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Forecasting stock market trends using support vector regression and perceptually important points

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***Abstract*—Intelligent stock trading systems use soft computing techniques in order to make trading decisions in the stock market. However, the fluctuations of the stock price make it difficult for the trading system to discover the underlying trends. In order to enable the trading system for trend prediction, this paper suggests using perceptually important points as a turning point prediction framework. Perceptually important points are utilized as a high-level representation for the stock price time series to decompose the price into several segments of uptrends and downtrends and define a trading signal which is an indicator of the current trend. A support vector regression model is trained on this high-level data to make trading decisions based on predicted trading signal. The performance of the proposed trading system is compared with three other trading systems on five of the top performing stocks in Tehran Stock Exchange, and obtained results show a significant improvement.**

Keywords— Stock price prediction, Trend prediction, Intelligent trading system, High level representation, Perceptually important points, Support vector regression

I. INTRODUCTION

Stock market is a nonlinear, noisy and non-stationary dynamic system, which is affected by many factors like political and social issues and economic conditions. The relationship of the stock price with many of these factors is not clear. This makes stock market forecasting a challenging task. Machine learning and soft computing techniques have widely been used for predicting the stock market. Neural networks and back propagation algorithm have been applied for the stock price prediction [1–2]. They use stock price time series or several technical indicators as the inputs to train a neural network for the prediction of the next day closing price. But the stock price is subjected to such noise and complexity that the prediction results may not be satisfactory. In order to improve the performance of neural networks, neuro-fuzzy systems are used in various forms. An adaptive network-based fuzzy inference system (ANFIS) is used in Zagreb Stock Exchange for five days ahead prediction of the Crobex index [3], and Takagi-Sugeno-Kang (TSK) fuzzy rule-based system is utilized for the prediction of IBM stock [4]. The risk-adjusted performance of ANN and ANFIS in intraday trading in London Stock Exchange is compared, and the performance of ANFIS is shown to be more stable and promising [5].

Unlike the neural networks and neuro-fuzzy systems, support vector machines (SVM) have a high generalization capability and error toleration and are more immune to the danger of over-fitting and getting stuck at the local minima. The direction of Korean composite stock price index (KOSPI) is predicted by SVM in [6], and it is shown that SVM provides a promising alternative to neural networks. Henrique et al. use support vector regression (SVR) with daily and up to the minute frequencies for the stock price prediction in three different markets and conclude the superior performance of SVR to random walk models [7]. A comparison with BPN and case-based reasoning (CBR) for the stock trend prediction is done and it is reported that SVM outperforms the other two methods. [8]

Most of these studies use technical analysis for the prediction of the next day price or its direction. But the technical patterns and indicators are not well suited for the prediction of stock price, and they are more correlated to the stock trends. The inherent noise in the market causes the stock price to behave randomly at many times. This noise in the market is the result of the irrational behavior of the traders who make trading decisions based on wrong speculations, and it can be seen everywhere in the economy [9]. The changes of the stock price values are contributed to two main features; market noise and trends [10]. If a method is not employed by the trading system to distinguish between the trends and noise in the market, it would result in many wrong trading decisions.

The main contribution of this study is using perceptually important points in a trend prediction framework to forecast a trading signal based on trends of the stock price. It addresses the issue of noise in the stock market and attempts to ignore the short-term fluctuations of the stock price. There are very few researches that design the intelligent trading system in this manner. Fuzzy logic is applied with the technical analysis for the design of a fuzzy decision-making process [11]. Bao and Yang used turning points and technical indicators as high-level representations of the stock price, and then utilized probabilistic reasoning for the prediction of turning points [12]. Piecewise linear representation and neural networks (IPLR-BPN) are also used in a trading signal prediction framework [13]. And in [14], a trend-based segmentation method with support vector regression (TBSM-SVR) is utilized to predict the stock trend.

While these studies attempt to predict the stock trends, they are unable to distinguish between trend information and market

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noise. This study suggests training the learning model with high level representations of data, and designs an intelligent trading system which can capture the trends of the stock price and give reliable trading decisions.

