AES

ISSN: 2096-3246
Volume 53, Issue 02, June 2021

https://doi.org/10.5281/zenodo.12726403

Deep Learning Based Financial Data Prediction Method Using Long Short-Term Memory

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Keywords:

Long term short memory, neural network, deep learning, Wavelet transform, financial prediction.

ABSTRACT

This article presents a clustering method that concentrates on statistical noise reduction techniques utilising the Wavelet transform (WT) and evaluation to circumvent the challenges of current patterns in handling the non-stationary and non-linear characteristics of high-frequency critical time-domain records, specifically their poor generalizability possibility. Utilising the Neuronal Society of Fast Long-Term Short Memory (LSTM) and singular spectrum analysis (SSA), a model for information prediction is constructed. To avoid overemphasising learning, an early preventive strategy is included into the educational process after studying the stock data of the old-time group and building the time collection with special days based on community participation. Very fitting. As a last step, we utilise the state parameter transfer technique and the variable term batch to predict the remaining inventory charges on the test set. Our results show that the LSTM prediction model and the parameter optimisation approach, which is primarily based on variable length batches, outperform the traditional regression model in terms of generalizability and reduce the prediction errors of inventory fee valuation.

INTRODUCTION

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It is extremely challenging to do this, even though there has been tremendous progress in the last decade in the fields of real-world sciences, generation, and laptop networks, as well as in interdisciplinary research that promotes the cross-fertilization of disciplines and makes use of study strategies utilised in many other fields to predict economic market movements. Assume the role of a financial market forecaster. The focus on present-day theories of the financial markets, the interplay between domestic and global financial markets, and the specifics of the prediction horizon make studying financial market projections a challenging endeavour [1]. The author maintains that the money market is a multi-scale, non-linear, non-stationary system in C, and that several bothersome purchasing and selling extras are the primary causes of the economic market forecasting difficulty.
The pursuit of methods to foretell shifts in asset values dates back to the inception of financial markets. Prediction is an intriguing and difficult area of study, whether one is interested in the past, the present, or destiny. Herbal remedies were a common way for people in the past to plan their journeys, crops, and harvests since they couldn't comprehend the objective global meaning. Scientists in today's highly advanced society use a variety of mathematical models to foretell the future by integrating data from the past into these models for educational purposes; they then release new versions of these models by continuously adjusting the margin of error between the predicted and actual values. Predictive technology is being transformed into a work of romantic art by them.

Statistic analysis, system research, and deep mastery are the three main types of inventory forecasting. The technique is very useful for early prediction.

using statistical methods. Prediction accuracy is not always great, the stock price exhibits features of high noise and instability as a form of timekeeping facts, and it is often tough to apply classic statistical assessment procedures to complicated non-linear family members. A set of traditional hardware mastery algorithms for inventory prediction has been effectively used by experts and students across disciplines in recent years, thanks to the fast advancement of machine learning ideas and algorithms.
The release's generalizability is inadequate, despite the fact that these patterns may construct the non-linear link between past stock index records and future stock prices. The neural density community has a great knack for non-linear approximation and can recognise the capacity to connect across records by mastering numerous pieces of information, which is particularly useful when the stock price is low for a variety of reasons. Additionally, stock projections have shown promising outcomes. Predictions of timing data have made extensive use of the periodic neural network RNN. Networks with more than 10 layers might still cause RNNs to experience burst or opposite connection type gradient delay. Researchers have suggested the LSTM as an alternative to RNN because to its limitations in handling deep network time-series data.

model, which adds a memory-loss gate mechanism based on RNN and effectively solves the gradient fade and gradient burst problems.

I. A General Architecture for Deep Learning in Financial Market Forecasting

Forex market time series are notorious for their erratic, non-stationary, multi-scale, and non-linear fluctuations. Because of these features, predicting the expenses of the currency market is quite challenging. When trying to lower forecast accuracy, general prediction algorithms often struggle to reflect the complex and changeable properties of log fluctuations. Researchers have come up with a brilliant idea to research the pattern of fee changes in the Forex market: break down the one-of-a-kind data collection and examine the characteristics of each individual string. By integrating neural networks, principal factor analysis, and empirical model decomposition methods, this research presents a novel implementation of FEPA. To begin decomposing the data set, CFTSEMD-PCA-ANN uses a sliding window to extract the distinct financial time set. Then, it employs the EMD analysis rule set to transform the data set into distinct metrics for the critical functions, and finally, it uses the scoring algorithm to determine which critical items

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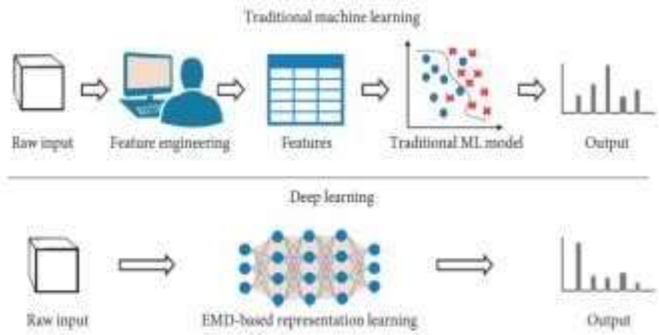
received the highest possible score.

