Improved Bitcoin Price Prediction based on COVID-19 data

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Abstract

Social turbulence can affect people's financial decisions, causing changes in spending and saving. During global turbulence as significant as the COVID-19 pandemic, such changes are inevitable.
Here we examine how the effects of COVID-19 on various jurisdictions influenced the global price of Bitcoin. We hypothesize that lockdowns and expectations of economic recession erode people's trust in fiat (government-issued) currencies, thus elevating cryptocurrencies. Hence, we expect to identify a causal relationship between the turbulence caused by the pandemic and Bitcoin price level.
To test the hypothesis, we merged datasets of Bitcoin prices and COVID-19 cases and deaths. We also engineered extra features and applied statistical and machine learning (ML) models. We applied a Random Forest model (RF) to identify and rank the feature importance and ran a Long Short-Term Memory (LSTM) model on the Bitcoin prices dataset twice: with and without accounting for COVID-19 related features.
We find that adding COVID-19 data into the LSTM model improved the prediction of Bitcoin prices.

1 Introduction

The COVID-19 pandemic influences many aspects of today's life. Growing numbers of new cases and deaths, unprecedented lockdown, and questionable leaders' responses synthesize an overwhelming uncertainty. As a result, we can see a nontrivial response from people. For example, since the beginning of the pandemic, the sales of guns and ammo have increased dramatically [1]. Hence, it suggests that people are opting in for the less conventional means to get feelings of safety in the pandemic's uncertain times.
We suggest that similar behavior may be found in other areas, for example in the search for money safety. As a result of the social turmoil, people may lose trust in state-controlled assets and move to a more novel and independent way to hold their investment – cryptocurrencies. Additionally, a possible change in the use of cryptocurrencies may be caused by other, more malicious, motivations that are still related to the pandemic. For illegal markets, the freeze of international travel may lead to the use of alternative ways of money transfer.
In this paper, we are exploring our hypothesis that the COVID-19 pandemic influences the prices of cryptocurrencies (Bitcoin). We are applying machine learning models to forecast the prices of Bitcoin with and without accounting for COVID-19.

2 Related Work

Researchers in many fields are interested to investigate the possible effect of such a nontrivial social turmoil as the global COVID-19 pandemic has caused. It is not surprising to see the growing number of research papers of this nature in finance implications. Relationships between the pandemic and prices of assets is a popular discussion topic among financial scholars and researchers.
One discussion is focused on the change in returns on assets such as cryptocurrencies. Conlon and McGee in their 2020 paper conclude that Bitcoin does not pass a heaven safety test [2] or exhibit high volatility.
Other discussions focus on the relationships between COVID-19 and the assets.
For example, Demir et al. [3] investigate the relationship between COVID-19 and cryptocurrencies. The researchers found that Bitcoin initially had a negative correlation but at a later stage the correlation turned to be positive. Going further, in another paper Goodell & Goutte determine that COVID-19 caused a rise in Bitcoin prices [4].
At this point, the available COVID-19 pandemic related research in finance and machine learning is still scarce but highly relevant. Therefore, we are aiming to add to the academic discussion with our contribution by examing the effect of accounting for the COVID-19 pandemic data in the cryptocurrency prices forecasting.

3 Data acquiring and preprocessing

We acquired our Bitcoin dataset using the Bitfinex API [5]. The data consisted of values per minute for the following features: open price, close price, and volume. Our data for the COVID-19 pandemic was acquired from the World Health

Organization[1].This data contained the following daily measures: cumulative number of cases, number of new cases per 24 hours, the cumulative number of deaths, and the number of new deaths per last 24 hours. Each of the datasets had corresponding values starting from January 6, 2020, and until September 5, 2020. We also engineered additional features by calculating mean, kurtosis, and skew for each feature. This step also helped to address the issue of a different number of samples in the Bitcoin dataset (which had samples per minute) and the COVID-19 dataset with daily values. The final merged dataset had values per day and a total of 246 samples of data with 37 features. Our dataset and code are available for the public on Github[2].

4 Model Setup

We performed our calculations in Python 3.6.9[3] and stored our version-controlled code and data on Github.
First, we intended to identify the most sensitive features out of the 37 that we were gathered. Since the initial dataset for COVID-19 was relatively small (less than a year of data), we wanted to reduce the number of features to prevent overfitting the model. We started with applying a Random Forest (RF) model to get the ranked feature importance list.

We used the scikit-learn library to get the Random Forest Regressor function. Our RF model with all features had a mean absolute error of 37.17 and an accuracy of 99.49 %. After running this model using important features only, we got a mean absolute error of 22.6 and an accuracy of 99.7 %. The RF model identified seven important features that are related to the Bitcoin market. We continued with the planned statistical approach.
To identify more features, we ran a Pearson correlation and analyzed the correlation matrix together with p-values of the features. After identifying features with a correlation higher than 0.6 and a p-value lower than 0.05 we added 12 more features. The final pre-procced dataset contains 19 features.
This final set of features includes two groups: 1) sums and minimum values of daily COVID-19 data including new, cumulative, and fatal cases, 2) open, high, mean, and close daily prices of Bitcoin.

