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Bitcoin Price Prediction Based on Other Cryptocurrencies Using Machine Learning and Time Series Analysis

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Abstract

Cryptocurrencies, which the Bitcoin is the most remarkable one, have allured substantial awareness up to now, and they have encountered enormous instability in their price. While some studies utilize conventional statistical and econometric ways to uncover the driving variables of Bitcoin's prices, experimentation on the advancement of predicting models to be used as decision support tools in investment techniques is rare. There are many different predicting cryptocurrencies' price methods that cover various purposes, such as forecasting a one-step approach that can be done through time series analysis, neural networks, and machine learning algorithms. Sometimes realizing the trend of a coin in a long run period is needed. In this paper, some machine learning algorithms are applied to find the best ones that can forecast Bitcoin price based on three other famous coins. Second, a new methodology is developed to predict Bitcoin's worth, this is also done by considering different cryptocurrencies prices (Ethereum, Zcash, and Litecoin). The results demonstrated that Zcash has the best performance in forecasting Bitcoin's price without any data on Bitcoin's fluctuations price among these three cryptocurrencies.

Keywords: Cointegration, Time Series Models, Machine Learning, Bitcoin, Price Prediction

1. Introduction

Time series prediction can be used in different areas, such as predicting climate changes, population variations, the demand for any staff, and financial markets [1]. Economic time series is one of the most exciting and practical branches which can give a brilliant insight into financial markets. There are many different financial time series data, such as stocks and bond prices, energy prices, etc. Time series models, other processes, and their changes can be tracked to recognize what has happened and what will happen in the future. In financial fields, many various digital currencies are having been analyzed through different aspects.

A cryptocurrency is an advanced resource intended to function as a trade mechanism that utilizes solid cryptography to verify monetary exchanges; every unit of it can be controlled through different applications. Cryptographic forms of money use decentralized control rather than incorporated computerized cash and focal financial systems [2]. The decentralized control of every digital currency works through circulated record innovation, ordinarily, a blockchain, that fills in as an open budgetary exchange database. Bitcoin, first discharged as open-source programming in

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2009, is commonly viewed as the principal decentralized digital money. Since Bitcoin's arrival, more than 4,000 different digital currencies have been made, such as Ethereum, Litecoin, Zcash, etc. Bitcoin has become one of the most popular assets in the cryptocurrency market. Unlike traditional credit currencies, Bitcoin allows people to transfer money or purchase commodities via a peer-to-peer payment network without a centralized regulatory body [3].

Cryptocurrencies have means, variances, and covariances that change over time, which is called non-stationary. Non-stationary behaviors can be random walks, trends, cycles, or combinations of the three. Non-stationary data are unpredictable and cannot be modeled or forecasted [4]. The results obtained by using non-stationary time series may be spurious in that they may indicate a relationship between two variables where one does not exist. The non-stationary data needs to be transformed into stationary data to receive reliable results. In contrast to the non-stationary process with a variable variance and a mean that does not remain near, or returns to a long-run mean over time, the stationary process reverts around a constant long-term mean and has a constant variance independent of time. Using non-stationary time series data produces unreliable and spurious results and leads to poor understanding and forecasting in financial models. The solution to the problem is to transform the time series data so that it becomes stationary [5].

There are a few sorts of motivation for time series which are fitting for various purposes. For example curve fitting, is the way toward developing a curve, or mathematical function that has the best fit to a series of information focuses [6], function approximation, choose a function among a very much characterized class that intently coordinates ("approximates") an objective function in an errand explicit manner, prediction, and forecasting, etc. Prediction and forecasting in time series are developed by various models like Autoregressive (AR), Moving Average (MA), Autoregressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA), Autoregressive Conditional Heteroskedasticity (ARCH), Generalized Autoregressive Conditional Heteroskedasticity (GARCH), Adaptive Neuro-Fuzzy Inference System (ANFIS), and Artificial Neural Networks (ANN) are used as artificial intelligence models for analyzing the time series data.

This paper's main contribution is around forecasting the price of cryptocurrencies using a new approach based on the cointegration of different currencies to make them stationary for being predictable and determine the best coordination of cryptocurrencies. Analyzing the cointegration has two steps; first, we regress the dependent variable on the independent variable. The statistical tests should be run on equations to test null-hypothesis that is the condition in which both currencies are cointegrated. Following the first contribution, the second one estimates the best lag of models based on different performance criteria.

The rest of this paper is organized as follows. Section 2 reviews different estimating models of digital currency time series found in the literature. Section 3 exhibits the outline of what is done in this study and its methods to make them clear and understandable. Section 4 depicts the recommended approaches and their scenarios in foreseeing prices. The best empirical construction demonstrates in Section 5. The study is concluded, and the outcomes of the suggested model and other instability foreseeing models are introduced and discussed in Section 6. Finally, future work was presented.

2. Literature Review

Autoregressive Integrated Moving Average (ARIMA) and lagged forward price modeling were used to forecast the price of lead and zinc prices. Dooley and Lenihan [7] have indicated that both methods can be useful for price prediction in mine industries. Concerning zinc, there was no definitive proof to propose that one model was better than the other in its forecasting ability. On account of lead, it was discovered that the ARIMA model works better. In this investigation, Ediger and Akar [8] used the ARIMA and regular ARIMA (SARIMA) techniques to assess Turkey's future essential energy demand request from 2005 to 2020. Khashei and Bijari [9] utilized a hybrid methodology that combines ANN and ARIMA for forecasting time series. They have compared their model to different methods such as ARIMA, ANN, and Zhang's hybrid model, and they achieved better performance. Their model's mean Square Error (MSE) was considerably smaller than utilizing only the Artificial Neural Networks (ANN) or ARIMA models in prediction. Their forecast horizon was 1, 6, 12 months, and the one-step-ahead forecast had the smallest MSE.

Khashei and Bijari [10] utilized ARIMA models' exceptional capacity in linear displaying to distinguish and amplify the current linear structure in the information. Afterward, a Multilayer Perceptron (MLP) was utilized to decide a model to catch the basic information, create process, and forecast the future, using preprocessed information. Experimental outcomes with three understood genuine informational collections demonstrate that the proposed model can be a rugged path to yield a broader and more precise model than Zhang's hybrid model, and both of the component models utilized independently, consequently, can be used as an elective determining apparatus for anticipating time series. Another research introduces an adaptable calculation dependent on ANN and Fuzzy Regression to adapt to excellent long-time oil value in unsure and complex conditions [11]. Analysis of variance (ANOVA) and Duncan's Multiple Range Test (DMRT) was connected to test the hugeness of the conjectures obtained from ANN and FR models. It was presumed that the chose ANN models significantly beat the FR models as far as Mean Absolute Percentage Error (MAPE). Besides, the Spearman relationship test was connected to checking and approving the results. The proposed adaptable ANN– FR algorithm might be effectively changed to be connected to other complexes, non-linear, and questionable datasets [12].

Khandelwal, Adhikari, and Verma [13] developed a new approach using Discrete Wavelet Transform (DWT) to improve the time series determining exactness. DWT is utilized to break down the in-test preparing dataset of the time series into the two parts: linear and non-linear. Therefore, the ARIMA and ANN models independently perceived and predicted the remaining estimated parts individually. The experimental outcomes with four certifiable time series exhibit that the proposed technique has yielded prominently and preferred figures over ARIMA, ANN, and Zhang's hybrid model. Buncic and Moretto [14] has utilized data from the London Metal Exchange (LME) to estimate month to month copper prices using the newcomer proposed Dynamic Model Averaging and Selection (DMA/DMS) structure and also eighteen predictor variables were used, including different financial series. Their data covered an out-of-sample period of about ten years, engaging standard statistical measurement criteria and demonstrating that R square of DMA can be as high as 18.5 percent.

In another research, a proposed methodology for addressing the problem of predicting minimum and maximum day stock prices for Brazilian distribution companies based on feature selection and ANN is applied [15]. They concluded that it is vital to determine what kinds of features should be in the database when working with time series for prediction. Therefore,

considering different attributes, companies' stocks can be influenced differently. Fan, Wang, and Li [16] established an MLP network model to predict short terms after recognizing coal cost's disorganized qualities. The model performance was evaluated using four different MAPE, Root Mean Square Error (RMSE), direction statistic, and Theil index. They indicated the MLP, which they applied to their data, had better performance than the ARIMA model. Gangopadhyay, Jangir, and Sensarma [17] have built up a model to clarify and conjecture gold prices in India, utilizing a vector error correction model. They recognize speculation choice and inflation support as prime stimuli of their information. This can be valuable with the end goal of portfolio decision making for financial specialists. An essential step for the strategy was gotten from the Reserve Bank of India's site. The model showed that the gold price has a long-term relationship with the stock market index, oil price, exchange rate, and oil price.

Pradeepkumar and Ravi [18] claimed that their proposed Particle Swarm Optimization trained Quantile Regression Neural Network (PSOQRNN) can be utilized as a feasible option in anticipating unpredictability. They contrasted the adequacy of PSOQRNN and the conventional instability anticipating models, i.e., GARCH and a few ANNs. They found that their model overcame these models as far as MSE, on a larger part of the eight money related time series. In this paper, Long-Short Term Memory (LSTM) networks were connected to a vast scale monetary market forecast mission on the S&P 500, from December 1992 until October 2015. It exhibited that an LSTM network can successfully remove significant data from money related time-series information. Contrasted with irregular timberlands, standard profound nets, and calculated relapse, it was the technique for a decision concerning predicational precision and regarding day by day returned after exchange costs [19].

