Application of Market Cycle Analysis and LSTM in Prediction of Stock Price Movements

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Abstract. The stock market prediction has been carried out by several ways in data science using deep learning approaches to capture profitable trading opportunities and making the trading plans. However, it is widely believed there are two main issues involved in it, i.e., efficient market hypothesis and low information noise ratio. Therefore, a prediction based model will be affected by noises thus hard to produce a prediction. In this paper, two methods will be presented for forecasting stock future performance. To be specific, LSTM (long-short time memory) and cycle analysis are implemented to predict the future period that gives a higher return than average times. According to the analysis, introducing the time analysis as a variable to input could significantly increase the accuracy of predicting the return for the next few weeks. These results shed light on guiding further exploration of the different ways of extracting periodic behaviors of the market and marking predictions based on the analysis.

Keywords: Stock prediction; random forest; LSTM; Market Cycle Analysis.

1. Introduction

It is widely believed that finance plays an essential role in society development and financial market could reflect in advance many aspects of economy and provide a measurement of the value. There is a wide range of objects could be traded like stocks, bonds, futures and currencies. The products in all these categories are massive, thus it is required to introduce an effective way of predicting how they will develop with time and how they are interlinked with each other.

Prediction financial market has always been a subject studied by industry, academics, and countries due to potential high rewards. The scopes could range from all kinds of data, some uses basic macro economic data including GDP, CPI, PPI, consumer confidence etc. [1]. one could also use sentiment analysis gathered from social media or questionnaires, other data such as past price actions using technical analysis across different time frames could also be used to this end, and many existing articles use time series data of the past to predict the future price movements [2]. To use data collected due to the non-linearity of stocks, one potential way is to use deep neural networks which supports an activation function that could give an produce an model for prediction [3].

To be specific, Zhang uses contextual data such as financial reports from both economy journals and financial news, market sentiment form social media like twitter and facebook etc aside from basic price data [4]. The author then primarily used BERT method in NLP to score different sentiment and apply them to analysis and obtain a higher stock movement directional accuracy. Similarly, Narayana Darapaneni et al. also used tweet data feed to extract information and categorized data into four distinct groups [5]. Then, they use deep learning techniques to forecast the future price changes. However their result in trend forecasting is not satisfactory and significant changes might be needed to gain any insightful result.

Applying deep neural networks to stock prediction task is also a popular option [6-10]. Taylan Kabbani modeled stock market as POMDP(partially observed markov decision process), which process the state space three parts: cash balances,technical signals and fundermental signals by present time and used the popular Actor-Critic Agent(essentially two main set of networks)to make decision and refine the stretegy [6]. The addition of technical indicators and sentiment scores of the news has significantly improved the agent's performance and the superiority of using a continuous action space over a discrete one to solve the trading problem.

This paper is motivated by time series analysis which plays an important role in signal processing and functional analysis in engineering and math. This study generally assumes that people's behaviour could be modelled by a sequence of waves acting on different aspects of financial market and the market movement is the result of resonance of people's overall cumulative behaviour that would present us cyclic properties. The rest part of this paper is organized as follows: The Sec 2 will be about the how the data is obtained and how they are used to form the input variables and how they are used by our convolutional neural networks. The Sec 3 will be focused on the analysis of the conclusions for the actual performance of our introduced time cyclic analysis in comparison with the traditional method of generating the input variable. The final part of this paper examines the advantage and drawbacks present in the method and possible ways to improve the time series analysis method and how they are linked to the modern ways of getting the alpha factor of quant research nowadays.

