A Study on Machine-Learning-Based Prediction for Bitcoin’s Price via Using LSTM and SVR

Xia Zhang\textsuperscript{1}, Weimin Qi\textsuperscript{1} and Zhiming Zhan\textsuperscript{1,}\textsuperscript{*}

\textsuperscript{1}School of Physics & Information Engineering, Jianghan University, Wuhan, China, 430056

*Corresponding author e-mail: jasonzzm@tom.com

Abstract. Bitcoin plays an increasingly crucial role currently, whose of prices are challenged to be predicted when compared to the index of any traditional stock markets. With the accent of machine learning and deep learning, it is urgent to find out whether a machine learning model can or cannot see the way that the changes of Bitcoin’s price or volume interact over some period of time leads to a price increase or decrease within next few days. Testing results indicated that, the proposed two machine learning models built by LSTM and SVR were capable to capture longer-range dependencies and performed accurately by producing state-of-the-art results.

1. Introduction

Bitcoin is one type of cryptocurrency, a form of electronic cash. It is a decentralized digital currency without a central bank or single administrator that can be sent from user to user on the peer-to-peer bitcoin network without the need for intermediaries [1].

Transactions are verified by network nodes through cryptography and recorded in a public distributed ledger called a block-chain. The way to trade bitcoins seems easy that bitcoin wallet has a unique and private key which is used to confirm the transfer of bitcoins between users. Bitcoin was invented by an unknown person or group of people using the name Satoshi Nakamoto [2] and was released as open-source software in 2009 [3].

Bitcoins are created as a reward for a process known as mining. They can be exchanged for other currencies, products, services, and so on [4]. Research produced by University of Cambridge estimates that in 2017, there were 2.9 to 5.8 million unique users using a cryptocurrency wallet, where most of them were using bitcoin [5].

Bitcoin has been criminals’ “favourite”, which has been used in over 95% crypto criminal cases [6] [7]. Indeed, many of the recent drug busts involving fentanyl purchases were uncovered through block chain analysis [8] because buyers paid for the illegal opioid with bitcoin [9] especially for the contents of multimedia’s security [10]. Chang’s research team [11] tried to discover the relationship between major criminal rates and Bitcoin’s price changes via collecting data from social TV system where information hiding could provide the research with more detailed data [12]. Although Liang [13] used tree-like topology algorithm to further analyse those data and claims the relationship mentioned above was too complicated to fully discovered, it is still worthy to keep trying by other researchers [14].

Bitcoin faces critical resistance at $10,700 [15] which is the convergence of the Bollinger Band 1h-Lower [16], the previous daily low, the Simple Moving Average 5-15m [17], and the BB 4h-Lower.

If it breaks above this critical level, there are a few caps [18] awaiting it on the upside but substantial resistance is only at $11,400 [19] where we see the confluence of the BB 1h-Upper and the Fibonacci
38.2% one-month [20]. Trading in bear markets is always risky and harder than usual [21]. Always think twice what should be optimal investment strategies [22] before you made a decision.

2. Bitcoin Datasets and Pre-processing

We downloaded the prices at market opening, closing, the highest price and the lowest price for every single day. And then, we pre-processed those prices as Figure 1 shows.

![Figure 1. Bitcoin’s Prices and Pre-processing](image1)

Before building a neural network, it is worth seeing how less complex and more easily interpretable time series models perform. The graph above is a plot of the original data, with the moving averages and standard deviations for a window length of 7 days. The Dickey Fuller tests for p-value of its hypothesis: that the time series is represented by a unit root and the time series is not stationary, since p-value = 0.316 means we do not reject the Dickey Fuller hypothesis. The data is not stationary.

After logarithm calculation, the data could be transformed to Figure 2 which is better.

![Figure 2. Bitcoin’s Prices after Logarithm](image2)
Figure 3. Bitcoin’s Prices after “Differenced” Logarithm Pre-processing

As Figure 3 indicated, after graphing the “differenced” function, the data is much more clustered by now, where the log differences are expected to be small enough. Hence, the pre-processed data would be better to use for artificial neural network’s learning then.

3. Experimental Results

3.1. LSTM Prediction

Long short-term memory (LSTM) is an artificial recurrent neural network (RNN) architecture widely used in the research of deep learning, which has the feedback connections unlike standard feed-forward ANN so that make it as a “more general purpose computer”.

The results of real prices versus prediction prices—produced by deep learning LSTM—are as Figure 4 shows below, where different window sizes are 3 days and 7 days respectively.

