacent PIPs p_1 e p_2.

$$\text{Slope}\,(p_1,\, p_2) = s = \frac{y_2 - y_1}{x_2 - x_1} \tag{2.6}$$

$$x_c = \frac{x_3 + s y_3 + s y_2 - s^2 x_2}{1 + s^2} \tag{2.7}$$

$$y_c = s x_c - s x_2 + y_2 \tag{2.8}$$

$$\text{PD}\,(p_3,\, p_c) = \sqrt{(x_c - x_3)^2 + (y_c - y_3)^2} \tag{2.9}$$

3. **Vertical Distance (VD)**

Calculates the VD (2.10) between the test point p_3 and the line connecting the two adjacent PIPs p_1 e p_2.

$$\text{VD}\,(p_3,\, p_c) = |y_c - y_3| = \left| \left(y_1 + (y_2 - y_1)\, \frac{x_c - x_1}{x_2 - x_1} \right) - y_3 \right| \tag{2.10}$$

These three distance methods were tested in [18], using 2500 points of data from Hang Seng Index (HSI), and the Vertical Distance (VD) method proved to be the best in capturing the shapes of patterns.

After the identification of PIPs in time series, the next step is to detect pattern based on this representation. In order to do that two distinct methodologies were used in [19]. The first is based on templates and the second is based on rules.

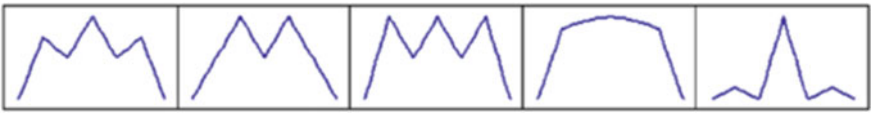


Fig. 2.17 Five typical patterns represented by 7 PIPs. *Source* Ref. [19]

I. Pattern detection based on templates

In this approach, the structure of the patterns is defined visually which allows comparison point-to-point between the time series and the patterns. In Fig. 2.17 it is possible to observe a set of well-known patterns with length equal to 7 PIPs.

As different time series may have different amplitudes, it is necessary to normalize the PIPs identified in the time series in order to facilitate the comparison between the different time series (e.g. range 0–1). After that, the Amplitude Distance (AD) between the pattern's template and time series is calculated through point-to-point direct comparison, Eq. (2.11).

$$\mathrm{AD}\,(\mathrm{SP},\,Q) = \sqrt{\frac{1}{n}\sum_{k=1}^{n}\left(\mathrm{sp}_k - q_k\right)^2} \tag{2.11}$$

The variables SP and sp_k denote the PIPs identified in the time series P and the variables Q and q_k denote the PIPs of the pattern template. It is also necessary to consider the horizontal distortion (time dimension) of the time series against the pattern templates. The Temporal Distance (TD) between P (time series) and Q (pattern template) is defined in Eq. (2.12).

$$\mathrm{TD}\,(\mathrm{SP},\,Q) = \sqrt{\frac{1}{n-1}\sum_{k=2}^{n}\left(\mathrm{sp}_k^t - q_k^t\right)^2} \tag{2.12}$$

where sp_k^t and q_k^t denote the time coordinate of the sequence points sp_k and q_k, respectively. In order to take both horizontal and vertical distortion into consideration in the similarity measure, the formula of this measure is defined as:

$$D\,(\mathrm{SP},\,Q) = w_1 \times \mathrm{AD}\,(\mathrm{SP},\,Q) + (1 - w_1) \times \mathrm{TD}\,(\mathrm{SP},\,Q) \tag{2.13}$$

where w_1 represents the weight of AD and TD that is specified by the users. The results of this methodology are represented in Table 2.2.

II. Pattern detection based on rules

One disadvantage of the template-based methodology is the difficulty of defining the relationship between the relevant points. In this approach, a set of rules between

PIPs is created to describe the shape of the patterns. For example, in the Head-and-Shoulders pattern, the two shoulders must be lower than the point that defines the head and must have a similar degree of amplitude.

Using the patterns from Fig. 2.17 and assuming that all of them have a length of 7 PIPs, sp1 until sp7, a set of rules can be defined for each pattern. The set of rules that define the Head-and-Shoulders pattern are the following:

- sp4 > sp2 e sp6
- sp2 > sp1 e sp3
- sp6 > sp5 e sp7
- sp3 > sp1
- sp5 > sp7
- diff(sp2, sp6) < 15%
- diff(sp3, sp5) < 15%

The set of rules that define the other four patterns of Fig. 2.17 can be found in [19].

After the definition of a set of rules for each pattern, the time series are represented by its PIPs, in this case by 7 PIPs, and those who comply with all the rules of a pattern are identified as one. The results of this approach are represented in Table 2.2 and in general, were lower than the results of the previous approach (template-based). However, this approach obtained excellent results in the distinction between the Head-and-Shoulders pattern, Triple Top pattern and Double Top pattern. The advantages of this new approach, i.e. PIPs representation and detection of patterns based on templates or rules are:

- High complexity reduction of time series and patterns because only a small set of points are used to represent time series and identify patterns.
- Possibility to detect complex and detailed patterns.

The main disadvantage of this approach is related with the detection of patterns, where the number of PIPs that define the patterns and the time series must always be equal in order to enable the comparison point-to-point in the template-based methodology or the validation of rules in the rule-based methodology. For example, the Head-and-Shoulders pattern of Fig. 2.17 is represented by 7 PIPs, which force the time series to be represented by the same number of PIPs to be possible to compare them with the pattern. To resolve this problem a DTW (Dynamic Time Warping) algorithm was used in [20] to find an optimized alignment between two sequences combined with the three distance measures described previously (ED, PD and VD). Using this algorithm it is possible to measure the similarity between a pattern and a time series with different lengths of PIPs.

2.3.3 *Symbolic Aggregate approXimation (SAX) Representation*

Traditionally, the representation of time series and its dimensionality reduction was made through numeric methods like Wavelet Discrete Transform [21]. The SAX representation approach [22] allows defining metrics between data representation, which is related with the real distance between time series. The SAX representation solves the problem related with the distance between the real data and its representation because it is possible to obtain a lower bounding approximation for the distance measures and also this representation allows a significant reduction of the data dimensionality of time series.

In [23] was used a method based on SAX to represent time series with the aim of identifying patterns, which begins by dividing larger time series in smaller time series windows. The data of each smaller time series is then normalized, according to Eq. (2.14), to guarantee that the time series can be compared between each other. In Eq. (2.14), x_i corresponds to a point of the time series, μ_x and σ_x correspond to the mean and standard deviation of the time series, respectively.

$$x_i' = \frac{x_i - \mu_x}{\sigma_x} \tag{2.14}$$

After the normalization of data it is necessary to reduce its dimensionality in each time series and to do that the Piecewise Aggregate Approximation (PAA) method was used [24]. With PAA a time series is divided in equal segments, where each of them is represented by its arithmetic mean (2.15).

$$\bar{x}_j = \frac{w}{n} \sum_{i=\frac{n}{w}(j-1)+1}^{\frac{n}{w}j} x_i' \tag{2.15}$$

where w represents the number of segments, n represents the time series size and x_i' is the data point in the window. As can be seen in Fig. 2.18, this process allows the representation of a time series by the arithmetic mean of each segment, which makes a set of data points to be now represented only by its mean (red line).

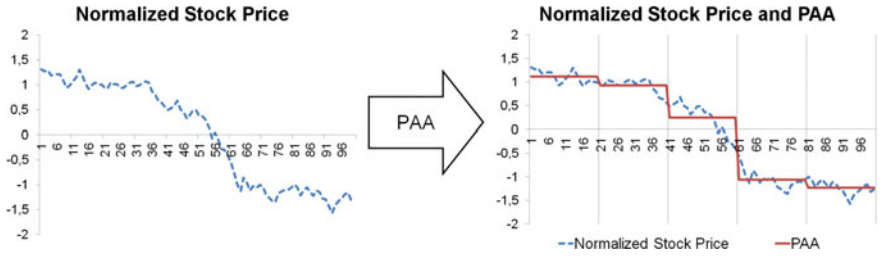


Fig. 2.18 PAA representation. *Source* Ref. [23]

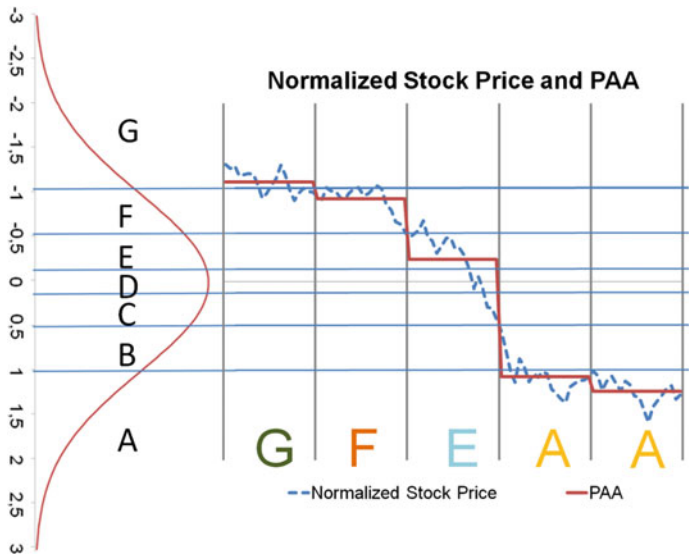


Fig. 2.19 SAX representation. *Source* Ref. [23]

Table 2.1 Breakpoints for a intervals of the normal distribution curve

	$a = 3$	$a = 4$	$a = 5$	$a = 6$
β_1	−0.43	−0.67	−0.84	−0.97
β_2	0.43	0	−0.25	−0.43
β_3		0.67	0.25	0
β_4			0.84	0.43
β_5				0.97

Source Ref. [23]

After the application of PAA, the amplitude of each time series is divided in equiprobable intervals, using a normal distribution curve over the vertical axis, where breakpoints are calculated to produce equal areas for each interval under the curve. Thus, it is possible to assign a different symbol to each interval and consequently assign a symbol to each segment by determining to which interval the segment belongs, as illustrated in Fig. 2.19. Applying this method to all segments of a time series allows the representation of the time series by a sequence of SAX symbols (string).

To find patterns with this approach, the SAX sequences of symbols must be compared with each other or compared with well-known SAX sequence that defines some wanted pattern. To measure the similarity between SAX sequences two distance measures were used: MINDIST (2.17) and ALPHAB.DIST (2.18). The ALPHAB.DIST method proved to be faster than the MINDIST due to the fact that does not need to identify the breakpoints of Table 2.1.

Fig. 2.20 Chromosome used in GA. *Source* Ref. [23]

$$\text{dist}\,(p_i, q_i) = \begin{cases} 0 & \text{se } |i-j| \leq 1 \\ \beta_{j-1} - \beta_i & \text{se } i < j-1 \\ \beta_{i-1} - \beta_j & \text{se } i > j+1 \end{cases} \tag{2.16}$$

The β's are the breakpoints defined in Table 2.1.

$$\text{MINDIST}\,(P, Q) = \sqrt{\frac{n}{w}} \sqrt{\sum_{i=1}^{w} (\text{dist}\,(p_i, q_i))^2} \tag{2.17}$$

$$\text{ALPHAB.DIST}(T, P) = \sqrt{\sum_{i=1}^{W} (T_i - P_i)^2} \tag{2.18}$$

where Ti e P_i are the symbols i of the sequence T and P, respectively.

