Attention Based Stock Price Prediction

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Abstract—The abstract goes here.

Index Terms—Computer Society, IEEEtran, journal, LaTeX, paper, template.

1 Introduction

This paragraph introduces the problem of the stock price prediction and its importance

A brief introduction to different techniques for price prediction then[?].

A brief introduction to ANN models and structures for stock price prediction

A brief look at different features and information used to predict stock prices

An introduction to the current problem (different information sources suitable for different situations) and the challenges

List current work innovations and contributions

present the rest of the paper structure

2 Literature Review

A paragraph to start the literature review.

2.1 Categorization of DNN models

A brief categorization of the proposed DNN models for stock price prediction

Explain the structure of the models based on MLP network.

Explain the structure of the models based on CNN network.

Explain the structure of the models based on RNN network.

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2.1.1 Notes

1) The existing forecasting methods make useof both linear (AR,MA,ARIMA) and non-linear algorithms(ARCH,GARCH,Neural Networks),but they focus on predictingthe stock index movement or price forecasting for a singlecompany using the daily closing price. The proposed methodis a model independent approach. Here we are not fitting thedata to a specific model, rather we are identifying the latentdynamics existing in the data using deep learning architectures.In this work we use three different deep learning architectures forthe price prediction of NSE listed companies and compares theirperformance. We are applying a sliding window approach forpredicting future values on a short term basis.The performanceof the models were quantified using percentage error [1].
2) This paper proposes a novel application of deeplearning models, Paragraph Vector, and Long Short-TermMemory (LSTM), to financial time series forecasting. Investorsmake decisions according to various factors, including con-sumer price index, price-earnings ratio, and miscellaneousevents reported in newspapers. In order to assist their decisionsin a timely manner, many automatic ways to analyze thoseinformation have been proposed in the last decade. However,many of them used either numerical or textual information,but not both for a single company. In this paper, we proposean approach that converts newspaper articles

into their dis-tributed representations via Paragraph Vector and models thetemporal effects of past events on opening prices about multiplecompanies with LSTM. The performance of the proposedapproach is demonstrated on real-world data of fifty companieslisted on Tokyo Stock Exchange [2].

3) We present an Artificial Neural Network (ANN) approach to predict stock market indices, particularlywith respect to the forecast of their trend movementsup or down. Exploiting different Neural Networks architectures, we provide numerical analysis of concrete financial time series. In particular, after a brief r´esum´e of theexisting literature on the subject, we consider the Multi-layer Perceptron (MLP), the Convolutional Neural Net-works (CNN), and the Long Short-Term Memory (LSTM) recurrent neural networks techniques. We focus on theimportance of choosing the correct input features, along with their preprocessing, for the specific learning algorithm one wants to use. Eventually, we consider the S&P500 historical time series, predicting trend on the basisof data from the past days, and proposing a novel approach based on combination of wavelets and CNN, whichoutperforms the basic neural networks ones. We show, that neural networks are able to predict financial time seriesmovements even trained only on plain time series data and propose more ways to improve results [3].
4) We propose a deep learning method for event-driven stock market prediction. First, events areextracted from news text, and represented as densevectors, trained using a novel neural tensor net-work. Second, a deep convolutional neural networkis used to model both short-term and long-term in-fluences of events on stock price movements. Ex-perimental results show that our model can achievenearly 6% improvements on S&P 500 index predic-tion and individual stock prediction, respectively,compared to state-of-the-art baseline methods. Inaddition, market simulation results show that oursystem is more capable of making profits than pre-viously reported systems trained on S&P 500 stockhistorical data [4].
5) This paper plans to forecast these short - term prices of stocks. 10 unique stocks recorded on New York Stock Exchange are considered for this review. The review essentially focuses on the prediction of these short - term prices leveraging the power of technical analysis. Technical Analysis guides the framework to understand the patterns from the historical prices fed into it, and attempts to probabilistically forecast the fleeting future prices of the stock under review. The paper discusses about two distinct sorts of Artificial Neural Networks, Feed Forward Neural Networks and Recurrent Neural Networks. The review uncovers that Feed Forwards Multilayer Perceptron perform superior to Long Short-Term Memory, at predicting the short - term prices of a stock [5].
6) In general, stock market is very complex nonlinear dynamic system. Accordingly, accurate prediction of stock market is a very challenging task, owing to the inherent noisy environment and high volatility related to outside factors. In this paper, we focus on deep learning method to achieve high precision in stock market forecast. And a deep belief networks (DBNs), which is a kind of deep learning algorithm model, coupled with stock technical indicators (STIs) and two-dimensional principal component analysis ((2D) 2 PCA) is introduced as a novel approach to predict the closing price of stock market. A comparison experiment is also performed to evaluate this model [6].
7) Stock market is considered chaotic, complex, volatile and dynamic. Undoubtedly, its prediction is one of the most challenging tasks in time series forecasting. Moreover existing Artificial Neural Network (ANN) approaches fail to provide encouraging results. Meanwhile advances in machine learning have presented favourable results for speech recognition, image classification and language processing. Methods applied in digital signal processing can be applied to stock data as both are time series. Similarly, learning outcome of this paper can be

