Forecasting Directional Changes in Financial Markets

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Abstract: Financial forecasting is an important research area. Most researches in forecasting use time series, which sample market prices at fixed intervals; for example, daily closing prices. Directional Change (DC) is an alternative approach for sampling market price, which records price changes that the observer considers significant. The DC approach aims to capture directions price movements – whether they are on the rise, or in decline. Little forecasting research has been done under the DC framework. In this paper we formulate a forecasting problem under this framework. In particular, we aim to answer the question of whether the current trend (up or down) will continue for a particular percentage (which is decided by the investor) before the trend ends. The success of forecasting depends on the variables that one uses. In this paper, we introduce three independent variables and prove that they are useful for our forecasting problem. We show that these variables can help two forecasting algorithms, namely J48Graft and M5P, to answer the above question. We tested our variables and algorithms in two sets of data, namely gold price and EUR/USD exchange rates. Experimental results suggest that our approach outperforms random forecasting in both data sets; in some cases, forecasting accuracy was over 80%. These results confirm that the independent variables identified are useful for forecasting under the DC framework.

Keywords: Directional changes, forecasting, Aroon indicator, J48Graft, M5P

1. INTRODUCTION

Forecasting financial time series is a very common objective. Many machine learning approaches have been introduced for this purpose, in the majority of cases with focus on stock price prediction. To this end, models have been developed based on Hidden Markov Model (e.g. Hassan & Nath, 2005), Artificial Neural Network (e.g. White, 1988), Support Vector Machine (e.g. Das & Padhy, 2012) and Genetic Programming (e.g. Tsang & Li, 2002; Garcia-Almanza & Tsang, 2011). Hybrid methods merging multiple techniques are also commonly found in the literature. For example, Hassan (2009) combines a HMM with Fuzzy model; Wang and Leu (1996) propose an ARIMA-based Neural Networks model, and Yang, Wu, & Lin (2012) propose a hybrid model that combine Genetic Algorithm with Fuzzy Neural Networks. Iqbal et al. (2013) provide a survey of different state of the art methods used for stock forecasting. Most research in the literature use interval-based data summaries. In other words, they sample market prices at fixed time intervals, let it be days, minutes, etc.

Directional Changes (DC) is an alternative approach to summarize market price movements (Guillaume et al., 1997). Under the DC framework the market is cast into alternating upward trend (which we call uptrend) and downward trends (which we call downtrend) (Tsang, 2010). Here, a trend is identified as a market price's change of a minimum of a given threshold. This threshold, we name it θ, is predefined by the observer; usually expressed as percentage. A trend ends whenever a price change of same threshold, θ, is observed in the opposite direction. For example, a market downtrend ends when we observe a price rise of magnitude θ; in this case we say that the market change its direction to uptrend. Similarly, a market's uptrend ends when we observe a price decline of magnitude θ; in this case we say that the market changes its direction to downtrend (see Fig. 1).

In this paper we formulate a novel forecasting problem under the DC framework. The task is to predict the price at which the trend will reverse. More specifically, we want to forecast whether the current trend (either uptrend or downtrend) will continue in the same direction for a specific percentage

– this percentage is determined by investor. Answering this question is useful for investment decisions; for example, it could help a trader to decide whether to take a long or short position.

Forecasting crucially depends on the variables that one uses. As a first attempt to tackle this forecasting problem, we introduce three independent variables in this paper. We attempt to prove that they are useful for the proposed forecasting problem.

This paper continues as follow: Directional Changes are explained in Section 2. Section 3 provides the formal definition of our objective. In Section 4 we present our approach for forecasting the end of trend. We introduce three independent variables and briefly describe two forecasting algorithms. Section 5 presents details of our experiments in testing our approach. The results are reported in Section 6. The analysis of these findings is discussed in Section 7. We conclude the findings in Section 8.

2. DIRECTIONAL CHANGE (DC)

Directional change (DC) is an alternative way to summarize price changes. In this section, we explain that, while interval-based summarizes sample market prices at fixed intervals, sampling points in directional change summaries are data-driven.

Under the DC framework, the market is divided into alternating uptrends and downtrends. Consider a market in a downtrend. Let P_{EXT} be the lowest price in this downtrend and P_c be the current price. We say that the market switches its direction from a downtrend to an uptrend whenever P_c is greater than the P_{EXT} by at least θ, (θ is the threshold pre-determined by the observer). Similarly, if the market is in an uptrend, P_{EXT} would refer to the highest price in this uptrend. We say that the market switches its direction from an uptrend to a downtrend if P_c is lower than P_{EXT} by at least θ.

Each trend is composed of a DC event and an overshoot event (see Fig. 1). Formally, a DC event is detected when we come across a price P_c that satisfies condition (1). If condition (1) holds, then the time at which the market traded at P_{EXT} is called an 'extreme point' (e.g. points A and C in Fig. 1), and the time at which the market trades at P_c is called a 'DC confirmation point' (e.g. points B and D in Fig. 1). Note that an extreme point is the end of one trend and it's also the start of the next trend which has an opposite direction. The extreme point is only recognized in hindsight – it is recognized precisely at the DC confirmation point.

$$\left| \frac{P_c - P_{EXT}}{P_{EXT}} \right| \geq \theta \tag{1}$$

A DC event starts with an extreme point and ends with a DC confirmation point. An overshoot event (OS event) starts at the DC confirmation point and ends at the next extreme point. A pseudo-code for defining DC events corresponding to a predetermined threshold θ can be found in (Glattfelder, Dupuis, & Olsen, 2011).

It is worth reiterating that we only know the market has changed direction in hindsight; we only detect a DC event when a DC confirmation point is observed. The question is: could one forecast when the next DC event will take place? In this paper, we formulate a forecasting problem based on the DC concept. Given a threshold θ, the task is to forecast, at the DC confirmation point, whether the trend will change at a certain price.
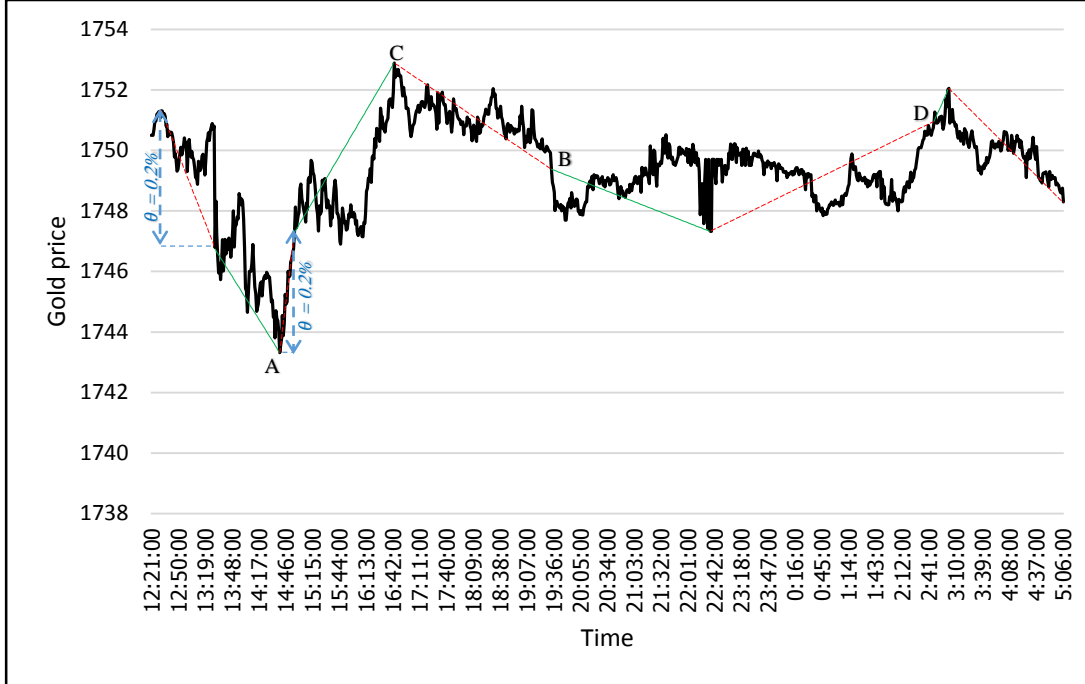
Fig. 1: DC-based summary. The black line indicates minute-by-minute gold prices sampled from17/10/2012 12:09:00 PM to 18/10/2012 5:07:00 AM (UK time). The dashed red lines indicate Directional Change (DC) events with $\theta = 0.2\%$ and green lines indicate Overshoot (OS) events.

