Price Prediction of Cryptos and the Future Impact

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Abstract*- Cryptocurrency is the new booming global currency. It is an asset that emerged because of the advancement of financial technology. This has created a big opportunity for research. However, forecasting cryptocurrency prices is still very difficult due to price volatility and dynamism. Around the world, there are hundreds of cryptocurrencies that are used. This paper intends to find out a model to predict the prices of three types of cryptocurrencies, namely Bitcoin (BTC), Dogecoin (Doge), and Ethereum (ETH). The importance of having this model is that it can have significant economic ramifications by helping investors and traders to pinpoint cryptocurrency sales and purchasing. Initially the goal was to use parameters like Stock Prices such as S&P 500 index, AMD, NVIDIA, and in social media context, Google, and twitter trends. However, upon research new conclusions came into light. For the final models, the correlation for all the three cryptocurrencies along with some other independent variables were used. Also, a graph of all the three parameters and individual cryptocurrencies are plotted to know the influence. Feature scaling is used to improve the performance of the model.

Keywords—Bitcoin, Dogecoin, Ethereum, prediction, Random Forest.

I. INTRODUCTION

Cryptocurrencies are a new way of using and interacting with the financial world. They aim to put the power and potential of your money back into your hands in a unique, fair, and secure way. The industry has the potential to change the world and curb so many of the issues that lead to inequality and corruption. Over the years there has been a lot of bad press and misconceptions about cryptocurrency. The cryptocurrency movement has matured into a vast array of real-world solutions and gained support from the same people who tried to talk it down. It is quickly becoming the financial powerhouse of the future with much more revolutionary technology emerging from the shadows. For our research, we focused only on 3 cryptocurrencies namely Bitcoin, Ethereum and Dogecoin.
The reason we chose these cryptocurrencies is because Bitcoin and Ethereum have been in the market for quite a long time and have also experienced sudden boom in their values. Dogecoin is a new type of cryptocurrency and the perfect example to illustrate our intent.

Basic understanding of each crypto:

- Bitcoin: The first cryptocurrency with the most outstanding, popular as well as the highest market capitalization. It was created in 2009 by Satoshi Nakamoto.
- Ethereum: Like Bitcoin, Ethereum also has become one of the most invested cryptocurrencies in recent years.
- Dogecoin: It emerged in 2015, uses a blockchain technology from Litecoin.

One way to look at the price prediction challenge for cryptocurrencies is to identify potential factors which will help us out in determining the prices. An important argument which can be made here is that there can be numerous factors which might affect the prices of these cryptocurrencies and hence determination of such factors is very tricky. However, as a starting point, we had shortlisted several factors based on the general trends and their relative significance. These include the S&P 500 index which is an index keeping track of the stocks of the top 500 large cap US companies. The basic building blocks of any cryptocurrency are Blockchain algorithms that require computing platforms, PCs, servers and more specifically CPUs & GPUs to run on, which is provided by AMD and NVIDIA. They make blockchain transactions faster and secure. Crypto miners usually purchase huge numbers of NVIDIA and AMD GPUs to acquire ETH, BTC, and other giant digital tokens.

II. MOTIVATION

This boom of new investors in the crypto market prompted us to become one. What started as a carefree investment back in April 2017 in the crypto market, became an obsession soon. Bitcoin's value was 1000 USD. Bitcoin value doubled within a month which made investors quite pleased and encouraged additional investment. Until August the market was on a bullish run apart from 1 week in September, the market was on an all-time high in December 2017 when bitcoin's value reached 19k USD.
In early 2018 the value of the market started dipping, with bitcoin at 6800 USD in February 2018 was a cause of concern for investors. The market then was on an up and down phase with its value ranging from 11.5k to 6.3k from March to November 2018. With a disruption in the US-China trade deal,

global recession, this variation of crypto prices could be explained.

The value of the market then dipped from December 2018 to March 2019 and was in a range of 3000-4000 USD. The market then started to increase from April to September 2019, its value increasing to 10.5k in mid-September.

However, from October 2019 to March 2020 market entered another up and down phase, with its value of 8200 USD in October 2019,8900 USD in March 2020.

The market then entered a bearish run till October 2020 with itsvalue reaching 12k.

Moreover, the market then entered a bullish run since then, with its value reaching 63k in April 2021 which was an all-timehigh.

The market did experience a certain downfall throughout mid-2021, however, since July 2021 it has been on a bullish run with its value reaching 60K in October 2021.

The increase/ decrease in the value of bitcoin raised 3 questions.

1. What factors could have led to this?
2. Did these factors occur at the same time when themarket experienced these fluctuations?
3. How statistically significant these factors were on thecrypto market.

