Analysis of Cryptocurrencies

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***Abstract*—Cryptocurrency has emerged as one of the latest financial instruments in the financial markets. The cryptocurrency market is known for its erratic and volatile behavior. The cryptocurrency market is evolving daily at unprecedented speeds over a relatively short time span. Since the release of the pioneer cryptocurrency, Bitcoin, into the market, over 550 cryptocurrencies have been developed. Although the concept of electronic currencies dates back to 1980's, Bitcoin was launched in 2009 by pseudonymous developer Satoshi Nakamoto, and was the first decentralized cryptocurrency. When analyzed thoroughly and studied for seasonal trends, one can make an informed decision on investing in cryptocurrencies. Cryptocurrencies although very volatile, do result in high returns. In this paper, we aim to conduct a detailed analysis of the top three ranked cryptocurrencies namely Bitcoin, Ethereum and Ripple. We intend on conducting correlation analysis between these currencies to determine any relationship in prices. We also would like to develop a model to predict the prices of Bitcoin.**

Keywords—Bitcoin, Ethereum, Ripple, Blockchain, Cryptocurrency Market, Simple Moving Average, Exponential Smoothing Forecasting, ARIMA.

I. Introduction

Cryptocurrency is an electronic currency that uses the internet as its medium of exchange. Cryptographic functions are employed so as to conduct financial transactions in a safe and secure manner. Cryptocurrencies leverage blockchain technology to gain decentralization, transparency as well as immutability. Although the conception of cryptocurrencies is recent, its history and origins date back to the 1980's. An American cryptographer named David Chaum conceived the first-ever anonymous cryptographic electronic money called ecash. Two years later, he implemented it through Digicash, which was an early form of cryptographic electronic payments. It required user software to withdraw notes from the bank. Specific encrypted keys were then designated before it could be sent to the recipient. This made for untraced ability by the issuing bank, the government, or any third party. Bitcoin, which is the first decentralized cryptocurrency was created in 2209 by a pseudonymous developer Satoshi Nakamoto. It used SHA-256, which is a cryptographic hash function, as its proof of work scheme.

Unlike physical money, that is backed by a physical asset (ex: the dollar was previously backed by gold), cryptocurrency doesn't have any physical backing , which makes it hard for people to understand the fundamental cores of the currency and why exactly are they trading using cryptocurrency (other than the fact that it's decentralized and doesn't involved third parties or government bodies) . It was investigated whether cryptocurrency pricing bears similarity to stocks: none of the risk factors explaining movements in stock prices applies to cryptocurrencies in their sample. Moreover, movements in exchange rates, commodity prices, or macroeconomic factors of traditional significance for other assets play little to none role for most cryptocurrencies. As far as risk is concerned, factors like revealed scams or flaws in this coin exchange trends to drastically decrease the value of the coins. The authors find, notably, that the market risk of cryptocurrencies is driven by Bitcoin, suggesting some degree of homogeneity in the crypto market. Considerable chunks of financial literature go against the neoclassical predictions, they say that, there is certain ambiguity regarding crypto, this uncertainty is due to: 1) complicated technology which new traders won't understand 2) unclear fundamental cores. This makes the market volatile and at high risk, yet the market shows considerable volume on a daily basis. To reduce this uncertainty gaining data is very important, this means analysis data from previous times, catch the pattern, and to be able to approximate the future price. Factors that affect prices include, the internet searches regarding crypto for that period, meaning what value it holds in the eyes of the greater masses. Also moves made by top influential traders, can cause herding where thousand new traders mimic the moves made by them, this leads to bullish and bearish periods.

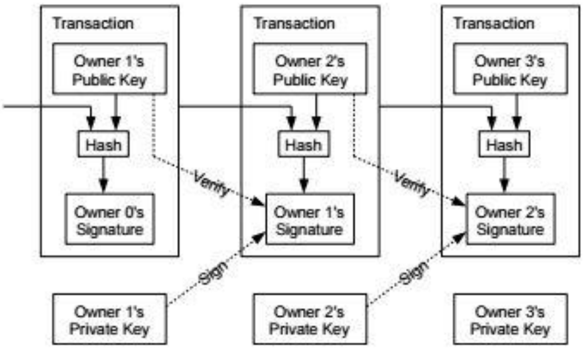
Activities such as paying tuition, investment, donating to charities and paying for simple goods and services are all part of the use of cryptocurrencies. They account for more than 50% of all transactions of cryptocurrencies. Amongst these many uses; prospective investment opportunities are what is gathering people's attention. According to the portfolio theory, it advocates the diversification of investments and allocating assets strategically so as to maximize returns. Since the cryptocurrency market is such a volatile market, when used as a financial instrument for investing depending on market conditions, it can yield very high returns. This topic is rightfully followed by Market condition research, and how it is very significant especially in cryptocurrencies. Many experts noted a cryptocurrency bubble in 2017 as prices grew by 900%. In 2018 however, Bitcoin faced a collapse in its value, prompting many researchers to study and analyze bubbles and extreme conditions in cryptocurrency trading.