Before we continue, we refer to other studies that have shown that the concept of DC helps us to understand financial markets. For example, Masry (2013) presents a study that deciphers FX market activity based on the DC concept. Her approach lays *"the foundations for understanding how FX market activity changes as the price movement progresses"* (Masry, 2013, page 3) and explains how minor differences of market activities can change the price trend under definite conditions. In addition, Bisig, Dupuis, Impagliazzo & Olsen (2012) define the so-called Scale of Market Quakes (SMQ) based on the DC concept. SMQ aims at quantifying the FX market activity at main economic and political events declarations. Furthermore, Glattfelder, Dupuis & Olsen (2011) discover scaling laws which unveil new characteristics in FX market. Many of these scaling laws are based on the DC concept. Finally, Dupuis & Olsen (2012) provide an example of how to make benefit of the DC concept in a High Frequency Trading (HFT) model.

Finally, we should note that DC as described in this paper (based on Guillaume et al., 1997) is completely different from both the "Direction-of-Change" concept in (Skabar, 2008) and the "Change Direction" concept in (Park, Lee, Song, & Park, 2009). They both used interval-based datasets (daily close value); neither a threshold θ was used, nor DC event was defined. Instead they tried to forecast when a given stock index will switch its trend direction (upward or downward) at daily closing price without measuring the magnitude of price's change. Their models aimed to answer the question: "will today's close price extend yesterday's trend?"

3. PROBLEM FORMULATION

In this section, we formally specify a forecasting problem under the DC framework. To help us explain the formulation, we summarize the major variables and their notations used in this paper in Table 1. The main variables in our analysis are θ, P_{EXT}, OSV_{OS}, P_{DCC^*}, and OSV_{EXT}. A pseudo code for computing these variables, for each trend, is given in Appendix A.

3

Table 1: List of notations used in this paper.

Name / Description	Notation
Threshold	θ
Current price	P_c
Price at extreme point: price at which one trend ends and a new trend starts (e.g. points *A, C* in Fig. 1)	P_{EXT}
Lowest price at an uptrend DC confirmation point: The least price change required at a downtrend to confirm that direction has changed to an uptrend	$P_{DCC^*} = P_{EXT} \times (1 + \theta)$
Highest price at a downtrend DC confirmation point: The least price change required at an uptrend to confirm that direction has changed to a downtrend	$P_{DCC^*} = P_{EXT} \times (1 - \theta)$
Overshoot value (OSV) at any point: • At the DC confirmation point (e.g. point *B, D* in Fig. 1) we name it OSV_{OS} • At the end of an OS event (e.g. points *A, C* in Fig. 1) we name it OSV_{EXT}	$OSV = ((P_c - P_{DCC^*}) \div P_{DCC^*}) \div \theta$

We stipulate that the ith trend starts at P_{EXT}^i and ends at P_{EXT}^{i+1}. We denote the OSV at P_{EXT}^{i+1} with OSV_{EXT}^i because it is computed at the end of the OS event of the ith trend (not the $(i+1)^{\text{th}}$ trend).

Clearly, there is a lot of incentive to predict P_{EXT}^{i+1}. In this paper, we choose to forecast on OSV_{EXT}^i. The attractiveness of forecasting OSV_{EXT}^i instead of P_{EXT}^{i+1} is that the former is a relative value (relative to θ, which is the user's measure of significance) while the latter is an absolute value. Relative values are comparable between series. By forecasting OSV_{EXT}^i, we are effectively forecasting P_{EXT}^{i+1} because:

$$P_{EXT}^{i+1} = P_{DCC^*}^i \times (1 + OSV_{EXT}^i \times \theta) \tag{2}$$

We adopt the following notation throughout this paper: we use OSV_{EXT} to denote the vector containing all OSV_{EXT}^i for all the trends. The same convention applies to other variables P_{EXT}, OSV_{OS}, and P_{DCC^*}. It is worth reiterating that directional changes can only be confirmed in hindsight. Therefore, at the DC confirmation point of ith trend we can compute $P_{DCC^*}^i$ but not OSV_{EXT}^i, hence the above forecasting problem.

We formulate the problem as a Boolean forecasting problem. At the DC confirmation point of the ith trend, we would like to predict whether $OSV_{EXT}^i < d$ for a constant d. Note that based on Equation (2) we can deduce rule (3):

$$if \left(OSV_{EXT}^i < d\right), then \ P_{EXT}^{i+1} < P_{DCC^*}^i \times (1 + d \times \theta) \tag{3}$$

In addition, if we replace OSV_{EXT}^i with d in Equation (2), then we can obtain Equation (4):

$$((P_{EXT}^{i+1} - P_{DCC^*}^i) \div P_{DCC^*}^i) = d \times \theta \tag{4}$$

Why is this forecasting problem worth studying? According to Table 1, the price at the ith DC confirmation point is approximately equal to $P_{DCC^*}^i$. Suppose the ith trend is an uptrend (the arguments in a downtrend is similar). If a trader takes a long position at the ith DC confirmation point and closes the position at the forecasted price P_{EXT}^{i+1}, then $d \times \theta$ represents the expected profit (see Equation 4). Hence, the trader can use d to control the profit target.

4. APPROACH TO FORECASTING END OF TREND

In the previous section, we have explained that our task is to predict whether $OSV_{EXT}^i < d$. In this section we provide a novel approach to answer this problem. Note that forecasting OSV_{EXT}^i to be less than d is equivalent to predicting that the current i^{th} trend, assumed to be an uptrend, will reverse at price less than P_{EXT}^{i+1} which is computed according to rule (3) (i.e. we predict that the next DC event will occur before the price reaches $(1 + d \times \theta)$ above the price $P_{DCC^*}^i$ of the current trend). Similar conclusion can be made for a downtrend.

Forecasting is only possible if one can define the target variable which value we attempt to predict. We also need to identify variables that the target variable is dependent on. Therefore, our first

4

challenge is to define a variable that represents the question "is $OSV_{EXT}^i < d$ $True$?". Then we shall introduce variables that could help us to answer this question. Finally, we shall describe two forecasting algorithms for testing the relevance of these variables.

4.1. Chosen variables

We define the Boolean variable $BOSV_{EXT}$ as the target variable in our forecasting problem. Our task is to forecasting whether $BOSV_{EXT}^i$ is $True$ or $False$, as defined in Expression (5). The value of $BOSV_{EXT}^i$ depends on the value of the unknown variable OSV_{EXT}^i and the constant d:

$$(BOSV_{EXT}^i = True) \ if \ and \ only \ if \left(OSV_{EXT}^i < d\right), \ else \ (BOSV_{EXT}^i = False) \tag{5}$$

How could one predict the value of $BOSV_{EXT}^i$? Identifying appropriate independent variables for a given forecasting problem is non-trivial in general. Our task is particularly difficult because existing technical indicators for interval-based summaries are not compatible with the DC framework. For example, Ehlers's leading indicator (ELI) (Ehlers, 2002), Aroon indicator (Chande & Kroll, 1994), Relative Strength Index (RSI) and average directional movement index (ADX) (Wilder, 1978) in their original form cannot be applied to the DC framework, as they assume that data are sampled at fixed intervals. Below we present three variables which could be used to predict the value of $BOSV_{EXT}^i$.

