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Failure in Stock Price Prediction: A Comparison between the Curve-Shape-Feature and Non-Curve-Shape-Feature Modes of Existing Machine Learning Algorithms

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Abstract

In the era of artificial intelligence, machine learning methods are successfully used in various fields. Machine learning has attracted extensive attention from investors in the financial market, especially in stock price prediction. However, one argument for the machine learning methods used in stock price prediction is that they are black-box models which are difficult to interpret. In this paper, we focus on the future stock price prediction with the historical stock price by machine learning and deep learning methods, such as support vector machine (SVM), random forest (RF), Bayesian classifier (BC), decision tree (DT), multilayer perceptron (MLP), convolutional neural network (CNN), bi-directional long-short term memory (BiLSTM), the embedded CNN, and the embedded BiLSTM. Firstly, we manually design several financial time series where the future price correlates with the historical stock prices in pre-designed modes, namely the curve-shape-feature (CSF) and the non-curve-shape-feature (NCSF) modes. In the CSF mode, the future prices can be extracted from the curve shapes of the historical stock prices. Conversely, in the NCSF mode, they can't. Secondly, we apply various algorithms to those pre-designed and real financial time series. We find that the existing machine learning and deep learning algorithms fail in stock price prediction because in the real financial time series, less information of future prices is contained in the CSF mode, and perhaps more information is contained in the NCSF. Various machine learning and deep learning algorithms are good at handling the CSF in historical data, which are successfully applied in image recognition and natural language processing. However, they are inappropriate for stock price prediction on account of the NCSF. Therefore, accurate stock price prediction is the key to successful investment, and new machine learning algorithms handling the NCSF series are needed.

Keywords: stock price prediction, financial time series, machine learning method, deep learning method.

1 Introduction

The financial market is indeed a complex and giant system [1, 2, 3]. The financial time series analysis is an important access to touch the complex laws of financial markets [1, 2, 3]. Among many goals of the financial time series analysis, one is to construct a model that can extract the information of the future return out of the already known historical data, such as stock prices, financial news, economic events, and political events [4, 5, 6, 7, 8].

Before constructing a model that can extract the information of the future return out of the historical data, researchers need the prior knowledge of the markets and investigate issues such as whether the information of the future return is contained in the already known historical data? Or, is there a correlation between the future return and the historical stock prices? According to the efficient market hypothesis (EMH) [9, 10, 11], stocks always trade at their fair value on exchanges. thus, no investors can outperform the overall market through stock selection or market timing, the higher returns can only be obtained by purchasing riskier investments. Therefore, according to the EMH, there is no correlation between the current prices and the future prices of the stock market, i.e., any change in the stock prices is completely independent of the past prices. However, there are different opinions on the issue of EMH [9, 11, 12, 13], and higher returns can be obtained by technical analysis such as expert stock selection and market timing in real investments [14, 15, 16, 17, 18]. Many anomalies challenge the EMH. For example, in terms of market transactions, the mystery of equity premium, the mystery of volatility, scale effect, calendar effect, etc. Forsythe et al. [19] first propose that investors continuously obtain information from market trading activities, in other words, trading realizes the process of transmitting private information. Since then, asset transaction price deviating from its basic value and bubble phenomenon has also been found in other countries [20]. Darrat et al. [21] find that the stock return on Monday is significantly lower than that on other trading days [22, 23]. And this conclusion is also applicable to the Tokyo Stock Exchange [24]. In addition, when buying or holding financial products, the EMH cannot explain the winner-loser effect [25, 26], the book-to-market ratio effect [27, 28] and closed-end fund discount [29, 30]. With the development of behavioral finance [31], the irrational behavior of investors has been gradually discovered by scholars (such as disposal effect, dividends mystery, irrational over trading, etc.). This paper attempts to re-examine the theory and different opinions of the EMH, and put forward the future market research direction on the basis of behavioral finance. In this regard, we cannot deny that the historical data of financial markets contains information on the future return. Therefore, it is of great significance to analyze the hidden features and laws of historical financial data, including stock prices, financial news, economic events, and political events.

Stock prices are typical data that are accessible and intuitive. There are research studying how to extract future return from the known historical stock price. Before the popularity of machine learning methods, researchers investigate the financial time series from analytical and statistical methods. For example, the fractional market shows that the financial market has the characteristics of fractional and non-linearity [32, 33, 34, 35]. Spectrum analysis methods [36], such as the Fourier transform [37, 38] and the wavelet transform [37, 39, 40] are applied to the financial time series analysis. The auto regressive model (AR), the moving average model (MA), the auto regressive and moving average model (AR-MA), and etc., are proposed to model the market [1, 2, 3]. Besides, the generalized autoregressive conditional heteroskedasticity model (GARCH) is proposed to model and forecast conditional mean and volatility [41]. Other hybrid models such as ARMA-GARCH [42, 43] and its improved ARMA-GARCH-M [44] model are proposed. However, the statistical method is not suitable for actively discovering various potential rules from numerous data [45]

With the popularity of machine learning methods, researchers use machine learning methods to investigate the financial time series. For example, the SVM [4, 46], the recurrent neural network (RNN) [47] and its generalization LSTM [48, 49] network, and the convolutional neural network (CNN) [50, 51] are applied in financial time series forecasting. A multi-scale recurrent convolutional neural network (MSTD-RCNN) [52] is proposed and proved to improve the accuracy of data prediction. The hybrid models which is the combination of the statistical method and the machine learning method such as multi forecast model of ARIMA and artificial neural network (ANN) [53], the FEPA model (FTS-EMD-PCA-ANN) [54], nonlinear autoregressive neural network model [55] are used in modeling the financial time series. Beyond the model structure design, other researchers focus on the data. For example, Ref. [56] evaluates several augmentation methods applied to stocks datasets using two state-of-the-art deep learning models and shows that several augmentation methods significantly improve financial performance when used combined with a trading strategy.

The majority of the researches focus on how to improve the model's behavior in forecasting the future return and most of the proposed models have improved the forecasting accuracy. However, some research report a failure of the deep learning approach on financial time series analysis [57]. One argument for the machine learning used in stock price prediction is that they are black-box models which are difficult to interpret [58]. Moreover, it is challenged by problems such as over fitting, sensitivity to parameter selection and noise, slow convergent speed, computational power requirement [59, 60]. One solution to these problems is combining machine learning with equilibrium asset pricing [61, 62, 63, 64]. In this paper, we try to explain these problems from a new perspective. In our opinion, the prior knowledge on how the future stock prices or return is correlated with the historical stock prices should be obtained before designing an effect algorithm or model. Unfortunately, to our knowledge, not much research concerns the question about in what mode the future return is correlated with historical stock prices. Alternatively, how is the information of the future return contained in the historical stock price. With the absence of the prior-knowledge, one might become blind in choosing models.