Perceptually important points are used in order to describe a high-level representation of the stock price. They represent the time series with a series of data points based on their importance. These data points can help to decompose the time series into a series of uptrend and down trend segments. These segments are used for introducing a trading signal that indicates the current trend. The trading signal is used as the output of the trading model in the training process, and a set of technical indicators are chosen as the inputs. These inputs and outputs are fed to a support vector regression model for the purpose of training. The SVR model is used to predict the trading decision for the next day. With this strategy, the trading system is trained to buy at the beginning of an uptrend and sell at the beginning of a downtrend. The proposed trading system is tested on five of the top performing stocks in Tehran Stock Exchange and is compared with three other trading strategies.

The rest of this paper is organized as follows. Section 2 explains the architecture of the proposed intelligent trading system and describes its basic components. Several experiments and discussions for evaluating the performance of the proposed approach are presented in Section 3. Sections 4 provides concluding remarks.

II. INTELLIGENT TRADING SYSTEM FOR THE PREDICTION OF STOCK PRICE TRENDS

A. *Perceptually important points*

Time series segmentation is a preprocessing technique and a high-level representation of the time series, which is used in pattern matching and trend analysis problems. There are many segmentation algorithms such as principle component analysis (PCA), piecewise linear representation (PLR), minimum description length (MDL) and perceptually important points (PIP) [15]. PIP method is specially designed for the representation of the financial time series and is introduced as a pattern matching tool [16]. In this method, a time series is identified as a sequence of data points which have different contributions in the overall shape of the series. Therefore, different data points can be sorted according to their importance. There are different criterions for evaluating the importance of a point in a time series. Vertical distance is defined as the distance of a data point from the line connecting two adjacent PIPs. The line which connects two PIPs is in fact the trend line, so the data point identified as the next PIP in each stage, is usually the turning point or the point of trend reversal. At each stage the data point with the greatest distance from its adjacent PIPs is identified as the next PIP. This process continues until a sufficient number of PIPs, which can preserve the overall shape of the time series, are selected. The slope of the trend-line in each segment determines whether the segment is an uptrend or downtrend.

In order to obtain a high-level representation of the stock price time series, we need to reduce the dimension of data by choosing the number of PIPs which are sufficient for preserving the overall shape of the time series representing the trends of the stock price. Choosing fewer PIPs may lead to missing some important trends, and selecting more PIPs results in the failure of the noise reduction process. The sufficient number of PIPs can be determined by the tree pruning approach which filters out the less significant data points when their vertical distances are below a threshold λ [21]. It is clear that this threshold value is about how much distance from the trend line should be identified as a trend reversal. Therefore, the threshold is chosen to be proportional to the variance of the vertical distances in the time series. So, the following prescription is suggested for the tree pruning threshold:

$$\lambda = 3\sigma_{\mathrm{d}} \tag{1}$$

Where σ_d denotes the standard deviation of the vertical distances in the train data. We will discuss this choice later, but it is worth noting that this approach makes the PIP identification process independent from the choice of the learning model.

B. *Trading signal generation*

The intelligent trading system gives a trading decision for the next day based on trading signal. The trading signal, which is the output of the trading system, should have a strong correlation with the inputs, and should indicate the current trend. It is defined according to price return series with Eqs. (2) and (3) for the uptrends and downtrends respectively.

$$\mathrm{t_k} = \frac{\mathrm{r_k} - \min\limits_{\mathrm{r_i} \in \mathrm{S_u}} \mathrm{r_i}}{\max\limits_{\mathrm{r_i} \in \mathrm{S_u}} \mathrm{r_i} - \min\limits_{\mathrm{r_i} \in \mathrm{S_u}} \mathrm{r_i}} \tag{2}$$

$$\mathrm{t_k} = \frac{\mathrm{r_k} - \max\limits_{\mathrm{r_i} \in \mathrm{S_d}} \mathrm{r_i}}{\max\limits_{\mathrm{r_i} \in \mathrm{S_d}} \mathrm{r_i} - \min\limits_{\mathrm{r_i} \in \mathrm{S_d}} \mathrm{r_i}} \tag{3}$$

The price return is indicated as r_i in the above equations, and S_u and S_d denote the uptrend and downtrend segments identified in the PIP identification stage, as each two consecutive PIPs form a segment. For an uptrend the value of the trading signal is always between [0, 1] and for a down-trend it is between [-1, 0]. Each time the trading signal passes through zero value, it is an indicator of a PIP point which in turn results in a buy/sell decision.

