Using A Feed Forward Neural Network Algorithm to Predict Prices of Multiple Cryptocurrencies

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ABSTRACT

This paper initially presents a nontechnical overview of cryptocurrency, its history, and the technicalities of its usage as a means of exchange. Bitcoin's working methodology and mathematical baseline is further presented in more depth. For the remaining majority of the paper, recent cryptocurrency price data of Bitcoin, Ethereum, Tether, Dogecoin, and Binance coin was used to train a machine learning model of Feed Forward Neural Networks to predict future prices for each of the datasets. Further and in conclusion, the results are discussed, and the efficiency and accuracy of these models are evaluated.

Keywords: artificial neural networks, bitcoin, cryptocurrency, dogecoin, ethereum.

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I. INTRODUCTION

The implementation of cryptocurrency was arguably the most significant breakthrough in humans' means of exchange since the 11th century when fiat money was first implemented in China. Indeed, despite the first appearance of fiat money about a millennium ago, it didn't grow widely popular until its implementation in the United States and across the world, in 20th century. In fact, even United States' national currency was not fiat-valued until 1971, when President Nixon segregated the monetary value of the United States Dollars from gold.

Cryptocurrency was first invented by cryptographer David Chaum in 1984. The process, initially called ecash, was introduced as a solution to address credit card fraud. Chaum takes money to be of the form $(x, f(x)^{1/3} \pmod n)$, with n being a composite securely chosen and has a factorization known solely to the bank, and $f(x)$ a one-way function. The proposed supply is first the customer picking x and r to supply the bank with $B = r^3 f(x) \pmod n$; then the bank returning $r f(x)^{1/3}$ and withdrawing one dollar from the account; then the customer extracting $C = f(x)^{1/3} \pmod n$ from B and giving the seller the pair $(x, f(x)^{1/3} \pmod n)$, and finally the seller directly verifying with the bank whether the token has already been deposited. The paper further introduces a system with enhanced security, using "untraceable coins". The process involves the bank using an RSA (public-key Rivest–Shamir–Adleman) mod n with factorizations kept secret, in addition to further secure variables [1].

Chaum's proposed methodologies created untraceable electronic cash, first implemented by his company DigiCash in 1995. Further developments in the field cleared the way for the introduction of Bitcoin in 2009. Bitcoin has gained wide

popularity since its initial price hikes in 2017 as well as further controversies in 2020. In June 2021, it was first accepted by a country's government (El Salvador) to be used as legal tender. Indeed, many private companies have been increasingly accepting its use in recent years.

II. BITCOIN'S WORKING METHODOLOGY

Bitcoin is established on the basis of a transaction log across a network of computers. It involves mechanisms that reward participation (a process of solving new mathematical equations that over time repeat less often and become harder called "mining"), bootstrap acceptance by early adopters, and defies any accumulation of power. In monetary macroeconomic terminology, it arguably has the potential to follow all mechanisms that any bona fide money does (a medium of exchange, a store of value, and a unit of account), with the exception of the "fiat" being the chain of Bitcoin networks rather than a conventional government [2].

While any conventional currency has a centralized banking system that controls for counterfeiting and ensures the scarcity of currency supply, mechanisms implemented in Bitcoin methodology claim to ensure scarcity and security using encryption methods described in the original research paper describing bitcoins [3]. Accordingly, the monetary supply of bitcoin is limited and increases by a portion of its previous increase factor every period. Using geometric series' sum, this guarantees limited supply in the long run. Entry to the market is open to everyone without any barriers, and each user's "wallet" file enables the storage of bitcoins in a peer-to-peer encrypted network. The network provides access to "block chain" data that simply logs the transactions as bitcoins [2].

Fig. 1. Bitcoin's Approach to Transaction Flow and Validation [2].

A distinctive feature of bitcoin and similar distributed ledger systems is decentralization. In addition to decentralization from power, such systems propose methods allowing them to perform autonomously. The decentralized ledger could be operated through a Proof-of-work (POW) consensus and incentive mechanism. The POW mechanism used by Bitcoin is one of a binomial random walk. Such a mechanism ensures that attackers would have to control at least 51% of the computing power in the system prior to being able to generate a sufficiently long blockchain that would take control [5].

An ordinary asymmetric binomial random walk on a single-dimensional lattice, with steps $S(m)$ taken by walker at times $t = m$ are independently identically distributed random variables using binary law:

$$S(m) = \begin{cases} -1, & \text{with probability } p \\ 1, & \text{with probability } q = 1 - p \end{cases} \quad (1)$$

The probability $F(n, v)$ represents the probability that a particle moving towards one particular direction at a constant speed v while having another particle ballistically approaching it from the same direction, not touching one another up to time n . Given a straight wall established on a random (x, t) plane with $x = vt$, the configuration space of the problem is depicted below [6].