In order to break it down, we follow the EMD decomposition rule, which divides the dataset into eigenmodes with their own set of metrics, and then we use the main item evaluation technique on them.

Simplifying unnecessary statistics and reducing the dimensionality of fact decomposition. This article presents an updated version of the aggregate prediction model that incorporates decomposition and individual integration reconstruction. By doing so, the model becomes more adept at learning from economic time series and specific target attributes, leading to more accurate predictions. A diffusion neural network is suggested in this piece. To be more precise, the FEPA model incorporates inversion, basic problem analysis, and a forward EMD decomposition technique.

Fig.1 Deep learning algorithm based on the linear correlation coefficient



II. Adapting to the nonlinear and stochastic traits of monetary records, the FEPA blended prediction version uses the EMD decomposition set of rules to solve the economic prediction problem (as seen in the drift chart above). Then, to extract the best information and reduce noise disturbance, the dimensionality reduction technique correctly reduces redundant information and improves the model's reaction speed. Using the dimensionality reduction data, the neural community version is trained to make accurate predictions about the model's overall performance and to adapt to a wide variety of inputs.

III. MODEL

IV. When it comes to forecasting data collected over time, LSTM neural networks provide substantial benefits. This paper accomplishes the best prediction mistakes by combining the modern-day LSTM optimisation generation, using Early stopping technology to save you from overfitting problems, building a variable batch mechanism to realise an LSTM three-layer network, and conducting experiments on the TSLA inventory index.

a) Linear regression

Linear regression is the maximum primary system getting to know the set of rules, which builds a model based on facts to reflect the relationship between entering characteristics (independent variables) and goals (dependent variables), and then uses unused data to expect.

$$Y = \theta_1 X_1 + \theta_2 X_2 + \cdots + \theta_n X_n \quad (1)$$

b) Long Short-Term Memory (LSTM)

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One kind of RNN is the LSTM (Long Term Short Memory) network. Sepp Hochreiter and Jürgen Schmidhuber first reported the approach in Neural Computing. When it comes to analysing and predicting datasets connected to time, it outperforms a normal RNN. Using the daily facts of the Shanghai Composite Index and the Dow Jones Index as part of their investigations, Jiang et al. use RNNS and LSTM, respectively, to develop the publication, based on the outstanding time monitoring of the performance of the LSTM network. Next, they conducted experiments and discovered that the LSTM version of the neural network model suited the data better than the RNN model. The Dow Jones Index, however, does not fit this concept. Additional hidden characteristics, such as the impact of political statistics, etc., need to be input into the release in order to make an accurate prediction of the Dow Jones Index. There isn't a better way to forecast the Dow Jones Index since this metric is difficult to define. To make up for that, a different hybrid prediction model is being considered.

inside the current forecasting iteration. Combining ML and DL with time-series financial forecasting models is a common practice for decomposition techniques that use the empirical decomposition method (EMD) and single-spectrum assessment (SSA). Hybrid modes are better at capturing timing patterns than the basic single version, according to recent research. The expected rate of agricultural commodities is not linearly related to influencing factors. To account for this, Jia et al. have developed a neural community model called LSTM-DA (Dual Attention Long Term Memory). This model integrates the convolutional attention network, the long-term memory community, and the eye mechanism. By enhancing forecasting accuracy compared to the old signal model, this model is able to accurately portray the overall form of plant commodities over the following week via the anticipated shipping indication. To explain why RNNs are so good at reasoning about gradient disappearance and gradient explosion throughout the deep network's reverse derivation process, Hochreiter and his colleagues have turned to memory gate technology. From training to prediction, the LSTM model excels in every respect.

time spent walking, speech, signal, financial data collected throughout the day, etc.

The most vital structure of the LSTM version consists of three gates:

- The forgetting gate toes determine which data is filtered out by the cell.
- The enter gate determines which values passing thru the input gate are used to update the reminiscence nation.
- The output gate determines which parts of the cell reminiscence are output primarily based on the enter and cell reminiscence.

Formulas 2 to five provide the gated consciousness formulation of the standard LSTM shape. Ft first reads the contemporary time input xt and the ultimate time memory unit state information ht-1, and then outputs the cost among zero and 1 thru the sigmoid characteristic; the result is used to pick how a great deal of historical statistics is saved. Wi, Wf, and Wo denote weight, bi, bf, and bo denote partial self-assurance, Ct denotes reminiscence unit and σ denotes activation function.