In another research, a system for managing time series displaying a typical example was proposed. The technique was connected with regarding time series estimation utilizing k-Nearest Neighbor (kNN) regression. The critical thought is to gauge each extraordinary season using an alternate particular kNN learner. Every learner was individual since its preparation set contains models whose objectives have a place with the season that can be conjectured. Sezer and Ozbayoglu [20] proposed an arrangement that dissected financial time-series information and changed it into 2-D pictures. In this investigation, they endeavored to predict passage and leave purposes of the time series values as "Buy," "Sell," and "Hold" marks for beneficial exchanges. They utilized Dow Jones 30 stock costs and ETFs as their money related time-series information. The outcomes show, this new methodology executes significantly better versus Buy and Hold and different models over extensive stretches of out-of-test trials.

In another paper, the Economic Policy Uncertainty (EPU) forecast on the day by day scale is done based on Bitcoin prices that were restored from the date 18th July 2010 to 15th November 2017. By utilizing the Bayesian Graphical Structural Vector Autoregressive (BGSVA) model just as the Ordinary Least Squares (OLS) and the Quantile-on-Quantile Regression (QQR) is evaluated to assess the results. At that point, it noticed that the EPU has a prescient power on the Bitcoin restores. Primarily, the Bitcoin restores were contrarily connected with the adjustments in the EPU. In any case, Bitcoin can be utilized as a supporting instrument versus vulnerability in outrageous occasions of exposure since we likewise discovered that the impact is specific and noteworthy at the higher quantities [21].

Chou and Tran [22] offered an extensive revision and examination of a few time-series anticipating procedures for foreseeing the energy utilization of structures one-day ahead of time.

Numerous investigations had been completed utilizing five Artificial Intelligence (AI) methods (namely ANN, SVR, CART, LR, etc.) with data on constructions' energy utilization. A general analogy illustrated that using hybrid models is more effective than using single ones. LSTM can be combined with some different time series methods. Furthermore, Kim and Won [23] used LSTM with GARCH to forecast stock market volatility. Then they compared the results of their hybrid model with single models and achieved a better outcome.

Investigating the price explosion through Phillips, Shi, and Yu [24] approach, in [25], allows capturing extreme price movements in cryptocurrencies and expands limited knowledge of short- and long-term price behavior Bitcoin and other cryptocurrencies. Bouri, Shahzad, and Roubaud [25] stated that Bitcoin, in particular, was found to be more subject to long-lived explosivity. Logistic regression analysis showed that the probability of explosion periods in a cryptocurrency generally depends on an explosion in other cryptocurrencies and is towards a simultaneous explosion that does not necessarily depend on the size of any cryptocurrency.

Bouri, Gupta, and Roubaud [26] examine herding behavior in the cryptocurrency market and the outcome of mass collaboration and imitation. Conducting a window-rolling analysis on the data series illustrated a significant herding behavior that changed over time. Besides, using logistic regression showed that herding behavior occurs with increasing uncertainty. They claimed that their findings provide useful insights into portfolio and risk management, trading strategies, and market efficiency.

In [27], a set of measures to examine connectedness via return and volatility spillovers across six large cryptocurrencies was applied. The results showed that Bitcoin and Litecoin were at the center of the connected network of returns. The shocks arising from these two cryptocurrencies had the most significant effect on other ones. Connectedness via positive returns was not as strong as positive ones, and as far as the volatility spillovers were concerned, Bitcoin was the most influential cryptocurrency. Further analyses illustrated that trading volumes, global financial, and uncertainty effects were determinants of net directional spillovers.

A proposed methodology based on feature selection and machine learning methods is applied to the Bitcoin exchange rates, and it provides better results compared to the previous studies. Mallqui and Fernandes [28] utilized feature selection methods to find the most relevant attributes, then by analyzing the best attributes, they explain the behavior of the daily variation of exchange rate.

Alameer, Elaziz, Ewees et al. [29] did Long-term gold price forecasting. They considered a new metaheuristic method named Whale Optimization Algorithm (WOA) for training the Neural Network (NN), and the result was compared with the other metaheuristic optimization methods such as GA, PSO, and grey wolf, then they applied to an ARIMA model. The results have shown that the hybrid WOA-NN was superior to the other mixed methods. The proposed WOA–NN displays progress in the foreseeing precision acquired from the NN, PSO–NN, GA–NN, GWO–NN, and ARIMA models by 41.25%, 24.19%, 25.40%, 25.40%, and 85.84% was diminishing in MSE, individually.

To improve the exactness of the stock market costs anticipating, two-hybrid anticipating models are recommended, incorporating the two sorts of Empirical Mode Decomposition (EMD) with the LSTM [30]. Atsalakis, Atsalaki, Pasiouras et al. [31] utilized a complex neuro-fuzzy technique to forecast the direction of the Bitcoin price changes and compared the result with the

simple approach of neuro-fuzzy and ANN method and realized that the efficiency of their method was 71.21% higher than the other techniques which applied in their paper.

Bouri, Roubaud, and Shahzad [32] focus on the cryptocurrency market that intrigues investment communities, not least because of its substantial price spikes and slippage. The results proposed that the event of a jump in one cryptocurrency increments with a jump in other cryptocurrencies. Moreover, the discoveries infer the need to incorporate jumps and co-jumps when modeling cryptocurrencies' volatility dynamics within multivariate models.

In [33], correlations were found between the volatility surprises of eight prominent cryptocurrencies. To address the communications, they are based on the concept of volatility surprises and examine the causal relationships between the volatility of leading cryptocurrencies through the frequency-domain testing, distinguishing between transient and permanent causes. The results showed evidence of causality among volatility surprises that did not necessarily come from the largest cryptocurrency. It is suggested that the unexpected volatility of other cryptocurrencies in the heterogeneous cryptocurrency market is significant. The fact that the causes are different between short-term and long-term for some cryptocurrencies indicates the importance of low- and high-frequency causes when considering integration. It also suggests predicting the volatility surprise at specific frequencies, meaning that crypto-traders should monitor other cryptocurrencies when trading a cryptocurrency.

This study investigates the multi-scale dependence and market relationship with the five leading cryptocurrencies [34]. Using wavelet-based techniques that cover both time and frequency, the top results show that the cryptocurrency market's unstable trends coincide with high frequencies, and the period 2016-2018 shows the continuation of market contagions.

The comparison table of literature review is shown in **Table 1.** The main objectives of this paper are as follows:

- Checking the cointegration of Bitcoin with three other popular coins, to determining a coin which has the highest ability to be used as a predictor of Bitcoin price, especially in a situation that there is little information about Bitcoin;

- Forecasting the Bitcoin price based on other coins, using machine learning algorithms such as Linear Regression (LR), Gradient Boosting Regressor (GBR), Support Vector Regressor (SVR), Random Forest Regressor (RFR);

- Utilizing Time Series Analysis Models to recognize which coin fits the historical data better than others in the cointegration process.

3. Methodology

This section is divided into several parts that explain the fundamental of the techniques used in this paper and the description of the data of four well-known cryptocurrencies. Then, we clarify the new approach that may give us more insight into the price of Bitcoin based on the other digital currencies, so these parts will be as follows:

3.1. Data Description

For the practical application, four-digital coins were collected from coinmarketcap.com from 1st April 2018 to 31st March 2019. These are as follows:

Bitcoin

Bitcoin (Ƀ) is a digital currency, a type of electronic money. It is decentralized advanced cash without a national bank or single chairman that can be sent from client to client on the shared Bitcoin arrange without middle people's requirement.

Exchanges are checked by system hubs through cryptography and recorded in an open disseminated record called a blockchain. Bitcoin was designed by an obscure individual or gathering of individuals utilizing the name Satoshi Nakamoto and discharged as open-source programming in 2009. Bitcoins are made as a fee for an operation known as mining. They can be dealt with for various fiscal structures, things, and organizations. Research delivered by the University of Cambridge gauges that in 2017, there were 2.9 to 5.8 million remarkable clients using a digital currency wallet, the vast majority of them utilizing Bitcoin.

Ethereum

Another type of cryptocurrency is Ethereum, which is founded in 2015. It is based on a modified version of Nakamoto's theory. Ethereum was suggested in late 2013 by Vitalik Buterin, a digital cash specialist and programmer. Ethereum is the pioneer for blockchain-based smart contracts. Smart contracts take into account code to be run precisely as customized with no plausibility of downtime, control, and deceit or outsider impedance on the blockchain. The worth of the Ethereum token developed more than 13,000 percent in 2017, to over $1400. By September 2018, it had decreased to $200.

Litecoin

Litecoin (LTC or Ł) is a distributed digital money and open-source programming project discharged under the MIT/X11 license. The creation and exchange of coins depend on an open-source cryptographic convention and aren't overseen by any focal expert. Litecoin was an early Bitcoin spinoff or altcoin, beginning in October 2011. In specialized subtleties, Litecoin is about indistinguishable to Bitcoin.

Zcash

Zcash is a digital currency gone for utilizing cryptography to improve its clients' security contrasted with other digital money, such as Bitcoin. Zcash has a total fixed supply of 21 million units. Exchanges can be "transparent" and like Bitcoin exchanges, in which case a t-addr constrains them, or can be a kind of zero-learning verification called zk-SNARKs; the exchanges are then said to be "shielded" and are constrained by a z-addr.

3.2. Statistical Models and Artificial Intelligence Methods

This part explains some conventional statistical models like AR, MA, ARIMA, and ANFIS as intelligent methods that combine both fuzzy and artificial neural networks.

3.2.1. Autoregressive (AR)

An autoregressive model illustrates a sort of random process; all things considered, it is used to define time-fluctuating procedures in nature, financial aspects, etc. In machine learning, an AR model gains from a series of timed steps and accepts estimations from past activities as inputs for a regression model to foresee the next time step's value. AR models exploit how time-series information is successive – it's essential to preserve the order or sequence of the data to

make exact forecasts. The forecasts for autoregressive models are regressed on previous observations in the time series. These models use weighted sums of past values to figure future values. The notation AR(p) shows an autoregressive model of order p. It is characterized as:

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t \qquad (1)$$

Where φ_i is the *parameter* of the model, c is a constant, and ε_t is white noise – A white noise process is one with a mean zero and no correlation between its values at different times.

