Why Existing Machine Learning Methods Fails At Extracting the Information of Future Returns Out of Historical Stock Prices: the Curve-Shape-Feature and Non-Curve-Shape-Feature Modes

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Abstract: The financial time series analysis is important access to touch the complex laws of financial markets. 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 known historical stock data, such as stock price, financial news, and e.t.c. To design such a model, prior knowledge on how the future return is correlated with the historical stock prices is needed. In this work, 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. By applying various kinds of existing algorithms on those pre-designed time series and real financial time series, we show 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 kinds of 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 the image recognition and natural language processing. That is, existing machine learning methods that are good at handling the CSF series will fail at extracting the information of future returns out of historical stock prices. New models handling the NCSF series are needed in the financial time series analysis.

Keywords: Machine learning, Classification, Feature extraction, Financial time series, Deep learning

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1 Introduction

The financial market is indeed a complex and giant system [1–3]. The financial time series analysis is important access to touch the complex laws of financial markets [1–3]. 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 [4–8].

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 contained in the already known historical data? Or, is there a correlation between the future return and the historical stock prices? According to the effective market hypothesis (EMH) [9–11], 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 EMH, there is no correlation between the current price and the future price of the stock market, i.e., any change in the stock price is completely independent of the past price. However, there are different opinions on the issue of EMH [9, 11–13] and higher returns can be obtained by technical analysis such as expert stock selection and market timing in real investments [14–18]. In this regard, we cannot deny that the historical data of financial markets contains information of 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 prices. Before the popularity of machine learning methods, researchers investigate the financial time series from the perspective of analytical and statistical methods. For example, the fractional market shows that the financial market has the characteristics of fractional and non-linearity [19–22]. Spectrum analysis methods [23], such as the Fourier transform [24, 25] and the wavelet transform [24, 26, 27] 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 e.t.c., are proposed to modeling the market [1–3]. Besides is directly forecasting the future return, the generalized autoregressive conditional heteroskedasticity model (GARCH) is proposed to model and forecast conditional mean and volatility [28]. Other hybrid models such as ARMA-GARCH [29, 30] and its improved ARMA-GARCH-M [31] model are proposed. However, the statistical method is not suitable for actively discovering various potential rules from numerous data [32]

With the popularity of machine learning methods, researchers use the machine learning methods to investigate the financial time series. For example, the support vector machines (SVM) [4, 33], the recurrent neural network (RNN) [34] and it’s generalization long-short term memory (LSTM) [35, 36] network, and the convolutional neural network (CNN) [37, 38] are applied in financial time series forecasting. A multi-scale recurrent convolutional neural network (MSTD-RCNN) [39] 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) [40], the FEPA model (FTS-EMD-PCA-ANN) [41], nonlinear autoregressive neural network model [42] are used in modeling the financial time series. Beyond the model structure designing, other researchers focus on the data. For example, Ref. [43] evaluates several augmentation methods applied to stocks datasets using two state-of-the-art deep learning models and show that several augmentation methods significantly improve financial performance when used in combination with a trading strategy.

The majority of the research focused on how to improve the model’s behavior in forecasting the future return and most of the proposed models report a improving in the forecasting accuracy. However, there are research report a failure of the deep learning approach on financial time series analysis [44]. In our opinions, the prior-knowledge on how the future stock price or return is correlated with the historical stock price should be obtained before designing an effect algorithm or model. Unfortunately, to our knowledge, not many research
concern the question about in what mode the future return is correlated with the historical stock price. Or, how is the information of the future return contained in the already known 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 kinds of existing algorithms on those pre-designed time series, we find that various kinds of existing 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 real 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 kinds of 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 the image recognition, nature language processing, and e.t.c. 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 firstly give a brief review on various existing algorithms and secondly 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 price.

*The curve-shape features and simplified curve-shape features.* In the historical stock price, the curve-shape features are morphological shapes occurring in a window with 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 Fig. 1. In the following discussion, we consider
the simplified curve-shape features only and make no distinguish between the curve-shape
features and simplified curve-shape features.