In this paper, under the assumption that the market is not completely effective, we focus on the issue: in what mode the future return is correlated with the historical stock prices. We manually design several financial time series where the future return is correlated with the historical stock prices in pre-designed modes, namely the curve-shape-feature (CSF) and the non-curve-shape-feature (NCSF) modes. In the CSF mode, the future return can be extracted from the curve shapes of the historical stock prices. In the NCSF mode, the information of future return is not contained in the curve-shape of historical stock prices. By applying various existing algorithms on those pre-designed time series, we find that various models only perform well on the CSF mode series and fail on the NCSF mode series. By comparing the behavior of the same algorithm on the CSF mode series, NCSF mode series, and financial time series, we conclude that: (1) the major information of the future return is not contained in the curve-shape-features of historical stock prices. That is, the future return is not mainly correlated with the historical stock prices in the CSF mode. (2) Various existing machine learning algorithms are good at extracting the curve-shape-features in the historical stock prices and thus are inappropriate for financial time series analysis, although they are successful in image recognition, nature language processing, etc. It points out that beyond the existing models, new models that can extract non-curve-shape-features are needed in the financial time series analysis.

This paper is organized as follows: In Sec. 2, the pre-designed time series, including the CSF mode series and NCSF mode series, are introduced. In Sec. 3, we give a brief review of various existing algorithms and apply them on the CSF mode series, NCSF mode series, and the real series. In Sec. 4, we analyze the results. Conclusions and discussions are given in Sec. 5.

2 Pre-designed series: the CSF mode series and NCSF mode series

The prior knowledge that in what mode the future return is correlated with the historical stock prices is important in financial time series analysis. In this section, we manually design several financial time series where the future return is correlated with the historical stock prices in pre-designed modes, namely the curve-shape-feature (CSF) and the non-curve-shape-feature (NCSF) modes.

2.1 The CSF mode series

In this section, we introduce the CSF mode series. In the CSF mode series, the future return can be extracted from the curve shapes of the historical stock prices.

The curve-shape-features and simplified curve-shape-features. In the historical stock prices, the curve-shape-features are morphological shapes occurring in a window with a given size. There is a large amount of the curve-shape-features. In this work, we simplify the curve-shape-features by ignoring the magnitude of the stock prices and only considering the trend of increase and decrease, as shown in Figure 1. In the following discussion, we consider the simplified curve-shape-features only and do not distinguish between the curve-shape features and simplified curve-shape-features.

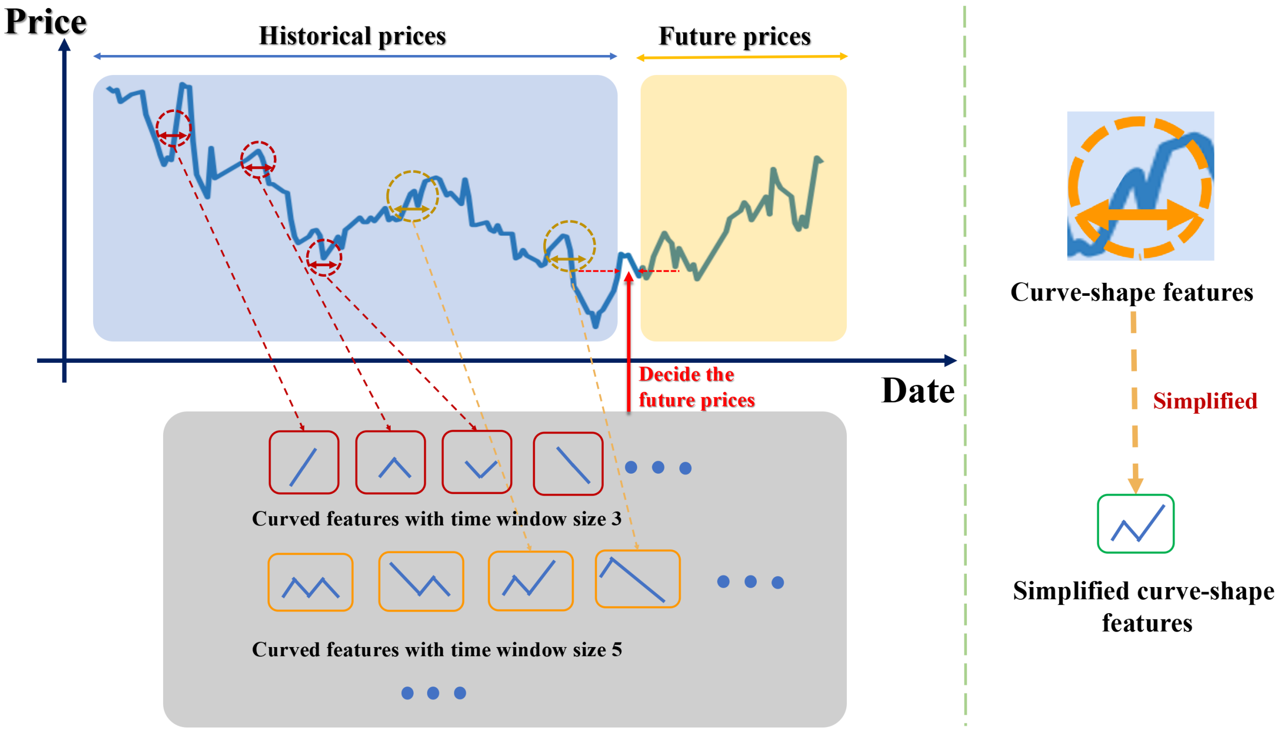

Figure 1: Examples of the curve-shape-features and simplified curve-shape-features. In the simplified curve-shape-features only the trend of increase and decrease is considered.

The effective curve-shape-features We can capture numerous different curve-shape-features from historical financial data. For example, curve-shape-features are intercepted within different-size windows, as shown in Figure 2. The curve-shape-features that are strongly correlated with the future return are the effective curve-shape-features. For instance, based on the simple and plausible assumption, the curve-shape-feature A occurs at a higher frequency in a positive return history series, then, A is an effective curve-shape-feature. The curve-shape-feature B occurs evenly in a positive and negative return history series respectively, and then, B is not an effective curve-shape-feature. If effective curve-shape-features exist, a combination of effective curve-shape-features can predict the future return.

The CSF mode series. In the CSF mode series, the future return can be extracted from the curve shapes of the historical stock prices. We manually assign a weight on the curve-shape-features. The summation of the weight of the features in a given historical stock price decides the future return. In the CSF mode series, those features with larger weight are effective curve-shape-features, as shown in Figure 3.