This paper provides a survey of 6 cryptocurrency papers across different academic disciplines such as finance and economics, artificial intelligence and computer science. We seek to understand the prevailing market conditions and underlying socio-economic impact. We would like to observe and study the impact of Bitcoin prices on the Ethereum and Ripple prices. We seek to perceive any sort of correlation or causal relationship amongst the various cryptocurrencies. We would like to comprehend the impact of global events on the prices of Bitcoin. Finally, we would like to develop a model to predict the prices of Bitcoin. The approach we want to explore and study is the Moving Average Forecasting technique.

II. THEORY

A. Premise

One of the distinguishing features of the cryptocurrency is that it is decentralized, it is not controlled by any central authority. It leverages the blockchain technology which makes it theoretically immune to government control and interference. Blockchain is a digital ledger of economic transactions that can be used to record not just financial transactions but any sort of data with value. To describe it in simpler words, Blockchain is a series of immutable data records with time stamps, which are managed by a cluster of machines. This cluster is independent of any controlling entity. These records also known as data blocks are protected by cryptographic functions and are bound to each other in a chain. Hence the name Blockchain. Cryptocurrencies can be sent directly between two parties using private and public keys. These transfers can be done with minimal processing fees, which allows users to avoid steep fees charged by traditional financial institutions.



III. RELATED WORK

Robert Hudson and Andrew Urquhart, in their paper on technical trading and Cryptocurrencies, perform a comprehensive study on the use of technical trading rules in cryptocurrency markets, using data from two Bitcoin markets and three other popular cryptocurrencies. They employed nearly 15,000 technical trading rules from the main five classes of technical trading rules and found significant predictability and profitability for each class of technical trading rule in each cryptocurrency. They utilized daily Bitcoin prices from two providers, CoinDesk and Bitstamp. CoinDesk represents an average of Bitcoin prices across leading global exchanges that meet criteria specified by CoinDesk. They also studied an actual exchange Bitcoin price, Bitstamp, which is one of the first, most popular and liquid Bitcoin exchanges. They used a number of performance metrics, like the Sharpe ratio, Sortino ratio and the Calmar ratio to assess the outcomes of the analysis. They adopted two broad approaches to deal with multiple hypothesis testing, namely family-wise error rate (FWER) and the false discovery rate (FDR).

They found that, on average, all five classes of technical trading rules generate significant annualized returns for all cryptocurrencies studied. For all cryptocurrencies and technical trading rules, the average return from a buy signal is positive and statistically significant while the average return from a sell signal is mostly negative indicating that the positive returns from technical trading in cryptocurrencies comes from the buy signals rather than the sell signals. The annualized average return for each family of rule in each cryptocurrency market are all statistically significant at the 5% level indicating the robustness of the results.

Yhlas Sovbetov, in their paper on Factors Influencing Cryptocurrency prices, examines the factors that influence prices of most common five cryptocurrencies such Bitcoin, Ethereum, Dash, Litecoin, and Monero over 2010-2018 using weekly data. They sampled big 50 market capped cryptocurrencies (these 50 crypto-coins forms about 92% of entire crypto-market). The derived data for market capitalization, trading volume, opening-closing prices, and high-low prices from Coinsmarketcap. They then calculated weight of each crypto-coins in the index on the basis of their market capitalization. The crypto 50 index was built by summing up all 50 weighted prices. They examined the characteristics of all series by employing Augmented Dickey-Fuller (ADF) unit root test to test if variables are integrated at the same degree. They employ the Autoregressive Distributed Lag (ARDL) cointegration framework in order to account both short- and long-run dynamics of cryptocurrency prices. The null hypothesis is tested using Wald Analysis to examine whether these series (cryptocurrency market variables and control variables) have statistically significant long-run interactions with the given data.