applied to speech time series data. Deep learning for stock prediction has been introduced in this paper and its performance is evaluated on Google stock price multimedia data (chart) from NASDAQ. The objective of this paper is to demonstrate that deep learning can improve stock market forecasting accuracy. For this, (2D)2PCA + Deep Neural Network (DNN) method is compared with state of the art method 2-Directional 2-Dimensional Principal Component Analysis (2D)2PCA + Radial Basis Function Neural Network (RBFNN). It is found that the proposed method is performing better than the existing method RBFNN with an improved accuracy of 4.8% for Hit Rate with a window size of 20. Also the results of the proposed model are compared with the Recurrent Neural Network (RNN) and it is found that the accuracy for Hit Rate is improved by 15.6%. The correlation coefficient between the actual and predicted return for DNN is 17.1% more than RBFNN and it is 43.4% better than RNN [7].

8) Our study attempts to provides a comprehensive and objective assessment of both the advantages and drawbacks of deep learning algorithms for stock market analysis and prediction. Using high-frequency intraday stock returns as input data, we examine the effects of three unsupervised feature extraction methods—principal component analysis, autoencoder, and the restricted Boltzmann machine—on the network's overall ability to predict future market behavior. Empirical results suggest that deep neural networks can extract additional information from the residuals of the autoregressive model and improve prediction performance; the same cannot be said when the autoregressive model is applied to the residuals of the network. Covariance estimation is also noticeably improved when the predictive network is applied to covariance-based market structure analysis. Our study offers practical insights and potentially useful directions for further investigation into how deep learning networks can be effectively used for stock market analysis and prediction [8].

9) In this paper, we propose a novel end-to-end model named multi-filters neural network (MFNN) specifically for feature extraction on financial time series samples and price movement prediction task. Both convolutional and recurrent neurons are integrated to build the multi-filters structure, so that the information from different feature spaces and market views can be obtained. We apply our MFNN for extreme market prediction and signal-based trading simulation tasks on Chinese stock market index CSI 300. Experimental results show that our network outperforms traditional machine learning models, statistical models, and single-structure(convolutional, recurrent, and LSTM) networks in terms of the accuracy, profitability, and stability [9].

10) . This paper focus on architectures such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), which have had good results in traditional NLP tasks. Results has shown that CNN can be better than RNN on catching semantic from texts and RNN is better on catching the context information and modeling complex temporal characteristics for stock market forecasting. The proposed method shows some improvement when compared with similar previous studies [10].

11) Deep neural networks (DNNs) combine the advantages of deep learning (DL) and neural networks and can be used to solve nonlinear problems more satisfactorily compared to conventional machine learning algorithms. In this paper, financial product price data are treated as a one-dimensional series generated by the projection of a chaotic system composed of multiple factors into the time dimension, and the price series is reconstructed using the time series phase-space reconstruction (PSR) method. A DNN-based prediction model is designed based on the PSR method and a long- and short-term memory networks (LSTMs) for DL and used to predict stock prices. The proposed and some other prediction models are used to predict multiple stock indices for different periods. A comparison of the

results shows that the proposed prediction model has higher prediction accuracy [11].