Once the above equation's parameters have been estimated, the autoregression can be used to forecast an arbitrary number of periods into the future.

3.2.2. Moving Average (MA)

In time series analysis, the Moving Average model (MA model), moreover called moving-average procedure, is a typical methodology for displaying univariate time series. The moving-average model determines that the upshot variable depends directly on the present and different past values of a stochastic (imperfectly forecastable) term. A moving average model of order q (i.e., MA(q)) is characterized as follows:

$$X_t = \mu + \varepsilon_t + \theta_1 \varepsilon_{t-1} + ... + \theta_q \varepsilon_{t-q} \qquad (2)$$

where μ is the mean of the series, $\theta_1, ..., \theta_q$ are the parameters of the model and the $\varepsilon_t, ..., \varepsilon_{t-q}$ are white noise error terms.

3.2.3. Autoregressive Integrated Moving Average (ARIMA)

ARIMA models are, in principle, the broadest class of models for anticipating a time series which can be made to be "stationary" by subtracting (if essential), may be related to nonlinear changes, for example, logging or deflating (if necessary), an ARIMA model is speculation of an autoregressive and moving average models. Both of these models are fitted to time series information either to all the more likely comprehend the information or to predict future points in the series. The AR part of ARIMA specifies that the interest's evolving variable is regressed on its own lagged values. The MA part denotes that the regression fault is a linear compound of fault terms whose values coincided at various times in the past. The "I" shows that the data values have been altered with the diversity between their values and the olden values. Every one of these attributes aims to fit the model throughout the data beyond what many would consider possible.

ARIMA models are commonly ARIMA(p, d, q) where parameters p, d, and q are positive integers, p is the order of the autoregressive model, d is the level of subtracting, and q is the order of the moving average model. This model as follows:

$$(1 - \sum_{i=1}^{p} \phi_i L^i)(1 - L)^d X_t = (1 + \sum_{i=1}^{q} \theta_i L^i) \varepsilon_t \qquad (3)$$

3.2.4. Machine Learning (ML)

One of Artificial Intelligence applications is machine learning, which gives systems the capability to learn and make better from experience without any definitive program spontaneously.

Computer programs have developed by accessing data and utilizing it for learning themselves in machine learning.

The way toward learning starts with perceptions or information to search for patterns in data and settle on better choices, later on, depending on the precedents. The essential point is to permit the PCs to adapt naturally without human mediation or help and change activities in like manner. Machine learning algorithms refer to the type of targets that can divide into regression models, classification models, clustering models, etc.

3.3. Cointegration

Cointegration is a statistical measurement of a collection $(X_1, X_2, ..., X_k)$ of time series variables. If at least two series are exclusively coordinated. In any case, some linear compound has a lower order of integration; at that point, the series is said to be cointegrated. The three primary techniques for testing cointegration are:

- Engle-Granger two-step method

- Johansen test

- Phillips–Ouliaris cointegration test

Several types of data are cointegrated; some of them are as follows:

Economic substitutes as heating oil and natural gas, platinum and palladium, corn and wheat, corn and sugar, etc.

3.4. Our proposal framework

In this part, we provide a brief discussion of the theoretical procedure of the experiment. Firstly, we analyze the data of the changing price of four different digital currencies to realize the main trends and figure out if they are stationary or not. As said before, the first purpose of this paper is to forecast the price of Bitcoin based on the other digital currencies. It is assumed that price fluctuations in each digital currency follow the random walk process. Therefore, it cannot be predicted. As it is nonstationary, there are many various ways to make a time series of information stationery. Several statistical tests determine whether a process is a random walk or not, such as Dickey-Fuller (DF) test, the Augment Dickey-Fuller (ADF) test, Ng-Perron test, DF-GLS test, ERS-point optimal test, and Phillips-Perron test. In this paper, we try to make a process (daily price of Bitcoin) stationary by subtracting the other process. Cointegration was checked to use different models.

Checking the cointegration of two processes have two steps, we regress the first variable (Y) on the second variable, so the equation will be Y-bX, and the Augmented Dickey-Fuller test or any other statistical test should be run on it to check if it is still random walk or not. Estimating the regression line for checking the cointegration can be executed through the following methods:

1.Ordinary Least Squares (OLS)

2.Fully Modified Ordinary Least Squares (FMOLS)

3.Dynamic Ordinary Least Squares (DOLS)

After checking the stationarity condition, statistical time series models as AR, MA, ARIMA, and neuro-fuzzy model that are categorized as AI models that can be applied on it, also we try to run a code to tune the parameters based on the performance criteria such as Akaike Information Criterion (AIC) and Bayesian Information Criterion. Then we try to cover all of the performance criteria to evaluate each method, such as:

1. Mean Square Error (MSE)

2. Mean Absolute Percentage Error (MAPE)

3. Mean Absolute Error (MAE)

4. Akaike Information Criterion (AIC)

5. Bayesian Information Criterion

4. Data Analysis and Models Deployment

In this section, the behavior of cryptocurrencies' prices, time series plots, models' execution, and evaluation criteria are discussed in detail. Then the cointegration between Bitcoin, as a fixed part, is checked with the other ones.

4.1. Time Series Plots

As mentioned before, cryptocurrencies' datasets indicated daily price changes throughout the year. The most crucial application of analyzing time series plot is to determine whether the process is stationary or not, along with this part. Also, autocorrelation function (ACF) can be a useful method to figure it out. To gain this information, time series are plotted (**Figure 1**).

As shown in **Figure 1**, the price fluctuations reach the pick in May and gradually fall until December. It shows that they are full of changes, making forecasting complex because the price of cryptocurrencies like stocks is random walks. Hence, they are not predictable, which makes us use another attribute to forecast them. This attribute is recognized as "return," which is a differencing that make the process stationary. In the following figures, firstly, the prices and returns' ACF are shown. Secondly, their returns are plotted to make sure differencing works as what we are expected.

The above figures (**Figures 2, 3, and 4**) are plotted to show the difference between the autocorrelation in Bitcoin price and Bitcoin price returns. As shown in Bitcoin prices' ACF, the Bitcoin price's ACF plot is not stationary, but we can see that the returns are entirely stationary.

As shown in the following figures (**Figures 5, 6, 7, 8, 9, 10, 11, 12, 13**), Ethereum, Litecoin, and Zcash also have the same Bitcoin condition. Their price fluctuations are not stationary, but we notice that they are stationary if we examine their price returns.

4.2. MA, AR and ARIMA Models for Price Returns

First of all, we apply the ARIMA models to each of the cryptocurrencies' price returns to predict a step forecast. We use ARIMA because these models include MA and AR models inside of it as we apply ARIMA (0, 0, q) and ARIMA (p, 0, 0), respectively. According to the previous section, all the returns were stationary; thus, they are ready to get models on them to forecast. The

ACF plots have shown that returns are not so simple, and we cannot execute a pure AR or MA model on them. The following graphs contain real values, fitted values, and also the forecasting part simultaneously. As usual, the confidence interval is about 95% percent. The graphs are as follows (**Figures 14, 15, 16, and 17**):

Different parameter values have been tested on Bitcoin returns, and the best outcome was p=1 and q=1 with one difference.

These figures are based on the ARIMA models, and the best values for parameters were gained using different programs that were coded to achieve the best performance rates. After the tuning process, we plotted the final results to show the function of the best models. **Figure 18** shows the quick results of the programs. The same processes as Bitcoin have been executed for the rest of them, and the best model for each one is ARIMA(2, 1, 1), ARIMA(2, 1, 1), and ARIMA(1, 1, 1) for Ethereum, Litecoin, and Zcash, respectively (**Figure 18**).

4.3. Machine learning prediction

Machine learning algorithms are utilized to predict the Bitcoin price and realize which cryptocurrencies (Ethereum, Zcash, and Litecoin) impact Bitcoin's price changes. To use different ML algorithms, firstly, we need to set a dataset that contains Ethereum's, Zcash's, and Litecoin's prices as independent variables and Bitcoin's price as the dependent variable. Then ML algorithms are applied to find out which cryptocurrencies can forecast the Bitcoin's price changes without any data on the trend of the Bitcoin's price.

Regression methods are one of the forecasting algorithms in machine learning, which Linear Regression algorithm, Gradient Boosting Regressor algorithm (GBR), Support Vector Regressor algorithm (SVR), Lasso Regression algorithm, and Random Forest Regressor algorithm (RFR) are used in this paper to achieve referred goals.

In all of these methods, 80 percent of data assigns to the training part, and the rest of 20 percent gives it to the testing part. After utilizing methods, MSE is calculated for each of them as an evaluation criterion. The MSE formula is as follow:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{4}$$

4.3.1. Support Vector Regressor algorithm

Support Vector Machines algorithm (SVM) as an ML method, divided into two parts: 1.Classification and 2.Regression. According to our goal, SVR is utilized with "Linear" kernel, MSE is calculated, and a comparison figure between real Bitcoin's price values and predicted ones by SVR is shown (**Figure 19**).

MSE = 516804.797833455

4.3.2. Linear Regression algorithm

The linear Regression algorithm is one of the simplest methods among machine learning algorithms that can produce appropriate answers. The MSE value shows that this method has better performance in comparison with SVR. The following figure (**Figure 20**) illustrates the real Bitcoin's price values and predicted ones by LR.

MSE = 421034.06468415906

4.3.3. Random Forest Regressor algorithm

Another ML algorithm is Random Forest Regression (RFR), an ensemble method formed by a few Decision Tree methods. RFR can be used in both classifiers and regression forms. This method's parameter is determined by their users, which the optimal one in this paper achieved experimentally, 207 trees. According to the MSE value, it shows that this method performs strictly better than two previous methods (**Figure 21**).