They find that, unrestricted long-run ARDL and restricted short-run error-correction analyses find statistically significant impact running from crypto-market factors such as total market prices, trading volume, and volatility on to five cryptocurrencies in long- and short-run respectively. The crypto-market beta derives a long-run multiplier of 0.79 on Bitcoin and 0.38 on Ethereum at 1% significance level. The findings indicate that Bitcoin and Ethereum have higher responsiveness to the market in the long-run. In case of short-run, a unit increase in cryptocurrency market return causes Bitcoin, Ethereum, Dash, Litcoin, and Monero to increase by 0.85, 0.39, 0.04, 0.12, and 0.09 units respectively in short-run. Trading volume appears to have significant long-run impact on Bitcoin at 1% significance level and on Ethereum, Litcoin, and Monero at 10% significance level. Likewise, volatility of the cryptocurrency market appears to be statistically significant determinant both in long- and short-runs for all cryptocurrencies. Lastly, error correction terms (ECT) in all models appear statistically significant at 1% level with negative sign complying with the ECM theory.

Kimberly Oostman, Gourang Aggarwal and authors of the paper Understanding Social Factors Affecting the Cryptocurrency Market performed an initial analysis of the problem of high volatility of the cryptocurrency market and its dependence on various social factors via a real-time study on the data collected for a period of six months. They identified a set of factors which affect the cryptocurrency market based on theoretical inputs and real-time market data and provided the correlation values of the identified factors with the rise or fall of cryptocurrency market using the data mining tool Weka. The paper is organized as follows: Section 1 of the paper provides a brief introduction to the world of cryptocurrency. Section 2 provides a literature review exploring the reasons behind the fluctuating market of cryptocurrency and the possible important attributes which the authors believe were not observed by other researchers. Section 3 examines the various attributes and how they affect the price by performing data mining using various tools and the techniques. The section presents a thorough analysis of these factors to gain knowledge. Section 4 concludes the paper and discusses future research directions. in the literature survey they've identified factors that affect the market to be: players in the crypto market, media affects, agenda setting and framing. some of the techniques they've used to gather this data in order to reach the previous conclusion are: 1) Data Collection has been performed via manual analysis of cryptocurrency data for six months by reading articles over the internet. Google News regarding cryptocurrencies from all major countries including the USA, India, Australia, EU etc. was read daily. Articles from Coindesk, Coinmarketcap, and Coinbase were followed as well as twitter post with cryptocurrency related hashtags were monitored on a daily basis.

Giancarlo Giudici, Alistair Milne and Dmitri Vingradov in their paper on Market Analysis and perspectives of Cryptocurrencies takes a relatively simpler approach, compare to other papers. This is an issue under Journal of Industrial and Business Economics, they have compiled the work of several papers to discuss various topics like, what exactly is cryptocurrency, why is it used, what factors tend to affect it, various perspectives (neo classical finance, behavioral finance, socio-economic perspectives etc). This paper provides only theoretical value, they have not used any summarization/visualization technique to understand the relationship between the factors that tend to influence it, it's a superficial, introductory issue which gives us a brief idea of the cryptocurrency market.

They start off by classifying cryptocurrency as a financial asset, they divide it into crypto utility asset and crypto security, they discuss topics such as ownership and transactions. In the neoclassical approach they discuss the differences and similarities between crypto and traditional financial assets and how they benefit individual with a short-term investment horizon. Under behavioral approach they mention instances where the neoclassical assumptions fail and the behavioral assumption stands, due to the fact that neoclassical assumptions don't take the 'human factor' into consideration and the fact that human emotions play a huge rule when it comes to takin financial definition. They later discuss the role of media and major players in the economic factors, global changes etc. They conclude by listing the positive and negative impacts cryptocurrency has, globally.

Technical Trading Rules in the cryptocurrency market is a paper that studies the moving average trading strategies, by employing the prices of the eleven most-traded cryptocurrencies in the 2016-2018 period. The moving average is a type of technical analysis tool wherein we smoothen out price data by creating a constantly updated average price. This helps in filtering out noise from sudden random short-term fluctuations in price. The average is taken over specific time frames. It can be anywhere from twenty minutes to ten days or even many weeks at a time. While most papers focus their research specifically towards Bitcoin as it has consistently been ranked as the number one cryptocurrency, this paper explores eleven cryptocurrencies which exhibit high market capitalizations. To make a proper statistical inference, the paper employs the multivariate test for jointly testing cryptocurrency markets. This paper also explores the profitability of long-term and short-term processes. It hypothesizes whether cryptocurrency markets are efficient or inefficient markets. This paper also contributes to research exploring the profitability and returns on technical trading rules among various asset classes.