An advantage of SAX representation is the simplicity to identify patterns because in this approach the identification is simply a comparison between two sequences of symbols, i.e. two strings. Other advantage is the simple implementation of this methodology and also the transformation of time series in SAX sequences of symbols is fast. The main advantage is that this approach allows a huge reduction of dimensionality of data and at the same time maintains the main characteristics of time series and patterns.

The authors of this study [23] also used genetic algorithms to optimize the investment strategies based on the total return. In Fig. 2.20 it is possible to observe the chromosome used and its genes. This chromosome is divided in 2 parts, in the first (first four genes) are the parameters that support the buy/sell decisions and in the second ($P_1 - P_w$) is the sequence of symbols that define the pattern, where each gene defines a symbol. The first two genes define the distances between the time series and the pattern that allow to identify if the pattern is presented and a buy order should be generated (Distance to Buy) or if it is not present and a sell order should be generated (Distance to Sell). The third gene (Days to Sell) defines the holding period to maintain the financial asset until it is sold. The fourth gene (Measure Type) defines which distance measure (MINDIST and ALPHAB.DIST) should be used to find the similarity between sequences. The results of this study are presented in Table 2.2.

Table 2.2 Results comparison of some studies presented [25]

Ref.	Year	Method	Used Data	Period		Financial Market	Algorithm Performance		Buy-and-Hold Performance	
[11]	2008	Bull Flag w/Matrix Template	Stock price	04/08/1967–12/05/2003		NYSE Composite Index	4.59% (Transaction average over the period)		1.83% (Transaction average over the period)	
[15]	2007	Bull Flag w/Matrix Template	Stock price	NASDAQ	TWI	NASDAQ and TWI	NASDAQ	TWI	NASDAQ	TWI
				03/04/1985–20/03/2004	01/06/1971–24/03/2004		4.38% (Transaction average over the period)	6.48% (Transaction average over the period)	3.27% (Transaction average over the period)	4.03% (Transaction average over the period)
[13]	2002	Hybrid Neural Network w/Pattern detection	Stock price and Vol.	24/07/1984–11/06/1998		NYSE Composite Index	66% (Days market goes up after buying order)		60% (Days market goes up after buying order)	
[17]	2015	Bull Flag w/Matrix Template	Stock price	22/05/2000–29/11/2013		Dow Jones Industrial Average Index	13% (Average return)		N/A	

(continued)

Table 2.2 (continued)

Ref.	Year	Method	Used Data	Period	Financial Market	Algorithm Performance	Buy-and-Hold Performance
[16]	2011	Uptrend pattern w/Matrix Template + GA	Stock price	1998–2010	S&P500 Index	36.92% (Total return)	−4.69% (Total return)
[19]	2007	Template-Based	Stock price	N/A	Several	96% (Hits on pattern identification)	N/A
[19]	2007	Rule-Based	Stock price	N/A	Several	38% (Hits on pattern identification)	N/A
[19]	2007	PAA	Stock price	N/A	Several	82% (Hits on pattern identification)	N/A
[23]	2013	SAX + GA	Stock price	1998–2010	S&P500 Index	16.28% (Average annual return)	7.79% (Average annual return)

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Chapter 3
SIR/GA Approach

Abstract In this chapter, the new approach to pattern discovery will be presented in detail. The objective of this research is to develop a pattern discovery algorithm that combines ideas from how humans identify patterns and automatic classification of the patterns. The method uses points that normally a human would consider important and then creates rules to describe the relationship between them. Then using GA and SAX makes a search for the relevant patterns in order to detect opportunities to enter/exit the market. This new approach, Symbolic Important Rules (SIR), is based on two different ideas from the related work: PIPs with rules and SAX representation. Also, the system's architecture and each of its modules that support this approach will be described later in this chapter.

3.1 Time Series Representation

The proposed method is divided into four steps, represented in Fig. 3.1. These steps are described here shortly and next each one in detail. First, the historical prices of a financial asset are divided into smaller time series all with the same size in order to identify patterns with the same time length. After this, it is possible to identify patterns in the time series but the dimension of data is too high, making this process very expensive in time and computational resources. Second, in order to reduce the dimension of the data, each time series is represented by its most relevant points, denominated Perceptually Important Points (PIPs). Third, rules are created that identify the relationship between two PIPs. The two PIPs need not be consecutive, it is possible to have rules between two PIPs that are apart to each other more than one unit. Finally, the fourth step where each different rule created is transformed to a different symbol in order to represent each time series by a sequence of symbols.

PIPs are points that a human looking at a time series would consider important to identify the pattern. The method used to identify PIPs is based on [19] that start by defining the first and the last point of a time series as the first two PIPs. Then the third PIP is the point of the time series with maximum vertical distance to the line between the first two PIPs. The next PIP will be then the point with maximum

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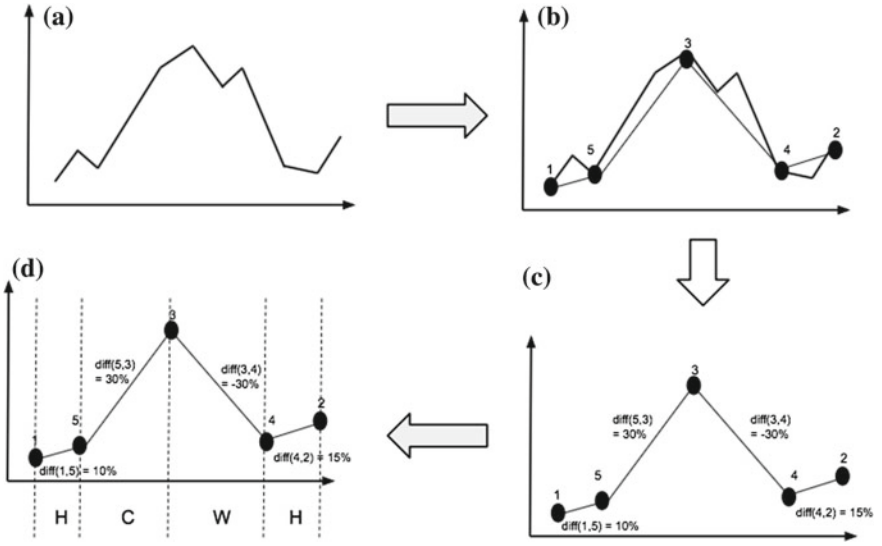

Fig. 3.1 SIR representation process. **a** A raw time series. **b** Identification of PIPs. **c** Creation of rules. **d** Mapping between characters and rules [1]

vertical distance to its two adjacent PIPs, i.e., between either the first and the second PIPs or the second and the last PIPs. This process continues until the limit of PIPs to identify in the time series is reached, as represented in Fig. 3.1b.

In the third step, rules are created according to the PIPs identified and the relations between them, see Fig. 3.1c. These rules are defined based on the percentage difference between two adjacent or nonadjacent PIPs, allowing the definition of different rules between one PIP and others. With these rules the normalization of data between time series is done because it is used the percentage difference between two points and not the absolute value difference of those points, an example is a rise from 5 to 10$ and a rise from 100 to 200$, where both have the same percentage difference (100%) but not the same absolute value difference (5 and 100).

In order to create five different types of rules, two variables x and y are defined, where each represents a percentage and the percentage y is higher than the percentage x. The five different types of rules presented in Fig. 3.2, can be described as:

1. Percentage difference between two PPIs higher than $y\%$—strong increase of price.
2. Percentage difference between two PPIs higher than $x\%$ and lower than $y\%$—slight increase of price.
3. Percentage difference between two PPIs higher than $-x\%$ and lower than $x\%$—sideways movement of price.
4. Percentage difference between two PPIs lower than $-x\%$ and higher than $-y\%$—slight decrease of price.
5. Percentage difference between two PPIs lower than $-y\%$—strong decrease of price.

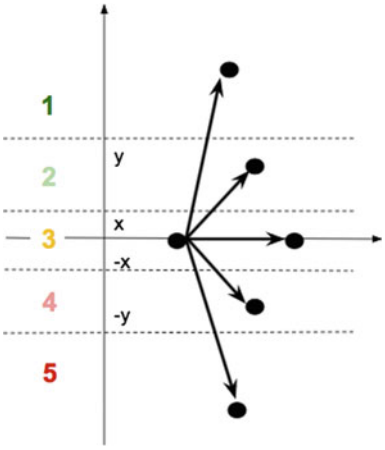

Fig. 3.2 The five types of rules between 2 PIPs [1]

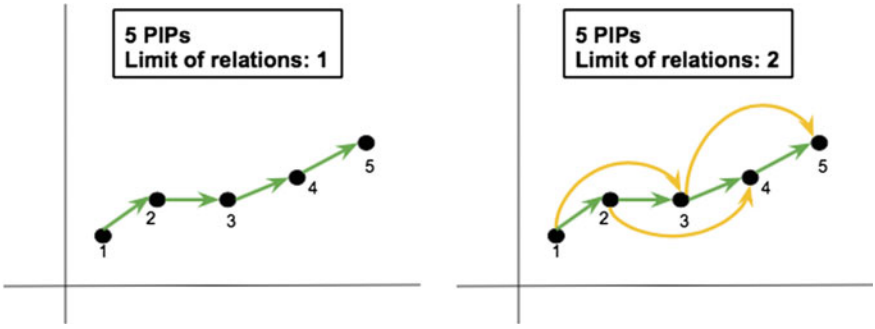

Fig. 3.3 Examples of rules definition [1]

The rules definition algorithm receives as input the PIPs of a time series and a maximum limit of relations between PIPs, which defines the maximum number of rules that can be defined between one PIP and the others. In Fig. 3.3 are represented two examples with five PIPs and different limits of relations between PIPs. In the first example (left) the limit of relations is one, therefore, the rules defined are only between adjacent PIPs (green arrows), i.e., between the first and the second PIPs, the second and the third PIPs, and so on. In the second example (right) the limit of relations between PIPs is 2, which means that each PIP can be related with its two following PIPs when possible, consequently the rules defined are the same of the first example (green arrows) plus the rules between one PIP and the next PIP to its adjacent PIP (yellow arrows).

The proposed algorithm, Fig. 3.4, begins by calculating the percentage difference between the first PIP and second PIP and according to the result assigns one of the five rules in Fig. 3.2. If the limit of relations between PIPs had not been reached the

```
Procedure RulesDefinition(P,l,x,y)
    P[1...m] = set of PIPs in time series
    l = limit of relations
   x = lower percentage, y = higher percentage
   For i=1 until size(P)
      For j=1 until l
         If Diff%(P[i], P[j+1]) > y
         Rule[i,j] = 1
         If Diff%(P[i], P[j+1]) > x AND Diff%(P[i], P[j+1]) < y
         Rule[i,j] = 2
         If Diff%(P[i], P[j+1]) > -x AND Diff%(P[i], P[j+1]) < x
         Rule[i,j] = 3
         If Diff%(P[i], P[j+1]) < -x AND Diff%(P[i], P[j+1]) > -y
         Rule[i,j] = 4
         If Diff%(P[i], P[j+1]) < -y
         Rule[i,j] = 5
End
```

Fig. 3.4 Pseudo code of the rules definition process

next rule assigned will be defined by the result of the percentage difference between the first and the third PIPs and so on until the limit is reached. After that, the process repeats with the second PIP until the limit is reached and after with the others, PIPs until the rule related with the percentage difference between the penultimate and the last PIPs is assigned, which terminates the algorithm.