Figure 4 demonstrates that a smaller window size would cause a lower loss and fewer epochs to reach model converged when compared to the result of window size = 7 days. Moreover, after 7 days in length this model still performs well although it is more likely to overshoot the closing price in favor of the day’s high.

3.2. SVR Prediction

A version of Support Vector Machine (SVM) for regression was proposed in 1996 which is named as Support Vector Regression (SVR) in brief. The SVR model depends only on a subset of the training
data, because the cost function for building the model does not care about training points that lie beyond the margin.

Figure 5. SVR Prediction for Bitcoin’s Prices vs. Real Prices

SVR was modelled for the price prediction; then, the differences between predicted prices and real prices are decently low enough (shown as Figure 5), which is proved that the proposed modelling method can be used for Bitcoin’s price prediction.

4. Conclusion

Nowadays Bitcoin has become more and more important, which may affect the whole society and the world in a lot of aspects especially for our safety and security. Thus, to predict Bitcoin’s price changes or trends will be essential. But, it is much more challenging other than traditional stock markets. The development of machine learning artificial intelligence brings new sights. Our idea behind Bitcoin’s price prediction is to find and also to model the patterns in the price and/or volume movement over some period of time. We proposed two machine learning models – based on LSTM and SVR – that can analyze and predict how the changes of Bitcoin’s price or volume interact over some period of time leads to a price increase either or decrease in next few days. Our experimental results show, the proposed models are decently sufficient to capture longer-range dependencies and have state-of-the-art performances.

5. Suggestions of Future Work

Compared to most other price spikes, more people have bought and held onto bitcoin in the rise. This signifies that any major drop is unlikely and $5000 may be a point of new resistance. More people entering the market, firstly, would increase demand and make Bitcoin more valuable. In addition, more volume manipulation by major cryptocurrency players is looking forward to drive Bitcoin’s price up. It may be that up to 90% of all crypto trades have been faked. Moreover, the same people cleverly trading to themselves to make it look as though the platform is more popular valuable than it is. Those pheromones may cause the prediction of Bitcoin’s price more difficult at the same time even more crucial; hence, future prediction research will be very worthy and urgent for the purpose of better supervising the whole market.
References

[1] Apaza, Carmen R. Integrity and accountability in government: Homeland security and the inspector general. Routledge, 2016.

[2] Lemieux, Pierre. "Who Is Satoshi Nakamoto?." Regulation 36.3 (2013): 14-16.

[3] Zimmer, Zac. "Bitcoin and potosi silver: historical perspectives on cryptocurrency." Technology and culture 58.2 (2017): 307-334.

[4] Xia, Zhang, and Chang Di. "Intelligent alarm system based on vibration sensor of optical fiber and grating." 2011 International Conference on Consumer Electronics, Communications and Networks (CECNet). IEEE, 2011.

[5] Hileman, Garrick, and Michel Rauchs. "Global cryptocurrency benchmarking study." Cambridge Centre for Alternative Finance 33 (2017).

[6] Ahmed, Mansoor, Ilia Shumailov, and Ross Anderson. "Tendrils of Crime: Visualizing the Diffusion of Stolen Bitcoins." arXiv preprint arXiv:1901.01769 (2019).

[7] Baek, Chung, and Matt Elbeck. "Bitcoins as an investment or speculative vehicle? A first look." Applied Economics Letters 22.1 (2015): 30-34.

[8] Kacian, Pavel, Miroslava Rajcaniovaa, and d’Artis Kancs. "The economics of BitCoin price formation." Applied Economics 48.19 (2016): 1799-1815.

[9] Gandal, Neil, et al. "Price manipulation in the Bitcoin ecosystem." Journal of Monetary Economics 95 (2018): 86-96.

[10] Balcilar, Mehmet, et al. "Can volume predict Bitcoin returns and volatility? A quantiles-based approach." Economic Modelling 64 (2017): 74-81.

[11] Brito, Jerry, Houman B. Shadab, and Andrea Castillo O'Sullivan. "Bitcoin financial regulation: Securities, derivatives, prediction markets, and gambling." Columbia Science and Technology Law Review (2014).

[12] Athey, Susan, et al. "Bitcoin pricing, adoption, and usage: Theory and evidence." (2016).

[13] McNally, Sean, Jason Roche, and Simon Caton. "Predicting the price of Bitcoin using Machine Learning." 2018 26th Euromicro International Conference on Parallel, Distributed and Network-based Processing (PDP). IEEE, 2018.