This paper conducts its studies using data from the time period between January 1,2016 and December 31st ,2018. It purposely excludes the data of Bitcoin, so as to ensure that experimental results are not dominated by Bitcoin, as it has predominantly affected the cryptocurrency markets for years. Currencies included for this study are as follows; Ripple, Litecoin, Ethereum, Dogecoin, Peercoin, BitShares, Stellar Lumen, Nxt, MaidSafeCoin and Namecoin. The trading rule implemented in this paper is the Variable Moving Average Oscillator. It generates trading signals employing a short-period and a long-period moving average of the specific index in consideration. The reason we behind compute the moving average is to identify the trend in the price movement of the various cryptocurrencies. Whenever the short-period moving average crosses over the long-period moving average, a new trend is said to be initiated. To make market-wide conclusions, a multivariate test is performed. They test the payoffs of the strategies implemented in the cross-section of all cryptocurrency markets and account for correlation between any two cryptocurrencies. This seems to be necessary because cryptocurrency returns are highly correlated with each other.

After performing all the various tests, results suggest that twenty day moving average trading strategy is the most successful irrespective of whether the Bitcoin is accounted for or not. Specifically, implementing the (1, 20) strategy, five of the ten cryptocurrencies generated payoffs that were statistically significant on at least a 5% level. Applying longer time horizons did not generate profits in any of the cryptocurrencies. In summary, the findings suggest that cryptocurrency markets do not exhibit market efficiency in its weak form.

Problem Statement and Proposed Solution

The cryptocurrency market is known for its high volatility and uncertainties, there are quantitative and qualitative factors that drive the price, quantitative meaning values like the trade volume, opening/closing prices, analyzing these over a period of time and finding a relationship amongst them helps in determining the prices. The qualitative factors being - human emotion, one of the biggest issues faced by investors when it comes to trading is to not invest or buy emotionally this usually means feeling insecure, or scared to lose a large investment so they pull out only to realize the prices have increased and they could've been profitable.

Often small time investors follow the moves made by the well established players in the field as they themselves don't have a rule book to play by , often big time investors belittle the value of a currency so that the prices are dropped , only to buy them at a cheaper price , now this benefits only the major investors , this creates a need for a set of guidelines to be set in order to smoothen out this type of discrepancy.

Other intangible factors include global changes, new monetary laws in different countries, restrictions (for example, in India we are allowed to trade only if the base currency is INR), new political leaders being elected, unemployment, recession, new bank laws, we aim to analyse the amount of impact these factors tend to have on the prices.

There has been discussion amongst researchers whether returns on financial assets, such as stock returns or commodity returns, are predictable; however, few studies have investigated cryptocurrency return predictability. We investigate whether one can predict daily returns on bitcoin based on its historical prices only. Although it is desirable to be able to predict returns, the objective of this analysis is less ambitious because of the short history of bitcoin and huge volatility of bitcoin returns. We aim to predict bitcoin prices using standard forecasting techniques such as Moving Average Process and Simple Exponential Smoothing. Other techniques which can be explored include ARIMA models and CART Decision Trees.

A popular indicator in all financial markets are Moving Averages. Cryptocurrency is no exception. The moving average (MA) smoothens prices over a certain amount of time. Moving averages are a lagging indicator which means they are based on previous price action. Researchers have concluded that a variable moving average strategy outperforms buy and hold for major cryptocurrencies.

Exponential smoothing is a time series forecasting method for data which is univariate in nature. Time series forecasting methods such as the Box-Jenkins ARIMA develop a model where the prediction is a weighted linear sum of recent past observations or lags. Exponential smoothing forecasting methods is similar to ARIMA. The prediction is a weighted sum of past observations, but the model explicitly uses an exponentially decreasing weight for past observations. Specifically, past observations are weighted with a geometrically decreasing value.