The first two variables derive from the Aroon trend indicator (Chande & Kroll, 1994). These two variables are: $AroonUp(n)$ and $AroonDown(n)$, which we define below. Generally, the Aroon indicators are applied to a financial time series to identify trends and the probability that the trends will reverse.

Suppose $P_0, P_1, P_2, \ldots$ are observations of prices in the market. At observation P_{t-0}, $AroonUp(n)$ and $AroonDown(n)$ are defined with reference to the previous n observations, together with the current observation P_{t-0}. In other words, we focus on a period of $n+1$ observations, with prices $P_{t-n}, \ldots, P_{t-1}, P_{t-0}$ where n is a parameter to the indicator. Here, P_{t-n} is the earliest observation in the period and P_{t-0} is the latest observation. Let m and m' be two indices such that P_{t-m} and $P_{t-m'}$ are the most recent highest price and lowest price respectively in this period; i.e. for all i in $0\ldots n$, we have $P_{t-m} \geq P_{t-i}$, $P_{t-m'} \leq P_{t-i}$. If there exists another index j (with j in $0\ldots n$) such that $P_{t-m} = P_{t-j}$ then $m < j$; the same applies for m' (i.e. if there exists another index k, with k in $0\ldots n$, such that $P_{t-m'} = P_{t-k}$ then $m' < k$). The formula corresponding to $AroonUp(n)$ is defined in Equation (6):

$$AroonUp(n) = \left((n-m) \div n\right) \times 100 \tag{6}$$

For example, let $n = 3$. If $P_{t-3} = 101$, $P_{t-2} = 102$, $P_{t-1} = 103$, $P_{t-0} = 10$, then $m = 0$ (because 104 is the highest price in this window). If $P_{t-3} = 104$, $P_{t-2} = 102$, $P_{t-1} = 106$, $P_{t-0} = 104$, then $m = 1$ (because 106 is the highest price in this window). If $P_{t-3} = 104$, $P_{t-2} = 102$, $P_{t-1} = 104$, $P_{t-0} = 104$, then $m = 0$ (because 104 is the highest price in this window, but P_{t-0} is the most recent). If $P_{t-3} = 104$, $P_{t-2} = 102$, $P_{t-1} = 103$, $P_{t-0} = 101$, then $m = 3$. $AroonDown(n)$ is computed exactly as the opposite mode, searching for lowest price instead of highest price. The formula corresponding to $AroonDown(n)$ is Equation (7). The $AroonUp(n)$ and $AroonDown(n)$ values are bounded between 0 and 100:

$$AroonDown(n) = \left((n-m') \div n\right) \times 100 \tag{7}$$

In our case, we want to compute the $AroonUp(n)$ and $AroonDown(n)$ variables under the DC context. To adapt these two variables to the DC concept we provide the following indications and examples:

- We define an observation per trend. Each observation comprises the two prices corresponding to the start and the end of a DC event. More explicitly, an observation is a couple of prices: the price at which a DC event starts, i.e. P_{EXT}, and the price at DC confirmation point, i.e. price at which the OS event starts (see Section 2).

Table 2: An example of DC-based summary (with $\theta = 0.1\%$) corresponding to minute-by-minute EUR/USD exchange rates sampled from 15/12/2011 3:44:00 PM to 16/12/2011 04:53:00 AM (UK time). The start of a *DC event* signifies the start of a new trend. The prices shown in this table refer to the mid price[1]). Here, the price at which a *DC event* starts represents the P_{EXT} of this trend. The price at which an *OS event* starts is the price at DC confirmation point (i.e. this is when a *DC event* ends and an *OS event* starts). Note that the change between the price at which a *DC event* starts and the price at which the *OS event*, of the same trend, starts is greater than or equal to $\theta = 0.1\%$.

Trend index	Trend direction	Event type	Price at which the event starts	Price extreme at which the trend start (P_{EXT})
1	Upward	*DC event*	1.29840	$P_{EXT}^1 = 1.29840$
		OS event	1.29990	
2	Downward	*DC event*	1.30245	$P_{EXT}^2 = 1.30245$
		OS event	1.30090	
3	Upward	*DC event*	1.30038	$P_{EXT}^3 = 1.30038$
		OS event	1.30175	
4	Downward	*DC event*	1.30224	$P_{EXT}^4 = 1.30224$
		OS event	1.30081	
5	Upward	*DC event*	1.29940	$P_{EXT}^5 = 1.29940$
		OS event	1.30072	
6	Downward	*DC event*	1.30238	$P_{EXT}^6 = 1.30238$
		OS event	1.30105	
7	Upward	*DC event*	1.30065	$P_{EXT}^7 = 1.30065$
		OS event	1.30200	
8	Downward	*DC event*	1.30430	$P_{EXT}^8 = 1.30430$
		OS event	1.30293	

- To calculate the $AroonUp(n)$ and $AroonDown(n)$ for an uptrend, we use the previous n uptrends. Similarly, to calculate the $AroonUp(n)$ and $AroonDown(n)$ for a downtrend, we use the previous n downtrends.
- In case of an uptrend:
  - To calculate $AroonUp(n)$ we use the DC confirmation prices. For example, with reference to Table 2, to calculate $AroonUp(3)$ when the 7th trend is confirmed (which is an uptrend), we use the DC confirmation prices of uptrends 1, 3, 5, and 7 respectively; namely 1.29990, 1.30175, 1.30072 and 1.30200. In other words, we obtain the following price series: $P_{t-3} = 1.2999$, $P_{t-2} = 1.30175$, $P_{t-1} = 1.30072$, $P_{t-0} = 1.30200$. Given that $n = 3$, we say $m = 0$.
  - To calculate $AroonDown(n)$ we use the P_{EXT} prices. For example, with reference to Table 2, to calculate $AroonDown(3)$ when the 7th trend is confirmed (which is an uptrend), we use the P_{EXT} prices of uptrends 1, 3, 5, and 7 respectively; namely 1.29840, 1.30038, 1.29940 and 1.30065. In other words, we obtain the following price series: $P_{t-3} = 1.29840$, $P_{t-2} = 1.30038$, $P_{t-1} = 1.29940$, $P_{t-0} = 1.30065$. Given that $n = 3$, we say $m' = 3$.
- In case of a downtrend:
  - To calculate $AroonUp(n)$ we use the P_{EXT} prices. For example, with reference to Table 2, to calculate $AroonUp(3)$ when the 8th trend is confirmed (which is a downtrend), we use the P_{EXT} prices of downtrends 2, 4, 6, and 8 respectively; namely 1.30245, 1.30224, 1.30238 and 1.30430. In other words, we obtain the following price series: $P_{t-3} = 1.30245$, $P_{t-2} = 1.30224$, $P_{t-1} = 1.30238$, $P_{t-0} = 1.30430$. Given that $n = 3$, we say $m = 0$.
  - To calculate $AroonDown(n)$ we use the DC confirmation prices. For example, with reference to Table 2, to calculate $AroonDown(3)$ when the 8th trend is confirmed (which is a downtrend), we use the DC confirmation prices of downtrends 2, 4, 6, and 8 respectively; namely 1.30090, 1.30081, 1.30105 and 1.30293. In other words, we obtain the following price series: $P_{t-3} = 1.30090$, $P_{t-2} = 1.30081$, $P_{t-1} = 1.30105$, $P_{t-0} = 1.30293$. Given that $n = 3$, we say $m' = 2$.

