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A LIMITED SYMBOL TRADES MARGIN PREDICTION SYSTEM

Mrs.T Sarada , Mrs.V Hemasree , rs.Y Basanthi
Assistant Professor[1,2] , Associate Professor
Department of CSE,
Viswam Engineering College (VISM) Madanapalle-517325 Chittoor District, Andhra Pradesh, India

Abstract—**Cryptocurrency is playing an increasingly important role in reshaping the financial system due to its growing popular appeal and mechant acceptance. While many people are making investments in Cryptocurrency, the dynamical features, uncertainty, the predictability of Cryptocurrency are still mostly unknown, which dramatically risk the investments. It is a matter to try to understand the factors that infiuence the value formation. In this study, we use advanced artificial intelligence frameworks of fully connected Artificial Neural Network (ANN) and Long Short-Term Memory (LSTM) Recurrent Neural Network to analyse the price dynamics of Bitcoin, Etherum, and Ripple. We find that ANN tends to rely more on long-term history while LSTM tends to rely more on short-term dynamics, which indicate the efficiency of LSTM to utilise useful information hidden in historical memory is stronger than ANN. However, given enough historical information ANN can achieve a similar accuracy, compared with LSTM. This study provides a unique demonstration that Cryptocurrency market price is predictable. However, the explanation of the predictability could vary depending on the nature of the involved machine-learning model.**

Keywords-ANN；LSTM；Cryptocurrency price prediction；neural network

I. INTRODUCTION

Cryptocurrency is the peer-to-peer digital moneyory and payment system that exist online via a controlled algorithem. When a miner cracks an algorithem to record a block of transactions to public ledger named blockchain and the cryptocurrency is created when the block is addedto the blockchain. It allows people to store and transfer through encryption protocol and distributed network [1]. Mining is a necessary and competitive component of the cryptocurrency system. The miner with more computational power has a better chance of finding a new coin than that of less [2]. Bitcoin is the first and one of the leading digital currencies (its market capitalisation had more than $ 7 billion in 2014, and then it increased significantly to $ 29 billion in 2017) [3, 4], which was firstintroduced by Satoshi Nakamoto in 2008. Among many features of bitcoin, the most impressive one is decentralisation that it can remove the involvement of traditional financial sectors and monetary authorities effectively due to its blockchain network features [4]. In addition, the electronic payment system of Bitcoin is based on cryptographic proof rather than the trust between each other as its transaction history cannot be changed unless redoing all proof of work of all blockchain, which play acritical role of being a trust intermediary and this can be widely used in reality such as recording charitable contribution to avoid corruption. Moreover, bitcoin has introduced the controllable anonymity scheme, and this enhances users' safety and anonymity by using this technology, for instance, we can take advantage of this property of blockchain to make identification cards, and it not only can protect our privacy but verify our identity.

Nowadays, investing in cryptocurrencies, like Bitcoin, is one of the efficient ways of earning money. For example, the rate of Bitcoin significant rises in 2017, from a relatively low point 963 USD on January 1ST 2017, to its peak 19186 USD on December 17th 2017, and it closed with 9475 USD at the end ofthe year [5]. Consequently, the rate of return of bitcoin investment for 2017 was over 880% [5], which is an impressiveand surprising scenery for most investors.

While an increasing number of people are making investments in Cryptocurrency, the majority of investors cannotget such profit for being inconsiderable to cryptocurrencies' dynamics and the critical factors that influence the trends of bitcoins. Therefore, raising people's awareness of vital factors can help us to be wise investors. Although market prediction is demanding for its complex nature [6, 7], the dynamics are predictable and understandable to some degree. For example, when there is a shortage of the bitcoin, its price will be increased by their sellers as investors who regard bitcoin as a profitable investment opportunity will have a strong desire to pay for bitcoin. Furthermore, the price of bitcoin may be easilyinfluenced by some influential external factors such as politicalfactors [5].

Although existing efforts on Cryptocurrency analysis and prediction is limited, a few studies have been aiming to understand the Cryptocurrency time series and build statistical models to reproduce and predict price dynamics. For example, Madan et al. collected bitcoins price with the time interval of 0.5, 1and 2 hours, and combined it with the blockchain network, the underlying technology of bitcoin. Their predictive model leveraging random forests and binomial logistic regression classifiers [1], and the precision of the model is around 55% in predicting bitcoin's price. Shah et al. used Bayesian regression and took advantages of high frequency (10-second) prices data of Bitcoin to improve investment strategy of bitcoin [8, 9].