2. Data and method

2.1 Data

The data used is gathered from both Yahoo Finance and Polygon.io and we constrained our analysis to stocks in S&P500 and they are usually more stable and owned by many fund thus having less statistical contingency, even though a wider range of data could be used such as major global indexes and other famous ETFs .The data with our variables of HLOCV(high, low, open, close, volume) of a single stock and a pre-treated technical indicators such as set of EMAs, MACD, KDJ, ATR indicators and in our random forest session we introduce a market cycle concept of the subject as a new variable, this way we can integrate these indicators to produce a stronger technical forecast model. We use a sliding windows (50days) both to the past as our input variable as X and an sliding windows (different size 30days) to the future as our prediction targets usually denoted as y in machine learning. The goal is to generalize the sliding windows as far as possible. The test period is form 1995.1.1-2022.7.22 with an unshuffled train-test split of 0.7/0.3, one could see that the test period mainly composed of two major bear markets and two bull market period to make our model prediction more representative of overall stock market.

2.2 Models

As the data is essentially time-series financial data so the more recent data could be assume to have a greater impact on the existing data set for the future data and LSTM is better at managing the gradient of the past data (i.e., the exploding and vanishing gradient problem), we tried a loss of combination of the input and output variables and tested all the super parameter related such as learning epochs and stacking of LSTM layers.

2.3 Preliminary Results: Architectures Explored

The Table 1 is the hyperparameters we set for our tests. the module is from keras.layers with the loss function being the MAPE (mean absolute percentage error), rmsprop optimization.

Table 1. Hyperparameters used for optimal test-set performance.

Hyperparameter	Value	Hyperparameter	Value
past history	100	Batch size	32
LSTM layer units	50	Epochs	100
Stack depth	3	Steps per epoch	100
Train-test split	70%/30%	dropout	yes

Time series analysis is a basic technique in quant finance. The series is a sequence exacted from a certain period of time of a certain variables observed in financial markets or the functional combination of these. The aim of the time series analysis is to using statistical model to fit the sequence into a model and use it to predict future results. Several models are used frequently, i.e., ARIMA, GARCH etc. However these models are based on two assumptions about the sequences that are not always satisfied :

- The mean is constant, which is not always true as for short time it is affected by emotion and sudden news and for a longer time the finance product would naturally grow to be more valuable.
- The covariance between two variable with fixed time interval still constant ,which is also always not true we could observe effect of clustering volatilities showing that returns could have a higher standard deviation (volatility) for a long period of time , that they present as a cluster of time.

Therefore, this study proposes the following structure. One could assume one property for financial markets. any price moving sequence would be formed by discrete, fixed period market cycles and each cycles could be represented by a sum of the math forms as follows, the mean of return changes are ignored as:

$$a_n \sin\left(\frac{2\pi}{T_n} t + b_n\right) \tag{1}$$

where Tn runs through the pre-fixed set {1,2,3,….,100} and an and bn are values one needs to decide so one could rewrite the above formular using as a combination of $\sin wt, \cos wt$. The leading coefficient can be obtained as:

$$a_n = \sum_{t=0}^{m} \sin\left(\frac{2\pi}{n} * t\right) * \mathrm{return}(t). \tag{2}$$

$$b_n = \sum_{t=0}^{m} \cos\left(\frac{2\pi}{n} * t\right) * \mathrm{return}(t). \tag{3}$$

$$f_n = \arctan\left(\frac{b_n}{a_n}\right) / \left(\frac{2\pi}{T_n}\right) \tag{4}$$

$$t_n = (a_n^2 + b_n^2)^{\frac{1}{2}} \tag{5}$$

$$\mathrm{cycle}(t) = \sum_{n=1}^{N} a_n \sin\left(\frac{2\pi}{T_n} t + b_n\right) \tag{6}$$

Here, a_n is the coeficient of the resulting sine series, b_n cosine series, f_n is the phase shift of each of the series, t_n is the amplitude of each wave and cycle(t) is the culmulative force presented by cycle force.

By picking out the largest t_n, one could find out the number which marks the significant cycle period thus one could compute at each time step how they are evolving. Fig. 1 shows the graph for sp500 during time:2007.01.01-2010.12.31, where one could observe shape peaks at 34, 82 and 206.