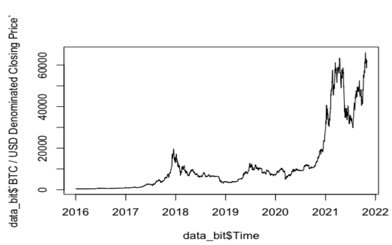
III. Approach

Data gathering and EDA:

We gathered the crypto data from charts.coinmetric.io bitcoin starts from 2010, Ethereum starts 2015, dogecoin 2014.

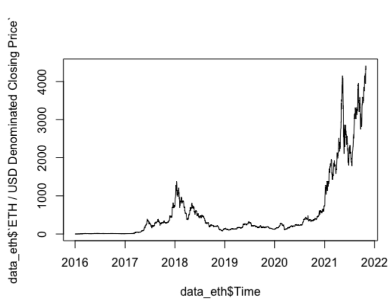
For all 3 cryptos we used line graphs to understand the trend of the crypto prices from its inception. For comparison, we chose a common time frame (i.e.) from January 1, 2016, to October 31, 2021.

<u>Bitcoin trend over time</u>:



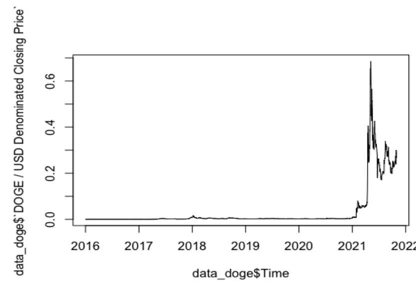
The graph above shows increasing values of Bitcoin from 2016 to 2021. We also observe sudden hikes in Bitcoin prices in the year 2018 and 2021.

<u>Ethereum trend over time</u>:



The next graph for Ethereum also shows increasing values from 2016 to 2021. We also observe similar spikes in Ethereum prices in the year 2018 and 2021.

<u>Dogecoin trend over time:</u>



The final cryptocurrency - Dogecoin also seems to follow a similar pattern observed in Bitcoin and Ethereum over the years 2016 to 2021.

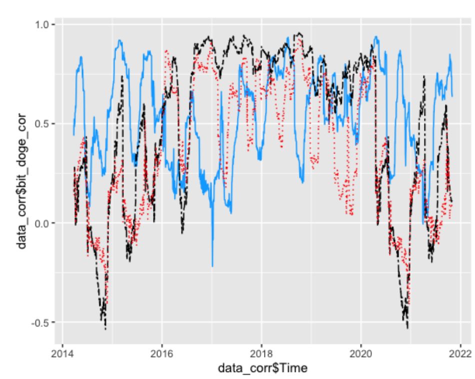
Upon studying the trends of the crypto prices, we were able to find a relationship between the increase/ decrease in the price of the cryptocurrencies.

1. All three cryptocurrencies showed an increase in price over time - from a period of January 1, 2016, to October 31, 2021.
2. We observe the same pattern of spikes in the graph, wherein the prices steeply hiked in 2018 and 2021.

These observations indicated that there is a strong correlation between each of the cryptocurrencies as they followed an almost similar pattern in pricing trends. Correlation is a statistical measure that expresses the extent to which two variables are linearly related.

We then fetched correlation data for Bitcoin-Ethereum, Bitcoin-Dogecoin and Ethereum-Dogecoin to further delve into the details and understand the relationship. This data was obtained from Coin metrics Inc. as they organize the world's crypto data and make it transparent and accessible to the public.

Correlation is defined numerically by a correlation coefficient, which is a value that takes a range from -1 to 1 as seen in the graph below.



With this graph we were able to establish a correlation between the prices of the crypto currencies.

We then had to decide on the independent variables for our ML models

Initially we shortlisted the below independent variables. Google trends, twitter trends, S&P 500 index

But as the data was fetched for each individual source - Bitcoin, Ethereum, Dogecoin, S&P500, Google Trends, Twitter Trends over time, (from 01 Jan 2016 to 31 Oct 2021), upon research, we observed that Google and Twitter trends cannot be considered as potential factors because of below limitations.

- Google trends: We were able to fetch Google trends for individual crypto as bitcoin, Ethereum, dogecoin. However, the data was unable to completely capture the story of the fall and rise of the crypto prices since google trends uses a different scale to determine the search of a crypto price which would then result in inaccurate models.

  The google trends data was between 1-100 which is based on the number of searches corresponding to the crypto keyword (bitcoin, Ethereum, dogecoin etc.) and then data is provided per week which would not be able to compliment the rise and fall of the crypto prices since it is volatile.

  Therefore, we opted not to move ahead with google trend data.