Their models had also achieved great success. In [5], an Multi- Layer Perceptron (MLP) based prediction model was presented to forecast the next day price of bitcoin by using two

sets of input: the first type of inputs: the opening, minimum, maximum and closing price and the second set of inputs: Moving Average of both short (5,10,20 days) and long (100, 200 days) windows. During validation, their model was proved to be accurate at the 95% level.

There has been many academic researches looking at exchang rate forecasting, for example, the monetary and portfolio balance models examined by Meese and Rogoff (1983, 1988) [12]. Significant efforts have been made to analyse and predict the trends of traditional financial markets especially the stock market [10, 11], however, predicting cryptocurrencies market prices is still at anearly stage. Compared to these stock price prediction models, traditional time series methods are not very useful as cryptocurrencies are not precisely the same with stocks but can be deemed as a complementary good of existing currency system with sharp fluctuations features. Therefore, it is urgently needed to understand the dynamics of cryptocurrencies better and establish a suitable predictive modelling framework. In this study, wehypothesise that time series of cryptocurrencies exhibits a clear internal memory, which could be used to help the memory-based time series model to works more appropriately if the length of internal memory could be quantified. We aim to use two artificial intelligence modelling frameworks to understand and predict the most popular cryptocurrencies price dynamics, including Bitcoin, Ethereum, and Ripple.

II. METHODOLOGY

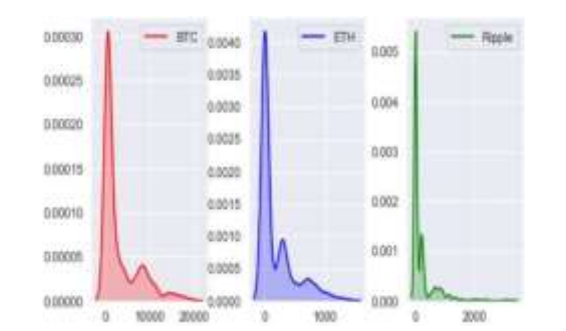

Figure 1. Density distribution of the price history from 7th August 2015 to 2nd June 2018, for Bitcoin (left panel), Ethereum (middle panel), and Ripple (right panel), respectively.

B. Models

Some works have been reported on the forecasting of financial markets using deep neural networks. In this study, we employ two prevailing deep learning models to analyse and predict cryptocurrencies price dynamics, including

fully-connected Artificial Neural Network (ANN) and Long- Short-Term-Memory (LSTM) Recurrent Neural Network. For the LSTM, it includes three layers, each having ten nodes. Each LSTM cell state contains three gates: a forget gate, an input gate, and an output gate. LSTM controls the loss oraddition of information through the gate to achieve the functionof ignoring or memory.

The forget gate is a Sigmoid function which has the input h_{t-1} and x_t where the former is the output of the last unit, and the

A. Data Collection & Data Analysis

The historical prices data for cryptocurrencies were collected from https://www.blockchain.com/markets, and the total number of samples is 1030 trading days between

latter is the input of this unit. The Sigmoid function can produce f_t which is a value in [0,1] for each item in C_{t-1} (internal state), '0' means that 'keep this completely' and '1' represents 'forget this completely', to control the extent of forgetting of the last unit.

7th August 2015 to 2nd June 2018. The price data

comprised of four elements namely opening, high, low, closing prices. In this study, we analyse the price of three of the most popuer cryptocurrencies: Bitcoin, Ethereum and Ripple. We take the four elements as the input of our

wmhoidcehl,waansdutsheednapsrtehdeicotuthpeutnoefxtthfeemwoddaeyl.s Wopeecnhinogospertihce opening price as the output for it reflects all the previous memories and events. The dataset was divided into training and testing sets according to

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an 80%，20% ratio as this can avoid overfitting during de model training. Themean price of the three cryptocurrencies: Bitcoin $ 3082.084, Ethereum $ 194.810, Ripple $ 0.223, and the 95% confidence interval of their historical price: [2834.034, 3330.134], [176.977, 212.642], [0.196, 0.248]. As is shown in Figure 1, Bitcoin and Ethereum price have sharp fluctuations, and their standard deviations are as

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (1)$$

An input gate produces i_t through a Sigmoid activation, andthe tanh function that generates potential internal state ($\vec{C}_t$). Both of them control how much new information will be addedto C_{t-1} to update the real internal state to C_t:

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right) \quad (2)$$

$$\bar{C}_t = \tanh\left(W_C \cdot [h_{t-1}, x_t] + b_C\right) \quad (3)$$

$$C_t = f_t * C_{t-1} + i_t * \bar{C}_t \quad (4)$$

The output gate O_t uses a Sigmoid function to determine which part of neuron state need to be output, and then we needto convert C_t to output h_{t-1}:

$$o_t = \sigma\left(W_o [h_{t-1}, x_t] + b_o\right) \quad (5)$$

high as 4063, 292, 0.43 respectively.

