

A NOVEL CRYPTOCURRENCY PRICE ANALYSIS WITH ARTIFICIAL INTELLIGENCE

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ABSTRACT

Cryptocurrency is playing an increasingly important role in reshaping the financial system due to its growing popular appeal and merchant 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 influence 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, Ethereum, 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.

1.INTRODUCTION

Cryptocurrency is the peer-to-peer digital money and payment system that exist online via a controlled algorithm. When a miner cracks an algorithm to record a block of transactions to public ledger named blockchain and the cryptocurrency is created when the block is added to the blockchain. It allows people to store and transfer through encryption protocol and distributed network. 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. 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) which was first introduced 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. 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 a critical 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 of the year. Consequently, the rate of return of bitcoin investment for 2017 was over 880%, which is an impressive and surprising scenery for most investors. While an increasing number of people are making investments in Cryptocurrency, the majority of investors cannot get 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 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 easily influenced by some influential

external factors such as political factors . 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, 1 and 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 , 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 . Their models had also achieved great success. In

2.LITERATURE SURVEY

1) Using the Bitcoin Transaction Graph to Predict the Price of Bitcoin AUTHORS: Greaves, A., & Au, B. with different objectives. A pre-defined set of minimum qualification levels should be distributed between the crew members with minimum training time differences, training expenses or a maximum of the training level with a limitation of the budget.

First, a description of the cosmonaut training process is given. Then four models are considered for the volume planning problem. The objective of the first model is to minimize the differences between the total time of the preparation of all crew members, the objective of the second one is to minimize the training expenses with a limitation of the training level, and the objective of the third one is to maximize

the training level with a limited budget. The fourth model considers the problem as an n -partition problem. Then two models are considered for the calendar planning problem.

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3. EXISTING SYSTEM

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 influence the value formation. 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 of the year. Consequently, the rate of return of bitcoin investment for 2017 was over 880%, which is an impressive and surprising scenery for most investors. While an increasing number of people are making investments in Cryptocurrency, the majority of investors cannot get 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 the dynamics are predictable and understandable to some degree.

4. PROPOSED SYSTEM

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, Ethereum, 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.

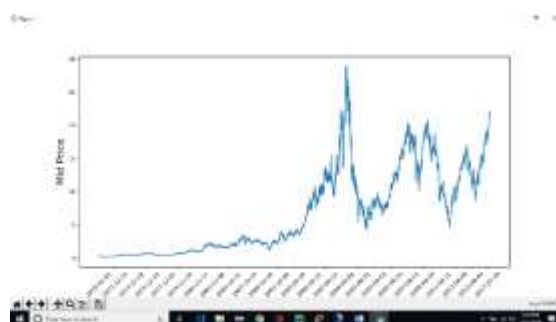
5.SYSTEM RCHITECTURE



6.RESULTS



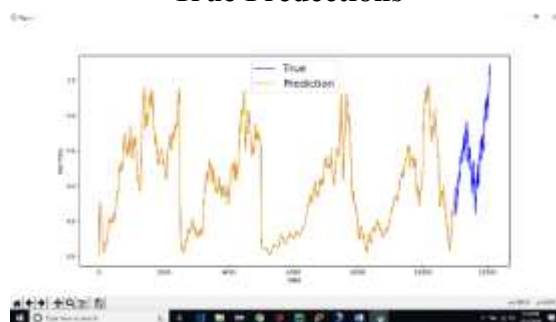
Agent view predictions dataset for test



Dataset analysis



True Predictions



Predictins



User can test the predictions

7.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, Ethereum, 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

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8.REFERENCE

- [1] Greaves, A., & Au, B. (2015). Using the bitcoin transaction graph to predict the price of bitcoin. No Data.
- [2] Hayes, A. S. (2017). Cryptocurrency value formation: An empirical study leading to a cost of production model for valuing bitcoin. *Telematics and Informatics*, 34(7), 1308-1321.
- [3] Shah, D., & Zhang, K. (2014, September). Bayesian regression and Bitcoin. In *Communication, Control, and Computing (Allerton)*, 2014 52nd Annual Allerton Conference on (pp. 409-414). IEEE.
- [4] Indra N I, Yassin I M, Zabidi A, Rizman Z I. Non-linear autoregressive with exogenous input (mrx) bitcoin price prediction model using so-optimized parameters and moving average technical indicators. *J. Fundam. Appl. Sci.*, 2017, 9(3S), 791-808`
- [5] Adebisi AA, Ayo C K, Adebisi MO, Otokiti SO. Stock price prediction using a neural network with hybridized market indicators. *Journal of Emerging Trends in Computing and Information Sciences*, 2012, 3(1):1-9
- [6] Adebisi AA, Ayo C K, Adebisi MO, Otokiti SO. Stock price prediction using a neural network with hybridized market indicators. *Journal of Emerging Trends in Computing and Information Sciences*, 2012, 3(1):1-9

[7] Ariyo AA, Adewumi AO, Ayo CK. Stock price prediction using the ARIMA model. In UKSim-AMSS 16th IEEE International Conference on Computer Modelling and Simulation (UKSim), 2014, pp. 106-112

[8] Ron, D., & Shamir, A. (2013, April). Quantitative analysis of the full bitcoin transaction graph. In International Conference on Financial Cryptography and Data Security (pp. 6-24). Springer, Berlin, Heidelberg.

[9] H. White, "Economic prediction using neural networks: The case of ibm daily stock returns," in Neural Networks, 1988., IEEE International Conference on. IEEE, 1988, pp. 451–458

[10] Kaastra and M. Boyd, "Designing a neural network for forecasting financial and economic time series," Neurocomputing, vol. 10, no. 3, pp. 215–236, 1996.

[11] H. White, "Economic prediction using neural networks: The case of ibm daily stock returns," in Neural Networks, 1988., IEEE International Conference on. IEEE, 1988, pp. 451–458 .

[12] Cheung, Y. W., Chinn, M. D., & Pascual, A. G. (2005). Empirical exchange rate models of the nineties: Are any fit to survive?. Journal of international money and finance, 24(7), 1150-1175.

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