The advantage of defining these rules in time series is to obtain an explicit definition of the relationships between the points, in terms of price movements. Many well-known patterns are defined by a specific set of rules between its points, as an example the Head-and-Shoulders pattern (Fig. 2.10) where the two shoulders in the pattern must have a null or almost null percentage difference between them (rule 3 Fig. 22) and both must be lower than the head of the pattern.

In the fourth step, all the rules defined are converted into characters, allowing the representation of time series by a sequence of characters (string). To do that, each of the five different rules is mapped to one different character in order to distinguish precisely the different trends of price represented by the different rules. The alphabet was chosen and the mapping between the characters and the rules are represented in Fig. 3.5.

To find new patterns the sequences of characters must be compared with each other or with a known sequence of characters to find some wanted pattern. In order to identify the match between sequences of characters, it is used (18) based on [23] to calculate the distance between two sequences and identify the level of similarity between them, through the ASCII code of each character, Fig. 3.6. Lower values mean more similarity between sequences and higher values mean the opposite.

The characters used for each rule were carefully chosen to improve the performance of the algorithm. Each character of the alphabet has a different ASCII code, where "*C*" = 67, "*H*" = 72, "*M*" = 77, "*R*" = 82, and "*W*" = 87, allowing the distinction of the different trends of price defined by the different rules. Rules more

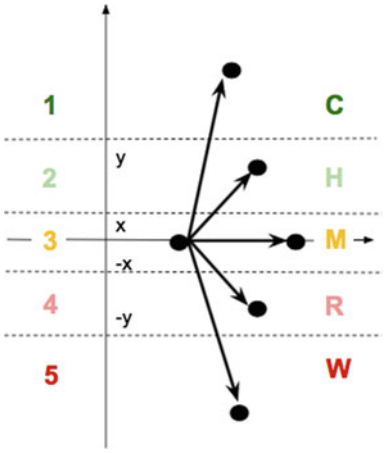

Fig. 3.5 Mapping between rules and characters [1]

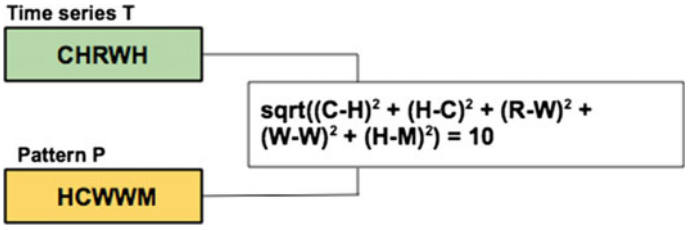

Fig. 3.6 Example of a distance calculation [1]

identical in terms of trend have a lower difference in ASCII code of the characters and rules less identical have a higher difference in ASCII code of the characters. The most contrasting rules, i.e., the strong increase and the strong decrease are mapped with the first and last character, "*C*" and "*W*" respectively, of the alphabet in order to hold the biggest difference (20) in ASCII code between all the characters. The sideways movement is mapped with the character "*M*" which is the character with the same distance to the characters that represent the opposite rules. From 1 to 5 the consecutive rules have smaller difference (5) between each other due to its higher similarity.

3.2 Investment Rules

The goal of this work was not only to identify patterns in time series but also to create investment rules based on the patterns identified. The algorithm analyses stock historical prices with the help of a sliding window of variable length and convert each

time series in a sequence of characters. Every time a pattern is identified in the time series a buying order is generated. After that, in order to evaluate the return of the operation an exit point should be defined and can be by three different methods or combinations between them:

1. By time: where is defined a variable holding period of days until the sell order is generated and the operation is closed.
2. By price: where is defined a variable *take profit* and a variable *stop loss*, which will limit both the profit and the loss of each operation, respectively. When one of the limits is reached, the operation is closed with loss or profit. The gain at the *take profit* level is often greater than the loss at the *stop loss* level so that the total profit depends on the success rate of operations. These variables are defined based on a positive and negative percentage over the stock buying price.
3. By pattern: where is defined an uptrend pattern with the goal of identifying it in each time series subsequent to the buying order. The operation is closed only when the uptrend pattern is not identified in one of those time series, which means that the prices stopped increasing. In order to identify the uptrend pattern, the time series following the buying order is represented by a sequence of characters using the method in Sect. 3.1. Then the uptrend pattern is represented by the sequence of characters "*C*", which means consecutive strong increases of the price. After that, the time series' sequence of characters is compared with the uptrend pattern's sequence of characters using the same distance method (18) that is used to generate buying orders, where the only difference is that in this case the distance, in terms of ASCII code, between characters "*H*" and "*C*" is 0 instead of 5 due to the fact that "*H*" represents also an increase of prices, which is what is supposed to happen to prices, so that the operation is not closed. Then, if the result of the comparison is higher than a threshold a sell order is generated, if not it means the pattern is identified in that time series so the process is repeated with the next time series until the pattern is not identified in some time series.

In Fig. 3.7, it is possible to observe an example, where the three methods described before are used simultaneously. After opening the position the exit by time defines a holding period of 35 days to close it (blue dashed line), the exit by price defines *take profit* (green line) and *stop loss* (red line) based on the buying price and the exit by pattern begins by representing the time series from day 47 to day 94 in a sequence of characters, according to the method of Sect. 3.1 and then compare it with the sequence {"*C*", "*C*", "*C*"} which represents the uptrend pattern, using the distance measure (18). In this example, the position is closed by price because the price reached the *take profit* level before the other methods generate sell orders.

3.3 Genetic Algorithms (GA)

To optimize the parameters related to the investment rules the Genetic Algorithm (GA) is used. The chromosome used to create the population is represented in Fig. 3.8.

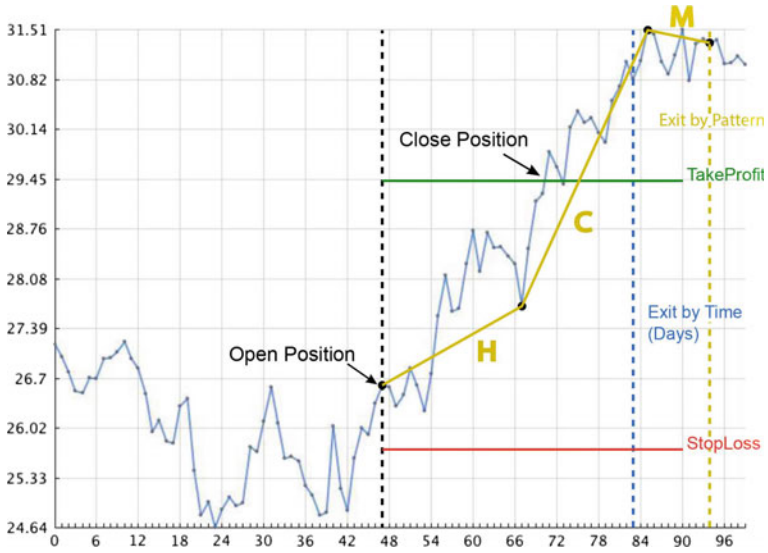

Fig. 3.7 Example with the three different exit methods [1]

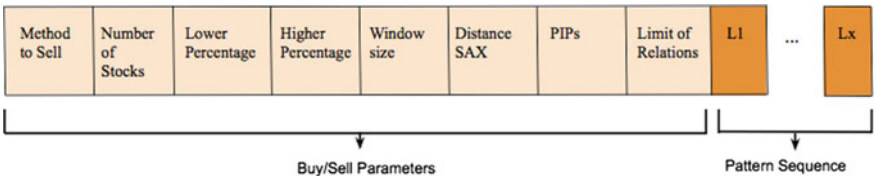

Fig. 3.8 Chromosome used in GA [1]

The chromosome is divided into two major parts. In the first part (first eight genes) are the parameters related to the buy and sell decisions and in the second part (L1,…,Lx) are the characters that represent the pattern sequence that will be identified in the time series. The genes of the chromosome are:

- **Method to Sell**—defines which exit/sell method or combination of methods, described in Sect. 3.2, is used in the investment strategy. This gene assumes a value between 0 and 6, where each value represents a different method or combination of methods between time, price, and pattern. In the exit by time, the holding period varies between the window size and 2 * window size. In the exit by price, the take profit variable varies between 5 and 50% and the stop loss variable between −5 and −20%. In the exit by pattern, the length of the time series which are compared with the uptrend pattern varies between the window size and 2 * window size.
- **Number of Stocks**—defines the size of the investment portfolio, i.e., the maximum number of different stocks that can be bought simultaneously. This gene can assume a value between 5 and 20 different stocks.

- **Lower Percentage**—represents the lower percentage used to define the intervals that originate the five types of rules of Fig. 22 (variable x and $-x$). This gene can assume values between 2 and 10% and also between -2 and -10%.
- **Higher Percentage**—represents the higher percentage used to define the intervals that originate the five types of rules of Fig. 22 (variable y and $-y$). This gene can assume values between 11 and 30% and also between -11 and -30%.
- **Window size**—represents the size of the sliding window that is used to divide the historical prices in smaller time series. The value of this gene varies between 20 and 100 days in order to be possible to identify patterns with different lengths.
- **Distance SAX**—represents the maximum distance that identifies a pattern in the time series in order to only identify time series that are similar to the pattern. This gene is used to generate buy orders and is also used in the exit by pattern to identify the uptrend pattern in time series. The distance value is from the distance measure ALPHABET.DIST (18) and it is dependent on the size of the pattern sequence of characters. Since the minimum difference between two characters of the alphabet, in terms of ASCII code, is five and the lowest possible sequence of characters is four, then the values of this gene vary between 0 and [(pattern size) − 4] * 5.
- **PIPs**—defines the number of relevant points to identify in each time series. The number of points depends on the window size because larger time series need to be represented by more points and smaller time series by fewer points in order to reduce the data dimensionality and at the same time maintain the main characteristics of the time series. This gene varies between 5 and the minimum value of window size/4 and 12, which guarantees that the minimum number of points identified in each time series is 5 and the maximum is window size/4 or 12 in the case where the window size/4 value is greater than 12.
- **Limit of relations**—indicates the maximum limit of relations between the PIPs that were identified in each time series and consequently defines the number of rules that will be created for each PIP with the other PIPs because each relation corresponds to a rule. This value depends on the number of PIPs because the number of points between the first and the last PIPs defines the maximum limit of relations, as an example if the number of PIPs is five then the maximum limit of relations between PIPs is four. Therefore, the values of this gene vary between 1 and the total number of PIPs—1.
- **L1,…,Lx**—defines the pattern sequence of symbols that will be used to identify in the historical prices of stocks, where each gene L represents a character of the alphabet {"*C*", "*H*", "*M*", "*R*", "*W*"}. The size of the sequence of symbols is defined by the number of rules, which is defined by the number of PIPs and its relations. The definition of each character is restricted by the previous characters assigned to the rules between the previous PIPs, in order to create valid sequences of characters. For example in the case where the character assigned to the rule between the first and second PIPs is "*H*", which means that the second point is higher than the first, and the character assigned to the rule between the first and third PIPs is "*R*", which means that the third point is lower than the first, implies that the third PIP is mandatorily lower than the second PIP and the character assigned to this rule must be only "*R*" or "*W*".