*The effective curve-shape features* We can capture numerous different curve-shape fea-
tures from historical financial data. For example, curve-shape features intercepted within
different-size windows, as shown in Fig. 2. The curve-shape features that are strongly
correlated with the future return is the effective curve-shape features. For example, 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 posi-
tive and negative return history series respectively, then, B is not an effective curve-shape
feature. 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 price. We manually assign a weight on the curve-
shape features. The summation of the weight of the features occur in a given historical
stock prices decide the future return. In the CSF mode series, those features with larger
weight are effective curve-shape features, as show in Fig. 3.

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

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.
2.2 The NCSF mode series: the momentum-featured series

In this section, we manually design a NCSF mode series, where the future return can not be extracted from the curve shape of the historical stock prices. In this series, the future return is determined by the number of rises and falls in the historical data. For the sake of convenient, we name it the momentum-featured 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 Fig. 4. The momentum-featured series is just one of the NCSF mode series.

![Diagram](image)

**Figure 4.** An example of the momentum-featured 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 Fig. 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 of 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 curve-shape features in the historical stock price. That is, the existing algorithms are effective for the CSF mode series and are inappropriate for the NCSF mode series.

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

In this section, we propose a statistical method that is designed to extract the effective curve-shape features in the series. For the sake of convenience, we name this method statistical method for curve-shape features (the SM-CSF model). In this section, we give an introduction of 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. And the effective curve-shape features are selected according to their unevenly occurrence times. For example, if the 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 the each effective
curve-shape feature to the future return. That is, a weight is assigned to each effective features and the weight is evaluated by linear regression method [45].

3.2 The existing algorithms: a brief review

In this section, we give a brief review of the existing algorithms, including the statistical methods, machine learning methods, and deep learning methods.

**Machine learning methods: support vector machine (SVM)** The SVM is a supervised learning model and related learning algorithm for data analysis in classification and regression analysis. Given a group of training instances, each training instance is marked as belonging to one or the other of the two categories. SVM training algorithm creates a model to assign the new instance to one of the two categories, making it a non-probabilistic binary linear classifier [46].

**Machine learning methods: random forest (RF)** It can be regarded as a basic classification method of decision tree. The decision tree is composed of nodes and directed edges. The internal nodes represent feature attributes, and the external nodes (leaf nodes) represent categories. RF is a bagging combination of different decision trees, which is based on decision tree. The decision tree selects an optimal feature (maximum information gain ID3, maximum information gain ratio C4.5, minimum Gini index) from the feature set to branch, while the random forest selects the optimal feature from the randomly selected feature subset to branch.

**Machine learning methods: multilayer perceptron (MLP)** The MLP is a kind of forward structure artificial neural network, which maps a group of input vectors to a group of output vectors. MLP can be regarded as a directed graph, which is composed of multiple node layers, and each layer is fully connected to the next layer. Except for the input nodes, each node is a neuron with a nonlinear activation function.

**Machine learning methods: bayesian classifier** Based on Naive Bayes formula, the maximum value of a posteriori probability is compared to classify. The calculation of a posteriori probability is obtained by the product of a priori probability and class conditional probability. A priori probability and class conditional probability are obtained by training data set.

**Deep learning methods: the embedded convolution neural network (CNN)** The convolutional neural network contains a feature extractor composed of convolution layer and subsampling layer. In convolution layer of convolution neural network, one neuron is only connected with some neighboring neurons. In a convolution layer of CNN, there are usually several feature maps. Each feature plane is composed of some neurons arranged in a rectangle. The neurons in the same feature plane share weights, and the weights shared here are convolution kernels. Convolution kernel is usually initialized in the form of random decimal matrix. In the process of network training, convolution kernel learn to get reasonable weights. Subsampling, also known as pooling, usually has two forms: mean pooling and Max pooling [47]. Convolution and subsampling greatly simplify the model complexity and reduce the model parameters.

We design an embedded convolution neural network [48]. In this network, firstly, embedding the input series, sparsely representing the original data, converting each value in
the series into vectors, learning into vector space. After that we convolute the embedded series by using 32 filters of size 5x7x9, then pooling them to extract the effective features. Finally, the output prediction value is calculated at the full connection layer.