The market noise affects the trading signal through the price returns, but we have made this choice deliberately to strengthen the correlation of the trading signal with the inputs. This trading signal not only differentiates between an uptrend and a downtrend, but also can capture the power of the trend in each data point according to the price return in that day. The identified PIPs, the trend lines and the generated trading signal for the FOLD stock are shown in Fig. 1. This trading signal clearly indicates the stock trend, and its variations reflect the market noise.

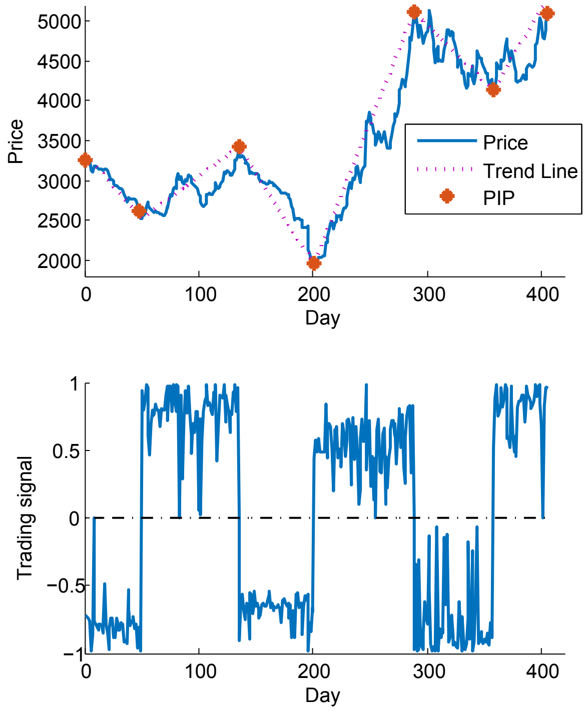

Fig. 1. Trading signal generation: price history, PIPs and the trend lines are shown in the upper figure. The lower figure shows the generated trading signal

C. *Technical analysis in the trading system*

Existence of trends in the stock price time series is an assumption of technical analysis. Technical indicators are certain functions of the recent price data which investors use to determine the current trend and trend reversals and they are regularly used as the inputs of trading systems. These indicators could be leading or lagging in relation to the stock trends. Leading indicators proceed the price movements and they can give predictive power in determining the turning points. These indicators are more useful during non-trending periods and very close to trend reversals or turning points. Lagging indicators, on the other hand, follow the price movements and give less predictive power and are more useful during trending periods. Therefore, a combination of leading and lagging indicators seems to be the proper choice for the inputs of the trading model. Table 1 shows a list of technical indicators which are used as input variables in this study [17].

D. *Support vector regression*

The task of regression is estimating an unknown real valued function f such that

$$y_i = f(x_i) + \delta_i \tag{4}$$

Where x_i is a multivariate input, y_i is a scalar output, and $S = \{x_i, y_i\}_{i=1\ldots N}$ is the finite training sample. δ_i denotes the independent and identically distributed random error. SVR first maps the input in a high dimensional feature space using a nonlinear mapping and then trains a linear model in this feature space [18]. The linear model is given by

TABLE I. TECHNICAL INDICATORS

Technical indicator	Formula
Exponential moving average (EMA)	$\mathrm{EMA}(c_t, n) = \frac{2}{n+1}\{c_t - \mathrm{EMA}(c_{t-1}, n)\} + \mathrm{EMA}(c_{t-1}, n)$
Moving average convergence and divergence (MACD)	$\mathrm{MACD}(c_t, m, n) = \mathrm{EMA}(c_t, n) - \mathrm{EMA}(c_t, m)$
Relative strength index (RSI)	$\mathrm{RSI}(n) = 100 - \frac{100}{1 + \frac{\mathrm{EMA}(\mathrm{Up}, n)}{\mathrm{EMA}(\mathrm{Down}, n)}}$
Stochastic K%	$K\%(n) = \frac{C_t - L_{t-n}}{HH_{t-n} - LL_{t-n}}$
Stochastic D%	$D\%(n) = \mathrm{EMA}(K, n)$
True strength index (TSI)	$\mathrm{TSI}(n, m) = \frac{\mathrm{EMA}(\mathrm{EMA}(r_t, n), m)}{\mathrm{EMA}(\mathrm{EMA}(\lvert r_t\rvert, n), m)}$