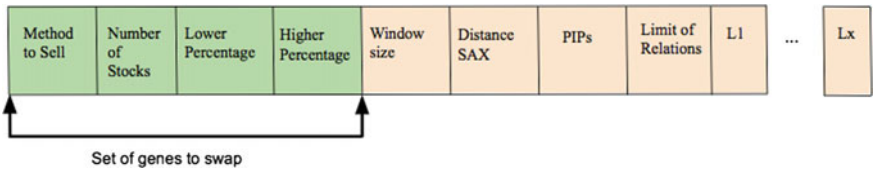

Fig. 3.9 Possible genes to swap in the crossover between two chromosomes with different sizes

The chromosomes could have different sizes due to the length of the sequence of characters, which depends on the number of rules that are defined through the PIPs and its relations, which are also dependent on the sliding window size. For this reason, the crossover operation between two chromosomes is done by two different ways, depending on the size of the chromosomes:

1. Chromosomes with different sizes

In this case, where the two chromosomes have different sizes the only possible genes that can be swapped are the ones that are not directly related with the size of the pattern sequence of characters. The genes that define the size of the sequence of characters of each time series that will be compared with the pattern sequence of characters cannot be swapped because the two sequences must have the same size to be possible to compare them. So only the first four genes or a set of them can be swapped between two chromosomes with different sizes, as illustrated in Fig. 3.9.

2. Chromosomes with same size

In this case, the two chromosomes have the same size which means that the size of the sequence of characters of both is equal, so the genes that are directly related with the size of the sequence of characters can be swapped and also the first four genes of the previous case, as illustrated in Fig. 3.10. The values of the genes that are related with the size of the pattern (green block in Fig. 3.10) are dependent on each other, which make them inseparable and as a single one, therefore in this operation they must be swapped together or none of them is swapped in order to ensure that they are not swapped individually which could cause irregularities in their values. The only case where the genes related with the pattern sequence (L1,…,Lx) can be swapped is when the limit of relations is one in the two chromosomes which means the characters do not have any restriction imposed by the previous characters of its sequence.

In the mutation operation, there are some restrictions as well. In this operation, only the first eight genes, i.e., the buy/sell parameters, can be mutated but when the limit of relations of a chromosome is equal to one, then the genes responsible for the sequence of characters (L1,…,Lx) can be mutated too because each character, in this case, does not depend on the characters of the previous genes.

Each chromosome corresponds to a different investment strategy, which is tested by the program where the fitness function that the GA optimizes is the Return On

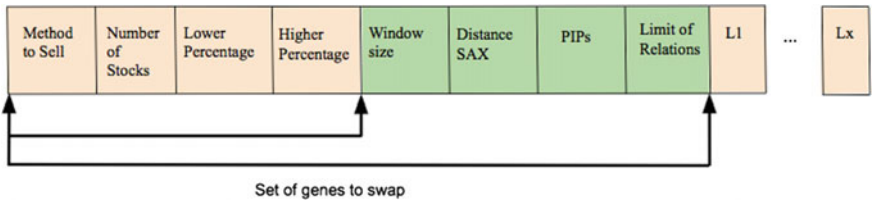

Fig. 3.10 Possible genes to swap in the crossover between two chromosomes with equal sizes

Investment (ROI), which is explained in detail in Sect. 4.1, of each investment strategy. The application begins, as illustrated in Fig. 3.11, by dividing the stocks historical prices in smaller time series of size equal to the value of the gene "Window size". Next, the time series is transformed into sequence of characters according to the method in Sect. 3.1 and using the values of genes "Lower Percentage", "Higher Percentage", "PIPs", and "Limit of Relations". Then the characters of the pattern sequence in the chromosomes are compared with the characters that represent the time series and if the distance between them is lower than "Distance SAX" the program generates a buying order. This process is repeated to all the stocks, in order to get a set of buying orders for the day after each time series identified as a pattern. After that, the set of buying orders is ordered according to the distance to the pattern, where the lowest distance will be on the top and the highest distance will be in the bottom of the set, aiming to buy the stocks whose time series are more identical to the pattern. In this order, the different stocks are bought until the limit of stocks that can be opened at the same time defined by the gene "Number of Stocks" is reached or there are no more to buy. For each stock/company, the amount of money invested is the same so the number of shares of each company that is bought is different because it depends on its share price at that moment. To determine the number of shares to buy, the balance is divided by the number of stocks/companies that can be bought (portfolio size—n^{o} stocks already bought) which represents the amount of money that can be invested in each stock. After that, this amount is divided by the share price of each company, which results in the number of shares that will be bought for each company. Finally, the operations are closed according to the exit method or the combination of exit methods defined by the gene "Method to Sell".

After testing all chromosomes in all the historical prices, a new population is created with the best chromosomes of the last population and with new chromosomes resulting from the crossover and mutation operations. The process described before itis repeated with the new population until the number of evolutions is reached or there are no improvements of the fitness function in consecutives generations.

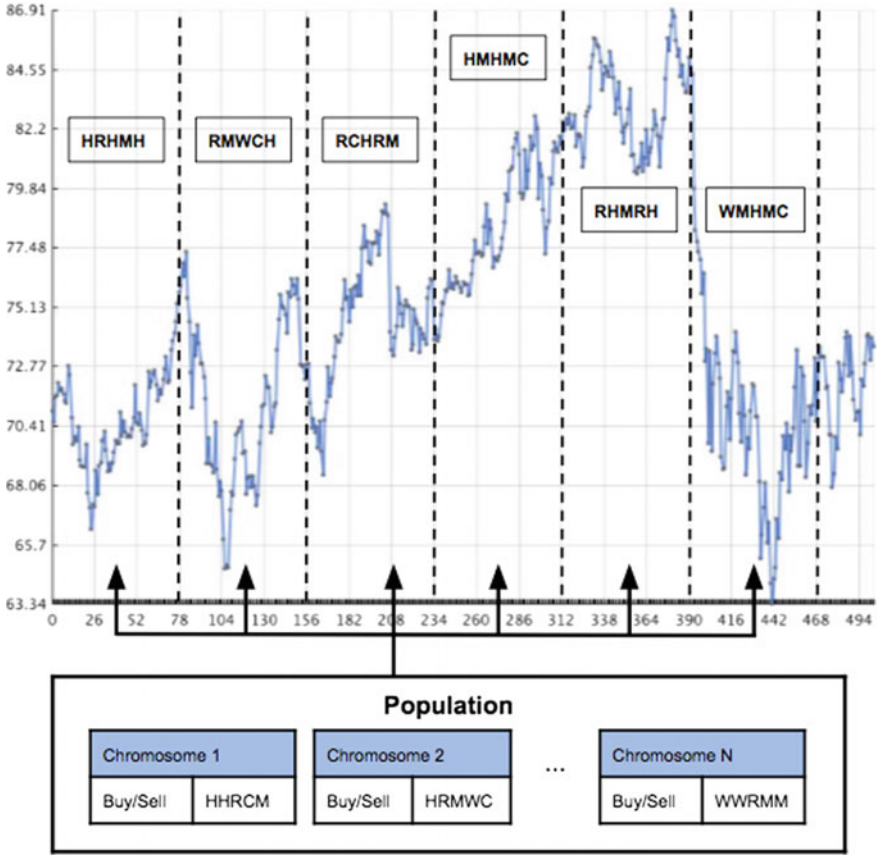

Fig. 3.11 Application process

3.4 System's Architecture

In the design of the system architecture, one of the most important requirements was the flexibility to extend and change the code of modules without affecting the others, therefore, modules should have a clear separation between them. For that reason, the proposed solution can be represented by a multilayer architecture, as illustrated in Fig. 3.12, composed of three layers: User Interface (presentation layer), Trading Algorithm (business logic layer), and Financial Data (data layer). Each module is described in detail in the next sections.

The solution was developed in Java, which is an object-oriented programming language, and the Genetic Algorithm module was build based on a Java framework called JGAP, which provided the basic structure of Genetic Algorithms.

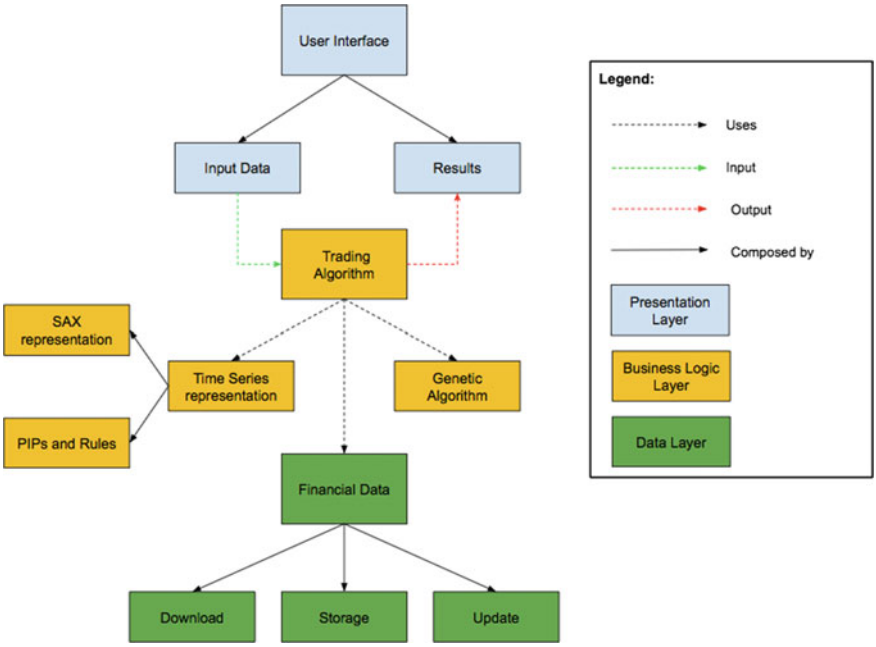

Fig. 3.12 System's architecture

3.4.1 User Interface

This module is responsible for the interface presented to the users, which is where users interact with the system. The user, through the interface, specifies parameters, like the start and end date of the period of training and test, the list of stocks, etc. that are going to be used by the Trading Algorithm module and then present the results obtained. In Fig. 3.13 the interface that is presented to the user, which is divided into three parts is represented. In the first part (1), the user specifies the input data like the start and end date of the training period and the list of stocks to analyse (.txt file), and also the size of the population and the number of generations of the GA.

In the second part (2), the best investment strategy (chromosome) and its pattern, obtained through the input data specified by the user in (1), is presented with its fitness value (ROI), as can be seen in Fig. 3.13. In the last part (3), the user specifies the period where this investment strategy will be tested and then the total return (%) for that period is presented to the user.