$AroonDown(n)$ and $AroonUp(n)$ are the first two chosen independent variables. The third one is OSV_{OS} previously identified in Table 1. To summarize, OSV_{OS}, $AroonDown(n)$, and $AroonUp(n)$ are the independent variables to be used to forecast the Boolean dependent variable $BOSV_{EXT}$.

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[1] $mid\ price = ((ask\ price + bid\ price) \div 2)$. See http://www.investopedia.com/terms/m/middle-rate.asp.

4.2. Algorithms: J48Graft and M5P

According to rule (5), our objective is to predict whether $BOSV_{EXT}^{i}$ is *True* or *False*. Such an objective can be seen as a classification task. For this purpose, we have chosen to use two machine learning algorithms in the literature: J48Graft and M5P.[2] Both algorithms belong to the decision tree classifier family. In this Section we provide a brief review about each algorithm.

J48 is the open-source Java implementation of C4.5 algorithm (Witten, Frank, & Hall, 2011). C4.5 algorithm descends from the simple divide-and-conquer algorithm for generating decision trees (Quinlan, 1993). J48 has three main steps. First, for each attribute λ it computes the normalized information gain ratio from splitting on λ. Let λ_best be the attribute with the highest normalized information gain. Second, it creates a decision node *nd* that splits on λ_best. Third, it recurs on the sublists obtained by splitting on λ_best, and add those nodes as children of node *nd*. The three steps are repeated until a base case is reached. This algorithm has multiple base cases (see Quinlan, 1993).

The J48Graft algorithm is an enhanced version of J48 (Webb, 1999). It adds nodes to a given decision tree in aim of reducing the prediction tree. It considers alternative classification for regions of the sample space that are not occupied by training examples. *"These classifications are generated by considering alternative branches based on the predecessor nodes to the leaf contained those identified region."* (Kokar, Venkatesan, Tandel, & Palivela, 2014, page 409). Finally, J48Graft has been reported to have better accuracy than J48 (Rajput & Arora, 2013).

M5P is a regression tree classifier based on the M5 algorithm for inducing trees of regression models (Quinlan, 1992). M5P is a model tree algorithm. It generates regression trees whose leaves are union of multivariate linear models. First, a decision-tree induction algorithm is applied to generate a tree. M5P uses a splitting criterion that minimizes the intra-subset variation in the class values down each branch. The splitting process repeats until the class values of all instances that reach a node differ marginally, or only a few instances remain. Second, after a tree is constructed, a bottom-up pruning algorithm is conducted. When pruning, an internal node becomes a leaf with a regression plane by computing the expected error for test data. Third, to remove severe discontinuities between the subtrees a smoothing procedure is applied that combines the leaf model prediction with each node along the path back to the root. Smoothing can be achieved by producing linear models for each internal node, as well as for the leaves, at the time the tree is built (Wang & Witten, 1997).

There are other methods for building decision trees. For example, genetic programming has been demonstrated to be useful for building decision trees in financial forecasting (Tsang & Li, 2002). The repository method and its variances have been found effective in post-processing decision trees to improve their performance (Jin, Tsang, & Li, 2009).

In this section, we have described the basic elements of our approach: the independent variables and two selected forecasting algorithms. Next, the performance of our approach is examined experimentally.

5. EXPERIMENTS

In order to verify whether $BOSV_{EXT}$ is predictable using the independent variables and the machine learning algorithms that we have chosen, we provide four sets of experiments. In the first set of experiments, we use minute-by-minute gold prices in order to test whether our approach can outperform random forecast. In the second set of experiments, we test whether the performance observed in the first set of experiments can be attained in another market; for this purpose, we apply our approach to another dataset composed of minute-by-minute EUR/USD exchange rate. The third set of experiments tests the significance of each of the selected independent variables identified in Section 4.1. The fourth set of experiments aims to examine the sensitivity of our approach to the choice of the Aroon indicator parameter n.

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[2] In preliminary experiments, we have tried other algorithms: ID3, ADTree, J48, and CART (Witten, Frank, & Hall, 2011). J48Graft and M5P show better accuracy than the others.

7

5.1. Performance of our forecasting approach in gold prices

To assess the performance of our forecasting approach, we apply it to minute-by-minute time series of gold price during the period from 16/10/2012 18:56:00 to 07/04/2014 13:54:00 (UK time) consisting of a total of 531308 observations. After running DC based analysis (see Appendix A) with a threshold of $\theta = 0.2\%$, we count 6464 trends. For each trend we compute the four variables: OSV_{OS}, $AroonUp(n)$, $AroonDown(n)$ and OSV_{EXT}. These variables constitute our new dataset D.

Based on the instructions provided in Section 4.1, concerning how to compute $AroonDown(n)$, and $AroonUp(n)$ in the DC context, we use uptrends to predict $BOSV_{EXT}$ in uptrends, and downtrends to predict $BOSV_{EXT}$ in downtrends. Therefore, we split our dataset D into two dataset D^A and D^B where D^A represents the set of downward trends and D^B represents the set of upward trends. Each of D^A and D^B contains 3232 observations. In this set of experiments, we focus on the downward trends dataset D^A. D^B is processed similarly.

Next, we set, arbitrarily, $n = 20$ in Equations (6) and (7) to compute $AroonDown(n)$, and $AroonUp(n)$[3]. Consequently, we eliminate the first 20 observations of D^A because they have neither $AroonUp(n)$ nor $AroonDown(n)$ values. Finally, we obtain 3212 downward trends in D^A.

The dependent variable $BOSV_{EXT}$ is defined with reference to d (see rule (5)). We have tried 11 different values corresponding to 11 quantile values: ($d = q_{25}$, q_{30}, q_{35}, q_{40}, q_{45}, q_{50}, q_{55}, q_{60}, q_{65}, q_{70}, q_{75}) where q_j is the number at which j % of OSV_{EXT} observations are less than q_j. Hence, we get 11 different datasets D_j^A (j=25, 30, 35,…, 75). In other words, if we apply rule (5) we should have j % of $BOSV_{EXT}$ values being *True* in the dataset D_j^A. For each dataset we replace the variable OSV_{EXT} with the corresponding variable $BOSV_{EXT}$ computed based on rule (5). All these datasets have exactly same values of the three independent variables. They only differ by the dependent variable $BOSV_{EXT}$ which can be only *True* or *False* according to the value of parameter d as described in rule (5). These datasets are used to test the performance of the learning algorithms given different level of *True-False* imbalance in the dependent variable $BOSV_{EXT}$. For example, in the dataset D_{25}^A we should have 25% of $BOSV_{EXT}$'s value are *True* and 75% are *False* and in the dataset D_{75}^A we should have 75% of $BOSV_{EXT}$'s value are *True* and 25% are *False*.

For each dataset D_j^A, we choose the first 3000 observations as a training set and the remaining 212 observations to be out of sample testing set. For each training set, we use the Weka software package (Witten, Frank, & Hall, 2011) to build the decision trees with J48Graft and M5P. Then we test the accuracy of the generated decision trees using the out of sample set.

5.2. Performance of our forecasting approach in a different market: EUR/USD exchange

The objective of this set of experiments is to examine whether our approach may provide similar accuracy, as in gold price experiments, in another market. Therefore, we repeat the experiments in minute-by-minute time series of EUR/USD exchange rate during the period from 15/12/2011 14:18:00 to 07/04/2014 13:04:00, which contains a total of 886429 observations. After running DC based analysis (see Appendix A) with a threshold of $\theta = 0.1\%$[4], we count 9852 trends. As in the previous experiment, we compute the four variables: OSV_{OS}, $AroonUp(n)$, $AroonDown(n)$ and OSV_{EXT}. These variables constitute our new dataset D. Next we save the downward trends and upward trends separately into two distinct datasets D^A and D^B respectively. In this experiment we proceed with the upward trends dataset D^B, which contains 4925 trends. As in the first experiment, the Aroon indicator's parameter is chosen to be $n = 20$. For the selection of parameter d, we try 11 different values corresponding to the 11 quantile values: ($d = q_{25}$, q_{30}, q_{35}, q_{40}, q_{45}, q_{50}, q_{55}, q_{60}, q_{65}, q_{70}, q_{75}) similarly to the gold price experiments. Hence, we get 11 different datasets D_j^B (j=25, 30, 35, 40, 45, 50, 55, 60, 65, 70, 75). For each dataset we replace the variable OSV_{EXT} with the corresponding variable

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[3] Note that in this set of experiments the Aroon parameter *n* refer to the previous *n* downward trends because we apply our approach to D^A.