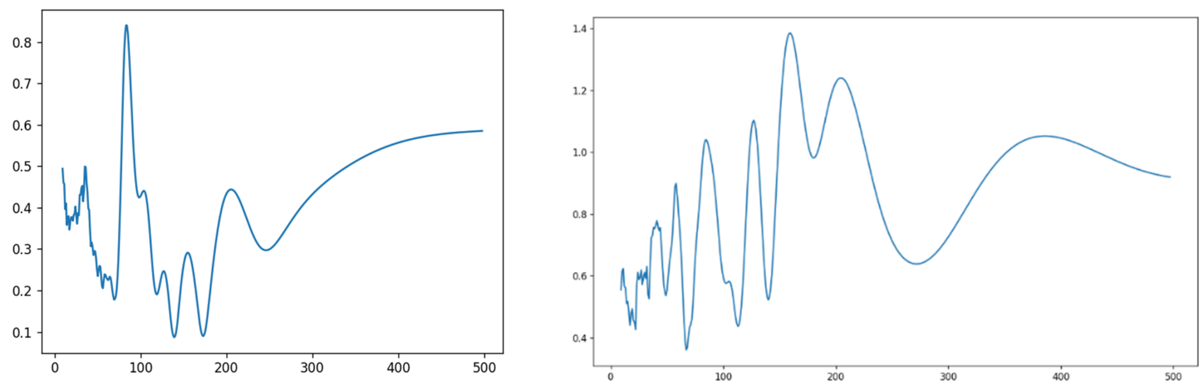

Fig. 1. the amplitude against the time period Tn.left is SPY and the right is AAPL during period:2007.01.01-2010.12.31

After one gathered the time period giving the maximum peaks by observing the graph and then make a function that adding up the sinuous wave by finding their respective coefficient. Therefore, this is then a time period indicator where the larger value of this sum signified the larger probabilities of getting a higher and positive returns while by contrast, the more negative sum of these wave would indicate a higher probability of negative return over the coming period

3. Results & Disucssion

One could analyse the cycle using different scales of time for a single stock, as in normal technical analysis, one could sometimes use candle bars with time periods like 1d, 1w, 1m, 3m and so on. Therefore, one could potentially have multiple waves indicating different periodic waves indicating how the market moves in cyclic structure in different time scales which provides a longer period time for our analysis. This study also introduces the analysis for different differentials for price series as the return is essentially first derivatives for the prices sequences and the scope could be expended to a stock market portfolio and making a buy and hold strategy that hedges the risk of a position.

However, this article mainly focuses on applying cycle function data that has a rolling window with size 40 which calculates the value for the future 40 days and the test set is the future 10 days return and one uses the metric that calculate the mean absolute error. For input, this paper used the KDJ momentum technical indicators combined with my cycle function. For contrast purposed, this study will also test the inputs using only the KDJ or the price of the stock and compare their performance in prediction accuracy over the coming forward period return accuracy. For output, it is about predictions for the next weeks return so that not a single return could give too much of a difference so as to avoid the neural networks converging to an averaging value. This research mainly focuses on the SPY fund which closely trace the performance of the well-known S&P500 major US stock indices. The major layout and parameters are summarized in Table. 2.

Here, this study implemented two layer of neural networks after the test using different numbers of intermediate layers of neural networks. According to the analysis, the best number is two as the above image illustrated in Fig. 2. One could see that introducing the cycle analysis makes neural networks gradually converging to the absolute loss which is smallest and faster than simply use the close as input. The network prediction achieved an absolute mean error of 0.0183 and a standard deviation of 0.155 (3.s.f). Therefore, one could see that the neural network predicts the direction of the market movement quite well and quickly.

Table 2. Summary of neural networks layout and parameters distribution.