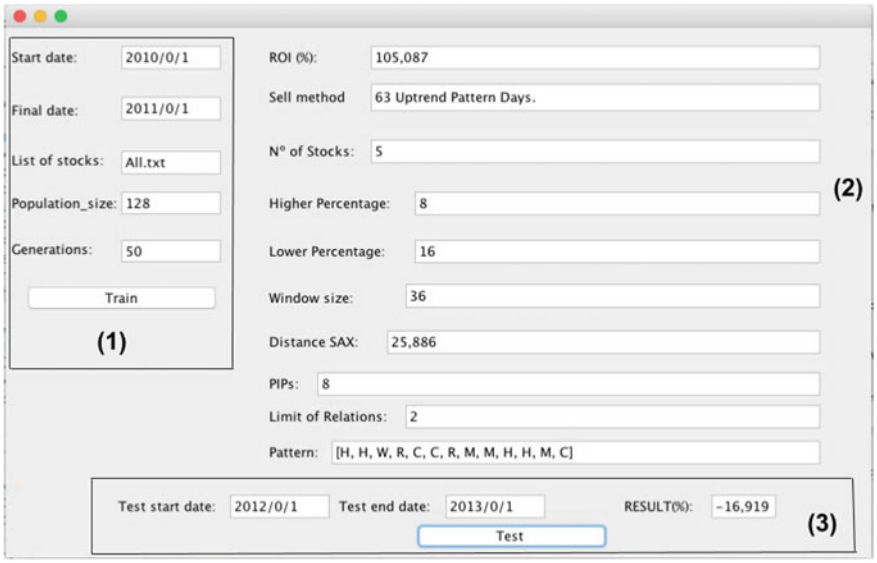

Fig. 3.13 User interface

3.4.2 Trading Algorithm

This module is the most important module of the whole solution. This module is responsible for the detection of patterns and also for the creation of investment rules (buy/sell decisions) based on Genetic Algorithms. In this module, the methods described in Sects. 3.1, 3.2, and 3.3 are performed, i.e., the representation of time series, the creation of investment rules and the evolution of the Genetic Algorithm.

This module is divided into two sub-modules: "Time Series representation" and "Genetic Algorithm". The first module is responsible for the representation of time series according to the method described in Sect. 3.1, which is based on PIPs with rules and SAX representation. The second module is the optimization module responsible for the implementation of the Genetic Algorithm. This module is divided into two major parts, as most of GA programs, where the first part is the training process where the parameters related to investment decisions (buy/sell) and the patterns are optimized and the second part is the test process where the best chromosomes from the training process are tested in order to prove the validity of the solution. As said before, this module was build based on JGAP framework, which provided basic genetic mechanisms that can be easily used to apply evolutionary principles to problem solution, and was designed to facilitate its usage and also to be highly modular to any kind of problems. For that reason, the basic structure provided by the framework was used but several components like the crossover and mutation operator, fitness function, etc. were modified to be able to address the restrictions

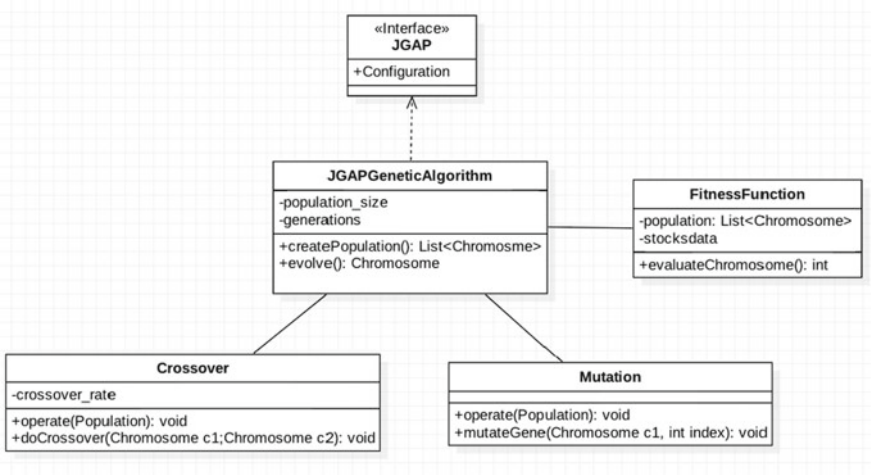

Fig. 3.14 UML class diagram of GA

and specifications (operations restrictions described in Sect. 3.3) of our approach, as illustrated in Fig. 3.14 where only the main attributes and methods are presented.

The Trading Algorithm module begins by receiving the input data from the user and then obtains the historical prices of the stocks for a certain period of time, through Financial Data module that will be described later. After that, uses the Genetic Algorithm module to create several investment strategies that will be applied to the historical prices of stocks, which are divided into smaller time series, where each is represented by a sequence of characters, using the Time series representation module, and then the distance between them and the patterns sequence of characters is calculated to generate investment decisions. After that, the best chromosomes (investment strategies) of the training period are tested in other period, using the same method, and the results are written in txt files. The difference in this test phase is that only the best chromosomes are tested instead of the whole population in the training phase. All this process is illustrated in Fig. 3.15.

3.4.3 Financial Data

This module is responsible for the financial data that is used by the Trading Algorithm module to identify patterns. In this module, it is possible to obtain the historical prices of a financial asset as well as save and update this data, in .csv format files. The data of the financial assets are obtained through Yahoo Finance platform, where it is possible to obtain the opening price, the closing price, the maximum price, the minimum price, and also the volume for each day of a period of time. The data is downloaded from

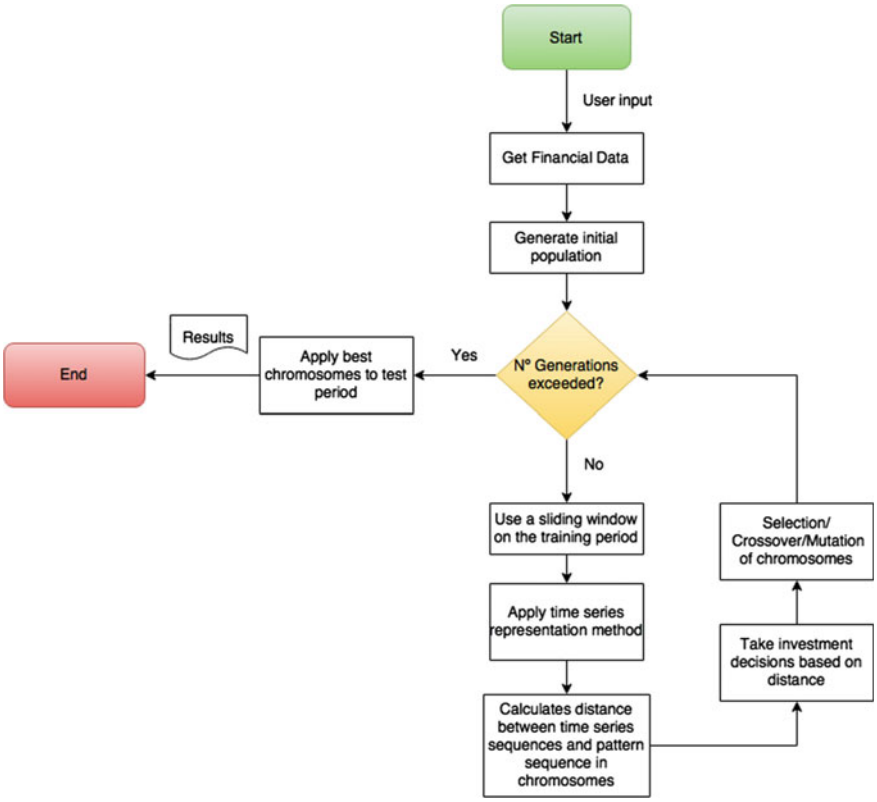

Fig. 3.15 Flow chart of Trading Algorithm module

the platform in .csv format files. In Fig. 3.16 it is possible to observe the structure of the data files of each financial asset.

Due to the fact that it is possible to have stock splits, i.e., the division of the existing shares of a company into multiple shares which means that each pre-split share has the same value of 2, 3, or 4 new shares, and also the opposite reverse stock splits, in the financial assets it is necessary to make a price per share adjustment in order to avoid irregularities in data that can generate false buy/sell signals. The Yahoo Finance platform provides, through column "Adj Close" in Fig. 3.16, the daily closing prices adjusted to these two factors, which are the prices used in the Trading Algorithm module, and is one of the main reasons why this platform was chosen to obtain the data.

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Date,Open,High,Low,Close,Volume,Adj Close
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2016-03-03,100.580002,101.709999,100.449997,101.50,36792200,101.50
2016-03-02,100.510002,100.889999,99.639999,100.75,33084900,100.75
2016-03-01,97.650002,100.769997,97.419998,100.529999,50153900,100.529999
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2016-02-12,94.190002,94.50,93.010002,93.989998,40121700,93.989998
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Fig. 3.16 Data Structure

Reference

1. Leitão, J., Neves, R.F., Horta, N.: Combining rules between PIPs and SAX to identify patterns in financial markets. Expert Systems with Applications, vol. 65, pp. 242–254. Reprinted with permission from Elsevier (2016)

Chapter 4
Experiments and Results

Abstract In this chapter the experiments and the results of the SIR/GA approach, presented in the previous chapter, are described. Firstly in Sect. 4.1, the metrics used to evaluate the SIR/GA approach are presented and then in Sect. 4.2 three different case studies on the application of the proposed solution are presented.

4.1 Evaluation Metrics

To evaluate this research, in order to realize if the proposed solution creates additional value for the decision-making moment (buy/sell) in financial markets, the metrics used were:

- Return On Investment (ROI);
- Total number of operations/trades;
- Success rate of operations (nº of success operations/nº of total operations);
- Average time in the market;

The Return On Investment (ROI) measures the amount of return (positive or negative) of an investment according to the cost of that investment. It is used to evaluate the efficiency of an investment and its formula is expressed in (4.1).

$$\text{ROI}(\%) = \frac{(\text{Gain from Investment} - \text{Cost of Investment})}{\text{Cost of Investment}} \times 100 \tag{4.1}$$

These metrics will be used in all the investment strategies. The ROI will be compared with the return of the Buy&Hold strategy, where its plan is to buy stocks and hold them for a long period of time, regardless of fluctuations in the market. This strategy is used as reference in the Market Efficient Hypothesis [1] that states that it is impossible to beat the market using any kind of studies or analysis because all the relevant information is always incorporated in the share prices, i.e. the prices already reflect the intrinsic value of the stocks. According to this theory, it is impossible for investors to buy undervalued stocks or sell overvalued stocks in the market.

J. Leitão et al., *Identifying Patterns in Financial Markets*, SpringerBriefs
in Computational Intelligence, https://doi.org/10.1007/978-3-319-70160-8_4

Fig. 4.1 S&P500 chart for the period 2010–2014

4.2 Case Studies

In this section three case studies are presented, where all were tested with 422 stocks of the S&P500 index. The program was tested with real market conditions with the close prices of the stocks. The daily close prices were obtained in Yahoo Finance platform from 2010 to 2014, which is a period defined as a bull market where prices rose sharply, as can be seen in Fig. 4.1. In the first two case studies the training and testing periods were the same but in the third study the periods were different in order to test the program in different situations.

4.2.1 Case Study nº1

In this case study, the goal was to simulate a real life scenario, where the solutions were trained in one year and then the best ones were tested in the next year, in order to assure that the solutions that are tested don't know the market behaviour in that year and also to assure that the algorithm is tested in distinct periods of time. All the operations that were closed in the end of each year without being by the exit method of its investment strategy start the next year opened in order to be closed by its exit method. Of the 4 testing years, the only where this did not happen was 2011 because it is the first and there is no year before.