[4] In a preliminary experiment, we computed the DC based analysis (Appendix A) for EUR/USD with threshold $\theta = 0.2\%$ (as in the previous gold price experiments). However, we obtained only 2736 trends (1368 are uptrends & 1368 are downtrends). Note that we need to use a threshold that would give us enough number of trends for our experiments. For this purpose, we preferred to choose another threshold $\theta = 0.1\%$.

$BOSV_{EXT}$ computed based on rule (5). All these datasets have exactly same values of the three independent variables. They only differ by the dependent variable $BOSV_{EXT}$. The first 20 observations was omitted because they have neither $AroonUp(n)$ nor $AroonDown(n)$ values. Next, we use the first 4500 observations as training set and the remaining observations as out of sample testing set.

5.3. Testing the significance of individual independent variables

In this experiment we provide a set of tests that aim to inspect the significance of each of the three independent variables. First, we chose, arbitrarily, two different datasets: $\underline{D}_{45}^{A}$, from the gold price experiment, and $\underline{D}_{50}^{B}$, from the EUR/USD price experiment. Secondly, for each dataset we run three tests. In each test, we eliminate one independent variable; then we try to forecast $BOSV_{EXT}$ using only the remaining two independent variables. Hence, we obtain three combinations: 1) $AroonDown(n)$, OSV_{OS}; 2) $AroonDown(n)$, $AroonUp(n)$; and 3) OSV_{OS}, $AroonUp(n)$. Each test is conducted independently. In each test we split the data into training set and out-of-sample set. Next we use the two selected variables only to train the J48Graft and M5P algorithms, using the training set, in order to generate new decision trees. Finally, we measure the accuracy of each decision tree using the out-of-sample set.

5.4. Sensitivity analysis on the Aroon indicator parameter n

In this set of experiments, we aim to assess the sensitivity of our results to the choice of the Aroon indicator parameter n. We use the dataset $\underline{D}_{50}^{A}$ from the gold price experiment (which has equal number of $True$-$False$ values to our dependent variable, as explained in Section 4.1). We try to forecast whether $OSV_{EXT} < q_{50}$ for 9 different values of n using both algorithms M5P and J48Graft. For each value of n we obtain new values of $AroonUp(n)$ and $AroonDown(n)$ according to Equations (6) and (7). Hence, we obtain 9 different datasets. Each dataset has different values of $AroonUp(n)$ and $AroonDown(n)$; but all datasets have the same values of OSV_{OS} and $BOSV_{EXT}$ which are computed by replacing OSV_{EXT} by q_{50} in rule (5) (because we use the dataset $\underline{D}_{50}^{A}$ throughout this set of experiments).

6. RESULTS

6.1. Performance of our forecasting approach in the gold price experiments

The objective of this set of experiments is to measure the performance of our approach for the prediction of $BOSV_{EXT}$. Table 3 shows the forecasting results, using the out of sample testing sets, corresponding to 11 different values of d using J48Graft and M5P (see Section 5.1). By using 11 datasets, we want to test the performance of the learning given different level of $True$-$False$ imbalance in the dependent variable. Fig. 2 shows the variation of accuracy of J48Graft and M5P in accordance to d. Appendix B illustrates the two decision trees corresponding to the prediction of $BOSV_{EXT}$ in $\underline{D}_{45}^{A}$ and $\underline{D}_{25}^{A}$ using J48Graft algorithm.

Table 3: Using gold price time series described in Section 5.1. Results of forecasting whether $OSV_{EXT} < d$ for 11 different values of d. $n = 20$ in all experiments.

| $d =$	J48Graft			$d =$	M5P		
	Precision	Recall	Accuracy		Precision	Recall	Accuracy
q_{25}	0.704	0.388	0.821	q_{25}	0.741	0.408	0.830
q_{30}	0.500	0.890	0.740	q_{30}	0.727	0.436	0.811
q_{35}	0.620	0.477	0.750	q_{35}	0.718	0.431	0.774
q_{40}	0.530	0.907	0.679	q_{40}	0.738	0.407	0.735
q_{45}	0.780	0.368	0.698	q_{45}	0.733	0.379	0.689
q_{50}	0.589	0.583	0.627	q_{50}	0.615	0.498	0.632
q_{55}	0.574	0.611	0.571	q_{55}	0.592	0.565	0.580
q_{60}	0.684	0.666	0.632	q_{60}	0.609	0.666	0.580
q_{65}	0.638	0.881	0.632	q_{65}	0.633	0.889	0.627
q_{70}	0.700	0.866	0.679	q_{70}	0.663	0.933	0.655
q_{75}	0.704	0.959	0.693	q_{75}	0.704	0.959	0.693
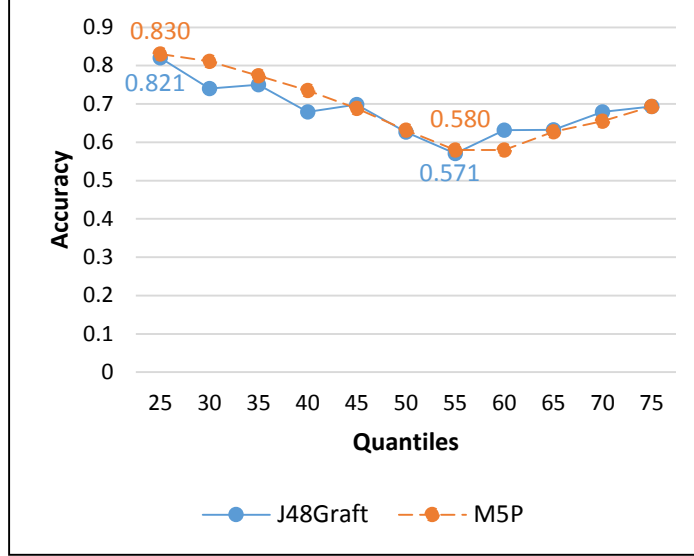
Fig. 2: Using gold price data. Accuracy of J48Graft vs. M5P for 11 different quantile values. The highest and lowest accuracy for each algorithm are shown.

6.2. Performance of our forecasting approach in the EUR/USD experiments

In our first set of experiments, we have tested the performance of our approach in the prediction of $BOSV_{EXT}$ in the gold market. In the second set of experiments we consider the EUR/USD market to verify whether we can attain similar accuracy in a different market. In order to get enough number of trends, we chose a different threshold value $\theta = 0.1\%$ (instead of $\theta = 0.2\%$) as explained in Section 5.2. In addition we chose to proceed with the uptrends dataset in order to measure the performance of our approach in the opposite trend direction (uptrends instead of downtrends as in the previous experiments). We forecast $BOSV_{EXT}$ in 11 different levels of $True$ and $False$ imbalance.

Table 4 shows the results of forecasting $BOSV_{EXT}$ for 11 different values of d using J48Graft and M5P. These results correspond to the out of sample testing sets of the upward trends dataset D^B of EUR/USD exchange rate as described previously in Section 5.2. Fig. 3 shows the variation of accuracy of J48Graft and M5P in accordance to d for the EUR/USD experiments.