MSE = 23365.60049452004

4.3.4. Gradient Boosting Regressor algorithm

Another ensemble method as a famous ML algorithm is the Gradient Boosting Regression (GBR), which contains some parameters. The best state of this method is coming forward when the number of estimators equal to 100, the learning rate equals 0.12, and the subsample equals 0.6. By comparing the MSE result of this method with previous methods, GBR is the most appropriate method to estimate Bitcoin's price. It is also understandable from the estimated line in the following figure (**Figure 22**):

MSE = 18359.190867996942

4.3.5. Lasso Regression algorithm

To gain the second goal, determine the most effective cryptocurrency for predicting Bitcoin's price without any information, the Lasso Regression algorithm is applied. The basis of this method is the data's variance changing. According to **Figure 23**, it can be realized that Zcash's price trend has the most capability to predict Bitcoin's price.

As a summary of all applied algorithms, **Table 2** gathers the applied method with some other evaluation criteria. The results shown that the Gradient Boosting Algorithm has the best accuracy and minimum mean square error.

4.4. Cointegration, our proposal method

In this section, the cointegration between Bitcoin and the other cryptocurrencies check through two steps. Adding this part can help us predict Bitcoin, as well-known crypto, one step ahead without any information about its previous trend. We recognize the relation between Bitcoin and other cryptos to use the best of them for foreseeing Bitcoin price.

As mentioned before, the first step is to regress Bitcoin's prices on other cryptos. Then we try to execute the augmented Dickey-Fuller test on them as the second part to figure out whether they are cointegrated or not. As the residuals are not stationary, first-order differencing is done for being compatible with ARIMA models. The whole process can be executed via this algorithm in python environment:

Pseudo code:

```
start
{
Add constant value to a crypto [1];
   Result = Ordinary Least Square model (Bitcoin, crypto(x))
   Bitcoin = regression_coeff * crypto[1] + residuals
   residuals = (Bitcoin - regression_coeff * crypto(x))
Dickey fuller test on residuals
   test result
}
end
```

After applying time series models on residuals, it is necessary to evaluate each model and decide the appropriate model based on these evaluation criteria. There are different measurements. Bayesian Information Criterion and Akaike Information Criterion are employed to assess the models.

$$AIC = Ln\left(\frac{\sum_{t=1}^{T}e_t^2}{T}\right) + \frac{2p}{T} \tag{5}$$

$$BIC = Ln\left(\frac{\sum_{t=1}^{T}e_t^2}{T}\right) + \frac{pLn(T)}{T} \tag{6}$$

T: number of periods

p: number of estimated parameters

e_t: residuals

The following graphs (**Figure 24**) tell about the forms and order of models, the first condition assigned to cointegration between Bitcoin and Ethereum and ARIMA execution with the order of p=1, d=1, and q=2:

The regression line is (Equation 7):

$$Bitcoin\_Price = 3510.527428 + 7.9343 \times Ethereum\_Price \tag{7}$$

P_value of the ADF-test:

$$3.018049e\text{-}05$$

AIC and BIC of their cointegration:

13

$$AIC = 4087.4245922612673$$

$$BIC = 4192.7285924245916$$

The second condition assigned to cointegration between Bitcoin and Litecoin and ARIMA execution with the order of p=0, d=0, and q=2 (it is MA(2)) (**Figure 25**):

The regression line is (Equation 8):

$$Bitcoin\_\Pr ice = 3120.255075 + 39.973767 \times Litecoin\_\Pr ice \qquad (8)$$

P_value of the ADF-test:

$$9.4400204e\text{-}05$$

AIC and BIC of their cointegration:

$$AIC = 4151.424592183152$$

$$BIC = 4166.728592612673$$

The third condition assigned to cointegration between Bitcoin and Zcash and ARIMA execution with the order of p=1, d=1, and q=2 (**Figure 26**):

The regression line is (Equation 9):

$$Bitcoin\_\Pr ice = 3053.563308 + 20.661674 \times Zcash\_\Pr ice \qquad (9)$$

P_value of the ADF-test:

$$1.1552e\text{-}08$$

AIC and BIC of their cointegration:

$$AIC = 3978.591052327704$$

$$BIC = 3997.706281805119$$

The experimental results show that Zcash price can be the best predictor of the Bitcoin price among two other cryptos as it has the minimum value in AIC and BIC (shown in **Table 3**).

5. Sensitivity Analysis

There are many different ways to determine the best values of models' parameters. Sensitivity analysis in time series models refers to changing models' order. For instance, in MA models, we can change the number of periods that give the trend's smooth shape.

To achieve the best order in these models, we developed an algorithm that iterates different rankings and results preferred based on the models' evaluation criteria. The following plots (**Figure 27**) related to some of the time series models which was utilized above:

As shown in regression line estimation by RFR figure, the evaluation criteria, especially BIC, were calculated using different orders to reach the optimum value (minimum). In the left graph, d and q were constant (=1), but p iterates and got the optimal order, the same processes have been

done for each of the parameters, so as it has done in the right one (p and d are constant). These procedures have been done for the whole model through the paper.

6. Discussions and Conclusions

Nowadays, many people mine and trade different kinds of cryptocurrencies in a wide range. As their popularity increased daily, the demands of them enhanced simultaneously. Price prediction and asset speculation is a high-risk venture. Therefore, the importance of finding an appropriate way to predict their future values is undeniable. Because of their price volatility, it is too complicated to apply a stable model for forecasting. Thus, we decided to search for some features that can help us to predict their price. To find these features and their volatility are mean reverting, we used to gain the price returns. As an open market determines a cryptocurrency's value, this presents unique challenges around volatility that most currencies do not face. While cryptocurrency price prediction is an ever-moving target, market literacy is essential for getting the most value out of their participation in the crypto economy.

In this paper, Bitcoin's cointegration is checked with three other popular coins to determine a currency that has the highest ability to be used as a predictor of Bitcoin price, especially when there is little information about Bitcoin. The Bitcoin price based on other coins is forecasted by using machine learning algorithms such as Linear Regression (LR), Gradient Boosting Regressor (GBR), Support Vector Regressor (SVR), and Random Forest Regressor (RFR). Time series analysis models are applied to recognize which coin fits the historical data better than others in the cointegration process.

Therefore, at first, the relations among cryptocurrencies have been checked fundamentally by machine learning algorithms to ensure they have any connections. Then, each cryptocurrency's price trend had analyzed and plotted daily during a year to realize how they were acting by different kinds of time series models. After all, a finding of which two cryptocurrencies, Bitcoin as the stable base, had the most similarity, coming to the main contribution. The importance of finding the most similarity among three well-known cryptos showed itself when there is no/rare information on crypto (in this paper, worked on Bitcoin). Using the other crypto can predict what may happen one step forward. The cointegration between cryptocurrencies is suggested for the first time in the literature. According to the paper's goal, the cointegration between Bitcoin and three other cryptocurrencies was studied in four following stages:

1. Bitcoin's price regression on three other cryptos' prices.

2. Execution of ADF-test.

3. ARIMA model implementation on their residuals.

4. Criteria measurement's evaluation.

As a result, among the three cryptocurrencies (Ethereum, Zcash, and Litecoin), Zcash had the most trend's similarity toward Bitcoin. We also had seen this result by executing the Lasso Regression algorithm as an ML's method. In other words, as the information on Bitcoin price was less, the Zcash price information can be used to forecast the Bitcoin price one step forward.

As future work, we intend to work on more cryptocurrencies in a more extended period to receive more accuracy. Moreover, we plan to apply variate models on the cointegration's estimated equation. Another common way to predict the price of cryptocurrencies is to utilize deep learning

and its algorithms, which, due to their complexity, they are expected to predict prices more accurately. We plan to implement these algorithms to analyze their performances too.

Nomenclature

X_t model variable in time t

c constant number of the model

φ_i parameter of the model

ε_t white noise error

μ mean of the series

θ_i parameter of the model

p the order of the AR model

d the level of subtracting of ARIMA model

q the order of the MA model

$\emptyset_i$ parameter of the model

L   lag operator for period i

y_i real value of independent variable

$\hat{y}_i$ estimated value of independent variable

T number of periods

p   number of estimated parameters

e_t residuals error

n number of observations

Superscript

i lag index

Subscript

t time index

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Figures and Tables Captions' List

Tables and Figures

Table 1.

Authors	Methods														Data
	ARIMA	ANN	Fuzzy method	Zhang's hybrid	SARIMA	SVR	LSTM	CART	DMA	DMS	GARCH	BGSVA	EMD	Meta heuristic	
Dooley and Lenihan [7]	✓														Lead / Zinc Price
Ediger and Akar [8]	✓				✓										Energy Demand
Khashei and Bijari [9]	✓	✓		✓											Sunspot
Khashei and Bijari [10]	✓	✓		✓											Sunspot
Azadeh et al. [12]		✓	✓												Oil Price
Khandelwal et al. [13]	✓	✓		✓											Lynx Price
Buncic and Moretto [14]									✓	✓					Copper Price
Fan et al. [16]	✓	✓													Coal Price
Pradeepkumar and Ravi [18]		✓									✓			✓	Different Currency
Fischer and Krauss [19]							✓								S&P 500
Demir et al. [21]												✓			Bitcoin price
Chou and Tran [22]		✓			✓	✓		✓							Energy Consumption
Kim and Won [23]							✓				✓				Stock Market Prices
Alameer et al. [29]	✓	✓												✓	Gold Price
Cao et al. [30]							✓						✓		Stock Market Prices
Atsalakis et al. [31]		✓	✓												Bitcoin price
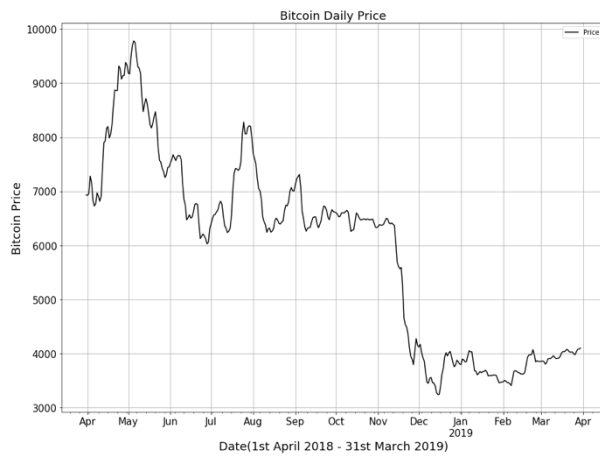
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(b)
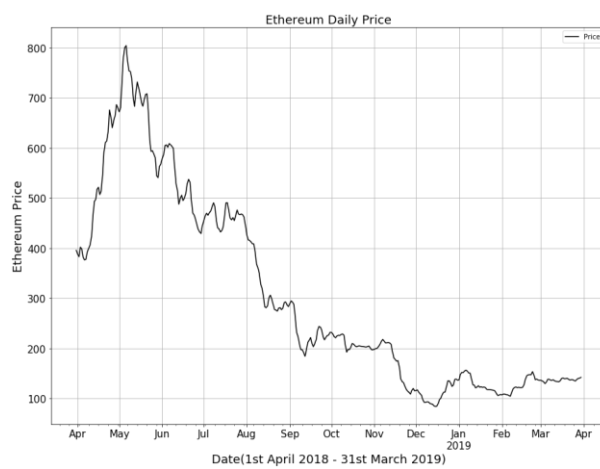
(c)