The GA parameters used were an initial population of 128 individuals and 50 generations as stop criteria. The tests were repeated for 5 runs in each year and the chromosome used was the one in Fig. 3.8. The results are represented in Table 4.1, which are the average of the 5 runs in each year of testing. The average SIR/GA and the best SIR/GA results were compared with the Buy&Hold strategy in terms of return for the same period, Fig. 4.2.

As can be seen in Table 4.1 the average return in each year was higher than the return of the Buy&Hold strategy. The years with the highest difference, in average

Table 4.1 Results of the average investment strategies in each year

Year	nº operations	Success rate (%)	Average days in the market	SIR/GA return			B&H return (%)
				Worst (%)	Average (%)	Best (%)	
2011	34	61.76	39	0.73	5.91	14.81	0.00
2012	34	61.27	43	3.18	15.19	31.47	13.41
2013	18	73.40	78	22.15	29.05	41.22	26.39
2014	12	70.31	103	3.83	17.88	27.76	12.39

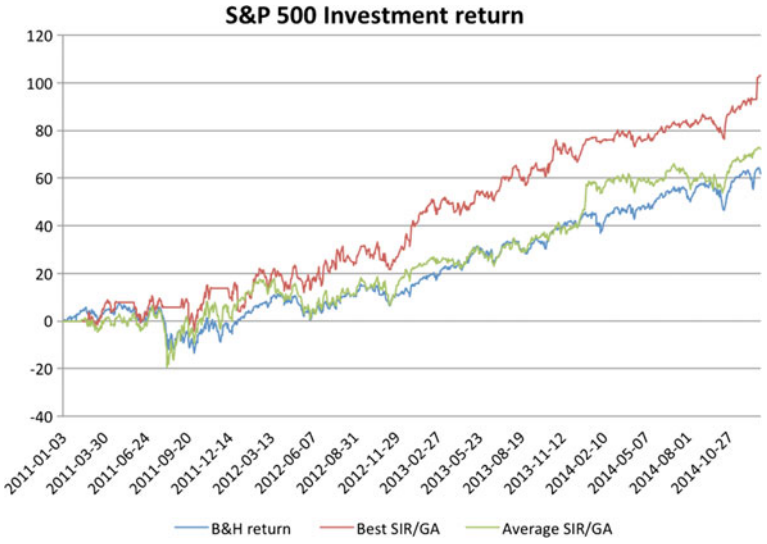


Fig. 4.2 S&P500 return of different strategies compared with B&H [2]

return to the Buy&Hold strategy were 2011 and 2014, 5.91 and 5.49% respectively, and the year with the lowest difference was 2012, 1,78%. The success rate of operations was always higher than 60%, where the highest percentage was 73.40% in 2013, and the lowest was 61.27% in 2012. The total average return for the 4 years was 72.18%, which outperformed the return of the B&H strategy (61.9%).

First Year—2011

This year was the worst of the testing period for S&P500 index, where the total return was approximately 0.00%. In this year the prices followed a sideways movement as illustrated in Fig. 4.3.

The investment strategy, which obtained the best result in this year, 14.81% of return, is represented in Fig. 40. The exit method used was by time, where the hold

Fig. 4.3 S&P500 index performance in 2011

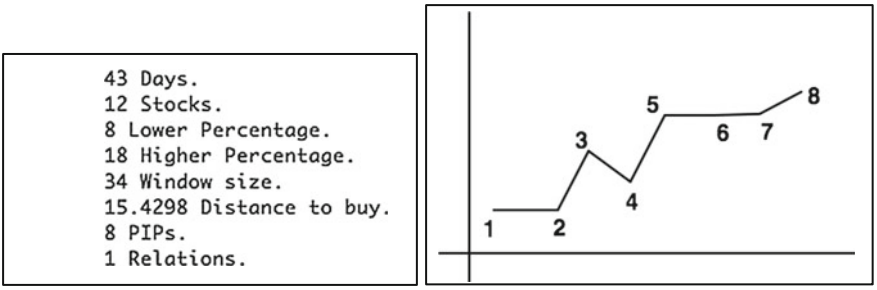


Fig. 4.4 Buy/sell rules and the pattern of the investment strategy with best result in 2011

period to close the operations was 43 days and the time series had a size of 34 days. This investment strategy used 8 PIPs and a limit of relations between them of 1, therefore the rules created were only between adjacent PIPs. The pattern used in this investment strategy looks for periods where there are bottoms (points 1 and 2) that are followed by an upward movement of prices (points 4–8). A possible representation of this pattern can be seen in Fig. 4.4.

In Fig. 4.5 it is possible to observe a real example where the pattern of this investment strategy was identified. This time series is from NBR stock in the period 03/01/2011–18/02/2011 (34 days) and is represented by its PIPs (points between black lines), which are similar to the pattern represented in Fig. 4.4. This time series like the pattern starts with a bottom that is followed by an upward movement of prices.

After the identification of the pattern in this time series, 312 shares of NBR were bought in the day after, 22nd of February, 2011, where each cost 26.48$. After that, using the exit/sell method of the investment strategy, the shares were sold 43 days after on April 25, 2011 at a price per share of 30.18$ which made a profit of 3.7$ per share and a return of 13.97% of the buying price, as illustrated in Fig. 4.6.

Fig. 4.5 NBR stock time series identified as a pattern

Fig. 4.6 Example of pattern identification and investment rule for NBR stock

Second Year—2012

In this year the total return of the S&P500 index was about 13.41%, which means the prices increased over the year, despite a significant decrease in May, as can be seen in Fig. 4.7.

The investment strategy, which obtained the best result in this year, 31.47% of return, is represented in Fig. 4.8. The exit method was defined by a combination of price and pattern. In the case of the exit by price the operations were closed with profit when the price reached 9.62% over the buying price and with loss when the price reached −10.47% over the buying price. In the case of the exit by pattern the time series after the buy order that were compared with the uptrend pattern, had a length of 51 days. The operations were closed 37 times by price and 17 times by pattern with this investment strategy.

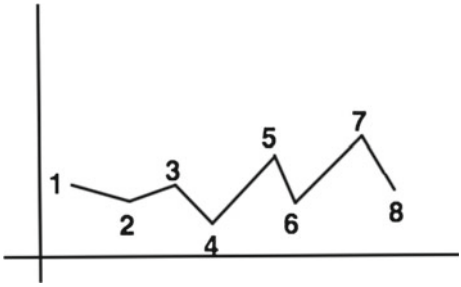
The pattern used in this strategy is represented in Fig. 4.9. This pattern represents a slight upward movement of prices where each successive peak (points 3, 5 and 7) and trough (points 4, 6 and 8) is higher.

Fig. 4.7 S&P500 index performance in 2012

```
9.62 TakeProfit and -10.47 StopLoss with 51 Uptrend Pattern Days.
14 Stocks.
8 Lower Percentage.
14 Higher Percentage.
38 Window size.
36.2922 Distance to buy.
8 PIPs.
3 Relations.
```

Fig. 4.8 Buy and sell rules of the investment strategy with best result in 2012

Fig. 4.9 Pattern of the investment strategy of 2012



In Fig. 4.10 it is represented an example of a pattern identification using this investment strategy. This time series is from CBG stock in the period 02/01/2012–27/02/2012 and, as can be seen, its PIPs are similar to the PIPs of the pattern in Fig. 4.9, where the main difference is the amplitude of the last peak that should be higher than the previous one, which is one of the reasons for the distance between the sequences of characters of the time series and of the pattern was 19.365.

After the identification of the pattern, 471 shares of CBG were bought at a price of 18.15$ each, in 28th of February 2012. In this operation the exit/sell method used was by price, where the take profit level was approximately 19.89$ (+9.62% of buying price) and the stop loss level was approximately 15.48$ (−10.47% of buying price). The operation was closed in 13rd of March 2012, which was the first day that the price exceed one of the levels, which in this case was the take profit (20.58$) as can be

Fig. 4.10 CBG stock time series identified as a pattern

Fig. 4.11 Example of pattern identification and investment rule for CBG stock

seen in Fig. 4.11. In this investment strategy, the take profit level was slightly lower than the stop loss, which is unusual, but in this case the majority of the operations closed by price where closed by the take profit level which is one of the reasons to the good result of this strategy.

Third Year—2013

This was the best year of the S&P500 index for the period under study, which obtained a return of approximately 26.39%. In this year, as can be seen in Fig. 4.12, the prices followed a continuous upward movement.

The best investment strategy obtained a return of 41.22%, and is represented in Fig. 4.13. This strategy used the exit by pattern to define the closing point, where the time series compared to the uptrend pattern had a length of 128 days and were identified by 6 PIPs with a maximum limit of relations of 3. The limit of distance used to identified as an uptrend pattern was 18.0629, which was also used to identified the pattern in Fig. 4.13 in the time series and generate buying orders.

An approximate representation of pattern used in this strategy, Fig. 4.13, is similar to the well-known Double Bottom pattern where the point 2 defines the first bottom

Fig. 4.12 S&P500 index performance in 2013

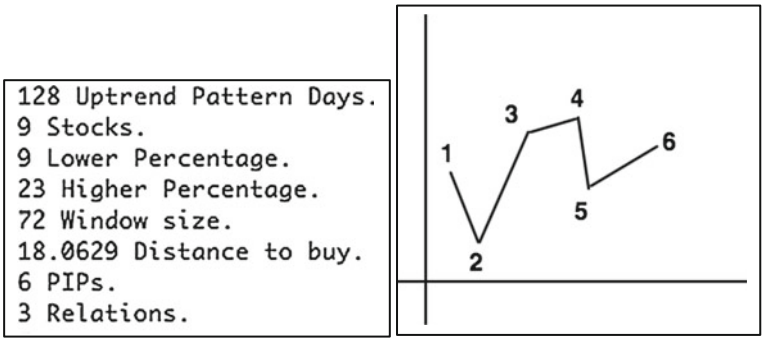


Fig. 4.13 Buy/sell rules and the pattern of the investment strategy with best result in 2013

and the point 5 the second bottom. This pattern normally signals a reversal of the downtrend into an uptrend. The pattern of Fig. 4.13 could also be seen as an upward movement of prices where the second trough (point 5) is higher than the first (point 2).

In Fig. 4.14 is illustrated an example of a time series from SLM stock that was identified as a pattern. This time series has a length of 72 days and is more similar to the second possible view of the pattern of Fig. 4.13, which is defined by an upward movement with two successive troughs, where the second is higher than the first.

After the identification of the pattern in the time series 1764 shares of SLM were bought in the day after. Using the exit/sell method of the investment strategy to close this operation, the time series subsequent to the buying order, with a length of 128 days, was represented by a sequence of characters (defined by its PIPs and rules) and then compared with the sequence of characters "C" with the same length in order to identify the uptrend pattern. In this case the uptrend pattern was not identified in the time series because the distance between them was greater than 18.0629 which can be justified by the sequence of characters of this time series (red string in Fig. 4.15), which is composed by several characters "M" that represent a sideways movement

Fig. 4.14 SLM stock time series identified as a pattern

Fig. 4.15 Example of pattern identification and investment rule for SLM stock

and not a increase of prices. So, the shares of SLM were sold and the operation was closed. This process is illustrated in Fig. 4.15.