Collectively, the methods are sometimes referred to as ETS models, referring to the explicit modeling of Error, Trend and Seasonality. For the same amount of lag, the simple exponential smoothing (SES) forecast is somewhat superior to the simple moving average (SMA) forecast because it places relatively more weight on the most recent observation--i.e., it is slightly more "sensitive" to changes occurring in the recent past than what has historically happened long before.

We aim to also study the correlation among the various cryptocurrencies such as Bitcoin with Ripple and Ethereum. We will be using the Pearson Coefficient and will also be plotting maps to gain a visual understanding of the correlation. We will also study the effects that global events have on Bitcoin prices. We predict that event such as the 2016 US election or even the global pandemic, have had significant impact on Bitcoin prices.

To begin our analysis, we must first conduct data preprocessing and cleaning. The mismatched values in this dataset can be replaced by the mean value corresponding to the particular time intervals. The values of the Market Cap and Volume attributes must be converted to type float by removing the intermediate commas. The values in the dataset seem to be of the same scale. There is no need for any transformation. All the attributes are relevant for the analysis. There seems to be no redundant attributes. Hence there is no need for dimensionality reduction.

EXPERIMENTAL RESULTS

The first step to our analysis is to study the correlation between Bitcoin and other cryptocurrencies such as Ripple and Ethereum. The closing prices of all three cryptocurrencies between the period 2016-2018 has been plotted and depicted. At first glance they all seem to follow a similar pattern, sharp spike from July 2017-jan 2018, but this cannot confirm any linear relationship between the three , hence correlation analysis is done. To conduct correlation analysis, we calculate the Pearson Coefficient. Depending on the value of the coefficient, we can determine if the three currencies are linearly related.

```
In [7]: df.cov()
Out[7]:
```

	Close_bt	Close_et	Close_rp
Close_bt	8.757252e+06	909983.746213	791.783987
Close_et	9.099837e+05	69765.103918	96.678489
Close_rp	7.917840e+02	96.678489	0.102784

```
In [8]: df.corr(method='pearson')
Out[8]:
```

	Close_bt	Close_et	Close_rp
Close_bt	1.000000	0.906095	0.816229
Close_et	0.906095	1.000000	0.879875
Close_rp	0.816229	0.879875	1.000000

As depicted above, the coefficient between bitcoin and ether is 0.90 approx. and between bitcoin and ripple is 0.81 approx., both suggesting that a linear relationship exists. It has been observed that the price of bitcoin tends to change first, either increase or decrease and the other two currencies fill follow that direction more or less.

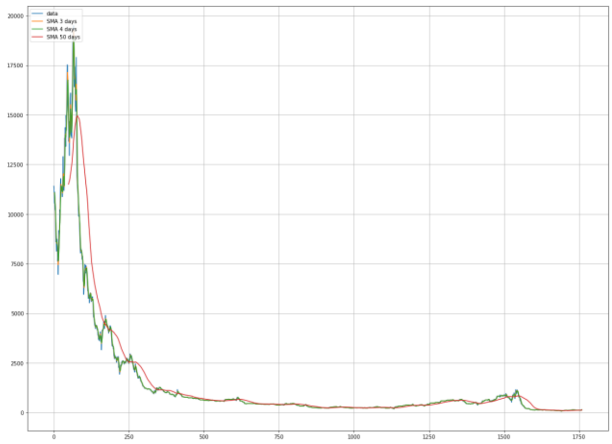
We go on to proceed with the impact global events have had on the cryptocurrency prices, specifically that of Bitcoin. In our report an evident spike is seen between mid-2017 to 2018. Prices soared by a whopping 1,813 percent. What caused this sudden spike? A whale. According to research a single whale is someone who holds large quantities of bitcoins, was behind the iconic rise.

This event is an example of market manipulation, the prices of bitcoin were in fact driven by a stable coin called tether (a second generation token) .Tether was created without the US dollar backing it up , this currency was then used to buy chucks of bitcoin, obviously driving bitcoin's prices up. Bitfinex which is based in Hong Kong control a large part of tether, it was a bit of a controversy, investigations were conducted to see if Bitfinex had manipulated the market for their gain. Events can both, impact prices negatively and positively, here in India, Finance Minister Arun Jaitley, in his Union Budget 2018 speech, declared cryptocurrency as "not a legal tender". In 2018 April, the country's apex bank, in its bi-monthly Monetary Policy Statement, landed a firm blow on digital currencies. The RBI, with immediate effect, banned all regulated entities from dealing with or providing services to anyone who dealt with or made transactions with cryptocurrency, that led to price drops.