(d)

Figure 1
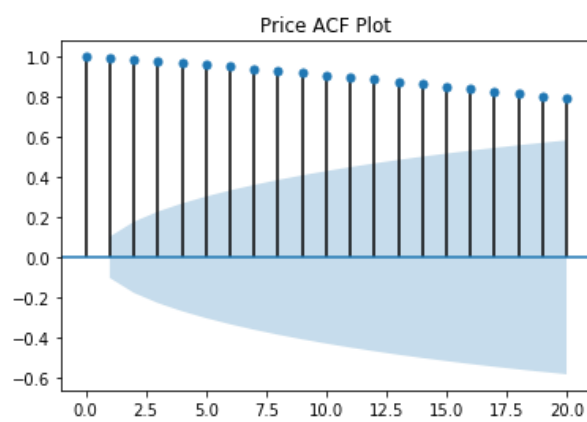
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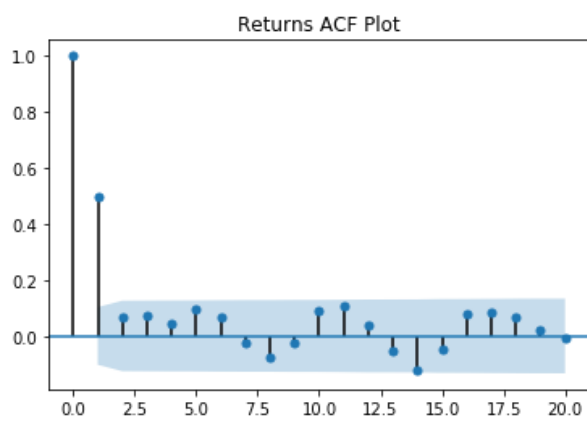
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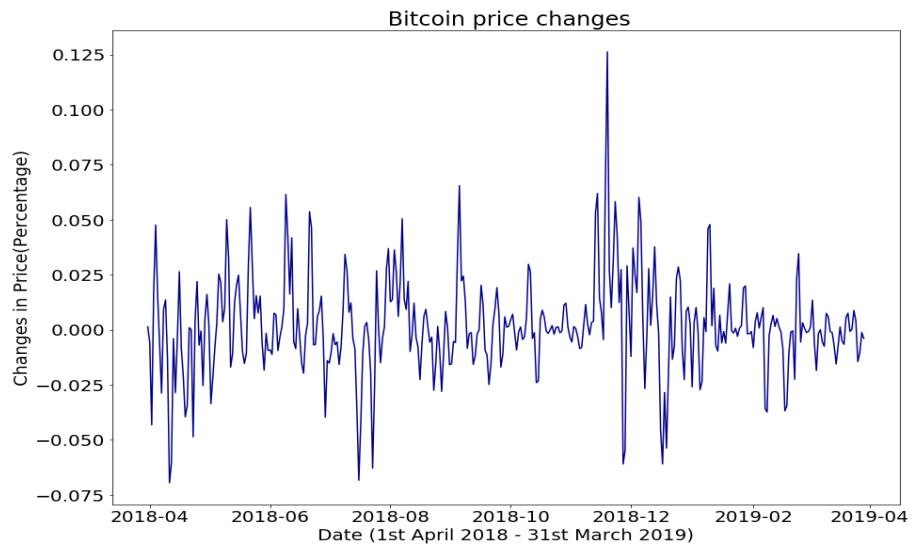
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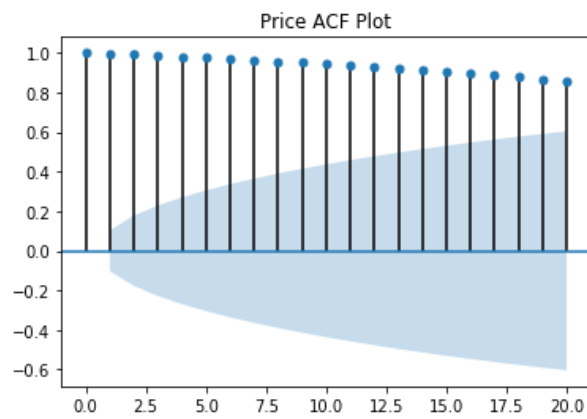
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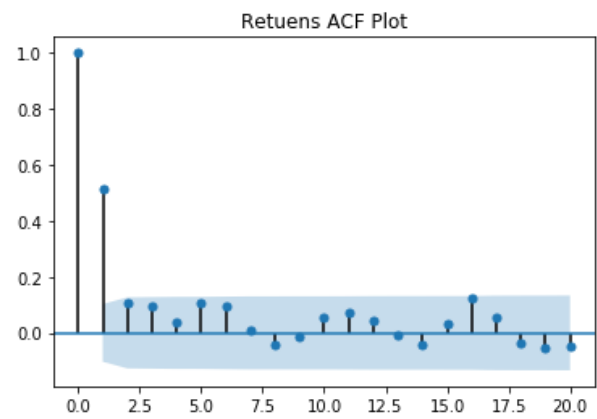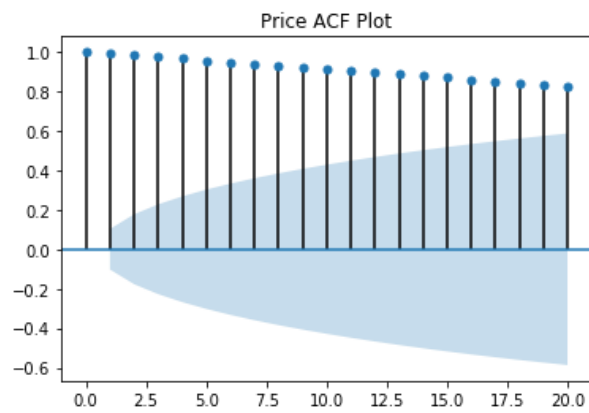
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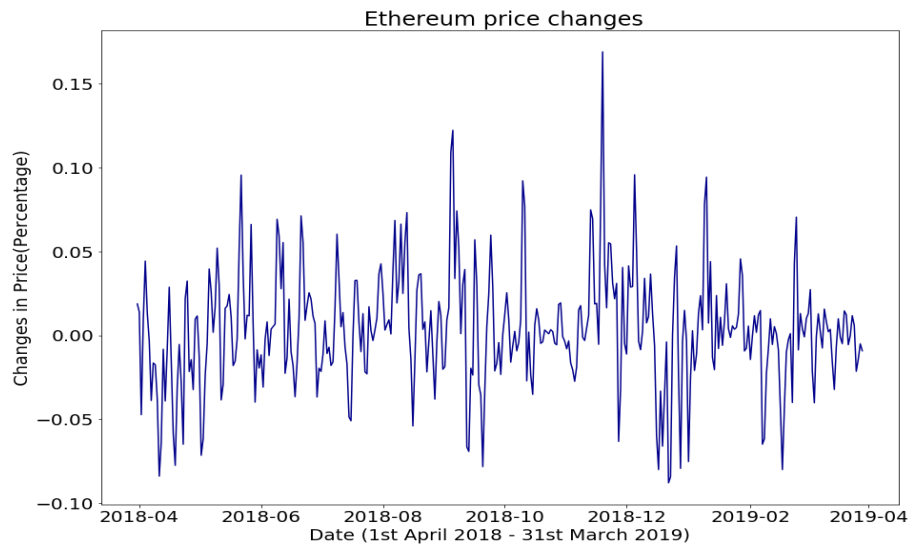
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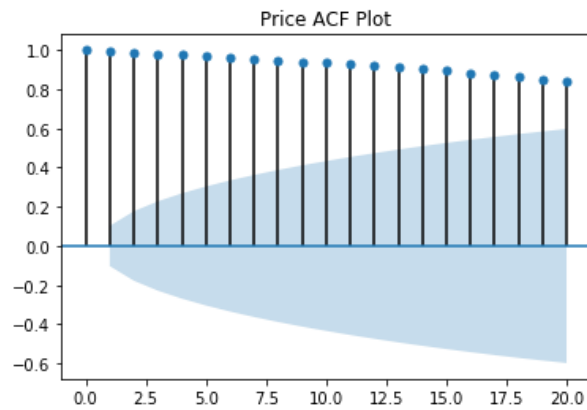
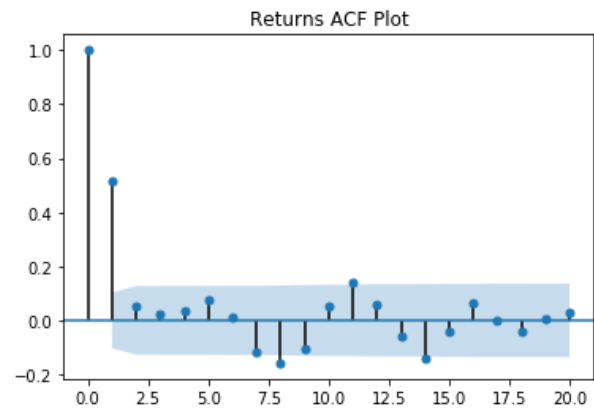**Figure 8**
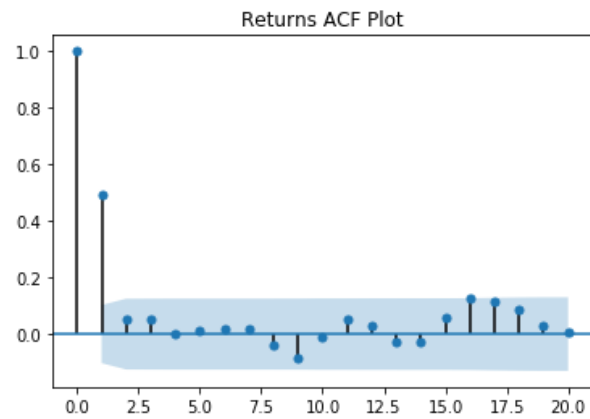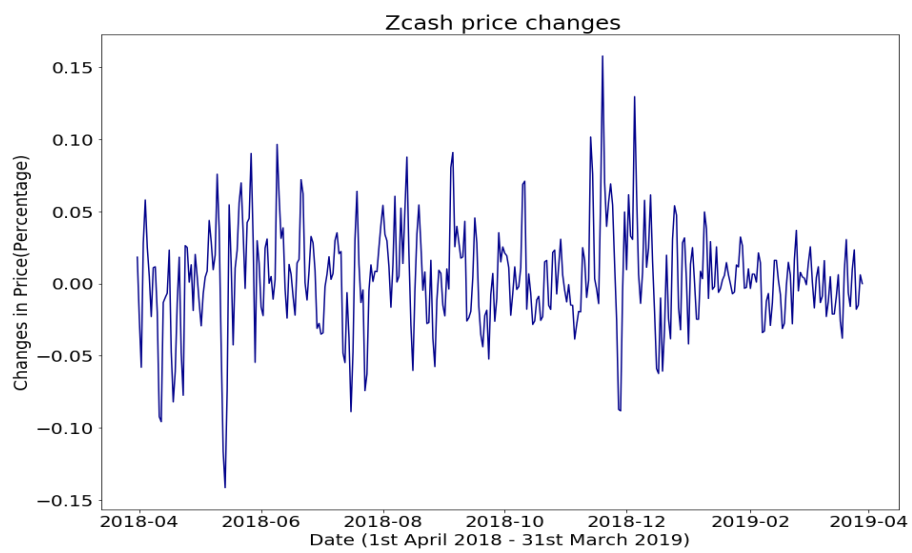