Deep learning methods: the embedded long short-term memory neural network (LSTM)
LSTM is an improved RNN. LSTM networks consist of LSTM units. LSTM unit is composed of cells having input, output and forget gates. These three gates regulate the information flow. With these features, each cell remembers the desired values over arbitrary time intervals. LSTM cells combine to form layers of neural networks [49].

Based on the biLSTM, we structure an embedded biLSTM, where we embed the input series firstly, which converts each value in the series into a vector, this process can represent the series sparsely in vector space. Next, the embedded series is input from forward LSTM and backward LSTM in one time step. Forward LSTM and backward LSTM are calculated to get two sets of hidden vectors with valid features. Then two sets of hidden vectors are stitched together to get the final hidden state [50]. The model’s output layer calculates the predicted value based on parameters such as hidden state and weight, and the Loss function use the cross-entropy.

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

In this work, the CSF and NCSF series are generated manually. According to the generation rules of the CSF and the NCSF series, we can easily design a model that can extract the information of future return from such series. With this regard, we consider the model as the model of ground truth, because it extracts the maximum degree of information from the CSF and the NCSF series. For the sake of convenient, we name them the ground truth model for the CSF series (GT-CSF) and 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 design the model. For example, we know the weight for each curve-shape features and the threshold of the score. 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 to design the model. For example, we know the ratio between ups and downs that decide the future return. By directly calculating the ratio of ups and downs and comparing it with the threshold, we can give the trend of future return.

An overview of the methods is given in Fig. 6.
4 The results and analysis

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

4.1 The criteria

We give a criterion to judge the behavior of the algorithms 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 random selected samples. 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 price. Otherwise, algorithm A is ineffective on the series.
4.2 The result of the CSF mode series

![Curve-shape-featured series graph](image)

*Figure 7. The result of the CSF mode series*

4.3 The result of the NCSF mode series

![Non-curve-shape-featured series graph](image)

*Figure 8. The result of the NCSF mode series*
Figure 9. The result of several models (deep learning models, statistical model) for CSF mode series.

From these different models, we put forward the first four with the best effect and put them in Figure 8. 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.

4.4 The result of the real series

Figure 10. The result of the real stock series
4.5 The result of the random generated series

![Random generated series](image)

**Figure 11.** The result of the random generated series

4.6 The analysis

We conclude that in the real financial time series, less information of future return is contained in the curve-shape manner and more information is contained in the non-curve-shape manner. 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 the 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 data.

5 Conclusions and outlook

Through the above research results, we can see that statistical models, machine learning models, and deep learning models can give effective classification and prediction results for the curve-shape-featured data, however, for the non-curve-shape-featured data which does not contain the significant laws, these multi domain models cannot effectively classify them, that is also completely consistent with our speculation.

This is also sufficient to explain that in the financial data, due to a large number of combined curve-shape-features and non-curve-shape-features, the current forecasting methods cannot provide effective answers to the trend of future income. At the same time, we also pay attention to that in the financial market, different participants and researchers
have their own subjective combination of characteristics, because according to the different time scales, a lot of combined curve-shape-features can be observed from the historical data, so everyone form their own judgment methods, such as those experienced investors. Therefore, the complex and diversified combination of curve-shape-features also affects the above model to judge the future income results differently.

Our breakthrough in this research is to prove the existence of effective curve-shape-features from complex financial data. These features of different curve-shape patterns contain effective information that affects future income results. According to the different combination methods and orders of various data-shape forms, the formed laws and speculative results also be different. In addition, the data are mixed with a large number of non-curve-shape-featured data (disorderly and random data). In the test of A-shares and Hong Kong stocks data, the test results of the three domain models are invalid, which indicates that the market is not effective under the premise of this theory, if we want to predict the future trend by analyzing the historical data, we can either analyze more historical data to extract enough effective features, so as to improve the more accurate basis for the future trend. Or we can only design more complicated and more powerful models (more intelligent models), more accurate parameters, more complicated data processing and model optimization.

In this experiment, we use supervised models and discrimination models. These models can be understood as completely relying on data volume, just like use memory. Therefore, the data classification and prediction effect of curve-shape-features is better. For complex data that cannot identify the laws, they cannot make effective classification and prediction. So, we turn to the use of generative models in the next step: AE, GAN, etc.

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