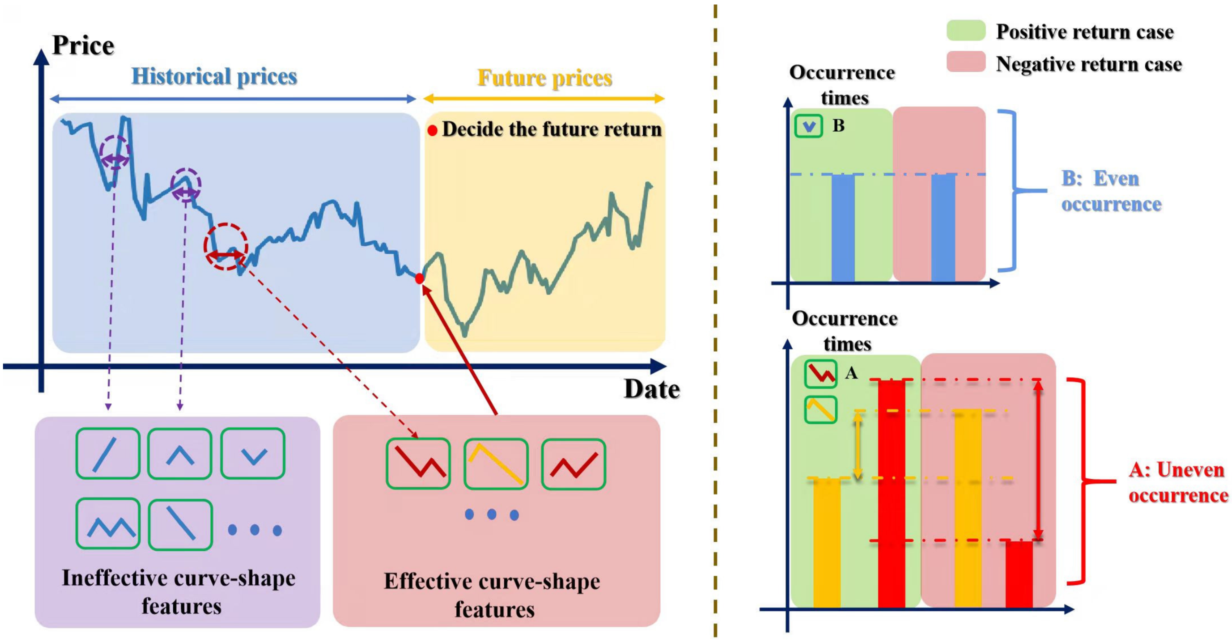

Figure 2: Examples of effective curve-shape-features. Effective curve-shape-features occur unevenly in the time series with positive and negative returns and decide the future returns.

2.2 The NCSF mode series: the momentum-featured series

Beyond the CSF mode series, there are still many hidden and unexplored laws in the historical stock prices, we name it the NCSF mode series. In this section, we manually design an NCSF mode series, where the future return can not be extracted from the curve-shape-of the historical stock prices. There are many possible realizations of the NCSF mode series, in this work, the future return is determined by the number of rises and falls in the historical data. For convenience, we name it the momentum-featured series. That is the momentum-featured series is one kind of the NCSF mode series. For example, for a historical data with in a fixed-size window, the ratio of the amount of rising data to the total amount of data is calculated. When the ratio exceeds a given value, say 0.7, the future return will be positive with a high probability, as shown in Figure 4. We are studying on how to design new NCSF mode series.

2.3 The selected four kinds of series

In this section, we introduce the four kinds of series that are used in the following experiment, and they are: (1) the CSF mode series, (2) the momentum-featured series which is a typical NCSF mode series, (3) the real stock series, and (4) the random generated series, as shown in Figure 5.

In the series, the maximum size of the time window is 20, that is, the next days return is decided by the prices in previous 20 days.

3 The methods and the experiment settings

In this section, various existing algorithms are applied on the four kinds of series, including a new proposed statistical method, the existing machine learning methods, and the existing deep learning methods. The result shows that the existing algorithms are good at extracting the CSF in the historical stock prices. That is, the existing algorithms are effective for the CSF mode series and are inappropriate for the NCSF mode series.

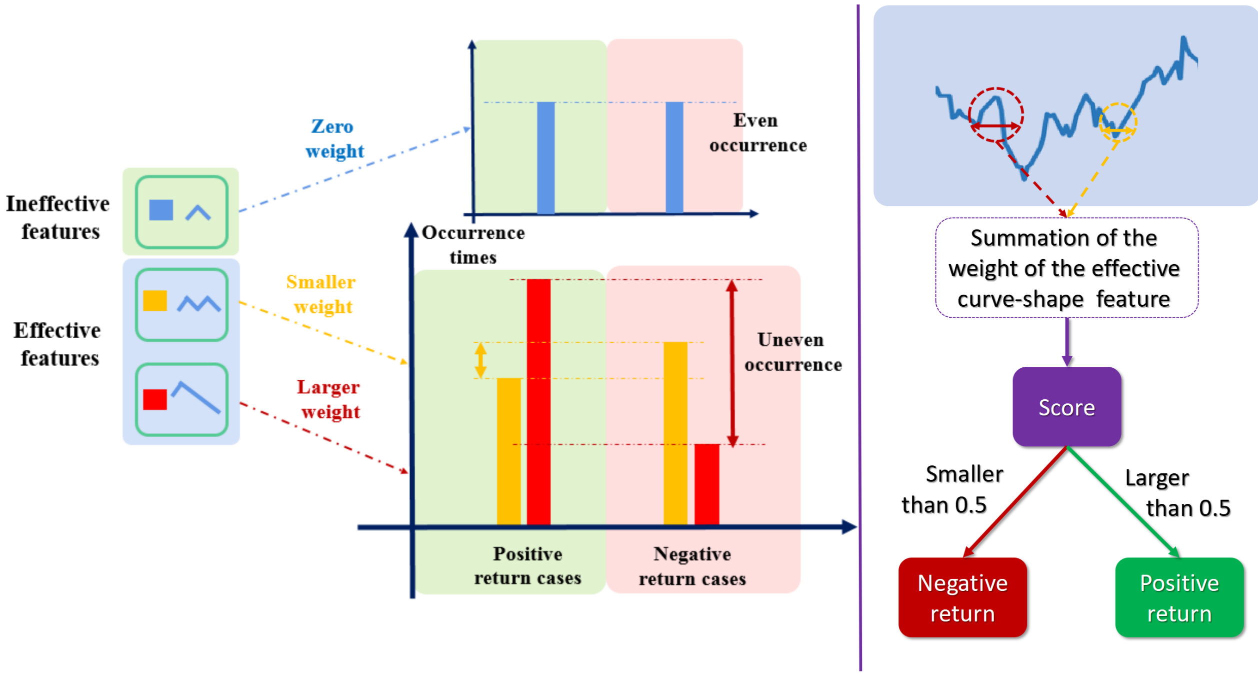

Figure 3: Examples of effective curve-shape-features with weights and CSF mode series. The effective curve-shape-features with higher degree of uneven occurrences have larger weights. The summation of the weight of the effective curve-shape-features in a time series, namely the score of the time series, decide the future return. For example, if the score beyond a threshold, the future return will be positive with a high probability.

3.1 The proposed statistical method for curve-shape-features (the SM-CSF model)

In this section, we propose a statistical method designed to extract the effective curve-shape-features in the series. For convenience, we name the method statistical method for curve-shape-features as SM-CSF model. In this section, we give an introduction to the SM-CSF model.