12) To date, designing a good deep learning model depends on how well the user can extract the features that represent all the characteristics of the training data. Among the various available features for training and test data, we determined that the use of event binary features can make stock price prediction models perform better. An event binary feature refers to a 0 or 1 value describing whether an indicator is satisfied (1) or not (0) for any given day and stock. We proposed and compared a stock price prediction model with three different feature combinations to verify the importance of binary features. As a result, we derived a prediction model that defeated the market (KOSPI and KODAQ (KOSPI (Korea Composite Stock Price Index) and KOSDAQ (Korean Securities Dealers Automated Quotations) is Korean stock indices)). The results suggest that deep learning is suitable for stock price prediction [12].
13) This paper has performed a novel analysis of the parameter look-back period used with recurrent neural networks and also compared stock price prediction performance of three deep learning models: Vanilla RNN, LSTM, and GRU for predicting stock prices of the two most popular and strongest commercial banks listed on Nepal Stock Exchange (NEPSE). From the experiments performed, it is found that GRU is most successful in stock price prediction. In addition, the research work has suggested suitable values of the look-back period that could be used with LSTM and GRU for better stock price prediction performance [13].
14) This paper is inspired by the recent success of using deep learning for stock market prediction. In this work, we analyze and present the characteristics of the cryptocurrency market in a high-frequency setting. In particular, we applied a deep learning approach to predict the direction of the mid-price changes on the upcoming tick. We monitored live tick-level data from 8 cryptocurrency pairs and applied both statistical and machine learning techniques to provide a live prediction. We reveal that promising results are possible for cryptocurrencies, and in particular, we achieve a consistent 78% accuracy on the prediction of the mid-price movement on live exchange rate of Bitcoins vs US dollars [14].
15) In this paper, a comparative study is-done on two time series datasets ”Occupancy Dataset” and ”Google StockPrice Dataset”. Both these datasets are used for multivariate and univari-ate time series forecasting. Prediction was done for ’temperature’ fromOccupancy dataset and ’open’ from Google Stock Price dataset. Variousstate of the art sequence transduction, deep learning models are used.The models used are Long-Short Term Memory (LSTM), Gated Recur-rent Unit (GRU), Convolution Neural Network (CNN) and Multi-layerPerceptron (MLP). In additon, ARIMA model is used for univariate analysis. LSTM and GRU models showed excellent results for multivariatetime series forecasting. In univariate analysis, all the model showed ex-cellent results , although ARIMA displayed a poor result on Google StockPrice dataset. Mean square error is used as a metric for checking theaccuracy for the model. LSTM and GRU models are the best modelsfor multivariate time series forecasting. Except ARIMA, all the modelsdescribed have a higher accuracy for univariate prediction [15].
16) Stock price index is an essential component of financial systems and indicates the economic performance in the national level. Even if a small improvement in its forecasting performance will be highly profitable and meaningful. This manuscript input technical features together with macroeconomic indicators into an improved Stacking framework for predicting the direction of the stock price index in respect of the price prevailing some time earlier, if necessary, a month. Random forest (RF), extremely randomized trees (ERT), extreme gradient boosting (XGBoost) and light gradient boosting machine (LightGBM), which pertain to the tree-based algorithms, and

recurrent neural networks (RNN), bidirectional RNN, RNN with long short-term memory (LSTM) and gated recurrent unit (GRU) layer, which pertain to the deep learning algorithms, are stacked as base classifiers in the first layer. Cross-validation method is then implemented to iteratively generate the input for the second level classifier in order to prevent overfitting. In the second layer, logistic regression, as well as its regularized version, are employed as meta-classifiers to identify the unique learning pattern of the base classifiers. Empirical results over three major U.S. stock indices indicate that our improved Stacking method outperforms state-of-the-art ensemble learning algorithms and deep learning models, achieving a higher level of accuracy, F-score and AUC value. Besides, another contribution in our research paper is the design of a Lasso (least absolute shrinkage and selection operator) based meta-classifier that is capable of automatically weighting/selecting the optimal base learners for the forecasting task. Our findings provide an integrated Stacking framework in the financial area [16].