$$f(x, \omega) = \omega^T \varphi(x) + b \tag{5}$$

Where ω denotes the weight vector, φ(x) is the mapping function and b is the bias term. Hence, the regression problem reduces to finding the weight vector and the bias term in the feature space. SVR finds these values with the minimization of a cost function consisting of two terms. A term for reducing the model complexity by minimizing $\|\omega\|^2$, and a term for minimizing the empirical risk on the training sample. This cost function is formulated as follows:

$$R = \frac{1}{2}\|\omega\|^2 + \frac{C}{N}\sum_{i=1}^{N} L_\varepsilon(f(x, \omega), y) \tag{6}$$

C is a positive constant called regularization parameter and $L_\varepsilon(f(x, \omega), y)$ is called ε-insensitive loss function suggested by [24]

$$L_\varepsilon(f(x, \omega), y) = \begin{cases} |f(x, \omega) - y| - \varepsilon, & |f(x, \omega) - y| \geq \varepsilon \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

While many neural network models are in the danger of falling into the local minima, the solution to the above problem tends to be the global minimum. Thus, for the stock market data which has a high level of noise and complexity, this feature can be really effective.

III. EXPERIMENTAL RESULTS AND DISCUSSION

This section presents several experiments to test the effectiveness of the proposed intelligent trading system. The performance of the proposed approach is compared with three other trading strategies. Buy and hold strategy is the optimal trading strategy in an efficient market and is used as the standard benchmark. The proposed trading system is also compared with

IPLR-BPN [13] and TBSM-SVR [14]. Five stocks from Tehran Stock Exchange (TSE) have been chosen for the experiments. TSE is an emerging market with more than 36 industries involved. These five stocks have been chosen from the list of top ten companies in the value of trade at the end of the test period [19]. The historical data are from January 2010 to March 2014[1] and are publicly available on TSE website [20]. In the sequel, the detailed steps of training and testing the trading system are described.

A. *Performance Measures*

The trading systems are compared based on their average Rate of Return ROR, standard deviation of ROR, winning ratio to the B&H strategy, and Sharpe ratio. Since the trading system predicts a series of buy and sell points, a reasonable criterion for testing the performance of the model could be the rate of return (ROR) of its trading decisions. The trading systems are compared based on their average ROR, standard deviation of their ROR, winning ratio to the B&H strategy and Sharpe ratio. The return of the B&H strategy is assumed as the benchmark return in the calculations. Rate of return is a highly popular metric for evaluating the efficiency of an investment or comparing the profitability of different trading strategies. It is defined in Eq. (8), where n is the number of transactions, B_i and S_i denote the buy and sell price for each trade, a is the tax value and b is the transaction fee which are based on the Stock Exchange Commission rules in TSE [21].

$$ROR = \prod_{i=1}^{n}\{(\frac{(1-a-b)S_i-(1+a)B_i}{(1+a)B_i})+1\}-1 \qquad (8)$$

Sharpe ratio is a measure for risk-adjusted return and describes how much excess return you receive for the extra volatility you endure for holding a riskier asset. It is calculated with Eq. (9) in which the return of the B&H strategy is assumed as the benchmark return ROR_b in the calculations.

$$\mathrm{S_a} = \frac{\mathrm{ROR_a} - \mathrm{ROR_b}}{\sqrt{\mathrm{var}\ (\mathrm{ROR_a} - \mathrm{ROR_b})}} \qquad (9)$$

B. *Performance of the PIP-SVR and comparison with other trading systems*

In order to perform a statistical analysis on the performance of the trading systems, a two year window is selected randomly on the stock data and the trading systems are tested for a three month test period. 30 samples of data are taken for each of the five stocks. Table shows the statistical results of the performance of the trading systems. The average ROR of PIP-SVR, TBSM-SVR and IPLR-BPN outperforms that of B&H strategy which indicates the success of trading systems. Furthermore, we can see that PIP-SVR scores a better Sharpe ratio and average ROR in comparison with TBSM-SVR and IPLR-BPN.