$$h_t = o_t * \tanh(C_t) \quad (6)$$

The ANN model used in this study is a fully-connected multi-layer perceptron that imitates the structure and function of the human brain, and it has a strong ability of in approximating non-linear data. In this experiment, our ANN model has three components: the input layer, hidden layer, and output layer. Each layer has ten nodes. The input layer gives a weight w_{ij} to the input, and there is an activation function-Sigmoid function f. Then x_i he output of the hidden layer will be passed to the output layer which is the same as the last process, and then we can get the final output.

$$y_i = f\left(X_i\right) = f\left(\sum_{j=1}^{n} w_{ij} x_j\right) \quad (7)$$

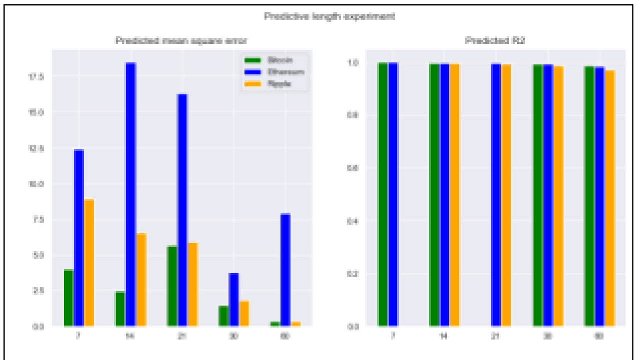

Figure 2. Performance of ANN model, given 7, 14, 21, 30, and 60 days price history as input features. Left and right panels represent model-data mean square error and Pearson correlation.

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$$f(x) = \frac{1}{1+e^{-x}} \quad (8)$$

We use the historical data to predict the trend of the cryptocurrency market, but what can the historical memory length that we use produce the most relevant results? With the same length of historical memory, will the different range of memory that we want to predict influence the accuracy of the model? We analyse the most appropriate internal memory and predictive memory length in understanding the cryptocurrency price dynamics. We try five different internal memory lengths: 7, 14, 21, 30, 60 days, and then combine with five predictive memory lengths: 1, 3, 5, 7, 14 days.

RESULTS AND DISCUSSION

A. *ANN Estimate of time Series Memory*

For the first part of ANN model, we use an ANN model to predict the price of Bitcoin one day into the future using five different lengths of memory: 7, 14, 21, 30 and 60 days. To measure the error between the data and model, we use the mean square error and the correlation. The results of our modelling experiments are shown in Fig.
2. It shows that the price of cryptocurrencies exhibits a long-term self-explain feature. By learning the full history of the previous month, the ANN model prediction of Ethereum is largely improved, compared with those short-term cases (blue bars in Fig. 2). Furthermore, concerning Bitcoin and Ripple, an even longer history of price (60 days, green and orange bars in Figure 2) is beneficial. However, we also find that solely increase the length of historical data as input features not necessarily induce a better model, the model performance is offset by introducing more model parameters (as increase of input features). For example, for Ethereum, using 60-day price history as input features performs worse than using 30-day price history. Nevertheless, all ANN models generally capture the variation of the price dynamics, indicated by the high correlation between observed and modelled cryptocurrencies prices (Fig. 2 right panel).

For the second part of ANN experiment, we need to figure out the most efficient predictive length (1, 3, 5, 7, 14 days) of cryptocurrencies prices given a 30-day historical memory. As shown in figure 3, for the Bitcoin and Ripple, one day price in the future can be predicted relatively well, and we also observed that the prices in three days of Ethereum could be forecasted more accurate than its other prices in the future.

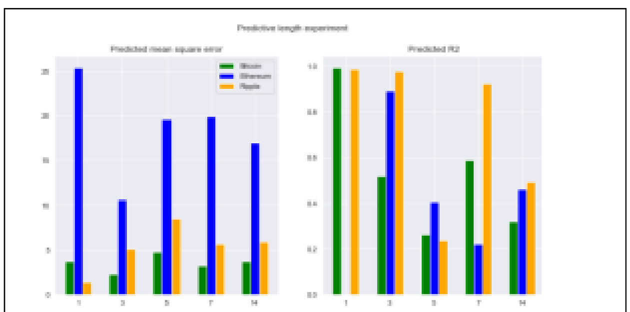


Figure 3. Performance of ANN model, given 1, 3, 5, 7, 14 days of predictive length. Left and right panels represent model-data mean square error and Pearson correlation.