In the SM-CSF model, we firstly collect all possible simplified curve-shape-features in given window sizes, say window sizes 4, 5, 6, and 7. Secondly, we count the occurrence times of each curve-shape-features in the positive and negative samples. Furthermore, the effective curve-shape-features are selected according to their uneven occurrence times. For example, if feature A occurs 100 times in the positive samples and 1000 times in the negative samples, we consider A as an effective curve-shape-feature. Finally, the linear regression method is applied to find the weight that evaluates the importance of each effective curve-shape-feature to the future return. That is, a weight is assigned to each effective feature and the weight is evaluated by linear regression method [65].

3.2 The existing algorithms: a brief review

In this section, we give a brief review of the existing algorithms, including machine learning methods and deep learning methods. The source code of the involved algorithms can be obtained by sending email to the corresponding author.

Machine learning methods: the SVM. The SVM [4, 46, 66, 67] is a typical supervised machine learning algorithm and the key idea in the SVM is the support vector and nonlinear kernel function that enable the algorithm to find a nonlinear hypersurface in the feature space separating the positive and negative samples well. The SVM algorithm is implemented by scikit-learn [68], an open machine learning toolkit.

Machine learning methods: the RF. The RF [69] is a bagging combination of different decision trees (DT) [70], which are useful tools for classification. The key idea in the decision tree is to form a tree structure. The tree is constructed by splitting the data set into subsets based on an attribute value test. This process is repeated on each derived subset, namely, the recursive partitioning. The

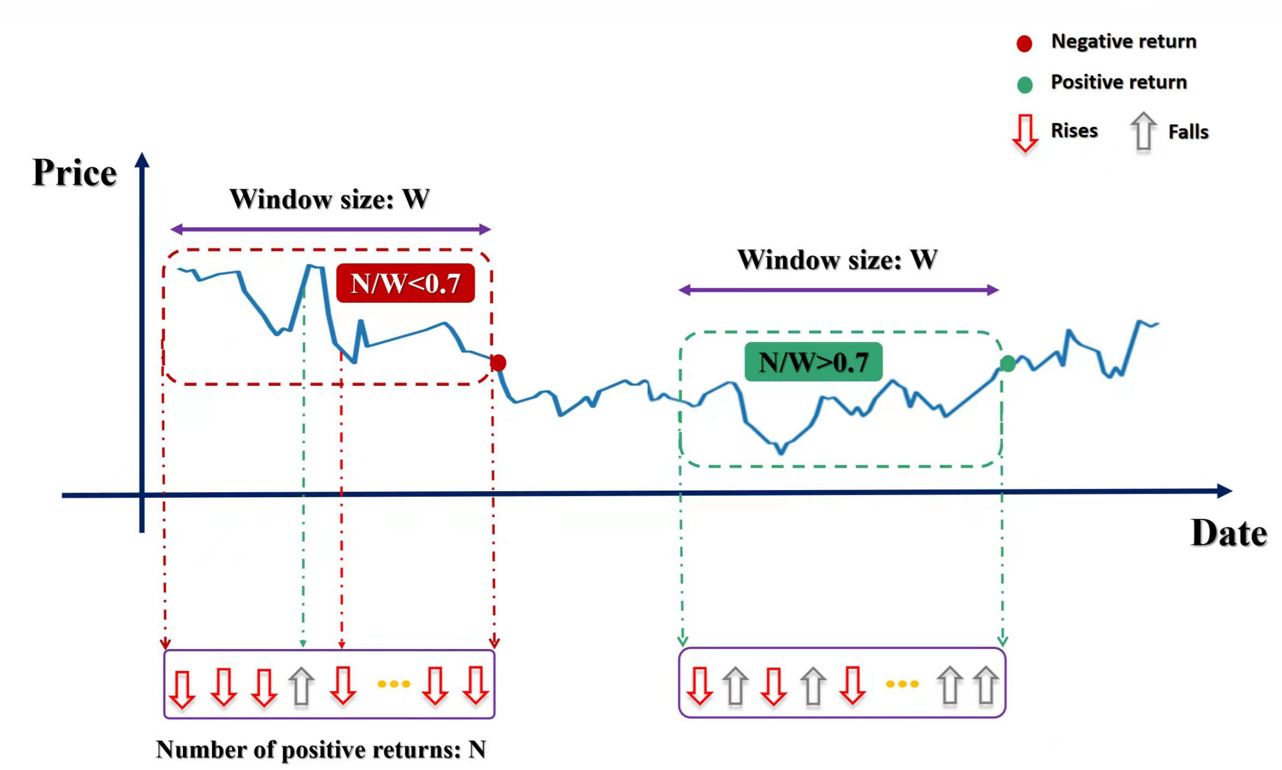

Figure 4: An example of the momentum-featured series

recursive partitioning stops when the subset at a node has the same value. The RF algorithm is implemented by scikit-learn [68].

Machine learning methods: the MLP. The MLP [71] is a typical feedforward neural network which is good at finding the target function that maps a multi-dimensional input to a multi-dimensional output. The key idea in the MLP is the fully connected hidden layer and nonlinear activation function. The MLP algorithm is implemented by scikit-learn [68].

Machine learning methods: Bayesian classifier. A Bayesian classifier [72] is a statistical classifier that is based on the Bayes formula. Unlike other algorithms such as the SVM, RF, and MLP, the Bayesian classifier is a probabilistic model, or generative models, and requires the prior-knowledge of the joint distribution of input features and output labels. The Bayesian classifier algorithm is implemented by scikit-learn [68].

Deep learning methods: the embedded CNN. The CNN [73, 74] is an effective feature extractor that can extract location independent features from structured raw data, such as iconic features in an image. The key idea in the CNN is the convolutional and pooling operations. In the convolution operation, a rectangular convolution kernel is used to scan the important features of the structured data. The pooling operation, or down sampling, is used to select the most representative features and reduce the calculation amount.

In this work, the input historical stock prices is a 20-dimensional data, the CNN is used to extract the curve-shape features. Moreover, we design an embedded CNN where the embedding technique [75] is used. The embedding is a useful technique to help the network "understanding" the low dimensional data. For example, the word embedding helps the network "understand" the meaning of a word. In the embedded CNN, the 20-dimensional input data is transformed into a high dimensional data with a size of 20×16 by converting each value in the series into a 16-dimensional vector. After that the CNN with 32 filters of size 5x7x9 is used. For both CNN and embedded CNN algorithms, the cross-entropy between real label and predicted label is treated as the loss function. The learning rate is 0.005 and the batch size is 512. The CNN and the embedded CNN algorithms are implemented by Tensorflow [76], an open deep learning toolkit.

