Cryptocurrency Price Analysis Using Artificial Intelligence

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Abstract:

Cryptocurrency is playing an increasingly vital role in altering the financial system due to its rising public appeal and mechant acceptability. While many individuals are making investments in Cryptocurrency, the dynamical aspects, unpredictability, the predictability of Cryptocurrency are still mainly unknown, which drastically jeopardize the investments. It is a matter to attempt to grasp the aspects that infiuence the value formation. In this research, we employ sophisticated artificial intelligence frameworks of fully connected Artificial Neural Network (ANN) and Long Short-Term Memory (LSTM) Recurrent Neural Network to examine the price dynamics of Bitcoin, Etherum, and Ripple. We discover that ANN tends to depend more on long-term history while LSTM tends to rely more on short-term dynamics, which imply the efficiency of LSTM to use relevant information concealed in historical memory is greater than ANN. However, with enough historical knowledge ANN may attain a comparable accuracy, compared with LSTM. This research presents a unique indication that Cryptocurrency.

Keywords: ANN LSTM

I. INTRODUCTION

Digital money and a payment system that operates online via a regulated algorithm are known as cryptocurrencies. A cryptocurrency is generated when a miner successfully breaks an algorithm to add a new block to the blockchain, a public ledger that records transactions. It enables users to store and transmit data via a dispersed network and an encryption mechanism. Cryptocurrency mining is an essential and competitive part of the system. The odds of a miner discovering a new currency are higher for the one with greater computing power. The first digital currency, developed by anonymous user Satoshi Nakamoto in 2008, is Bitcoin. Its market capitalization was over $7 billion in 2014 and surged to $29 billion in 2017. There are numerous practical applications for bitcoin, but its decentralization—the ability to eliminate the need to redo the proof of work for every blockchain—stands out. This has numerous potential applications, including the recording of charitable contributions in a way that prevents corruption. For example, we can use this feature of blockchain to create identification cards; they can both protect our privacy and verify our identity. Bitcoin has also introduced the controllable anonymity scheme, which enhances users' safety and anonymity when using this technology. Putting money into Bitcoin and other cryptocurrencies is one of the best methods to make money these days. As an example, the value of Bitcoin increased dramatically in 2017, going from a low of 963 USD on January 1ST to a high of 19186 USD on December 17th, and finally closing the year at 9475 USD. As a result, most investors were astounded by the 880% rate of return on bitcoin investments for 2017. Being astute investors may be aided by cryptocurrency price forecast. Traditional financial sectors and monetary authorities are able to properly forecast market movements thanks to the properties of the blockchain network. Also, most people who put money into cryptocurrency via electronic payment systems won't see a return on their investment since they don't give a hoot about the dynamics of cryptocurrency or the important aspects that affect bitcoin trends. Consequently, instead of relying on faith between demanding parties, the Bitcoin system relies on cryptographic verification, and despite its complexity, its dynamics are predictable and intelligible to a certain extent. For instance, when there is a scarcity of bitcoin, dealers would likely raise prices to attract buyers who see the cryptocurrency as a potentially lucrative investment opportunity. In addition, external variables, especially political ones, may have a significant impact on the price of bitcoin. While there has been little research on cryptocurrency forecasting and analysis so far, what little there is has focused on understanding cryptocurrency time series and developing statistical models to replicate and forecast price patterns. For instance, Madan et al. integrated the blockchain network—the technology behind bitcoin—with data gathered every half an hour, one hour, and two hours. Their algorithm uses binomial logistic regression classifiers and random forests to forecast the price of bitcoin with a 55% accuracy rate. Using Bayesian regression and Bitcoin price data collected at high frequency (10 seconds), Shah et al. improved Bitcoin trading strategy. Additionally, their models had been very successful. In, a prediction model for the next day's Bitcoin price was introduced using Multi-Layer Perceptron (MLP). The model takes two types of inputs: first, the opening, minimum, maximum, and closing prices. The second type of inputs uses the moving average of both short (5, 10, 20 days) and long (100, 200 days) windows. Their model's accuracy at the 95% level was shown during validation.

Meese and Rogoff (1983, 1988) looked at 97 portfolio balance models and monetary models that dealt with exchange rate forecasts, among many others. The stock market and other conventional financial markets have been the subject of much research and trend forecasting, but the process of estimating the value of cryptocurrency markets remains in its infancy. Since cryptocurrencies are not directly comparable to stocks but rather a supplementary product to the current monetary system with characteristics of rapid volatility, conventional time series approaches are not very helpful in predicting their prices. This highlights the critical requirement of developing a deeper understanding of cryptocurrency dynamics and a reliable predictive modeling approach. We postulate in this research that cryptocurrency time series display a distinct internal memory, which, if measured, might be used to improve the performance of the memory-based time series model. Bitcoin, Ethereum, and Ripple are three of the most widely used cryptocurrencies, and we want to apply two AI modeling frameworks to learn about and forecast their price fluctuations.