Fig. 2. Configuration space of the asymmetric binomial random walk problem [6].

III. DATA AND METHOD

Historical cryptocurrency data was accessed through investing.com, for five trending cryptocurrencies. A novel aspect of this paper is to apply artificial neural network methods to newly trending cryptocurrencies. The five cryptocurrencies used in this paper are *Bitcoin*, *Ethereum*, *Tether*, *Dogecoin*, and *Binance coin*. For each of them, the daily USD price of 100 consecutive days (May 3, 2021, to August 10, 2021) was used. The daily prices include four rows of Price, Open, High, and Low for each. A simple evaluation of the used datasets shows great volatility in some prices over time. From a statistical point of view, this results in heteroscedastic data. Hence taking the assumption of volatility into account for prediction would be realistic as the nature of the cryptocurrency market implies frequent experiencing volatility.

The implemented Neural Network algorithm is a three-layer Feed Forward Neural Network (FFNN). The three layers include an input layer taking the input variables, a hidden layer for capturing the relationships among variables, and an output layer predicting the final output [7]. Fig. 3 shows the FFNN in more detail.

Fig. 3. 3-layer Feed Forward Neural Network. Source: MATLAB.

We use Mean Squared Errors (MSE) to evaluate the efficiency of algorithms. The optimal number of epochs for best validation performance is automatically determined. For further comparison of efficiency across datasets, the regression plots and R-squared values are reported as well.

IV. RESULTS

The model performs strongly for the prediction of Binance Coin. Fig. 4 shows the multiple regression plots (training, validation, test, all) of the model used for Binance Coin. The R-squared values being generally above 0.99 proves the strength of the model. Fig. 5 shows the most optimal validation performance, found to be at epoch 24.

The model performs mediocly for the prediction of Bitcoin. Fig. 6 shows the multiple regression plots (training, validation, test, all) of the model used for Bitcoin. The R-squared values are far apart from one another, lacking sufficient strength. Fig. 7 shows the most optimal validation performance, found to be at epoch 25.

The model performs well for the prediction of Dogecoin. Fig. 8 shows the multiple regression plots (training, validation, test, all) of the model used for Dogecoin. The R-squared values are generally above 0.96, proving model fitness. Fig. 9 shows the most optimal validation performance, found to be at epoch 12.

Fig. 4. Multiple plots of regression for Binance Coin. Source: The authors, MATLAB.

Fig. 5. Best validation performance for Binance Coin. Source: The authors, MATLAB.

Fig. 6. Multiple plots of regression for Bitcoin. Source: The authors, MATLAB.

Fig. 7. Best validation performance for Bitcoin. Source: The authors, MATLAB.

Fig. 8. Multiple plots of regression for Dogecoin. Source: The authors, MATLAB.

Fig. 9. Best validation performance for Dogecoin. Source: The authors, MATLAB.

The model performs strongly for the prediction of Ethereum. Fig. 10 shows the multiple regression plots (training, validation, test, all) of the model used for Ethereum. The R-squared values being generally above 0.99 proves the strength of the model. Fig. 11 shows the most optimal validation performance, found to be at epoch 393.

The model performs lowly for the prediction of Tether. Fig. 12 shows the multiple regression plots (training, validation, test, all) of the model used for Tether. The R-squared values are far from one another and generally lower than expected. The only optimal optimization is found to be at epoch 0.

Fig. 10. Multiple plots of regression for Ethereum. Source: The authors, MATLAB.

Fig. 11. Best validation performance for Ethereum. Source: The authors, MATLAB.

Fig. 12: Multiple plots of regression for Tether. Source: The authors, MATLAB.

V. DISCUSSION AND CONCLUSION

Based on the results, we find that the Feed-Forward Neural Network Algorithm is in most cases suitable for forecasting cryptocurrency values, as the performances are well, and errors are generally low. Undoubtedly, the market for most of the mentioned cryptocurrencies experienced unusual volatility in the selected time frame. Any low R-squared value may be due to such resulting heteroscedasticity in the data points. As a result, the predicted values take in the assumption that further volatilities may occur. Such an assumption is realistic, as it's often experienced within the cryptocurrency market.

The model can be further expanded into containing other neural network algorithms and/or different datasets. Other plausible neural network algorithms include (but are not limited to) GARCH, Recurrent Neural Networks, Bayesian Neural Networks, ANFIS, and so on. In terms of the data, the variety of data used in this paper may suffice for the context as most trending cryptocurrencies (with different underlying algorithm bases) were used. However, further research on the topic may take into account larger and/or smaller datasets. In general, with a higher number of datapoints accuracy is increased, but volatility (and thereby heteroscedasticity in data) may be increased as well. While long-term data is also useful, all economic agents, including but not limited to daily traders with a focus on short-term price hikes, could benefit from short-term data.

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