Deep learning methods: the embedded BiLSTM. The LSTM [73] is an improved recurrent neural network (RNN). The RNN is an useful feature extractor that can extract important features from

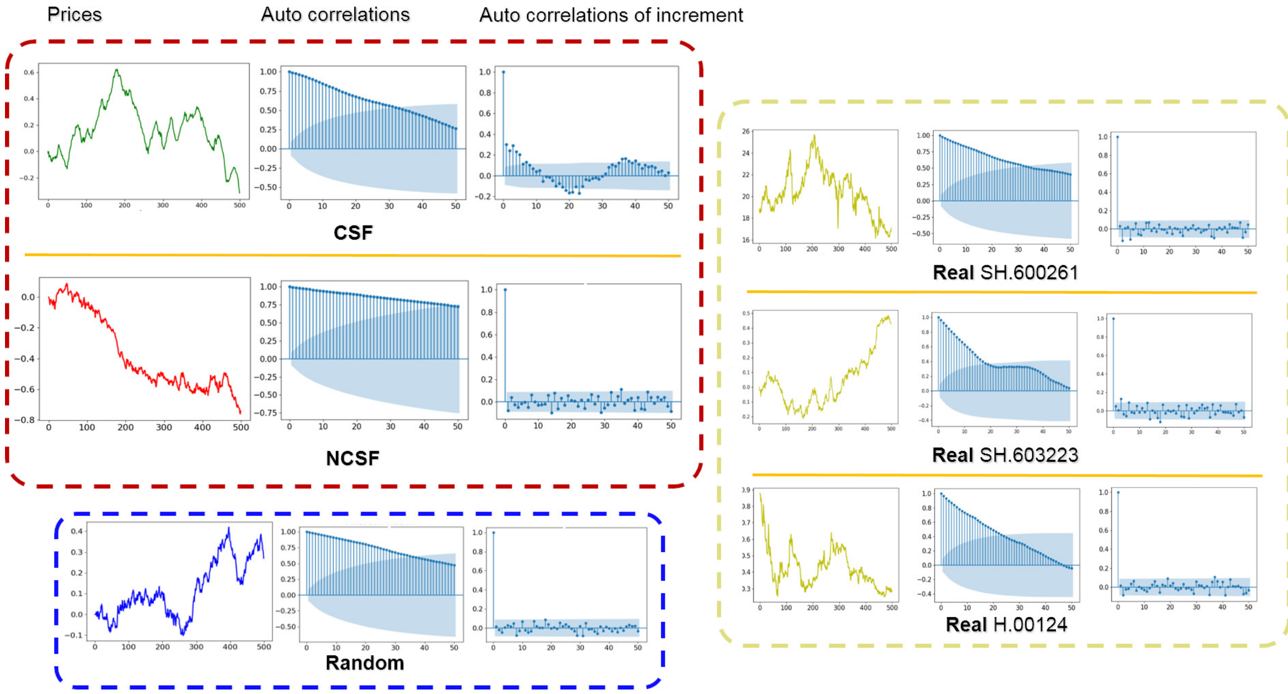

Figure 5: A diagram of the prices and autocorrelation function of the four kinds of series including the CSF mode, NCSF mode, random generated, and real series.

the historical time series. The key idea in the LSTM is the gates. For example the input gate, the output gate, and the forget gate. Those gates enable the LSTM to remember and forget information in historical time series. The BiLSTM [77] extracts important features from a time series twice, namely forward and backward.

Beyond the BiLSTM, we also provide an embedded BiLSTM, where the 20-dimensional input data is transformed into a high dimensional data with a size 20×16 by converting each value in the series into a 16-dimensional vector too. For both BiLSTM and embedded BiLSTM algorithms, the cross-entropy between the real label and predicted label is treated as the loss function. The learning rate is 0.005 and the batch size is 512. The BiLSTM and the embedded BiLSTM algorithms are implemented by Tensorflow [76]

3.3 The ground truth of the CSF and the NCSF mode series

Given that the CSF and NCSF mode series in this work are generated manually, according to the pre-designed rules, we can easily extract the information of future return from historical data in such series. Therefore, we can give the ground truth representing the maximum degree of information a model can extract from the CSF and the NCSF series. For convenience, we name them the ground truth model for the CSF series (GT-CSF) and the ground truth model for the NCSF model (GT-NCSF).

The GT-CSF model. In the GT-CSF model, the pre-designed rule is used to extract the information of future return. For example, the weights for each curve-shape-features and the threshold of the score are known. By directly calculating the score of the series and comparing it with the threshold, we can give the trend of future return.

The GT-NCSF model. In the GT-NCSF model, the pre-designed rule is also used. For example, we know the ratio between rises and falls that decide the future return. By directly calculating the ratio of rises and falls and comparing it with the threshold, we can give the trend of future return.

An overview of the methods is given in Figure 6.

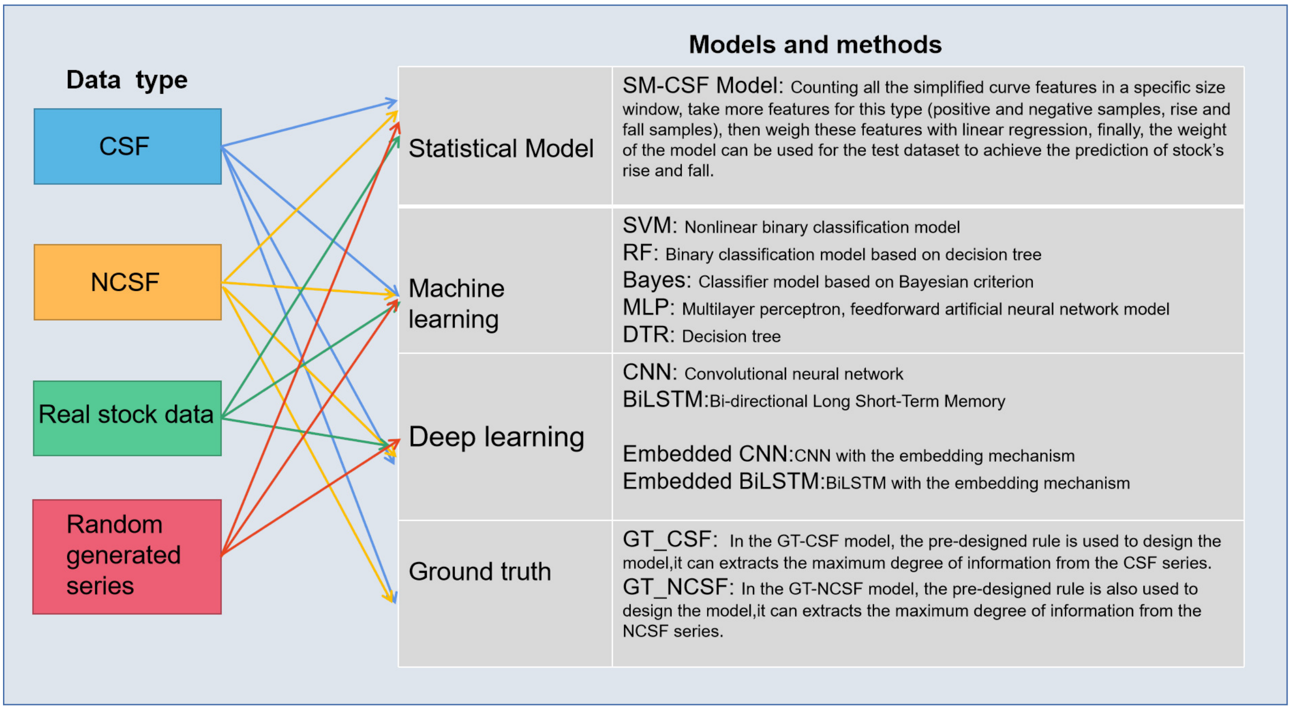

Figure 6: An overview of the methods.