II. METHODOLOGY

2.1 Data Collection & Data Analysis

A total of 1030 trading days spanning from August 2015 to June 2018 include the historical price data for cryptocurrencies retrieved from https://www.blockchain.com/markets. Opening, high, low, and closing prices were the four pillars that made up the price data. Here we take a look at the market value of Ripple, Bitcoin, and Ethereum, the three most popular cryptocurrencies. We provide the four variables into our model, which then uses them to forecast the opening price for the next several trading days. Since the result of the starting price takes into account all the past memories and experiences, we've decided to use it. It was decided to split the dataset in half, with 80% going into training and 20% into testing, in order to prevent overfitting during training the model. Cryptocurrencies Ripple ($0.223), Bitcoin ($3082.084), and Ethereum ($194.810), along with a 95% confidence interval of [2834.034, 3330.134], [176.977, 212.642], and [0.196, 0.248] for their historical prices. The price of Bitcoin and Ethereum exhibits extreme volatility, with standard deviations reaching 4063, 292, and 0.43 correspondingly, as seen in Figure 1.

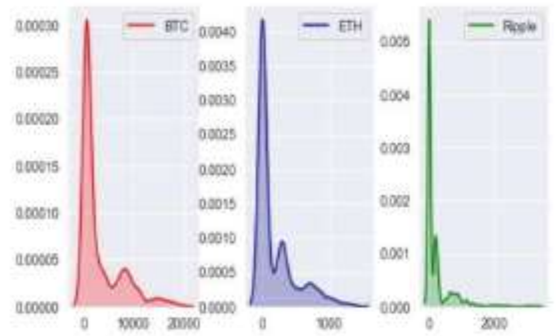

Figure 1.Density distribution of the price history from 7th August 2015 to 2nd June 2018, for Bitcoin (left panel), Ethereum (middle panel), and Ripple (right panel), respectively.

2.2 Models

There have been reports on the use of deep neural networks for financial market forecasting. We use two popular deep learning models—a fully connected Artificial Neural Network (ANN) and an LSTM Recurrent Neural Network—to analyze and forecast the price dynamics of cryptocurrencies in this research. Each of the LSTM's three layers has 10 nodes. There are three gates—an input gate, a forget gate, and an output gate—in each state of an LSTM cell. LSTM accomplishes its ignoring and memory functions by controlling the insertion or loss of information via the gate. The forget gate takes two inputs, ht1 and xt, where ht1 is the output of the previous unit and xt is the input of this unit. It is a Sigmoid function. Every item in Ct-1 (the internal state) may have a value in [0,1] assigned to it by the Sigmoid function; 0 means "keep this completely" and 1 means "forget this completely"; this allows you to determine the amount to which the final unit is forgotten.

$$ft = sigma(Wf.[ht1, xt] + bf) \quad (1)$$

An input gate produces *it* through a Sigmoid activation, and the tanh function that generates potential internal state (). Both of them control how much new information will be added to *Ct-1* to update the real internal state to *Ct*:

$$it = sigma(Wf.[ht\text{-}1,xt]+bf) \quad (2)$$

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

$$C_t = f_t * C_{t-1} + i_t * \vec{C}_t \quad (3)\ (4)$$

The output gate *Ot* uses a Sigmoid function to determine which part of neuron state need to be output, and then we need to convert *Ct* to output *ht-1*:

$$ot=_{sigma}(Wo[ht_{-1},xt\ ]+bo) \quad (5)$$

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

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 *wij* to the input, and there is an activation function-Sigmoid function *f*. Then *xi* 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.

$$Yi=f(xi)=f[_{\sum}j=1ton(wijxj)] \quad (7)$$

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

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.

III. RESULTS AND DISCUSSION

3.1 ANN Estimate of time Series Memory

Part one of the ANN model involves utilizing five alternative memory lengths—7, 14, 21, 30, and 60 days—to forecast the price of Bitcoin one day in the future. We use the mean square error and correlation to gauge the discrepancy between the data and the model. You can see the outcomes of our modeling trials in Figure 2. It demonstrates that cryptocurrency prices have a long-term self-explanatory characteristic. Compared to those short-term scenarios, the ANN model's forecast of Ethereum is much improved by learning the whole history of the preceding month (blue bars in Fig. 2). It would be helpful to have an even longer price history for Ripple and Bitcoin (60 days, green and orange bars in Figure 2) as well. While we do discover that longer historical data sets as input features can improve model performance, we also find that adding more model parameters (as input feature length increases) has the opposite effect. The strong association between the observed and modelled cryptocurrency prices (Fig. 2 right panel) suggests that ANN models often capture the variety in price dynamics; for instance, Ethereum's performance is lower when 60-day price history is used as input characteristics.