An interesting result is in terms of %Win which describes the number of times the trading system has outperformed B&H strategy or in other words the trades have outperformed no trading. The results show that PIP-SVR has a better chance of predicting long term trends than making trading decisions based on noise. Fig. 2 represents the ROR of three trading systems and B&H strategy. It shows that PIP-SVR gets a better ROR even in unusually high uptrend or downtrend markets as opposed with two other trading systems.

C. *The effect of the number of PIPs*

The selected PIPs basically describe the stock trends for the SVR model. Tree pruning approach with a threshold value dependent on the noise of the stock price was introduced in this paper for choosing the number of PIPs. Fig. 3 illustrates the effect of the number of PIPs on the overall rate of return and the number of transactions for FOLD stock. It is clear that there is a range of values for the number of PIPs that result in the acceptable performance of the intelligent trading system. Interestingly, the performance of the trading system is almost stable in this range, which shows that the learning system is not too sensitive to the number of PIPs. This ensures the proper performance of the trading system using the aforementioned tree pruning approach. Furthermore, it can be seen that the ROR approaches that of B&H strategy when the number of PIPs is outside this range which means that the trading system acts like a noise trader.

The predicted trading points on a six month test period for FOLD stock are shown in Fig. 4 using three different number of PIPs. It can be seen that if the number of PIPs is not sufficient to represent the time series, the trading model may not learn some of the important trends of the stock price. Conversely, if too many data points are selected as the PIPs, the trading model may confuse short term fluctuations of the stock price with trends. This results in overtrading and noise trading during trending periods.

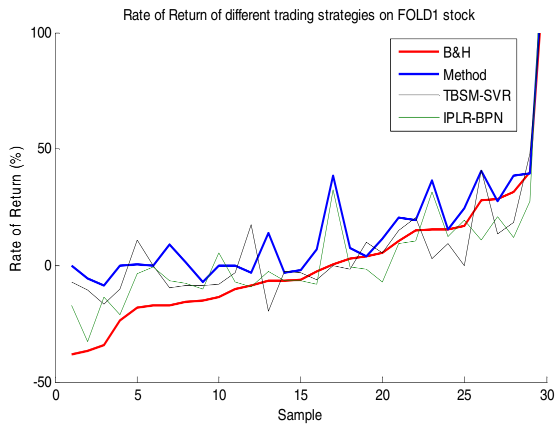

Fig 2. ROR of different trading strategies on 30 samples of data

[1] Before devaluation of Rial

TABLE II. PERFORMANCE RESULTS OF THE TRADING SYSTEMS

Stock	Method	Average ROR	σ_{ROR}	%Win	Sharpe Ratio
FOLD $\boldsymbol{B\&H_{ROR} = 2.90}$ $\boldsymbol{\sigma_{ROR} = 33.41}$	PIP-SVR	15.81	29.44	86	0.43
	TBSM-SVR	7.76	28.39	66	0.17
	IPLR-BPN	6.88	35.60	53	0.11
MRGN $\boldsymbol{B\&H_{ROR} = 1.05}$ $\boldsymbol{\sigma_{ROR} = 45.85}$	PIP-SVR	20.83	34.76	86	0.56
	TBSM-SVR	16.10	42.12	76	0.35
	IPLR-BPN	13.07	43.37	70	0.27
MAPN $\boldsymbol{B\&H_{ROR} = -0.87}$ $\boldsymbol{\sigma_{ROR} = 22.51}$	PIP-SVR	15.58	21.12	86	0.77
	TBSM-SVR	8.58	21.18	76	0.44
	IPLR-BPN	11.45	22.61	80	0.54
IKCO $\boldsymbol{B\&H_{ROR} = -14.23}$ $\boldsymbol{\sigma_{ROR} = 18.18}$	PIP-SVR	1.47	10.58	90	1.48
	TBSM-SVR	-5.90	11.65	53	0.71
	IPLR-BPN	-11.73	14.24	50	0.17
MKBT $\boldsymbol{B\&H_{ROR} = -1.13}$ $\boldsymbol{\sigma_{ROR} = 19.88}$	PIP-SVR	7.50	15.79	86	0.54
	TBSM-SVR	3.15	13.97	56	0.30
	IPLR-BPN	0.59	16.92	63	0.10

D. Benefits and drawbacks of PIP-SVR

Investigation of the trading results of PIP-SVR indicates that most of the trading points happened on the turning points, which means that the trading system has successfully ignored the market noise. Removing the effect of noise on the trading decisions has resulted in the reduction of the number of transactions. Namely, an average of three transactions in the three month test period can be seen in in the test results, whereas this number is five for TBSM-SVR trading system, and it is six for IPLR-BPN at the same test period.