Table 4: Results of forecasting whether $OSV_{EXT} < d$ corresponding to EUR/USD experiments.

| $d =$	J48Graft			$d =$	M5P		
	Precision	Recall	Accuracy		Precision	Recall	Accuracy
q_{25}	0.534	0.187	0.743	q_{25}	0.804	0.203	0.751
q_{30}	0.513	0.220	0.700	q_{30}	0.857	0.233	0.707
q_{35}	0.641	0.330	0.690	q_{35}	0.629	0.330	0.686
q_{40}	0.637	0.430	0.661	q_{40}	0.682	0.364	0.665
q_{45}	0.703	0.351	0.640	q_{45}	0.731	0.382	0.658
q_{50}	0.557	0.933	0.577	q_{50}	0.562	0.891	0.580
q_{55}	0.603	0.922	0.607	q_{55}	0.598	0.914	0.597
q_{60}	0.638	0.892	0.619	q_{60}	0.630	0.932	0.619
q_{65}	0.675	0.992	0.676	q_{65}	0.675	0.996	0.679
q_{70}	0.727	0.982	0.720	q_{70}	0.723	0.993	0.720
q_{75}	0.731	0.982	0.725	q_{75}	0.727	0.996	0.725
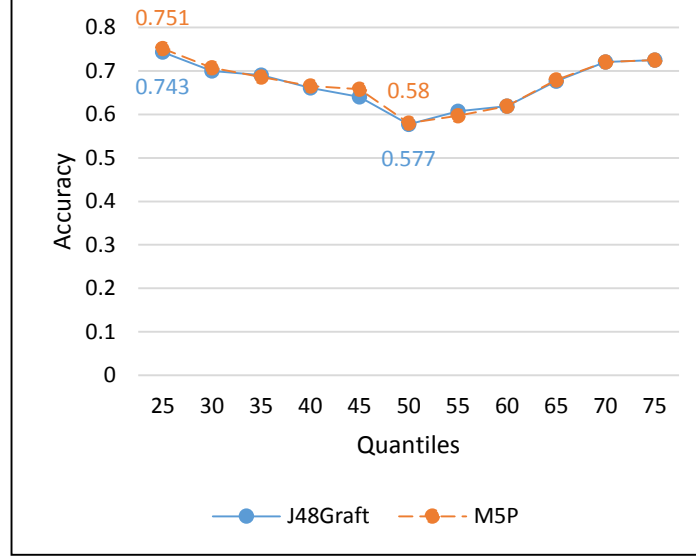
Fig. 3. Using EUR/USD rate data. Accuracy of J48Graft vs. M5P for 11 different quantile values. The highest and lowest accuracy for each algorithm are shown.

6.3. Significance of individual independent variables

In this section we aim to evaluate the significance of each independent variable. We provide the results of forecasting whether $OSV_{EXT} < d$ using three combinations; each of which consisting of two independent variables. The three combinations are: 1) $AroonDown(n)$, OSV_{OS}; 2) $AroonDown(n)$, $AroonUp(n)$; and 3) OSV_{OS}, $AroonUp(n)$. We use each combination to forecast whether $OSV_{EXT} < d$ in two datasets $\underline{D}_{45}^{A}$ and $\underline{D}_{50}^{B}$ as previously described in Section 5.3. The forecasting accuracies are shown in Table 5. The bottom row in Table 5 shows the accuracies, in bold, of forecasting whether $OSV_{EXT} < d$ using the three independent variables together (by referring to Tables 3 & 4). The consequences of removing each of these three variables are shown in the three rows above it.

Suppose we drop the $AroonUp(n)$ variable, and use $AroonDown(n)$ and OSV_{OS} only. Results in Table 5 suggest that the use of only these two variables decreases the accuracy of algorithm J48Graft in the experiment on dataset $\underline{D}_{45}^{A}$ from 0.698 to 0.624. Similarly, by using only these two variables the accuracy of forecasting using the M5P algorithm decreases from 0.689 to 0.611.

Suppose we drop the variable OSV_{OS} and only use the two variables $AroonDown(n)$ and $AroonUp(n)$. On dataset $\underline{D}_{50}^{B}$, the accuracy of J48graft decreases from 0.577 to 0.518 and the accuracy of M5P decrease from 0.580 to 0.526.

Suppose we drop the variable $AroonUp(n)$ and only use the two variables OSV_{OS} and $AroonUp(n)$. On dataset $\underline{D}_{45}^{A}$, the accuracy of algorithm J48 decreases from 0.698 to 0.582. Similarly, the accuracy of M5P decreases from 0.689 to 0.621.

Table 5: This table shows the accuracies of forecasting whether $OSV_{EXT} < d$ using different combinations of independent variables. Two datasets are used $\underline{D}_{45}^{A}$ (gold price experiment) and $\underline{D}_{50}^{B}$ (EUR/USD experiment).

Variables	$\underline{D}_{45}^{A}$ (gold price experiment)		$\underline{D}_{50}^{B}$ (EUR/USD rate experiment)	
	J48Graft	M5P	J48Graft	M5P
$AroonDown(n)$, OSV_{OS}	0.624	0.611	0.550	0.572
$AroonDown(n)$, $AroonUp(n)$	0.647	0.676	0.518	0.526
$AroonUp(n)$, OSV_{OS}	0.582	0.621	0.545	0.578
$AroonDown(n)$, $AroonUp(n)$, OSV_{OS}	**0.698**	**0.689**	**0.577**	**0.580**

6.4. Sensitivity analysis on the Aroon parameter n

Fig. 4 presents simple sensitivity analysis of our approach to the choice of the Aroon indicator parameter n (see Section 4.4.). It shows how the accuracy of both algorithms, J48Graft and M5P, varies according to parameter n. Fig. 4 highlights the best and worst accuracies among the chosen values of

parameter n for each algorithm. For example, the accuracy of M5P decrease by about 16.9% (from 0.632 in case of $n = 20$ to 0.525 in case of $= 50$) and the accuracy of J48Graft decreases by about 17.2% (from 0.627 in case of $n = 20$ to 0.519 in case of $n = 45$).
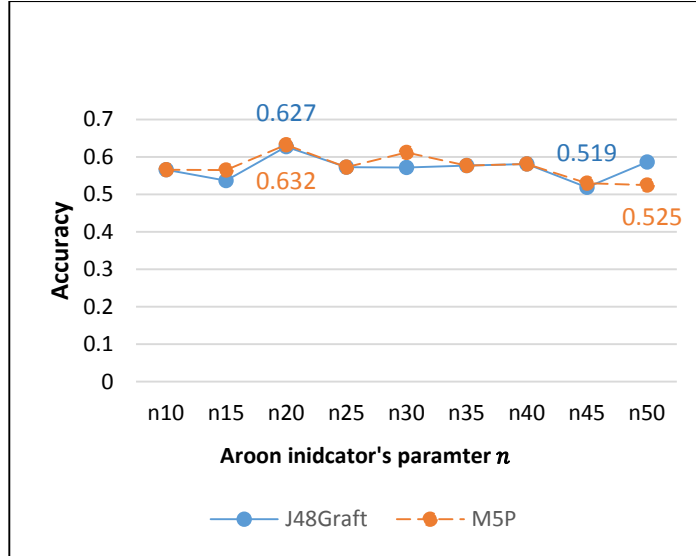

Fig. 4: Variation of accuracy of forecasting whether $OSV_{EXT} < d$ as function of the Aroon parameter n using J48Graft and M5P. These results correspond to the gold price test-dataset $\underline{D}_{50}^A$. The results corresponding to best and worst accuracy of both algorithms are presented.

7.   DISCUSSION

7.1. Interpretation of the results of gold price experiments

The objective of the gold prices experiments was to test whether our approach can perform better than random forecast. The accuracy of M5P algorithm in these experiments ranges between 0.580 and 0.830 according to the value of d (see Fig. 2). Bear in mind that the investor can choose the value of d (see rule (5)). Consequently, the investor can regulate the desired accuracy. Therefore, we consider this range of accuracy to be acceptable.