Figure 9
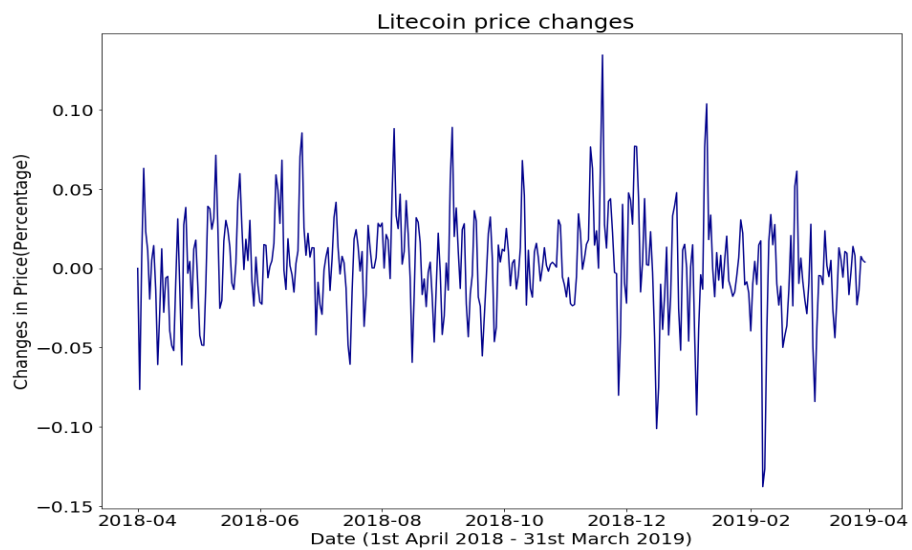
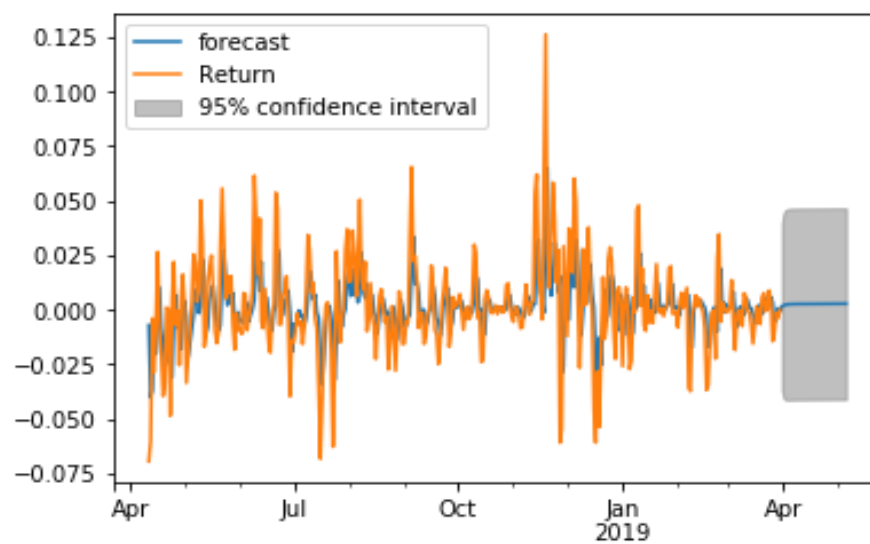**Figure 10**

Figure 11

Figure 12

Figure 13

Figure 14
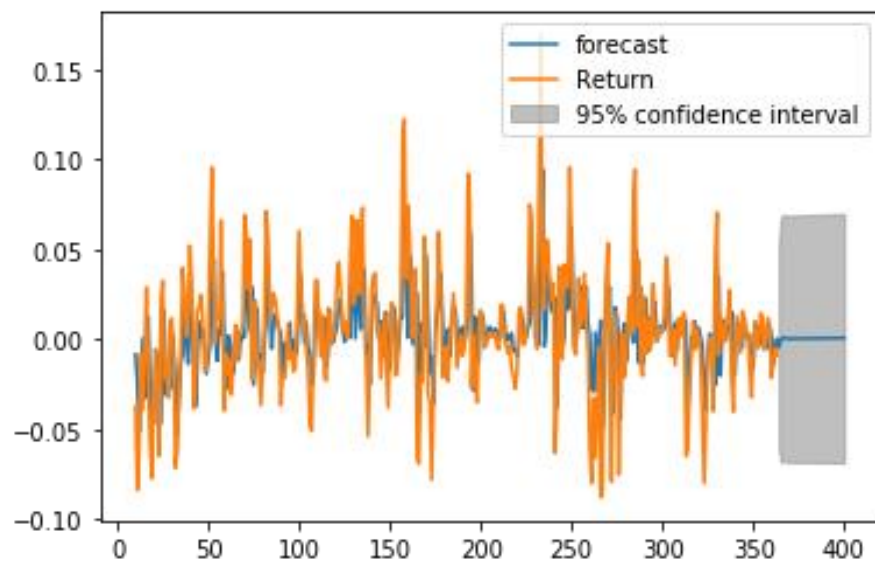
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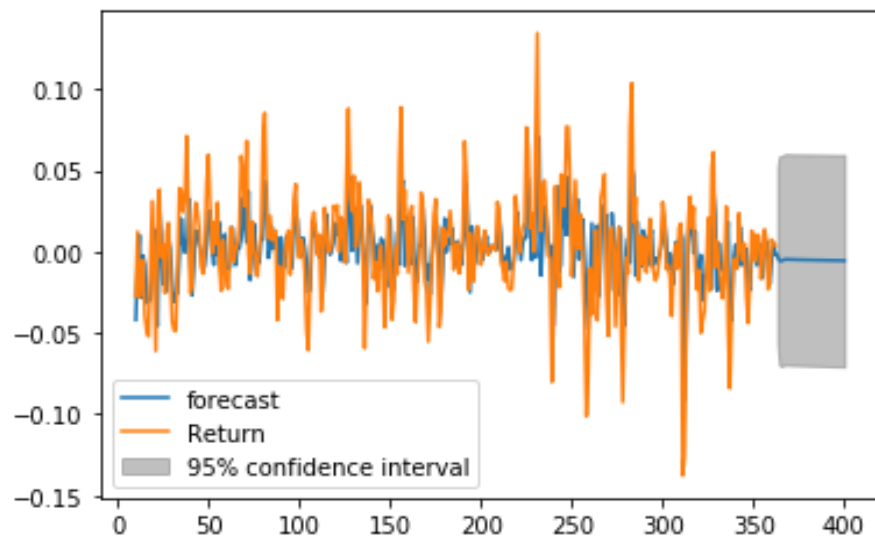
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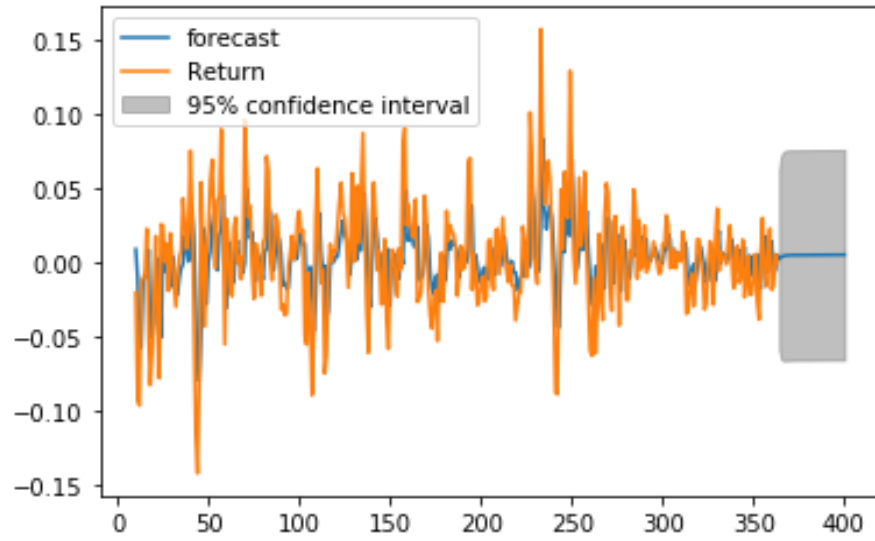
Figure 17