Layer(Sequential)	Output shape	parameters
lstm	(None,40,10)	480
lstm_1	(None,40,10)	840
lstm_2	(None, 10)	840
dense	(None, 10)	110
Total parameters:2270	Trainable parameters:2270	

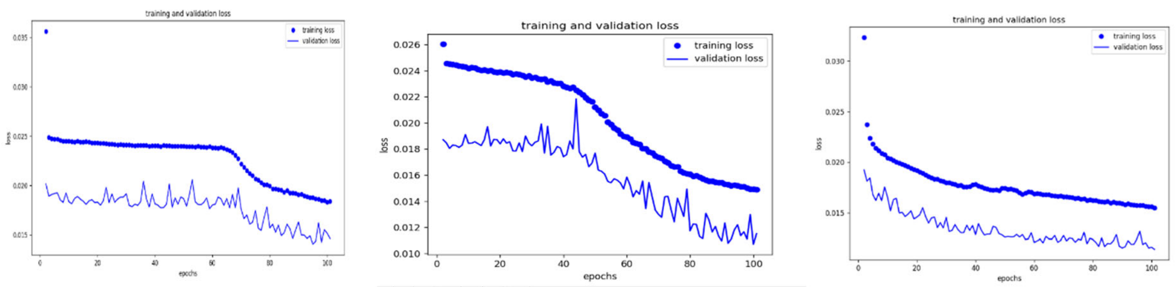

Fig. 2. These three graph respectively shows the performance using input only close price,close price and technical indicators,close price technical indicators and cycle analysis.

4. Limitations & Future outlooks

Cycle analysis usually require a substantial amount of data to get the frequency of the market. Therefore, if one do not have enough data in the data set, one would have overfit problems in the data set. One possible way to solve this issue is to consider the smaller time frame of the market and apply the cycle analysis so that this study would obtain a higher resolution and larger data set to avoid the problem of being overfit. Another way of solving is to consider different component of the indexes and sub-divide the indexes to different industry sectors and analysis their respective period and combine those periods according to their weight to the index.

Another major issue is that the peak period selection usually comes manually from graph and the graph could give a large number of peaks, as a result one would introduce a larger subjectivity to the analysis, one way to solve is to consider sharping the time series data via say taking higher levels of differences/derivatives, so as to sharp out the main peaks and give a better selection of the peaks. Another problem is that for our validation, one couldn't use them for the time series analysis as these will introduce future data, while the market could alter the period slowly due to economic conditions so one has to limit the size of validation data for the cycle analysis to a shorter period, the this will give us higher chance of being overfit although giving us a higher accuracy as we assume that the market cycle would alter in a short period of time. For solving this problem, it is feasible to introduce multiple longer periods of cycle analysis and these could reduce the lack of data problem, and possible shift in shorter period market cycle

Related area of work include wavelet analysis and we could take different function basis for example Fourier analysis where one picks a base market period and the method essentially subdivided the period to a integer number of division of the total market time. One could also introduce basis like $e^t\cos(t), e^t\sin(t)$. To take account of the exponential growth of the market. Researchers could use the time period shift in different products to hedge against the risk and reduce the volatility in the market. One could also introduce the different scales of time series data or taking multiple degrees of the derivative to sharp the data. One could also introduce new variables like economic indicators to obverse if periodic behaviour exists of not.

5. Conclusion

In conclusion, this paper investigates introducing cyclic analysis on financial time series would improve the neural network prediction performances. After a parallel comparison the finding are that integration of both technical methods and cyclic analysis would significantly outperform the one that uses only the close price sequence, both in terms of the accuracy and the standard deviation of the result to the real result and meanwhile the rate of converging speed is much faster than the raw model using only price as the input value. Furthermore, these set of method could generate to a wider range of financial series and we could develop the periodicity across different magnitudes. However, there is still subtle limitations to this method, as this method would require a substantial amount of data in as one needs to pick out the best time period that fits with the data in a large range and this would reduce the time available for making decisions. Another drawback is that this model is not working out well in some cases if there are multiple target period as picking the suitable period is still very subjective in this case. Nevertheless, this research provides us a way to integrated a longer period of data in our time variables as normally taking a fixed time window would ignore any effect of data preceding that window period and cycle analysis could provide an overall information regarding the series which is useful. The method could be generalised in various ways, e.g., taking multiple series or making analysis in a smaller time scale or different modelling mathematical basis to the problem.

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