17) This study intends to predict the trends of price for a cryptocurrency, i.e.Ethereum based on deep learning techniques considering its trends on time seriesparticularly. This study analyses how deep learning techniques such as multi-layer perceptron (MLP) and long short-term memory (LSTM) help in predicting the pricetrends of Ethereum. These techniques have been applied based on historical datathat were computed per day, hour and minute wise. The dataset is sourced from the CoinDesk repository. The performance of the obtained models is critically assessed using statistical indicators like mean absolute error (MAE), mean squared error(MSE) and root mean squared error (RMSE) [17].
18) However, very few studies have applied sequence models with robust feature engineering to predict future pricing. In this study, we investigate a framework with a set of advanced machine learning forecasting methods with a fixed set of exogenous and endogenous factors to predict daily Bitcoin prices. We study and compare different approaches using the root mean squared error (RMSE). Experimental results show that the gated recurring unit (GRU) model with recurrent dropout performs better than popular existing models. We also show that simple trading strategies, when implemented with our proposed GRU model and with proper learning, can lead to financial gain [18].
19) In previous studies, we have used price-based input-features to measure performance changes in deep learning models. Results of this studies have revealed that the performance of stock price models would change according to varied input-features configured based on stock price. Therefore, we have concluded that more novel input-feature in deep learning model is needed to predict patterns of stock price fluctuation more precisely. In this paper, for predicting stock price fluctuation, we design deep learning model using 715 novel input-features configured on the basis of technical analyses. The performance of the prediction model was then compared to another model that employed simple price-based input-features. Also, rather than taking randomly collected set of stocks, stocks of a similar pattern of price fluctuation were filtered to identify the influence of filtering technique on the deep learning model. Finally, we compared and analyzed the performances of several models using different configuration of input-features and target-vectors [19].
20) In finance, the weak form of the Efficient Market Hypothesis asserts that historic stock price and volume data cannot inform predictions of future prices. In this paper we show that, to the contrary, future intra-day stock prices could be predicted effectively until 2009. We demonstrate this using two different profitable machine learning-based trading strategies. However, the effectiveness of both approaches diminish over time, and neither of them are profitable after 2009. We present our implementation and results in detail for the period 2003-2017 and propose a novel idea: the use of such

flexible machine learning methods as an objective measure of relative market efficiency. We conclude with a candidate explanation, comparing our returns over time with high-frequency trading volume, and suggest concrete steps for further investigation [20].

21) In this work an effort is made to predict the price and price trend of stocksby applying optimal Long Short Term Memory (O-LSTM) deep learning and adaptive Stock Technical Indicators (STIs). We also evaluated the model for taking buy-sell decision at the end of day. To optimize the deep learning task we utilized the concept of Correlation-Tensorbuilt with appropriate STIs. The tensorwith adaptive indicatorsis passed to the model for better and accurate prediction.The results are analyzed using popular metrics and compared with two benchmark ML classifiers and a recent classifier based on deep learning. The mean prediction accuracy achieved using proposed model is 59.25%, over number of stocks, which is much higher than benchmark approaches [21].
22) Prediction of future movement of stock prices has been a subject matter of many research work. There is a gamut of literature of technical analysis of stock prices where the objective is to identify patterns in stock price movements and derive profit from it. Improving the prediction accuracy remains the single most challenge in this area of research. We propose a hybrid approach for stock price movement prediction using machine learning, deep learning, and natural language processing. We select the NIFTY 50 index values of the National Stock Exchange (NSE) of India, and collect its daily price movement over a period of three years (2015–2017). Based on the data of 2015–2017, we build various predictive models using machine learning, and then use those models to predict the closing value of NIFTY 50 for the period January 2018 till June 2019 with a prediction horizon of one week. For predicting the price movement patterns, we use a number of classification techniques, while for predicting the actual closing price of the stock, various regression models have been used. We also build a Long and Short-Term Memory (LSTM)-based deep learning network for predicting the closing price of the stocks and compare the prediction accuracies of the machine learning models with the LSTM model. We further augment the predictive model by integrating a sentiment analysis module on Twitter data to correlate the public sentiment of stock prices with the market sentiment. This has been done using Twitter sentiment and previous week closing values to predict stock price movement for the next week. We tested our proposed scheme using a cross validation method based on Self Organizing Fuzzy Neural Networks (SOFNN) and found extremely interesting results [22].
23) Mid-price movement prediction based on the limit order book data is a challenging task due to the complexity and dynamics of the limit order book. So far, there have been very limited attempts for extracting relevant features based on the limit order book data. In this paper, we address this problem by designing a new set of handcrafted features and performing an extensive experimental evaluation on both liquid and illiquid stocks. More specifically, we present an extensive set of econometric features that capture the statistical properties of the underlying securities for the task of mid-price prediction. The experimental evaluation consists of a head-to-head comparison with other handcrafted features from the literature and with features extracted from a long short-term memory autoencoder by means of a fully automated process. Moreover, we develop a new experimental protocol for online learning that treats the task above as a multi-objective optimization problem and predicts: 1) the direction of the next price movement and; 2) the number of order book events that occur until the change takes place. In order to predict the mid-price movement, features are fed into nine different deep learning models based on multi-layer perceptrons, convolutional neural networks, and long short-term memory neural networks. The performance of the