Bitcoin

ARIMA(p,d,q)	p	q	d	AIC	BIC
Model 1	1	0	0	2104.20	2101.30
Model 2	1	1	0	2056.20	2040.31
Model 3	1	1	1	1821.86	1806.29
Model 4	0	1	1	2423.25	2418.32
Model 5	0	0	1	2843.21	2820.45
Model 6	2	1	0	2024.32	2010.02
Model 7	2	0	1	2112.02	2118.32
Model 8	2	1	1	2090.12	2095.74
Model 9	1	2	1	2312.45	2308.42

Litecoin

ARIMA(p,d,q)	p	q	d	AIC	BIC
Model 1	1	0	0	2010.27	2008.10
Model 2	1	1	0	1960.42	1954.00
Model 3	1	1	1	1921.01	1916.89
Model 4	0	1	1	2003.21	1982.24
Model 5	0	0	1	2413.51	2401.21
Model 6	2	1	0	1650.31	1623.74
Model 7	2	0	1	1580.27	1560.12
Model 8	2	1	1	1557.62	1538.12
Model 9	1	2	1	1904.15	1890.42

Zcash

ARIMA(p,d,q)	P	Q	d	AIC	BIC
Model 1	1	0	0	1510.48	1506.14
Model 2	1	1	0	1492.12	1488.25
Model 3	1	1	1	1480.31	1464.73
Model 4	0	1	1	1743.34	1742.17
Model 5	0	0	1	1800.56	1794.20
Model 6	2	1	0	1624.54	1616.74
Model 7	2	0	1	1647.45	1635.74
Model 8	2	1	1	1552.64	1545.10
Model 9	1	2	1	1734.24	1719.46

Ethereum

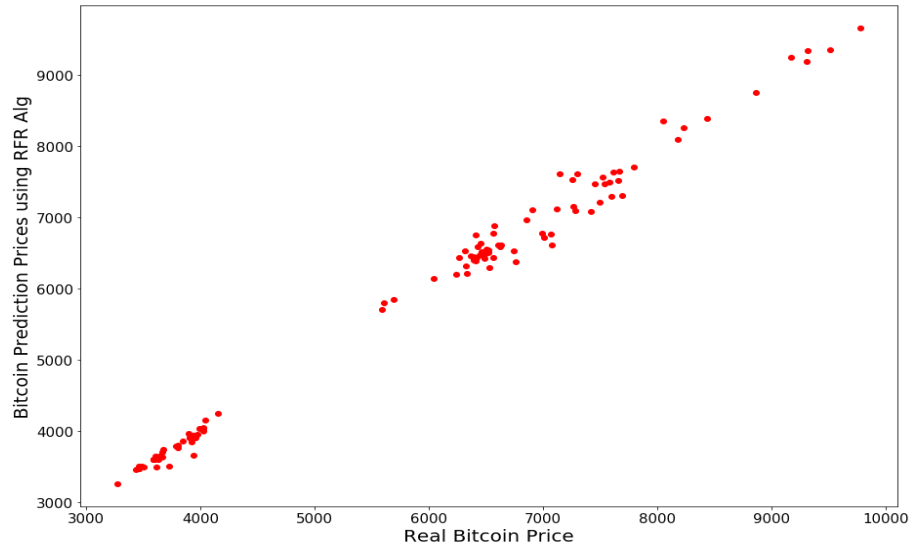| ARIMA(p,d,q)	P	Q	d	AIC	BIC
Model 1	1	0	0	1913.18	1903.37
Model 2	1	1	0	1991.51	1983.41
Model 3	1	1	1	1921.01	1916.89
Model 4	0	1	1	1942.72	1934.00
Model 5	0	0	1	1973.97	1964.49
Model 6	2	1	0	1705.47	1697.33
Model 7	2	0	1	1682.46	1674.78
Model 8	2	1	1	1645.84	1620.70
Model 9	1	2	1	1812.46	1802.75

Figure 18
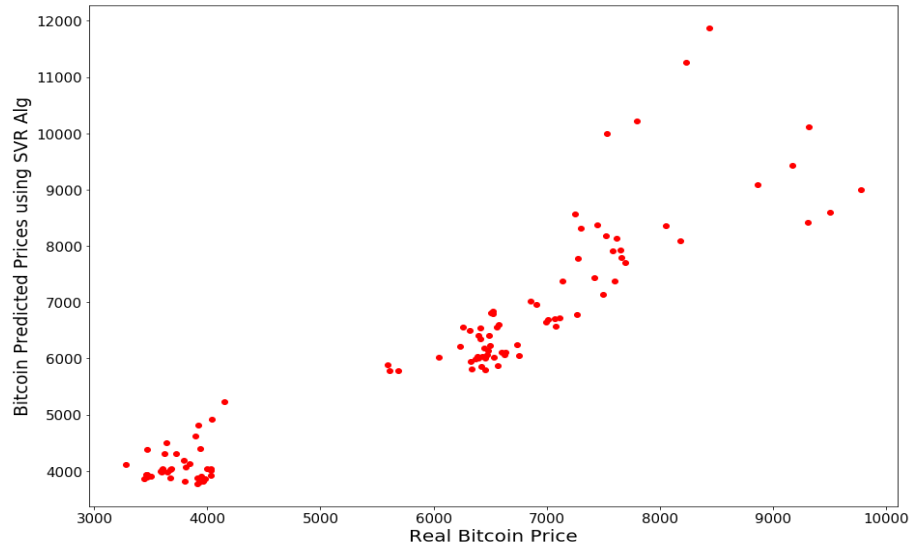
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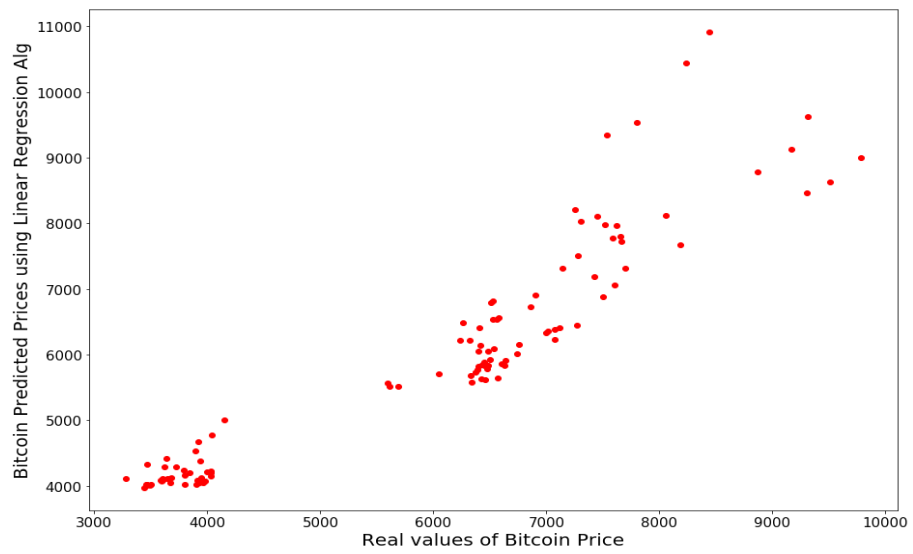
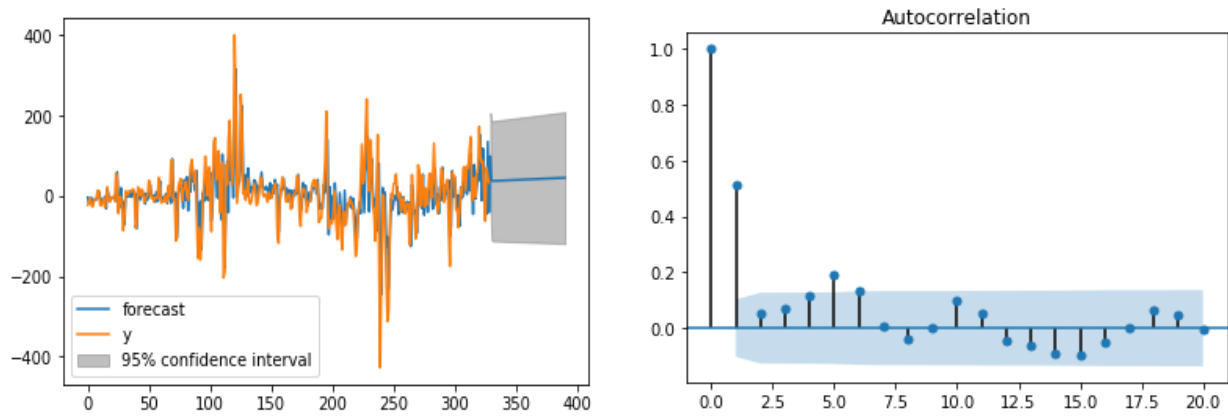**Figure 20**