Most of the trading points are at the neighborhood of the trend reversals. However, it can be seen that there is sometimes a delay between the turning point and the trading decision, which is the result of moving averages on the technical indicators. If we remove the moving averages from the inputs, we may reduce this delay, but there will be more noise trading at the ups and downs of the stock price.

It should also be pointed out that the trading system was designed to predict the stock price trends, which means that it can only be aware of the gradual increases and decreases in the stock price. Hence, this system is neither capable nor is designed for the prediction of spikes, jumps or sudden changes in the stock price. However, if the training history of the stock price contains sufficient instances of these sudden changes, the intelligent trading system may actually learn their relationship with the technical indicators and predict them in the future.

IV. CONCLUSION

Intelligent stock trading systems train a soft computing model on the history of the stock price to predict trading decisions. The usual noise in the stock market complicates the learning process and results in noise trading. This study addressed the problem of designing an intelligent stock trading system to remove the influence of noise on the trading decisions using perceptually important points and support vector regression which was named PIP-SVR. A set of leading and lagging technical indicators were chosen as the inputs. Perceptually important points were utilized to segment the price history to several uptrends and downtrends. These trends are not affected by the market noise and reflect the real information in the market and can be used in the generation of a noise-free trading signal. A support vector regression model that is trained on this data predicts the trading signal for the next day and is shown to be capable of making trading decisions based on stock price trends.

The proposed trading system was tested on five of top performing stocks in Tehran Stock Exchange. The resulted performance measures of PIP-SVR demonstrated that not only

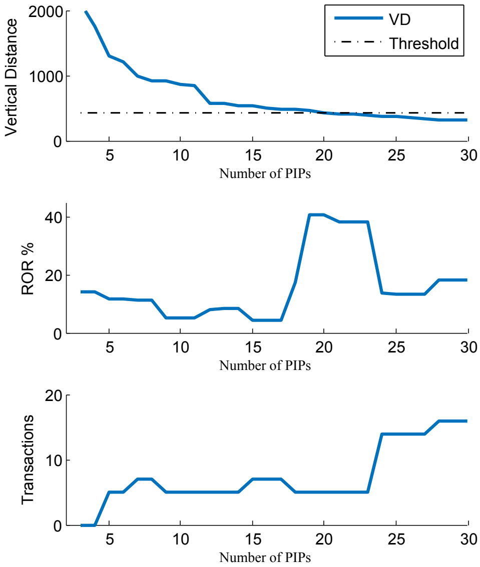

Fig. 3. Choosing the number of PIPs: the upper figure shows vertical distance of each selected PIP. The threshold is calculated by Eq. (1). The lower figures show the rate of return and the number of transactions of the trading system, when it is trained with this number of PIPs.

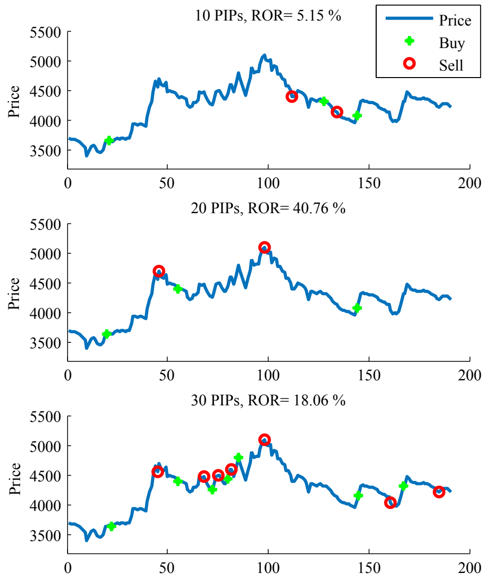

Fig. 4. The effect of the number of PIPs on the predicted trading points.

it can beat buy and hold strategy and be better than no trading, but also it consistently performs better than two other successful intelligent trading methods in terms of profit and risk.

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