4 The results and analysis

In this section, we show the results of different algorithms on the four series.

4.1 The criteria

To judge the behavior of the algorithms, we give a criterion as follows: in a given test data set, we calculate the precision of the positive return cases in selected samples by each algorithm and compare it with that of the randomly selected samples or that of the whole test data set. For example, we collect the positive return cases predicted by the algorithms, say 1000 rises predicted by the SVM, calculate the proportion of real rises, say 0.60 since there are 600 real rises, and compare it with that of randomly selected cases, say 0.50 since there are 500 real rises in the randomly selected 1000 cases. The precision given by the ground truth gives the upper bound over all the algorithms. For example, in the randomly selected samples, the precision of the positive return cases is 0.52. The ground truth is 0.75 evaluates the maximum amount of the information of future return that is contained in the historical prices. If the precision of selected samples by algorithm A is obviously larger than 0.52, then algorithm A is concluded to be effective. That is, algorithm A can extract the mode where the future return is correlated with the historical prices. Otherwise, algorithm A is ineffective on the series.

The following figures show the experimental results of various kinds of models on four kinds of series. In those plots, the Y-axis is the difference of precisions on selected cases by the algorithm and randomly selected cases. The X-axis is the size of training data (data size). The test data set in one experiment is always the same. Figures 7 and 8 are the results of various kinds of models on the CSF mode and NCSF mode series, respectively. For example, in Figure 7, the ground truth is ~ 0.30, and the average precision difference is ~ 0.15. The SM-CSF model gives the best precision difference ~ 0.25. In Figure 7, the ground truth is ~ 0.25, and the average precision difference is ~ 0.08. The MLP and BiLSTM give the best precision differences around ~ 0.15.

From these different models, we put forward the first four with the best effect and put them in Figure 9. Through comparison, it can be observed that the deep learning model is more suitable for extracting the CSF, while the extraction effect for the NCSF is poor. In addition, the results of the real series and randomly generated series are shown in Figures 10 and 11. Figure 11 shows that in the random generalized series, all algorithms fail and most give the precision difference ~ 0.0 or ~ -0.5

since the ground truth is 0.00. Figure 10 shows that in the real stock price series, some algorithms fail while other algorithms, such as the MLP, the SVM, the RF, and the DT, give low precision differences. However, the ground truth of the real stock price series is unknown.

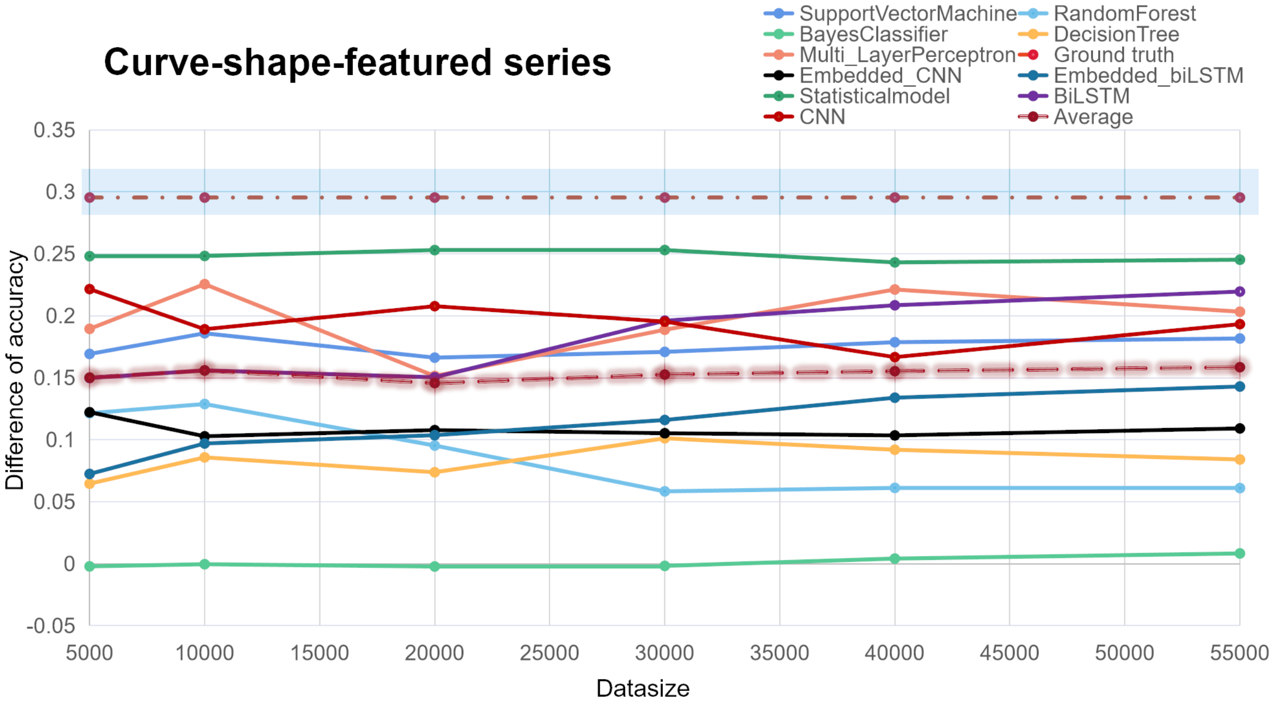

Figure 7: The result of the CSF mode series.