In order to compare our results to a random forecast approach, we focus on the results for $d = q_{50}$ (i.e. 50 % of $BOSV_{EXT}$ are $True$). This is where a random forecast would have an expected accuracy, precision and recall of 0.500. As can be seen in Table 3 in case of $d = q_{50}$, J48Graft has precision, recall and accuracy all larger than 0.580, which is better than the performance of random predictions. The results of gold prices experiments suggest that our approach outperforms random forecasting.

7.2. Comments on EUR/USD experiments' results

The objective of this set of experiments was to check whether our approach can provide similar accuracy when applied to another financial market. By comparing Fig. 3 and Fig. 4, we can conclude that in EUR/USD experiments, we get similar minimum accuracy as in the gold price experiments. The J48Graft algorithm shows minimum accuracy of 0.577 (case of q_{50} in Fig. 4) which is very close to the minimum accuracy obtained using same algorithm in gold price experiments (0.571 in case of q_{55}). The M5P algorithm show exactly same minimum accuracy of 0.580 in both markets (case of q_{50} in Fig. 4, and case of case of q_{55} in Fig. 3).

However, J48Graft show a maximum accuracy of 0.821 in gold price (in case of q_{25}) comparing to only 0.743 for same quantile in EUR/USD experiments. The M5P show a maximum accuracy of 0.830 in gold price (in case of q_{25}) comparing to only 0.751 for same quantile in EUR/USD experiments. Hence we conclude that the obtained accuracies in both set of experiments are, reasonably, similar.

An important note is that the results of EUR/USD experiments, shown in Table 4, were obtained using same independent variables and same Aroon parameter, n, value as in the previous experiments.

Note also that in these experiments we applied our approach to the uptrends dataset, D^B, instead of downtrends dataset, D^A, as in the first experiment.

7.3. The significance of independent variables

The main challenge is to discover a set of independent variables those are appropriates to the identified forecasting problem. We have proposed three variables, namely $AroonUp(n)$, $AroonDown(n)$ and OSV_{OS}. The question is: do all these variables contribute to the success of our forecast? To answer this question, we refer to Table 5 in Section 6.3, which presented the results of omitting each of the variables. In this section, we examine the results of omitting each of the variables with the results of using all the three variables.

The results highlighted in Section 6.3 suggests performance decreases if we drop any of the three independent variables. This shows that each of the independents variables contributes significantly to our forecasting task.

7.4. Sensitivity analysis of the Aroon indicator's parameter n.

To analyze the sensitivity of our approach to the parameter n (see Equations (6) and (7)), we try to forecast $BOSV_{EXT}$ in D_{50}^A using 9 different values of parameter n as explained in Section 4.4 based on Fig. 4, the accuracy of both algorithms decreases significantly, by 16.9% for M5P and 17.2% for J48Graft, from one value of n to another (see Section 6.4). Hence, this test provides evidence that our approach is sensitive to the parameter n. A general deduction is that if we want to apply our approach to another time series than gold price, then we should first conduct the sensitivity analysis to n.

7.5. Analysis summary

The results of both experiments show that our approach outperform random forecasting. Both experiments provide comparable results using same parameters' values (even though we have used two different thresholds and different trends' datasets). Therefore, we believe that our approach can be applied to other time series. The parameter d is essential to develop a trading strategy in a later research. Table 5 provide evidence that each independent variable is an important part of our approach. Based on Fig. 4, we conclude that our forecasting approach could be sensitive to the Aroon indicator's parameter n.

8. CONCLUSION

Directional change (DC) is a new, data-driven framework that aims to record significant price changes. In a DC-based summary, the market is cast into alternating upward and downward trends. In an upward trend, we say that the trend has changed (into a downward trend) if price has dropped from the highest point in the current trend by a certain threshold (e.g. 1%). That means we only know that the trend has changed in hindsight. Clearly, it will be useful if one could forecast how far the current trend will continue before the trend changes. This paper presents to first attempt towards this forecasting problem.

The first contribution of this paper is in formulating a forecasting problem in the context of DC. We have defined the Boolean variable $BOSV_{EXT}$, which indicates whether the overshoot value at the next extreme, OSV_{EXT}, will exceed a predefined value d. The objective is to predict whether $BOSV_{EXT}$ is true or false. In other words, we want to forecast the next extreme price, i.e. price at which the trend reverses.

Our second contribution is identifying three independent variables, and proving that they are relevant to the prediction of OSV_{EXT}. The independent variables are: OSV_{OS}, $AroonUp(n)$ and $AroonDown(n)$. We have adapted the Aroon variables from the literature to suit the DC framework. In order to prove that the identified independent variables are relevant to the prediction of OSV_{EXT}, we have applied them in two forecasting algorithms and conducted four sets of experiments.

13

Our first set of experiments was conducted using minute-by-minute gold price. The aim was to provide basic assessment of our approach. Results of the experiments show that our approach outperforms random forecasting in term of accuracy. It turns out that our approach can perform pretty well (showing minimum accuracy of 0.580) for different selected value of OSV_{EXT}; it achieved remarkable results (with accuracy up to 0.830) in some cases.

Our second set of experiments used minute-by-minute EUR/USD exchange rate. The aim was to test whether our results in the gold market was a one-off. Therefore, we kept the same parameter values that we used for the first set of experiments. The performance of our approach in the EUR/USD market was as good as its performance in the gold market. The results of this experiment suggest that performance of our approach in the gold market was not a one-off. The obtained results suggest that the independent variables are also relevant to the EUR/USD market.

In the third set of experiments, we show that each of the three independent variables is important to our approach. We showed that performance deteriorated if we eliminate any of the three variables in the forecast.

The final set of experiments showed that the results obtained using our approach can be sensitive to the choice of Aroon indicator parameter n. The accuracy may decrease by more than 16% for different values of n.

To summarize, this is the first attempt to forecast directional changes under the DC-framework. Our contribution is in formulating the forecasting problem, identifying a set of independent variables and proving that they are relevant to the forecasting task. Having established the predictive power of our approach, our next goal will be to embed this forecasting result into trading strategies.

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15

Appendix A: Pseudo-code to compute the variables defined in Section 3

In this appendix, we present the pseudo code of a procedure that finds all the directional changes in a series. The following procedure *DCBasedAnalysis* takes 2 parameters as input: the price time series ts and the threshold θ related to the DC concept as explained previously in Section 1. This procedure return a matrix *DCBasedAnalysis* which is composed of 3 numerical vectors: P_{EXT}; OSV_{OS} and OSV_{EXT}. Each row in *DCBasedAnalysis* represents one trend.

The following variables are used in the procedure *DCBasedAnalysis* below:

- P_{EXT}^i: The price extreme at which the ith trend starts. The vector P_{EXT} contains all computed P_{EXT}^i.
- OSV_{OS}^i: The overshoot value computed at i^{th} DC confirmation point as explained in Table1. The vector OSV_{OS} contains all computed OSV_{OS}^i.
- OSV_{EXT}^i: The overshoot value computed at the start of next trend as explained in Table 2. The vector OSV_{EXT} contains all computed OSV_{EXT}^i.
- P_c records the price currently being processed.
- The variable mode records the current mode, which is initialized to up.
- $P_{DCC^*}^i$ is the target price for directional change confirmation corresponding to the ith trend (under threshold θ).