We also study whether the onset of the global pandemic, the Corona virus had anything to do with cryptocurrency prices. As shown in the correlational analysis, bitcoin moves first then the other currencies change, hence we will address Bitcoin. In today's situation people aren't looking to gain more assets, but to liquefy the assets they already possess, and bitcoin is not the haven they seek. The issue is people still trust assets like land and gold more rather than digital currency. Prices of bitcoin dropped below $4,000, on 12th March. On the other hand, all around Europe have been forced to go cashless and have started to use online payment gateways and cryptocurrencies as a medium.

We next move on to creating models to predict Bitcoin prices. The first technique considered is the Simple Moving Average forecasting. We consider Bitcoin prices from the period of 2016 to 2018. Since cryptocurrency prices like Stock Market prices are characterized by an Open, High, Low and Close prices, for our prediction we take the Close price into consideration. We have proceeded to write a function to perform Simple Moving Average with the help of the Numpy library available in python. We compare our function with the built in "rolling' function to see if our function gives the same results, and indeed it does. We compute the values for a window of 3 days and 4 days. We then plot a graph to see how well the SMA does with predicting the prices from the 2016-2018 period. We also compute the Mean Squared Error for the SMA with a window of 3 and 4. The mean squared error with a window of 3 is 31460.41 and the mean squared error with a window of 4 is 49751.04. We also perform SMA with a window of 50 and we see that the MSE value drastically increases. Furthermore, when we plot the graph of SMA with windows of 3,4 and 50 against the actual data, the SMA with window 50 deviates the most from the actual data. The MSE value for the window of size 50 is 890886.21.

The graph shown, shows the plot of the various SMA models with different window sizes. The green line indicates the actual data and the red line indicates the SMA model with a window size of 50. As we can see it clearly deviates the most from the actual data.



We next move onto Exponential Smoothing Methods. Exponential smoothing is a time series forecasting method for univariate data that can be extended to support data with a systematic trend or seasonal component. It is a powerful method for forecasting time series data. This code is a fairly simple and straight-forward implementation of the three different exponential smoothing techniques. For simple-exponential-smoothing, we use only the level component to make predictions for the data. We vary the alpha levels to see the difference in the prediction results at different values of alpha. We then plot the forecasted values along with the original time series data and find the error in predictions using mean absolute percentage error (MAPE).

The error in the predictions for alpha = 0.3: 2.74%
The error in the predictions for alpha = 0.5: 1.53%
The error in the predictions for alpha = 0.9: 0.76%

We see that, simple-exponential-smoothing doesn't capture the time series accurately and can predict only a straight line. For double-exponential-smoothing (Holt's method), we use the level and trend components to make predictions for the data. We vary the alpha and beta levels to see the difference in the prediction results at different values of alpha and beta combined. We then plot the forecasted values along with the original time series data and find the error in predictions using MAPE.

The error in the predictions for alpha = 0.9 and beta = 0.1: 0.69%
The error in the predictions for alpha = 0.9 and beta = 0.5: 1.43%
The error in the predictions for alpha = 0.9 and beta = 0.9: 2.02%

We see that, although double-exponential-smoothing does a better job at making predictions, it still isn't sufficient and is only able to predict the general trend of the time series. For triple-exponential-smoothing (Holt-Winters method), we use the level, trend and seasonal components to make predictions for the data. We vary the alpha, beta and gamma levels to see how the predictions vary for different values We then plot the forecasted values along with the original time series data and find the error in predictions using MAPE.

The error in the predictions for alpha = 0.9, beta = 0.1 and gamma = 0.1: 0.92%
The error in the predictions for alpha = 0.9, beta = 0.1 and gamma = 0.5: 0.87%
The error in the predictions for alpha = 0.9, beta = 0.1 and gamma = 0.9: 0.88%
We see that triple-exponential-smoothing does a pretty good job at predicting the time
series data and outperforms the other two.

We move onto the final model of implementation which is an ARIMA model. ARIMA models are used when the time-series data is non stationary. ARIMA has the following three components and is represented as ARIMA(p,d,q):

1. Auto-regressive component with p lags AR(p).
2. Integration component (d).
3. Moving average with q lags, MA(q).

The main objective of integration component is to convert a non-stationary times series process to stationary process so that the Auto-regressive and Moving Average processes can be used for forecasting.