Figure 21
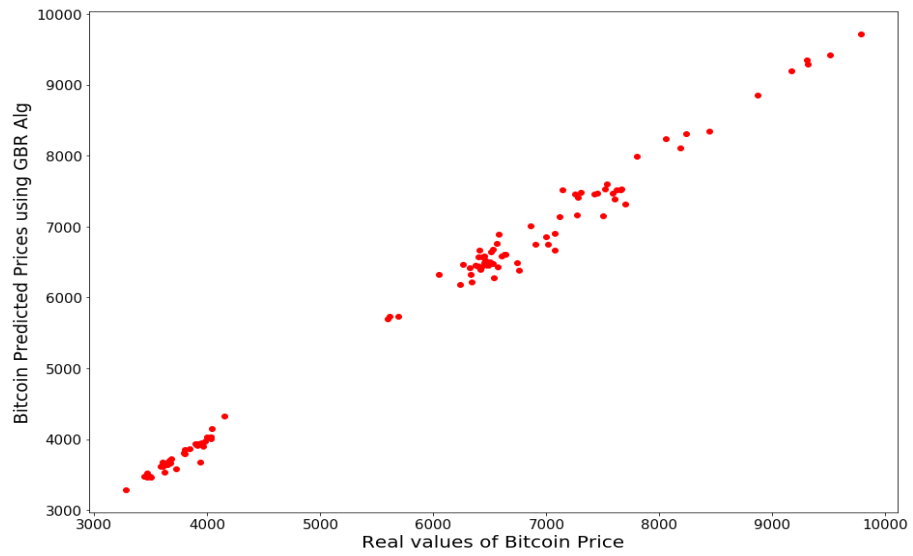
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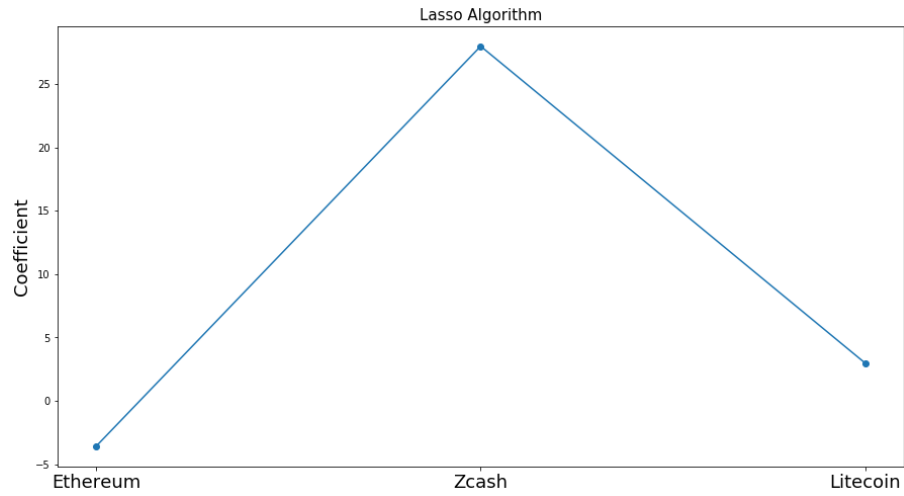
Figure 23

Table 2.

Algorithms Name	MSE	R^2	R^2 adjusted
SVR	516804.797833455	0.8345	0.8391
LR	421034.06468415906	0.8652	0.8689
RFR	23365.60049452004	0.9925	0.9927
GBR	18359.190867996942	0.994	0.9942

Figure 24
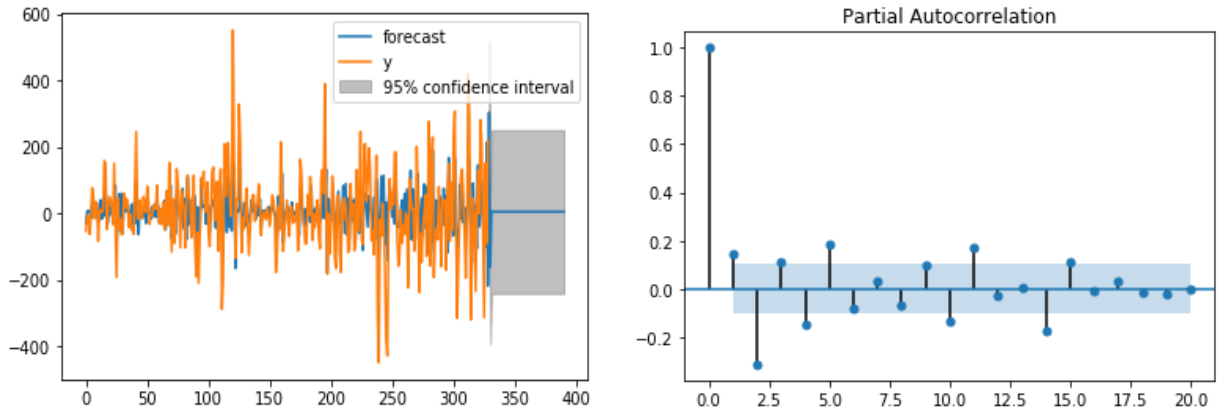
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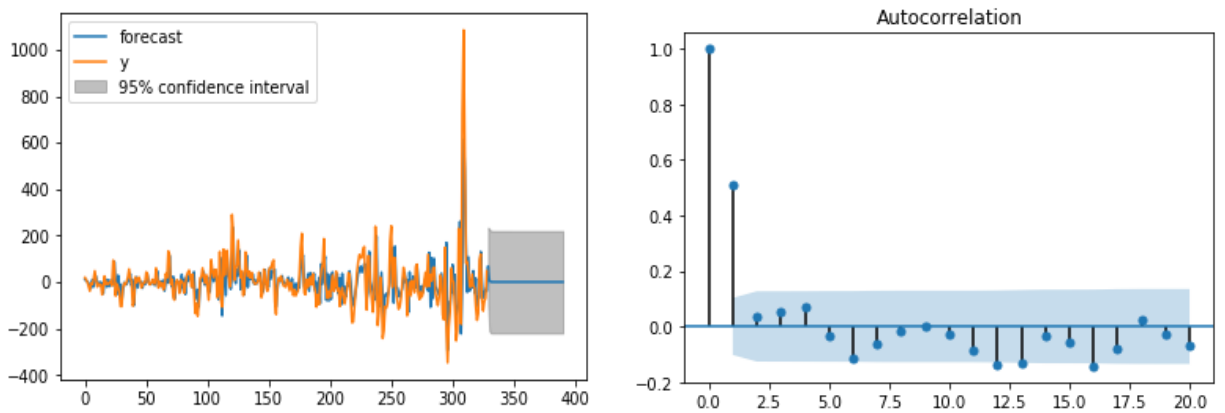
Figure 26

Table 3.

Cryptocurrencies Cointegration	AIC	BIC
Bitcoin-Ethereum	4087.4245922612673	4192.7285924245916
Bitcoin-Litecoin	4151.424592183152	4166.728592612673
Bitcoin-Zcash	3978.591052327704	3997.706281805119
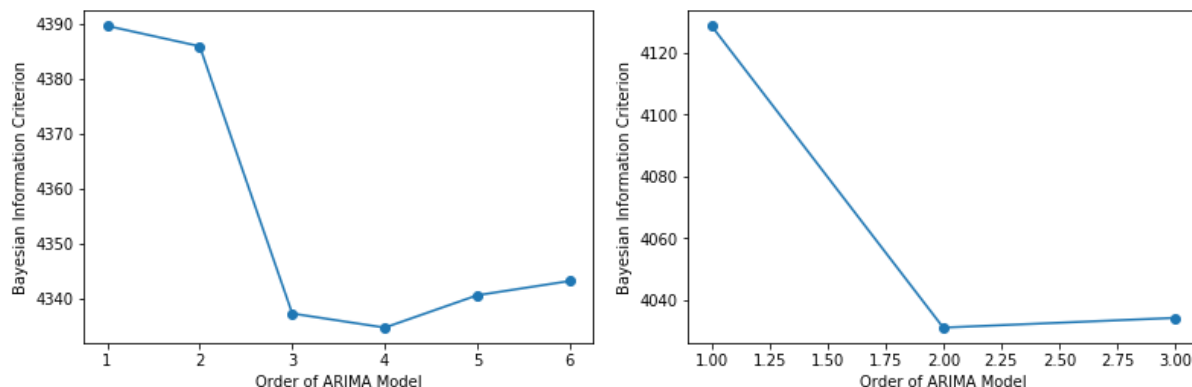
Figure 27

Authors' Technical Biography:

Negar Maleki: Negar Maleki has a master's degree in Industrial Engineering from the University of Tehran. Her main research interests are Machine Learning, Data Analysis, Statistical Inferences, Optimization, and Biomedical Data.

Alireza Nikoubin: Alireza Nikoubin has a master's degree in industrial engineering and is a research assistant at the University of Tehran. His main research interests are in financial markets and systems optimization. He is currently working on a method for portfolio optimization using data mining techniques.

Masoud Rabbani: Masoud Rabbani is Professor of Industrial Engineering in the School of Industrial and Systems Engineering at the University of Tehran. He has published more than 250 papers in international journals. His research interests include production planning, Maintenance planning, Mixed model assembly lines planning, inventory management systems, and applied graph theory.

Yasser Zeinali: Yasser Zeinali is a Ph.D. student at University of Alberta school of business. His research interests are data analytics, machine learning algorithms and its applications in business and healthcare.

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