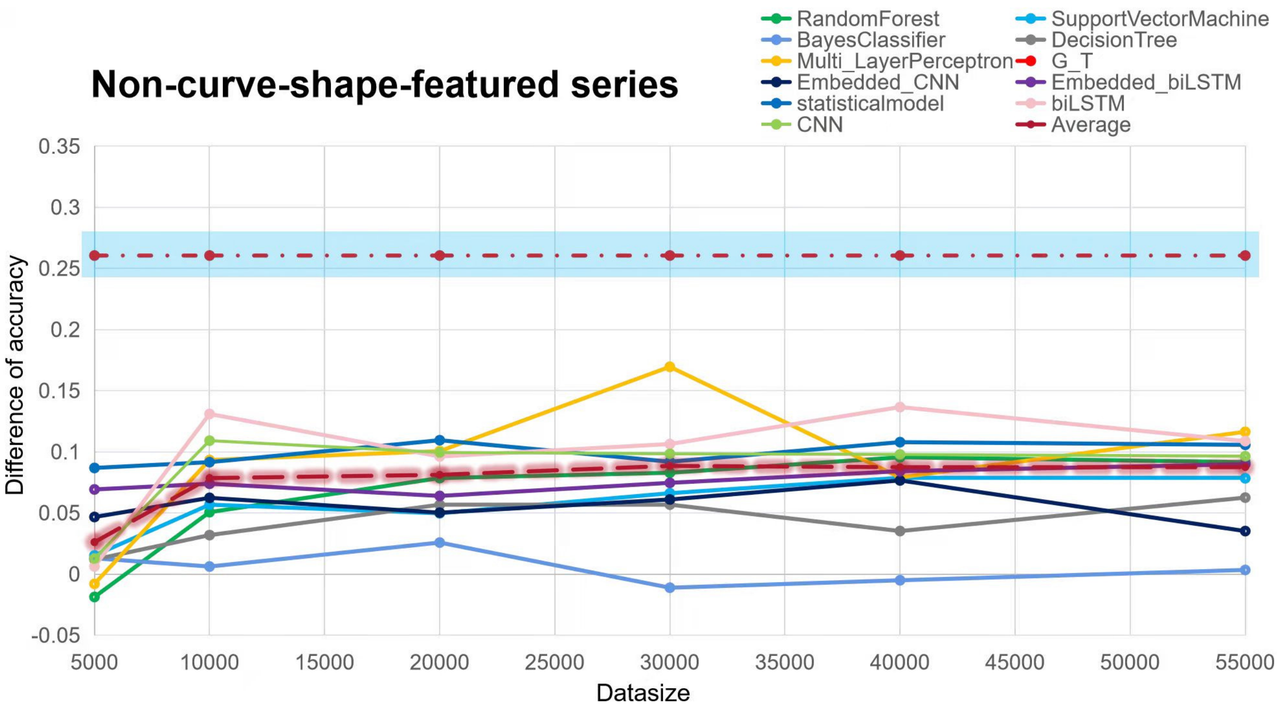

Figure 8: The result of the NCSF mode series.

4.2 The analysis

By comparing the behaviors of various algorithms on the CSF and NCSF mode series, we can see that these models are effective on the CSF mode series, indicating that they can effectively extract curve-shape-features. In contrast, they are less effective on of the NCSF mode series, see Figure 9.

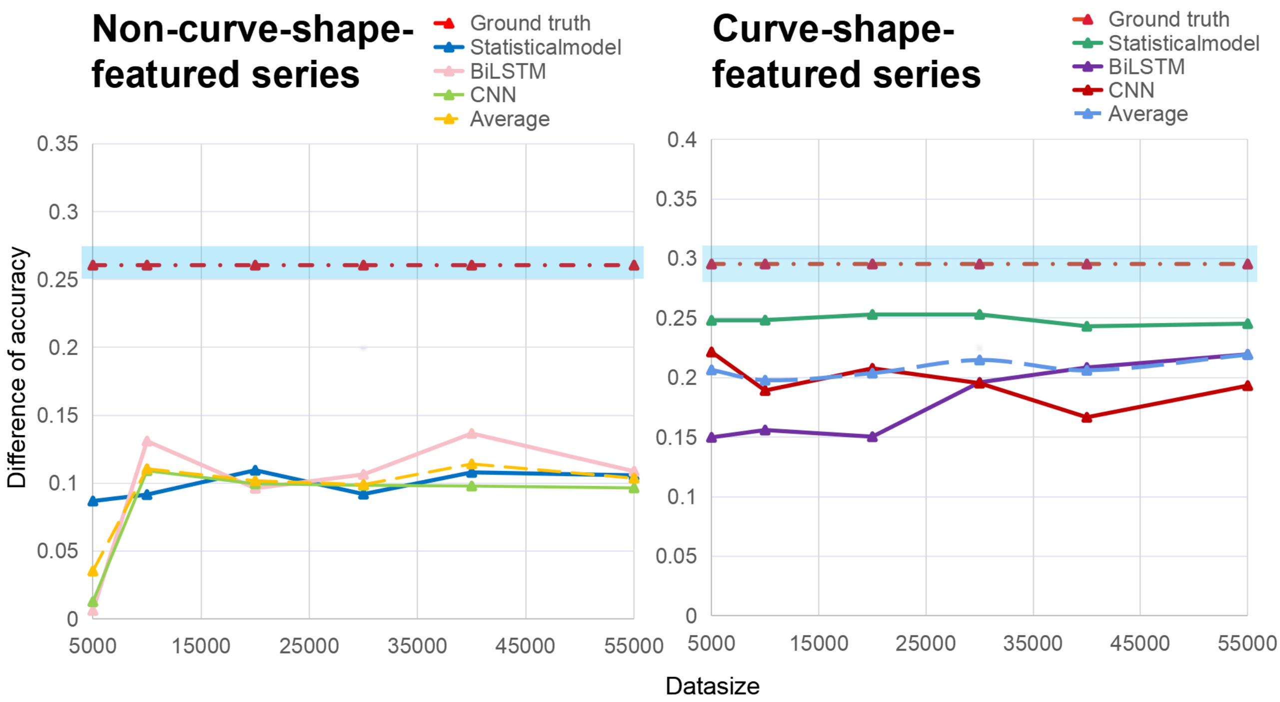

Figure 9: A comparison of top 4 models for the CSF and NCSF mode series.