Procedure *DCBasedAnalysis* (time series ts, threshold θ)
Initialize variables: $P_c = P_{EXT} = ts\,[1] = $ price of first observation, mode = up, $P_{DCC^*}^i = P_c \times (1 + \theta)$
Len = number of observations in ts
i=2
Loop until i=Len
   $P_c = ts[i]$
  if mode = down then
    if $P_c < P_{EXT}^{i+1}$ then
      $P_{EXT}^{i+1} = P_c$
    else if $(P_c - P_{EXT}^{i+1}) \div P_{EXT}^{i+1} \geq \theta$ then
$OSV_{EXT}^i = ((P_{EXT}^i - P_{DCC^*}^i) \div P_{DCC^*}^i) \div \theta$
$P_{DCC^*}^{i+1} = P_{EXT}^{i+1} \times (1 - \theta)$
$OSV_{OS}^{i+1} = ((P_c - P_{DCC^*}^{i+1}) \div P_{DCC^*}^{i+1}) \div \theta$
$P_{EXT}^{i+1} = P_c$
        mode = up
      end if
  else if mode = up then
    if $P_c > P_{EXT}^{i+1}$ then
      $P_{EXT}^{i+1} = P_c$
    else if $(P_c - P_{EXT}^{i+1}) \div P_{EXT}^{i+1} \leq -\theta$ then
$OSV_{EXT}^i = ((P_{EXT}^i - P_{DCC^*}^i) \div P_{DCC^*}^i) \div \theta$
$P_{DCC^*}^{i+1} = P_{EXT}^{i+1} \times (1 + \theta)$
$OSV_{OS}^{i+1} = ((P_c - P_{DCC^*}^{i+1}) \div P_{DCC^*}^{i+1}) \div \theta$
$P_{EXT}^{i+1} = P_c$
        mode = down
      end if
    end if
i=i+1
End Loop
$DCAnalysis = $ as.matrix (P_{EXT}; OSV_{OS}; OSV_{EXT})
Return *DCAnalysis*

Appendix B: Two samples decision trees based on gold prices experiments.

Below we illustrate two decision trees. Each decision tree is associated with an interpretation in form of *if- else* rules. Fig. B.1 illustrates the decision tree corresponding to the prediction of $BOSV_{EXT}$ for dataset $\underline{D}_{25}^A$ using J48Graft algorithm. Fig. B.2 illustrates the decision tree corresponding to the prediction of $BOSV_{EXT}$ for dataset $\underline{D}_{45}^A$ using J48Graft algorithm.
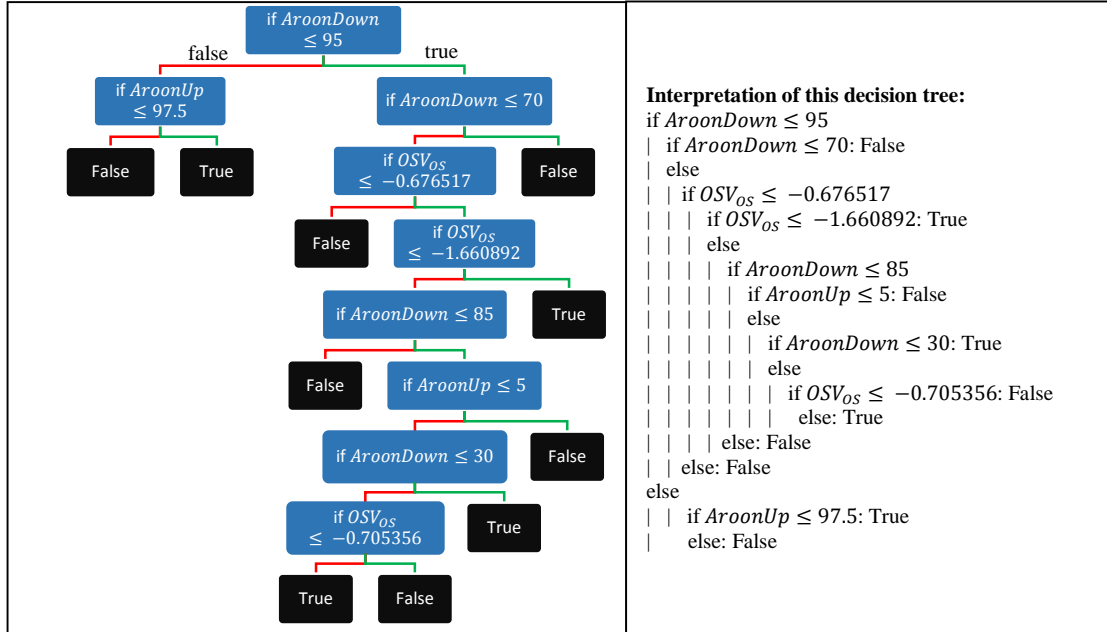

Fig. B.1. The decision tree generated by J48Graft algorithm to forecast whether $\boldsymbol{BOSV_{EXT}}$ based on the gold price dataset $\underline{\boldsymbol{D}}_{25}^A$ (see Section 5.1 for explanation). The black nodes (i.e. true and false nodes) refer to the forecasted value of whether $\boldsymbol{BOSV_{EXT}}$. Each blue node presents an if-condition. When the if-condition is true, we proceed with the right child node (i.e. the one corresponding to the green edge); otherwise we proceed the left child node (i.e. the one corresponding to the red edge).
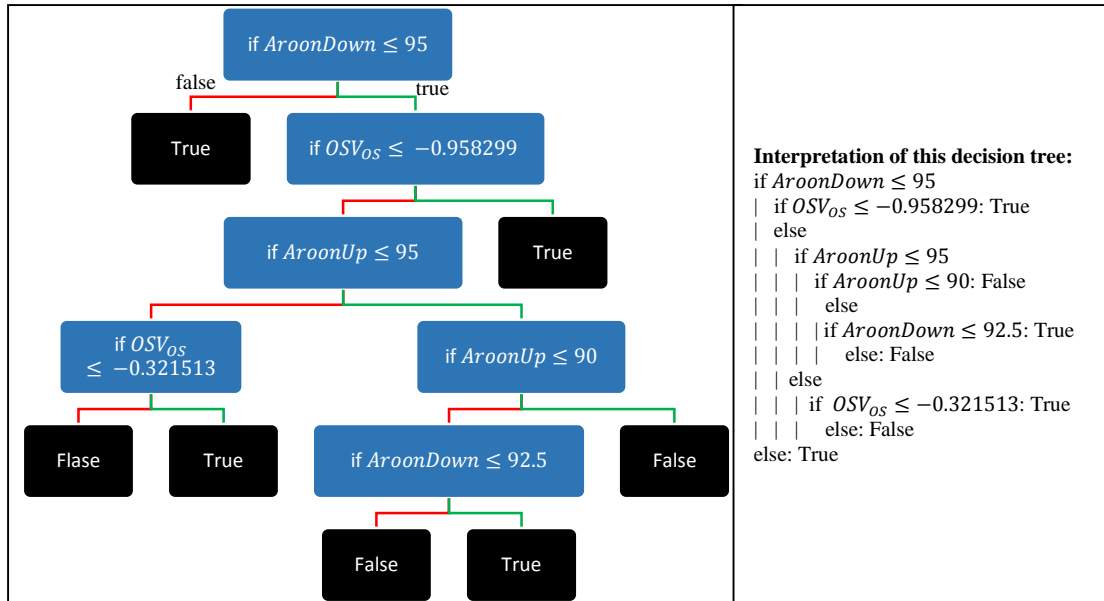

Fig. B.2. The decision tree generated by J48Graft algorithm to forecast whether $\boldsymbol{OSV_{EXT} < d}$ based on the gold price dataset $\underline{\boldsymbol{D}}_{45}^A$. The black nodes (i.e. true and false nodes) refer to the forecasted value of whether $\boldsymbol{OSV_{EXT} < d}$. Each blue node presents an if-condition. When the formulated if-condition is true, we proceed with the right child node (i.e. the one corresponding to the green edge); otherwise we proceed the left child node (i.e. the one corresponding to the red edge).