B. *LSTM Estimate of Time Series Memory*

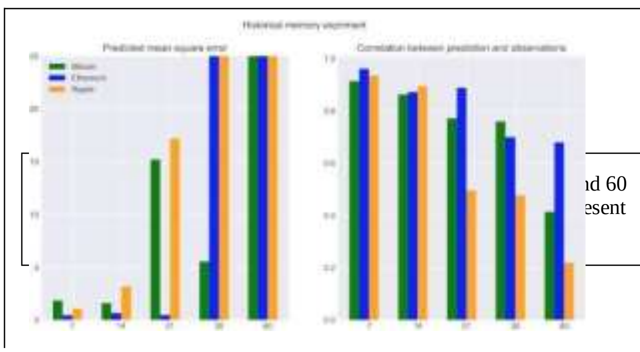
As for the LSTM model, it has a comparable performance with the ANN model in general, when predicting the one-day future prices of these cryptocurrencies, based on mean square error. It demonstrates that although ANN is lack of internal capability, it could effectively extract and use the useful information hidden in the historical price dynamics to predict a future price. While LSTM is intentionally designed to model the internal memory flow and its impact on future prediction, therefore, both ANN and LSTM are suitable for the cryptocurrencies price time series prediction.

We also find out that LSTM required the length of price history is different from that of ANN. LSTM generally prefer short historical memory. For example, LSTM with seven days of historical memory for Ethereum and Ripple or 14 days of historical memory for Bitcoin perform the best. The model-datacorrelation sharply declines as the length of historical memory

increase (Fig. 4 right panel). It indicates that LSTM reliesthe model prediction more on the most recent few days.

data are probably more useful for forecasting other lengths of future price.

Another limitation is the process of optimization and the parameters of our model are not being tested very well as the primary purpose of this experiment is to find out the reasonable historical memory length and predictive memory length, but it would be better if we could choose parameters based on grid search and try more different structural ANN and LSTM models.



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In predictive memory experiment, LSTM could best forecast next day price of the Bitcoin, Etherum, and Ripple, using their optimal historical length of memory identified before (Fig. 5). Compared with the ANN model, the LSTM model shows significant fluctuations while predicting different lengths of historical prices in the future.

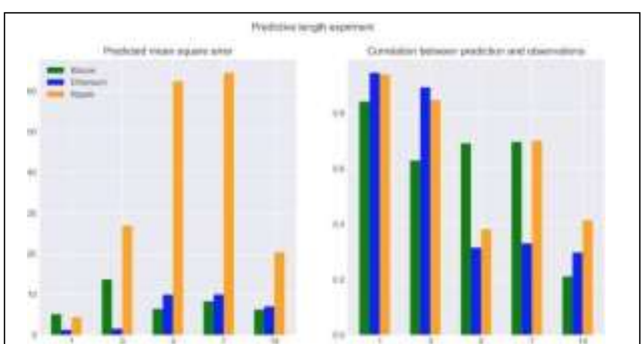

Figure 5. Performance of LSTM model, given 1, 3, 5, 7, 14 days of predictive length. Left and right panels represent model-data mean square error and Pearson correlation.

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C. Limitation and Future Work

This study is limited from several perspectives, which will be improved in our future studies. The first one is that we only choose three of the most representative digital currencies to analyse their price dynamics so that the result may be not generalised enough and we should apply the experiment to other cryptocurrencies like Litecoin, Tether, and Stellar.

Furthermore, five different lengths of memory have been used to predict the price of the digital currencies in one day because of the limitation of computational resources, so the best predictive memory length maybe cannot be found exactly, and the 30-day historical price

III. CONCLUSION

Cryptocurrency, such as Bitcoin, has established itself as the leading role of decentralisation. There are a large number of cryptocurrencies sprang up after Bitcoin such as Ethereum and Ripple. Because of the significant uncertainty in its prices, many people hold them as a means of speculation. Therefore, it is critically important to understand the internal features and predictability of those cryptocurrencies. In this study, we use two distinct artificial intelligence frameworks, namely, fully-connected Artificial Neural Network (ANN) and Long-Short- Term-Memory (LSTM) to analyse and predict the price dynamics of Bitcoin, Etherum, and Ripple. We showed that the ANN and LSTM models are comparable and both reasonably well enough in price prediction, although the internal structures are different. Then we further analyse the influence of historical memory on model prediction. We find that ANN tends to rely more on long-term history while LSTM tends to rely more on short-term dynamics, which indicate the efficiency of LSTM to utilise useful information hidden in historical memory is stronger than ANN. However, given enough historical information ANN can achieve a similar accuracy, compared with LSTM. This study provides a unique demonstration that Cryptocurrency market price is predictable. However, the explanation of the predictability could vary depending on the nature of the involved machine-learning model.

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