After exploring the data with statistical tools, we continued with the trainable model: the Long Short-Term Memory model (LSTM). We opted for an LSTM model above other deep learning models due to its superior performance in handling sequence dependence such as time series [6] as well as superior performance in comparison to trivial statistical models such as ARIMA [7]. We employed the LSTM model through Keras – a neural network Python library. We split the data for training, testing, and validation in the following ratio respectively: 70%-20%-10%.

5 Results

In our model, we use windows of data to make sets of predictions for 1 day based on 24 days of data. Hence, our prediction horizon is one day, and the window width is 25 days.
While choosing the window size, we tried multiple alternatives (5-100). Taking into account that the total number of samples is 246 (days), we chose 25 as final window size.
After training the LSTM model on the dataset with Bitcoin prices only there was a mean absolute error of 0.8285 with a loss of 1.1950.

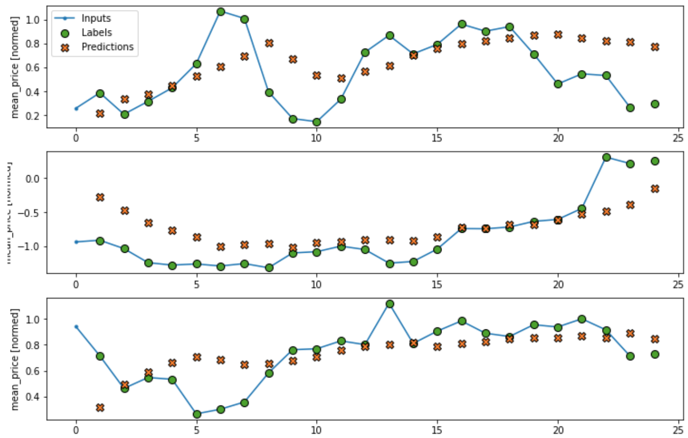
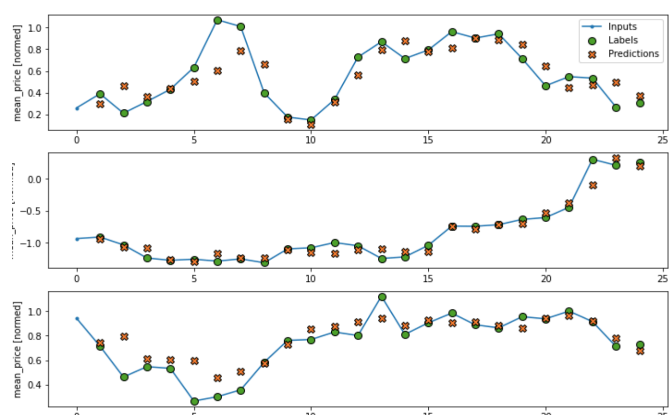


Fig 1. LSTM model set of predictions of daily Bitcoin prices (without COVID-19 features). Each graph is a separate window. Y-axes represent the samples (days), x-axes contain normalized values of the mean price of Bitcoin daily. The blue line connects the labels (green points), and the orange crosses are baseline predictions. The last, 25th, value is our prediction.

Next, we trained an LSTM model of the same hyperparameters and architecture but that included the COVID-19 features. After that, there was a mean absolute error of 0.6556 with a loss of 0.7011. This suggests that including extra COVID-19 cases may help to predict Bitcoin prices with greater precision.



[1] https://covid19.who.int/table
[2] https://github.com/PoliNemkova/crypto
[3] As implemented in Google Colab notebook

Fig 2. LSTM model prediction of Bitcoin prices including COVID-19 features. Each graph is a separate window. Y-axes represent the samples (days), x-axes contain normalized values of the mean price of Bitcoin daily. The blue line connects the labels (green points), and the orange crosses are baseline predictions. The last, 25th, value is our prediction.

6 Discussion

Our current results suggest that COVID-19 has influenced the market of Bitcoin. Since the Bitcoin price is responsive to external shocks [8], our findings confirm that COVID-19 is a significant external shock.

Our results are also consistent with the paper on behavioral finance where fear sentiment analysis shows the impact of investor sentiment on asset markets [9]. Due to the COVID-19 pandemic's sharply increasing death rate and unprecedented lockdowns and travel bans introducing high negative sentiment [9] the pandemic has impacted Bitcoin prices as well.

Our contribution can help financial managers to improve the robustness of their prediction model for a financial portfolio by including COVID-19 features in their deep learning model. Likewise, academic professionals can use our findings to research more detailed dependencies with the accumulation of more data about COVID-19.

7 Conclusion

COVID-19 pandemic has an extraordinary effect on many aspects of our society. We had to change our life and work routines as well as change our traveling habits. Our financial preferences are not the least aspect to change is our financial preferences. In this paper, we identified that the COVID-19 pandemic has a direct effect on the cryptocurrency market, in particular on Bitcoin prices.

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