(2) $$f_t = \sigma(W_f[h_{t-1}, X_t] + b_f)$$

(3) $$i_t = \sigma(W_i[h_{t-1}, X_t] + b_i)$$

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(4) $$\bar{C}_t = \sigma(W_{\bar{C}}[h_{t-1}, X_t] + b_{\bar{C}})$$

(5) $$C_t = f_t * C_{t-1} + i_t * \bar{C}_t$$

V. EXPERIMENT AND DATA ANALYSIS

A) DATASET

B) Ten to twelve months' worth of historical TSLA stock trading data, including 2416 daily line information, from June 29, 2010, to February 3, 2020, makes up the experimental data set. There are many sections to the exam. Part one of the experiment follows the standard procedures for systems analysis as they are expressed in the logical regression form. Figure 1 shows how the experiment's numerous functions and unpaired feature are decided by the regression coefficient. Figure 2 shows that the second part relies heavily on the long short-term memory (LSTM) deep learning model but doesn't give any consideration to functional engineering.

C) PERFORMANCE INDEX

To quantify the model's predictive power, this study used the MSE (mean square error) as its base. Finding the square difference between the actual value and the projected cost yields the MSE, which is used as an assessment indicator for the forecast version. The forecasting impact increases as expenses decrease. The result in equation (6) shows that yi

is the total price to examine the samples, y is the predicted value, and reflects the actual charges.

$$MSE = \frac{1}{M}\sum_{i=1}^{M}(y_i - \hat{y}_i)^2$$

D) Logical regression experiment and Analysis

1) Experimental data

E) A total of five input functions—entry rate, maximum fee, minimum cost, closure rate, and buy and sell quantities—are used in the first set of tests to forecast the completion fee. We separated the data into two parts in order to evaluate the regression version's predictive power: first, the educational group, which accounts for 80% of the total records each day, and second, the group, which accounts for 485 pieces of information used to evaluate the model's predictive power.

1) Result analysis

Table I shows the logical regression prediction MSE based on different historical review days. It can be seen from Table I that although the number of days in historical review is different, the minimum MSE is obtained when learning and predicting the data of the first three days as input features

Table.1 The Logical Regression of Forecasting the Future Closing Price of Stocks

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Volume 53, Issue 02, June 2021

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History Days	Max	Min	MSE Max value	MSE Min value	Feature Size
230 days	230	3	0.00402807553	0.001175531478	(254,1150)
200 days	200	3	0.00286570920	0.00122454775	(284,1000)
150 days	149	3	0.00192065929	0.001161704652	(334, 750)
100 days	100	3	0.00157065383	0.001229488032	(384, 500)
50 days	48	3	0.00127853162	0.001157540790	(434, 250)
30 days	29	3	0.00119995603	0.00112367297	(454, 150)
15 days	13	3	0.00116678440	0.001133684910	(469, 75)
10 days	9	3	0.00115623474	0.00112477457	(474, 50)

The number of days from the first research order can be chosen again by evaluating the MSE curves for different days of the overview. As demonstrated in Table I, MSE curves are studied for the base 10 days, 15 days, 30 days, 50 days, 100 days, and 150 days and are expected to align with the evaluation records for the first 10 days, 15 days, and 30 days, 50 days, 100 days, 150 days and so on. The MSE curves all obtain near the minimum in three days, i.e., for this set of information, the first three days' statistics for logical regression should be used to gain knowledge. The minimum MSE can be obtained by predicting the version of the regression.

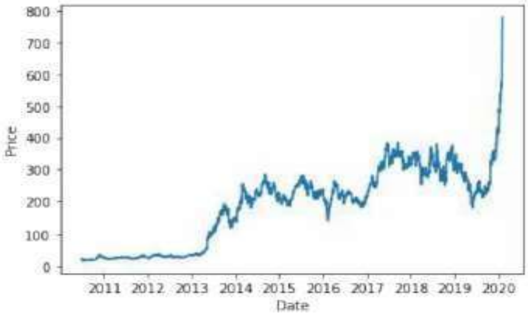

Fig.2 Historical closing price from 2010 to 2020

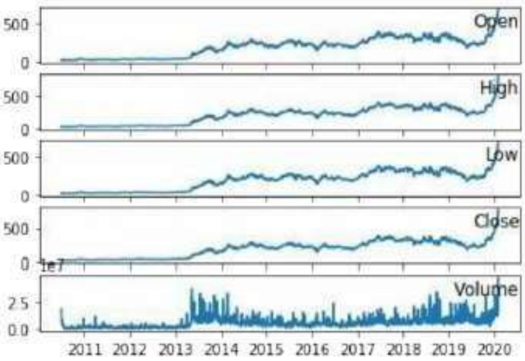

Fig.3 Data Distribution of each feature from 2010 to 2020

VI. CONCLUSION

The long short-term memory (LSTM) neural network model with a variable-duration impulse was the main focus of this research. There is a decrease in root mean square errors (MSE) as compared to the normal logical regression version. The current panels may be used to do more research on compliance studies' automated parameter optimisation. To enhance the accuracy of forecasts, market sentiment elements, such as news, may be pooled and used as input functions.

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