We first create and ARIMA Model with the parameters:
p =5, d = 1, q = 0. With this model we get an MSE of 1518.180.

Next, we create a model with the parameters:
p = 4, d = 1, q = 2. With this model we get an MSE of 1622.658.

Next, we create a model with the parameters:
p = 7, d = 1, q = 0. With this model we get an MSE of 1590.686.

Next, we create a model with the parameters:
p = 5, d = 1, q = 1. With this model we get an MSE of 1556.589.

Next, we create a model with the parameters:
p = 5, d = 2, q = 0. With this model we get an MSE of 1716.951.

We have created the models in such a way to see the effect of increase and decrease in the p, d and q parameters. The best value of MSE is obtained when the parameters are:

p = 5, d = 1, q = 0.

When we further increase the integration component, we see that the MSE increases considerably from 1518 to 1716. Increasing the MA ‘q’ component keeping other component values constant also slightly increases the MSE from 1518 to 1556. Increasing the AR ‘p’ component keeping other components constant increases the MSE from 1518 to 1590. A combination of decreasing the ‘p’ value and increasing the ‘q’ value increases the MSE from 1518 to 1622. Hence the most optimal result is found when the parameter values are p = 5, d = 1, q = 0.

CONCLUSIONS

After comparing the MSE values from all three models implemented, ARIMA yields the best results followed by Exponential Smoothing and Simple Moving Average technique. The reason being it employs both the Moving Average technique as well as the Auto-Regressive technique. The reason why the MSE value is still quite high is because we have performed the analysis on closing price, and Bitcoin prices are vulnerable to the highs and lows in the market conditions.

When a comparison is done between Simple Moving Average and Exponential Smoothing technique, Exponential Smoothing fares better as it gives more weight to current data. The newest price data will impact the prices more, with older price data having a lesser impact. Bitcoin prices are highly volatile in nature and many factors come into play in determining it’s prices hence current prices can be best predicted on recent past prices rather than on historic past prices. Furthermore, exponential smoothing techniques employ higher weights to more recent prices while the simple moving average technique assigns equal weights to all values.

When we make a comparison amongst the different SMA models the smallest window fared the best; that is the model with window size of 3 was better than model with window size of 4 or 50. This is expected as Bitcoin prices are more reliant on recent trends and prices and not necessarily on long term prices or events. The model with window size of 50 had the highest MSE and on plotting the graph of its predicted price against the actual data, it deviated to the greatest extent.

In our study we have also performed correlation analysis amongst Bitcoin, with Ripple and Ethereum. It has been observed that the price of bitcoin tends to change first, either increase or decrease and the other two currencies fill follow that direction more or less. Using this knowledge, investors and portfolio managers alike get an idea on how much of capital to allocate to various alternate coins. It is important that we don’t put all our eggs in one basket. Such methods of analysis can be used in aiding one’s financial decisions.

The onset of the global pandemic, Corona Virus in 2020, had a significant impact on Bitcoin prices. Prices of bitcoin dropped below $4,000, on 12th March. The reason for this is because there was a sudden need to liquidate assets. Many investors had margin calls in equity and those had to be met by liquidating other assets such as Bitcoin into cash. As of April 2020, the price of the Bitcoin was picking up to $7000 and it was estimated that it would take a while for prices to soar up again. As of November 2020, the price of Bitcoin has picked up to a $18,100.

Bitcoin prices, surprisingly did not show much volatility during the 2016 US presidential election. A mere 1.8% increase in the price was observed during the 24-hour trading period. Given the lack of involvement of the cryptocurrency industry in the 2016 election, there is no reason to believe that this will change in the 2020 election.

FUTURE WORK

Techniques such as Markov Chains can be used to predict Bitcoin prices due to their Stochastic and memory less nature. Furthermore, the CART Decision Trees could have been explored. Artificial Neural Networks can also be explored as a viable solution.

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CONTRIBUTION OF TEAM MEMBERS

Vibha Kurpad (PES1201800158): Assembly and compilation of Stage 1 Report and Final Report. Created the Simple Moving Average and ARIMA model for predicting Bitcoin prices.