proposed method is then evaluated on liquid and illiquid stocks (i.e., TotalView-ITCH US and Nordic stocks). For some stocks, results suggest that the correct choice of a feature set and a model can lead to the successful prediction of how long it takes to have a stock price movement [23].

24) Energy resources have acquired a strategic significance for economic growth and social welfare of any country throughout the history. Therefore, the prediction of crude oil price fluctuation is a significant issue. In recent years, with the development of artificial intelligence, deep learning has attracted wide attention in various industrial fields. Some scientific research about using the deep learning model to fit and predict time series has been developed. In an attempt to increase the accuracy of oil market price prediction, Long Short Term Memory, a representative model of deep learning, is applied to fit crude oil prices in this paper. In the traditional application field of long short term memory, such as natural language processing, large amount of data is a consensus to improve training accuracy of long short term memory. In order to improve the prediction accuracy by extending the size of training set, transfer learning provides a heuristic data extension approach. Moreover, considering the equivalent of each historical data to train the long short term memory is difficult to reflect the changeable behaviors of crude oil markets, a very creative algorithm named data transfer with prior knowledge which provides a more availability data extension approach (three data types) is proposed. For comparing the predicting performance of initial data and data transfer deeply, the ensemble empirical mode decomposition is applied to decompose time series into several intrinsic mode functions, and these intrinsic mode functions are utilized to train the models. Further, the empirical research is performed in testing the prediction effect of West Texas Intermediate and Brent crude oil by evaluating the predicting ability of the proposed model, and the corresponding superiority is also demonstrated [24].

25) In this paper, we propose a novel stock price prediction model based on deep learning. With the success of deep learning algorithms in the field of Artificial Neural Network (ANN), we choose to solve the regression based problems (stock price prediction in our case). Stock price prediction is a challenging problem due to its random movement. This hybrid model is a combination of two well-known networks, Long Short Term Memory (LSTM) and Gated Recurrent Unit (GRU). We choose the S&P 500 historical time series data and use significant evaluation metrics such as mean squared error, mean absolute percentage error etc., that conventional approaches have used. In experiment section, we have described the effectiveness of each of the component of our model along with its performance gain over the state-of-the-art approach. Our prediction model provides less error by considering this random nature (change) for a large scale of data [25].

2.2 Categorization of used features and information sources

A brief categorization of the used features and information to predict stock prices. If it is possible, point to pros and cons of each information source and compare them briefly.

Each information source or category, at least one paragraph

2.3 Current paper

Explain the importance of using right features at each timestep according to the market situation

Current paper importance(cite attention based models here !?)

3 Proposed Model

An introduction paragraph to start the section

3.1 A description of the problem

here a description of the problem along with the formulations goes.

3.2 Introducing Attention mechanism

A detailed introduction of the attention mechanism with required citation goes here.

Also The proposed attention mechanism in the current paper should be explained exactly here.

3.3 Define the other parts of the model

The other parts of the model should bee described here.

3.4 Summary of the proposed model

May be providing a summary of the proposed model with a figure of the whole architecture make sense in this subsection! (It should be double checked with Dr. Safabakhsh)

4 Experiments

A starting paragraph

4.1 Datasets

Explaining TSE and S&P datasets (Inclusion of TSE dataset in the current paper should be double checked with Dr. Hajizadeh and Dr. Safabakhsh)

4.2 Used indicators and features

Explain features and indicators used in the evaluations for each of the above-mentioned datasets

4.3 Evaluation metrics

Introduce evaluation metrics used in the paper (If necessary)

4.4 Evaluations and results

Here in this subsection the detailed evaluation processes and obtained results should be reported.

4.5 Discussion

A brief discussion of the obtained results and conclusions made on top of them should be placed here.

5 Conclusion

The conclusion goes here.

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Reza Safabakhsh Biography text here.