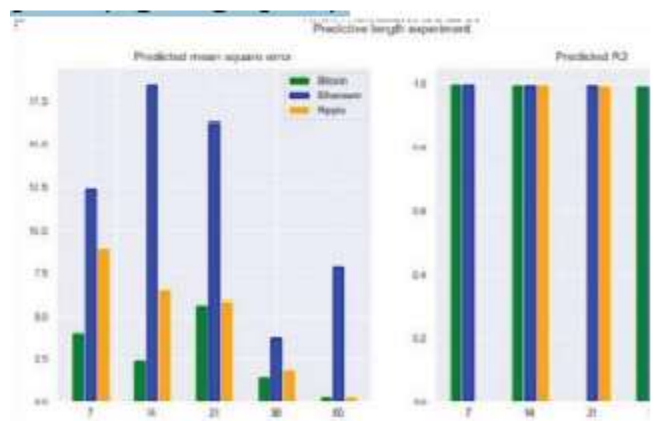

Figure 2. Performance of ANN model, given 7, 14, 21, 30, and 60 days price history as input features. Left and r panels represent model data mean square error and Pearson correlation.

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.

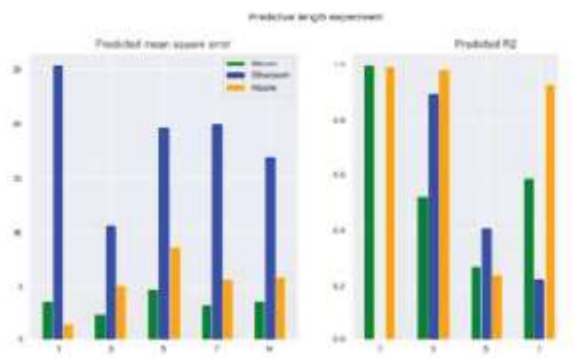

Figure 3. Performance of ANN model, given 1, 3, 5, 7, 14 days of predictive length. Left and right panels represent model-

3.2 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 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.

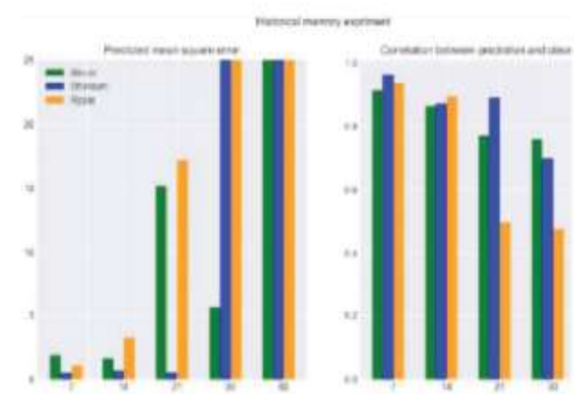

Figure 4. Performance of LSTM model, given 7, 14, 21, 30, and 60 days price history as input features. Left and right panels represent model data mean square error and Pearson correlation.

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-data correlation sharply declines as the length of historical memory increase (Fig. 4 right panel). It indicates that LSTM relies the model prediction more on the most recent few days. 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.

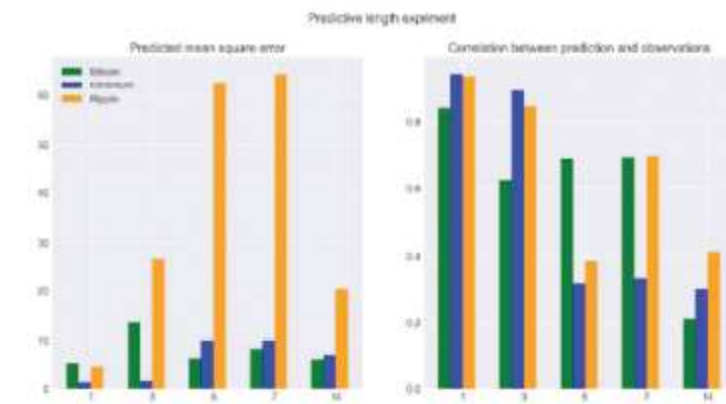

Figure 5: Performance of LSTM model, given 1, 3, 5, 7, 14 days of predictive length. Left and right panels represent model data mean square error and Pearson correlation.

3.3 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 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.

IV. CONCLUSION

Cryptocurrency, like Bitcoin, has taken the lead in decentralization. Ethereum and Ripple are just two of the many cryptocurrencies that emerged in the wake of Bitcoin. Many individuals keep them as a kind of speculation because to the substantial unpredictability in their value. Knowing the inner workings and predictability of such cryptocurrencies is, therefore, of the utmost importance. A fullyconnected Artificial Neural Network (ANN) and Long Short-Term Memory (LSTM) are the two AI frameworks used in this research to analyze and forecast the price movements of Ripple, Bitcoin, and Ethereum. While ANN and LSTM models have distinct underlying architectures, we demonstrated that they are similar and perform adequately in price prediction. We continue by delving further into how long-term memory impacts model forecasting. We discover that ANN is more likely to depend on long-term history, but LSTM is more likely to rely on short-term dynamics; this suggests that LSTM is more efficient than ANN at using the valuable information that is concealed in historical memory. But when compared to LSTM, ANN may attain comparable accuracy given sufficient historical data. The unique proof that the price of cryptocurrencies may be predicted is given by this research. Different machine-learning models may provide different explanations for the predictability.

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