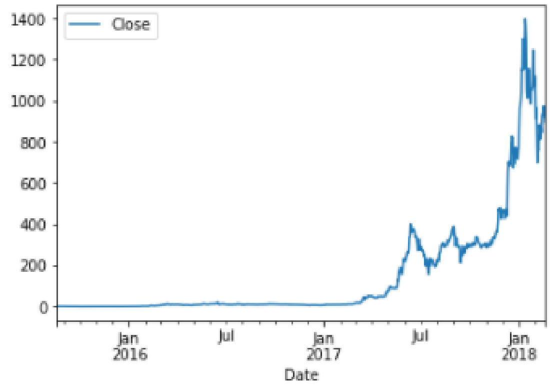
Shreya Sri (PES1201800132): Performed the Stock Taking and Data Preprocessing. Created the Exponential Smoothing Models.

Mahah Sadique (PES1201801529): Performed the Correlation analysis of the various cryptocurrencies. Studied the impact of various Global events on Bitcoin prices.

The project collaboration was an overall positive and constructive process. It presented us an opportunity to learn about how Cryptocurrency works and about the basics of Blockchain. We learnt a few interesting facts such as the number of Bitcoins is limited. There are 21 million units, out of which 80% of them have already been mined. Furthermore, no knows exactly who created Bitcoin. Satoshi Nakamoto is the pseudonym given to the anonymous founder.

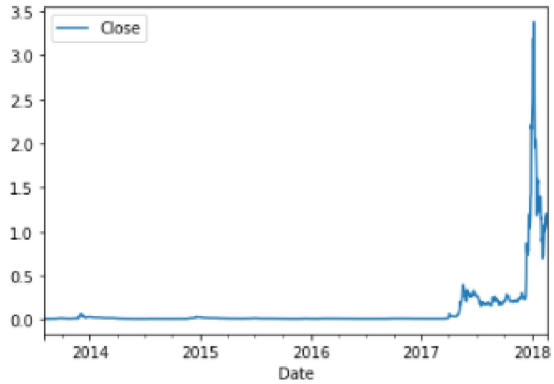
APPENDIX

<matplotlib.axes._subplots.AxesSubplot at 0x1b14c360ac8>



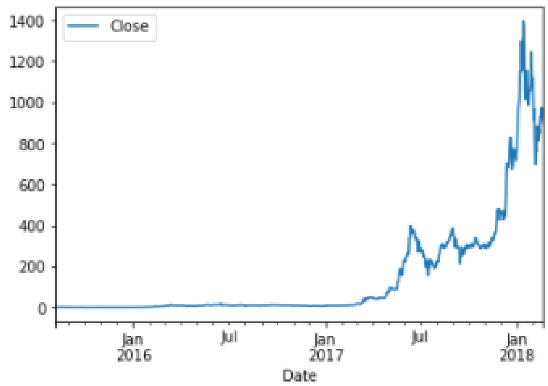
Closing Price of Bitcoin

<matplotlib.axes._subplots.AxesSubplot at 0x1f51cc4dcc8>

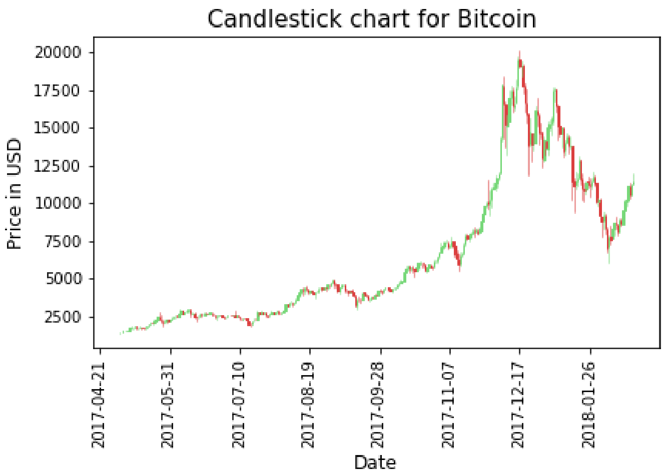


Closing price of ripple

<matplotlib.axes._subplots.AxesSubplot at 0x26f25f2cc88>



Closing price of Ethereum



Candlestick chart for Bitcoin
Price in USD
20000
17500
15000
12500
10000
7500
5000
2500
2017-04-21
2017-05-31
2017-07-10
2017-08-19
2017-09-28
2017-11-07
2017-12-17
2018-01-26
Date