Fourth Year—2014

In Fig. 4.16 it is represented the performance of the S&P500 index for this year. An upward movement of prices characterized this year, despite of having some bottoms. The return in this year was approximately 12.39%.

In this year the best investment strategy obtained a return of 27.76%, Fig. 4.17. The time series of 40 days were represented by 10 PIPs and the rules were created only between adjacent PIPs. The exit method used was a combination between time and price, where the holding period until the selling order was 68 days and the positive limit, *take profit*, was much higher than the negative limit, *stop loss*, which allows the operations to be closed or with high profits or with small losses. The operations were closed 11 times by time and 6 times by price.

In Fig. 4.18 is illustrated a possible representation of the pattern used in this strategy, which starts with an uptrend (points 1, 2 and 3) that is followed by a downward

Fig. 4.16 S&P500 index performance in 2014

```
68 Days to Sell with 48.2931 TakeProfit and -9.7409 StopLoss
7 Stocks.
6 Lower Percentage.
18 Higher Percentage.
40 Window size.
18.9016 Distance to buy.
10 PIPs.
1 Relations.
```

Fig. 4.17 Buy and sell rules of the investment strategy with best result in 2014

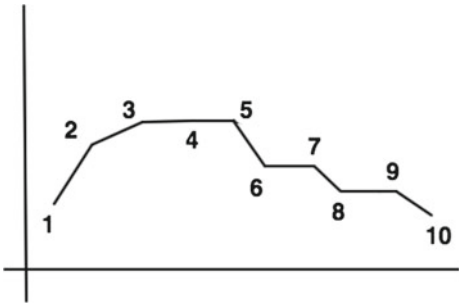


Fig. 4.18 Pattern of the investment strategy of 2014

trend (from point 5 to point 10), where each successive peak and trough is lower. Although this pattern is characterized by a downtrend instead of an uptrend like the patterns of the previous years, it allowed finding bottoms that were followed by an increase of prices, which originated the good performance of this strategy.

A real example of the identification of this pattern is illustrated in Fig. 4.19 for a time series of GOOGL stock in the period 03/03/2014–28/04/2014. This time series, represented by its PIPs (black line), has some differences to the pattern of Fig. 4.18

Fig. 4.19 GOOGL stock time series identified as a pattern

Fig. 4.20 Example of pattern identification and investment rule for GOOGL stock

but the main characteristics are similar, it starts by an upward movement that is reverse to a downward movement of price.

After the identification of the pattern, 24 shares of GOOGL were bought. Using the exit/sell method of the investment strategy, which was time and price, the method used in this case was the exit by time, where the holding period until the sell order was 68 days, so the shares were sold in 5th of August 2014 with a return of 6.86% of the buying price, as illustrated in Fig. 4.20.

4.2.2 Case Study nº2

In this case study, the goal was to simulate the previous case study with all the same conditions but the exit method used in all the investment strategies would be only

Table 4.2 Results of the average investment strategies in each year

Year	nº operations	Success rate (%)	Average days in the market	SIR/GA return			B&H return (%)
				Worst (%)	Average (%)	Best (%)	
2011	28	62.14	40	8.76	11.78	16.89	0.00
2012	23	62.93	65	9.27	19.06	44.16	13.41
2013	8	85.29	137	22.76	27.52	34.10	26.39
2014	11	66.07	105	8.98	17.92	25.23	12.39

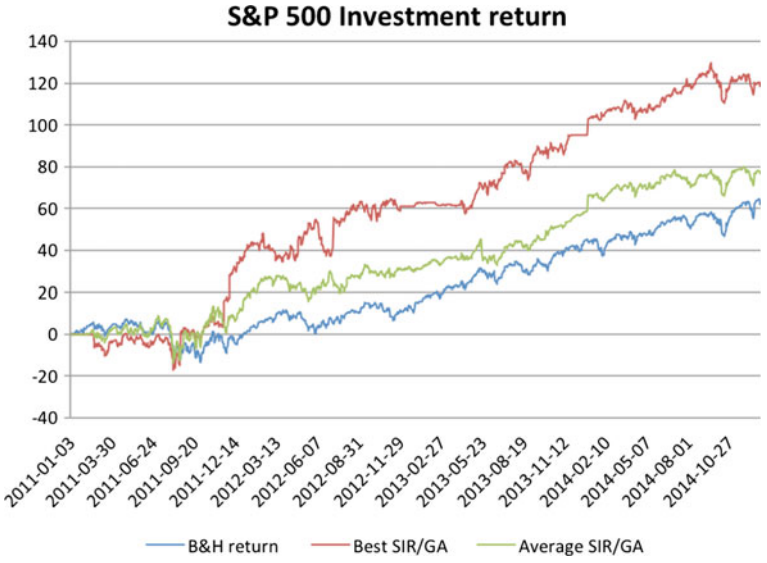


Fig. 4.21 S&P500 return of different strategies compared with B&H

the exit by pattern in order to prove the capability and strength of this type of exit method in a bull market.

In Table 4.2 are represented the average results of the 5 investment strategies in each year. The average SIR/GA results and the best SIR/GA results in each year were compared with the B&H strategy in terms of total return, Fig. 4.21.

As can be seen in Table 4.2, the average return in each year outperformed the return of the B&H strategy, where the first year (2011) was by far and away the highest in difference between the average and the B&H return (11.78%) and the 2013 year was the lowest in difference (1.13%). Comparing the average return of this case study with the average return of the previous case in each year, Table 4.3, it's possible to observe that the results were better in all years, except in 2013 where the return was slightly lower. This proves the capacity and the strength of the exit

Table 4.3 Comparison between results of the two cases studies

Year	Case study nº1 SIR/GA average return (%)	Case study nº2 SIR/GA average return (%)	Case study nº2 X Case study nº1
2011	5.91	11.78	Better
2012	15.19	19.06	Better
2013	29.05	27.52	Worst
2014	17.88	17.92	Better

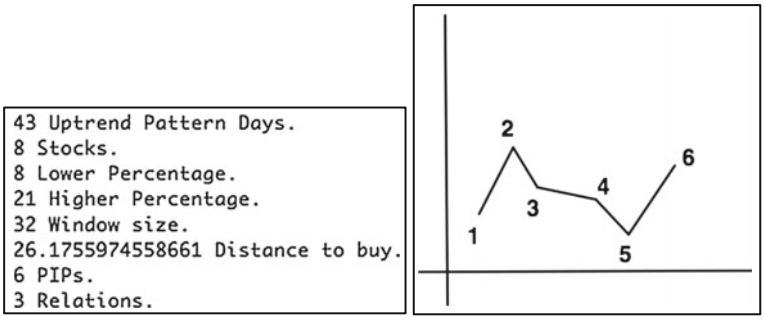


Fig. 4.22 Buy/sell rules and the pattern of the investment strategy with best result in 2011

by pattern to obtain good results in a bull market. The total average return for the 4 years was 76.7%, which outperformed the return of the B&H strategy (61.9%) and also the total return of case study nº1 (72.18%).

First Year—2011

The investment strategy, which obtained the best result in this year, 16.89% of total return, is represented in Fig. 4.22. The time series used to identify the uptrend pattern in the exit by pattern had a length of 43 days and where represented by 6 PIPs and 3 relations between them. The pattern used by this strategy has a peak (point 2) followed by a trough (point 5) that is followed by an upward movement, which is expected to originate an increase of prices.

In Fig. 4.23 a real example of the pattern identification by this investment strategy is illustrated. This time series is from JBL stock in the period 03/01/2011–16/02/2011 (32 days) and its representation by PIPs (black line) is similar to the pattern of the best investment strategy of this year (Fig. 58), which has a peak followed by trough that is followed by a significant increase of prices.

Second Year—2012

In 2012 the best investment strategy, which obtained 44.16%, Fig. 4.24, used 53 days as sliding window to identify the uptrend pattern in the time series and 50 days to identify the pattern of Fig. 4.24 in order to generate buying orders. This pattern is

Fig. 4.23 JBL stock time series identified as a pattern

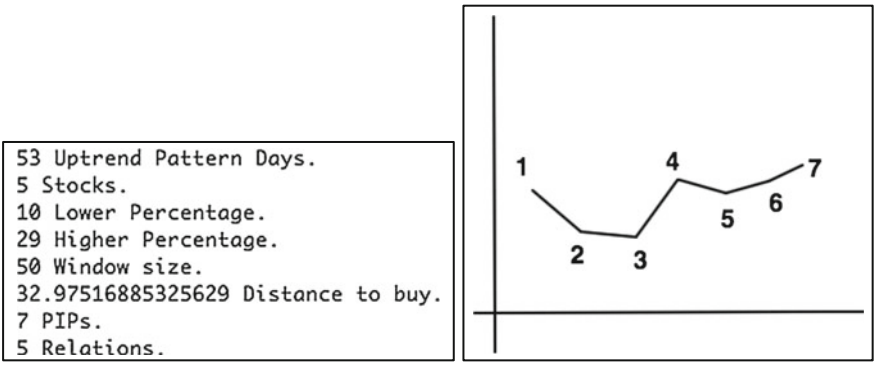


Fig. 4.24 Buy/sell rules and the pattern of the investment strategy with best result in 2012

defined with two successive bottoms (points 2 and 3; points 4, 5 and 6), where the second is higher than the first, which represents an upward trend.

A similar representation of this pattern in a time series is illustrated in Fig. 4.25 (black line). This is an example of the pattern identification by this investment strategy in a time series of the CME stock for the period 03/01/2012–14/03/2012 (50 days).

Third Year—2013

In 2013 the best strategy obtained a total return of 34.10% and is represented in Fig. 4.26. In this year the number of operations was the lowest in all the period, due to the high length of days of the sliding window of the investment strategies in this year, which in this case was 66 days and consequently in the time series that were used to identify with the uptrend pattern, which in this case was 94 days. The pattern used in this investment strategy is almost the reverse of the pattern used in 2011 (Fig. 4.22), which contains a trough (point 2) followed by a peak (point 6) and then a decrease of prices.

A real example of this pattern in a time series is illustrated in Fig. 4.27. This time series is from ADI stock for the period of 02/01/2013–05/04/2013 (66 days) and

Fig. 4.25 CME stock time series identified as a pattern

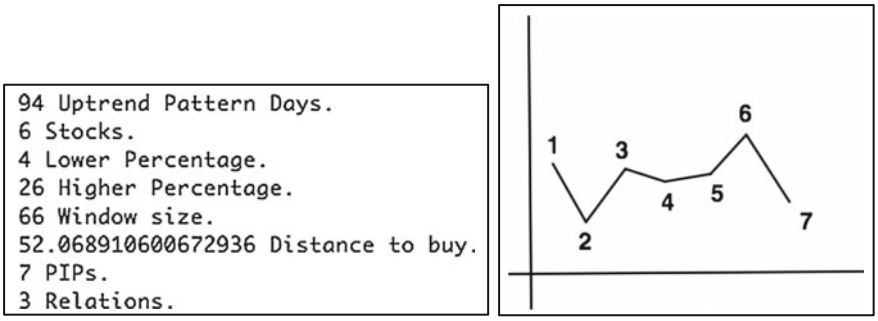


Fig. 4.26 Buy/sell rules and the pattern of the investment strategy with best result in 2013

its representation (black line) is similar to the pattern of Fig. 4.26, where the main difference is that the second peak is lower than the first and should be the opposite to be equal to the pattern.