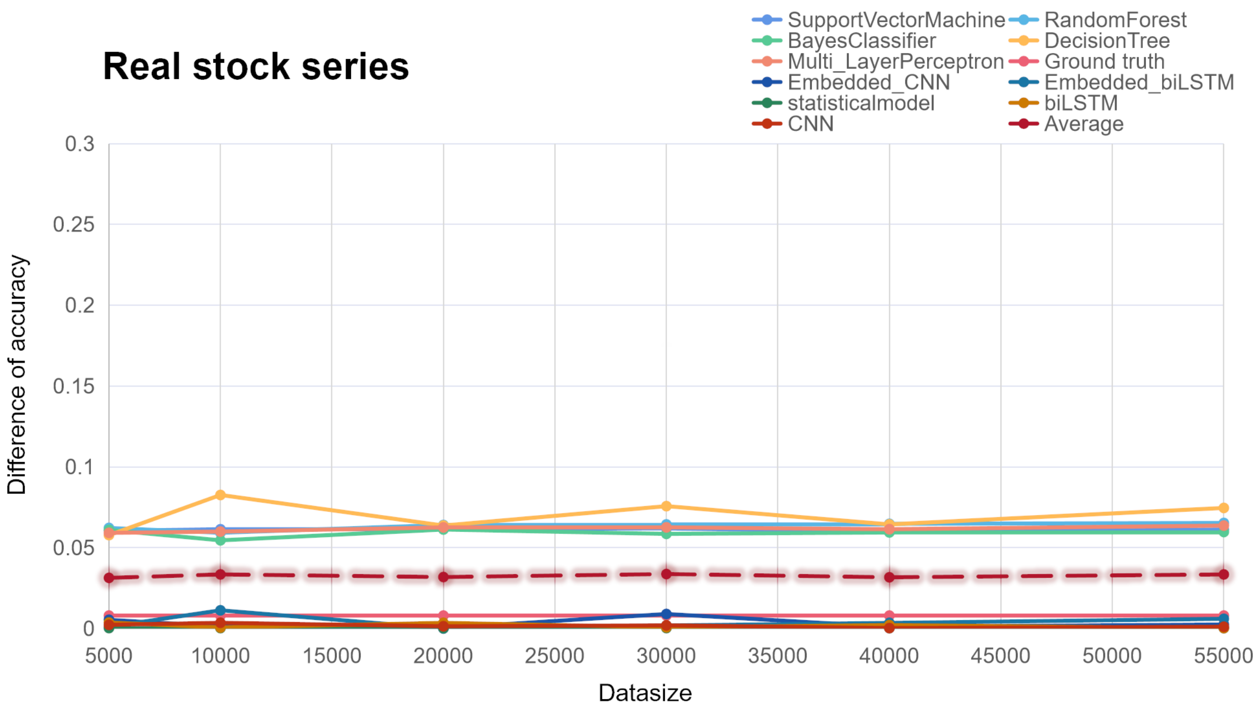

Figure 10: The result of the real stock series. Deep learning algorithms fail while other machine learning algorithms, such as the MLP, the SVM, the RF, and the DT, give low precision differences.

Considering the behavior of various algorithms on the real stock price series, see Figures 10, we conclude that in the real financial time series, less information of future return is contained in the curve-shape-features and perhaps more information is contained in the non-curve-shape-features, since the ground truth is unknown. It points out that beyond the existing models, new models that can extract non-curve-shape-features are needed in the financial time series analysis. We show that various kinds of existing machine learning models which are successful in image recognition and natural language processing are inappropriate in financial time series analysis. We also point out the reason: various kinds of existing machine learning models are good at extracting the curve-shape-features and the information of the future return is not all contained in the curve-shape-features of historical stock prices.

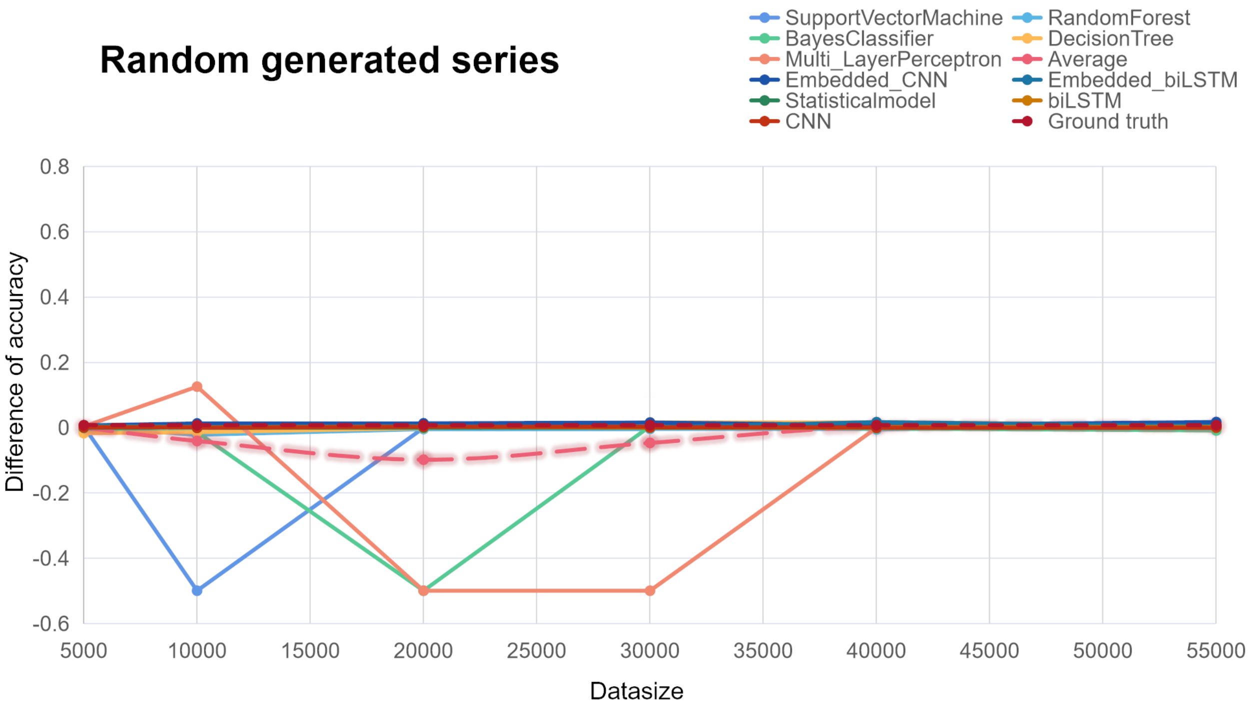

Figure 11: The result of the random generated series. In this case, most algorithms give predicted labels as either all rises or all falls. At these two cases, the precision difference is 0 or -0.5.

5 Conclusions and outlook

In this paper, under the assumption that the market is not completely effective, we focus on the stock price prediction. The innovation in this research is that we proved an interesting perspective to explore in what mode the future return is correlated with the historical stock prices. The main method can be summarized as two aspects: (1) we manually design financial time series where the future return is correlated with the historical stock prices in pre-designed modes, namely the curve-shape-feature (CSF) and the non-curve-shape-feature (NCSF) modes. In the CSF mode, the future return can be extracted from the curve shapes of the historical stock prices. In the NCSF mode, the information of future return can not. (2) By applying various kinds of existing algorithms on those pre-designed time series, we find that various kinds of existing models are good at handling the CSF mode series and are less effective in handling the NCSF model series.

Moreover, by applying the same algorithms on the real stock price series, we conclude that: (1) the major information of the future return, if exists, is not contained in the curve-shape-features of historical stock prices. That is, if the future return can be predicted by historical stock price data, it is not mainly correlated with the historical stock prices in the CSF mode. (2) Although various kinds of existing machine learning algorithms, including the deep learning algorithms, are successful in the fileds of image recognition, nature language processing, and etc. In the field of financial time series analysis, perhaps, they can not achieve the same successes. Beyond the existing models, new models that are effective in NCSF mode series, or can extract non-curve-shape features effectively, are needed.

The NCSF mode series and algorithms for the NCSF mode series can give a new insight into the stock price prediction thus explaining questions such as what is the upper bound of the information of the future return contained in the historical stock price data. We are working on design new NCSF mode series and new algorithms that are effective in the NCSF mode series.

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Author contributions

Jiayao Yang and Ping Zhang contributed equally to this work.

Conflict of interest

We declare that we have no financial and personal relationships with other people or organizations that can inappropriately influence our work, there is no professional or other personal interest of any nature or kind in any product, service and/or company that could be construed as influencing the position presented in, or the review of, the present manuscript.

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