Fourth Year—2014

In the last year, the best strategy, which obtained 25.23% in total return, is represented in Fig. 4.28. In this case the length of the time series used in the exit by pattern was 63 days and they were represented by 8 PIPs and a limit of 2 relations between PIPs. The pattern identified in the time series is characterized by a slight increase between points 1 and 8, as illustrated in Fig. 4.28.

In Fig. 4.29 is illustrated a case of a pattern identification by this investment strategy, in a time series of MTW stock from 11th of March 2014 to 15th of May 2014. The shape of this time series, represented by its PIPs, is similar to the pattern despite the time series have a slight decrease of prices in the end.

Fig. 4.27 ADI stock time series identified as a pattern

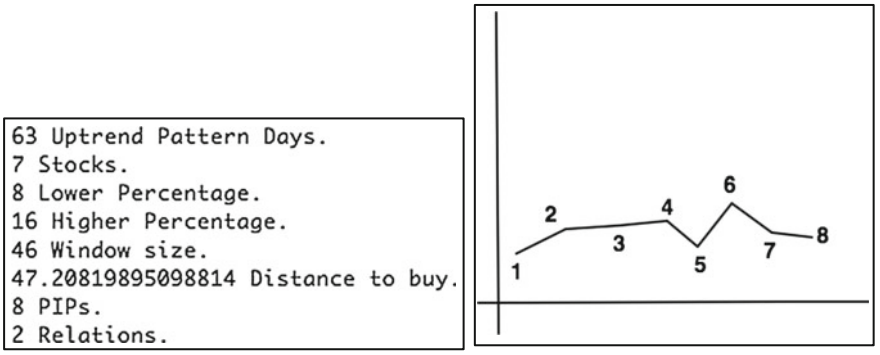


Fig. 4.28 Buy/sell rules and the pattern of the investment strategy with best result in 2014

Fig. 4.29 MTW stock time series identified as a pattern

Table 4.4 Average results of the 5 investment strategies

Period	nº operations	Success rate	Average days in the market	SIR/GA return			B&H return
				Worst	Average	Best	
2012/2014	86	68.84%	59	59.74%	78.45%	111.75%	61.91%

4.2.3 Case Study nº3

In the previous case studies, the period of training and testing was always 1 year, which is a small period of time to obtain investment strategies that can outperform constantly the market in longer periods of time. So, in this case study the goal was to expand the period of training of the previous case study in order to obtain more robust solutions and test them in consecutive years. For that reason, the period of training was 2010–2011 (2 years) and the five best solutions were tested in 2012–2014 (3 years). The tests were repeated 5 runs in the training period and then each of them was tested in the period of test. The GA parameters were the same of the previous case study, 128 individuals and 50 generations as stop criteria. The parameters optimized by the GA were the ones of the chromosome of Fig. 3.8.

The results are represented in Table 4.4, which are the average of the 5 runs for the period. The results like in the previous case studies were compared with the Buy&Hold strategy. The total average return of the investment strategies was higher than the return of Buy&Hold strategy in 17.23%, where the best strategy almost obtained the double (111.75%) of the Buy&Hold total return (61.91%).

In Table 4.5, are represented the individual results of each strategy. For each investment strategy the number of times each exit/sell method was used is presented, where the remaining times were closed by the end of the period. The total return of the first strategy was by far and away the highest with a result of 111.75%. The worst strategy in terms of total return was the third with 59.74% but with the second highest success rate of operations. The lowest success rate was 50% of the fifth strategy, which obtained the second best total return and the highest average days in the market. The second strategy was the highest in number of operations (188) and at the same time the highest in success rate with 72.87%.

In Fig. 4.30 it is possible to observe the total return over the period 2012–2014 of the best SIR/GA strategy and the average of the SIR/GA strategies that are compared with the Buy&Hold strategy. As can be seen in Fig. 4.30 the investment strategies, the best and the average, start to increase more significantly than the B&H strategy in the middle of the period (around August 2013) and continue to outperform the B&H until the end of the period.

In Fig. 4.31 is represented the best strategy for this period and its pattern, which obtained a total return of 111.75%. The exit method used by this investment strategy was by pattern, which proves again the capacity of this exit method to obtain good

Table 4.5 Results of each of the 5 investment strategies

Strategy	nº operations	nº operations closed			Success rate (%)	Average days in the market	SIR/GA return (%)
		Time	Price	Pattern			
1	83	–	–	81	69.88	31	111.75
2	188	71	105	–	72.87	36	69.28
3	55	19	–	31	70.91	58	59.74
4	54	48	–	–	68.52	75	68.37
5	50	–	–	43	50	99	83.11

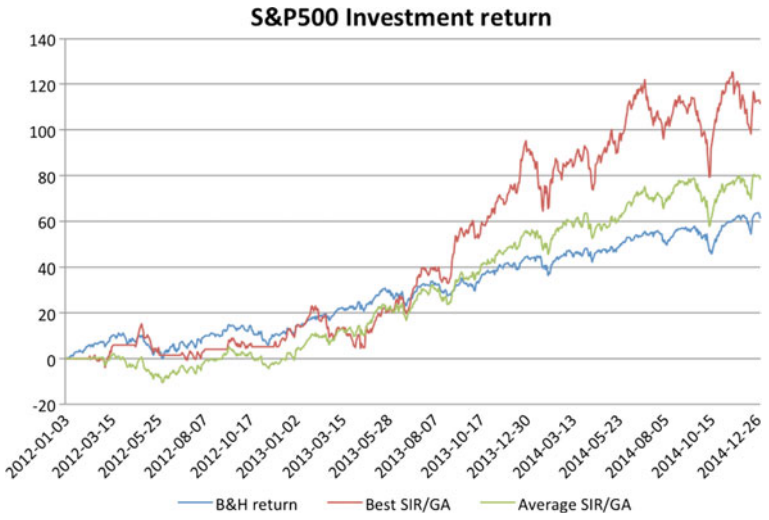


Fig. 4.30 S&P500 return of different strategies compared with B&H strategy

results in bull markets. The time series that were compared with the uptrend pattern had a length of 26 days. The time series were represented by 6 PIPs and the maximum limit of relations was 3. The pattern of this investment strategy is very similar to the Double Top pattern (Fig. 2.12 right), which is very curious due to the fact that the Double Top is a bearish pattern but in this investment strategy the pattern was successfully used in a bull market because it was used to find bottoms that were followed by upward movements.

In Fig. 4.32 it is possible to observe a real example where the pattern of this investment strategy was identified. This time series is from AKS stock in the period 12/09/2013–16/10/2013 (25 days) and is represented by its PIPs (black line), which are very identical to the pattern represented in Fig. 4.31. This time series like the pattern is characterized by two successive peaks and is similar to the Double Top pattern despite the second peak is lower than the first.

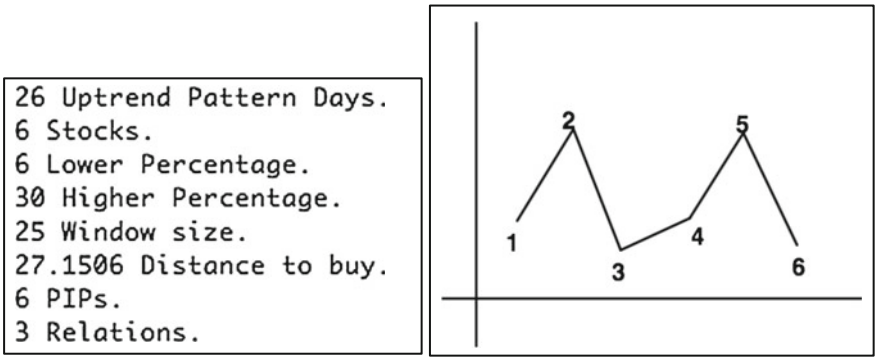


Fig. 4.31 Buy/Sell rules and the pattern of the investment strategy with best result in 2012, 2014

Fig. 4.32 AKS stock time series identified as a pattern

In Fig. 4.33 is illustrated the closing process of this example. After the identification of the pattern in the time series 7256 shares of AKS were bought in the day after that was 17th of October 2013. After that, using the exit/sell method of the investment strategy to close this operation, the time series subsequent to the buying order, with a length of 26 days, was represented by a sequence of characters (defined by its PIPs and rules through the method of Sect. 3.1) and then compared with the sequence of characters "C" with the same length in order to identify the uptrend pattern in this time series. This comparison resulted in the identification of the uptrend pattern in the time series, which can be observed by the shape of this time series (red line of first time series). For that reason, the process was repeated for next subsequent time series, and this time series was also identified as an uptrend pattern due to the fact that its shape is characterized by a upward movement (red line of second time series), so the process was repeated for the third subsequent time series. In this case the uptrend pattern was not identified in the time series because the distance between its sequence of characters and the sequence of characters "C" was greater than 27.1506, which can be observed by the shape of this time series (red line of third time series)

Fig. 4.33 Example of pattern identification and investment rule for AKS stock

that is a defined by a decrease of prices. For that reason, the shares of AKS were sold and the operation was closed in the day after of 3rd subsequent time series (11th of February 2014). This operation obtained a return of 59.66% of the buying price.

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Chapter 5
Conclusions and Future Work

Abstract This chapter summarizes the main features of the new approach described and developed in this work, and also the goals achieved. Also, several topics are raised for a future improvement on this work.

The new approach described and implemented, which was built on the definition of rules based on PIPs, SAX representation, and an optimization algorithm (GA), showed good potential on the stock market. The identification of PIPs allowed a huge dimensional reduction of the time series and, at the same time, maintained the main characteristics of its data. The creation of rules allowed the specific definition of relationships between the PIPs identified in time series. The mapping between rules and characters allowed the distinction of the different types of trends between the PIPs of time series and also allowed the representation of time series by a sequence of characters, which facilitated the identification of patterns. The GA allowed a huge flexibility of solutions and also allowed to define and identify several patterns with different sizes. This optimization algorithm has shown to be an excellent technique to find good solutions for this kind of problems.

The solution was tested with real data from S&P 500 index for the period 2010–2014, which is defined as a bull market where the prices increase over the time. In order to validate this approach, all the test results were compared with the Buy and Hold strategy, where the results of the SIRG/GA approach outperformed the B&H strategy in all case studies. The results proved the ability of this approach to perform well in bull markets. The usage of the exit/sell method by pattern proved to be an excellent option in this type of markets because this method remains in the market whenever the prices are increasing, which is the common trend of prices in this type of markets.

Some planned ideas to future work on this approach, in order to improve its capability, are as follows:

- Test the solution in other markets like European indexes (Euro Stoxx 50, DAX-30, etc.) to create a more robust solution.
- Include several technical indicators like OBV, RSI, etc., to support the decision of buying and selling in the investment strategies.

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- Add to the investment strategies the short operation in order to make the program much more completed for the real-life scenarios and to perform in bear markets too.
- Add an option to find some wanted and well-known patterns like the Double Bottom and Top, Head-and-Shoulders, etc.