  - Twitter trends:

    Fetching and analyzing twitter's data is a challenging task. We used Twitter's API and other libraries as well to fetch data that contained over more than 1 million tweets (related to cryptocurrencies). Unfortunately, even that huge amount of data couldn't help us out completely as our goal was to analyze data from 2016 till current date and the twitter's data was just for the current year. The other reason for us to not select Twitter trends for our analysis is because the mass at Twitter does not represent the whole population. Moreover, if we just focus on the Twitter population, our results will become biased due to the volume and the sentiments of tweets thereby hindering our main goal.

Data Manipulation done to perform regression and learning techniques:

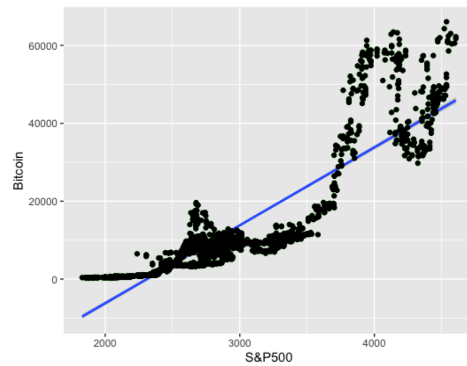
1. Data for Bitcoin has been available since 2010, for Ethereum since 2015 and for Dogecoin since 2014. To maintain data consistency, we filtered the individual crypto data, and the first row starts from 2016. We chose this year because by the start of 2016, all the three cryptocurrencies were prevalent in the market.
2. Since the data for the stock prices was not available for weekends due to market closure hence, we performed the preprocessing on that data to fill those missing values by using the closing price of Friday as those values. We did this as the price of cryptos changed even during the weekends.

<u>EDA between the dependent and independent variables</u>

Bitcoin:

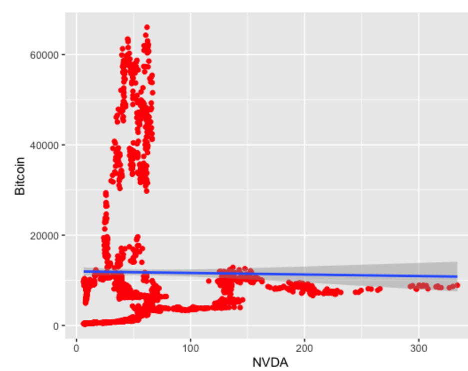
1. Bitcoin vs S&P 500

   The below graph shows positive linear relation between Bitcoin and S&P 500



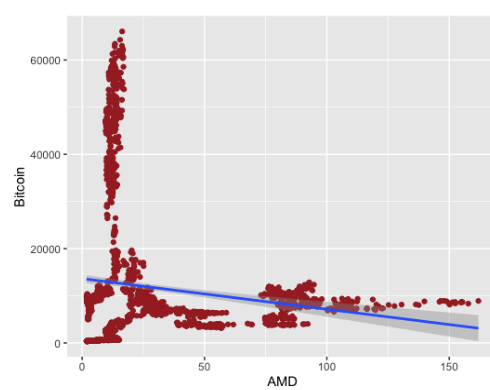
2. Bitcoin vs NVDA:

   The below graph shows slight negative relation between Bitcoin and NVDA



3. Bitcoin vs AMD:

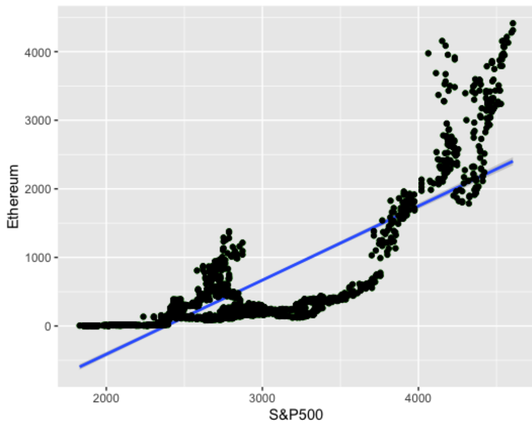
   The below graph shows negative linear relation between Bitcoin and AMD



Ethereum:

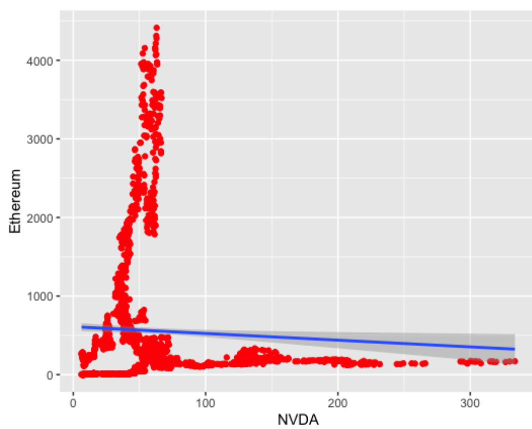
1. Ethe vs S&P 500

The below graph shows positive linear relation between Ethereum and S&P 500



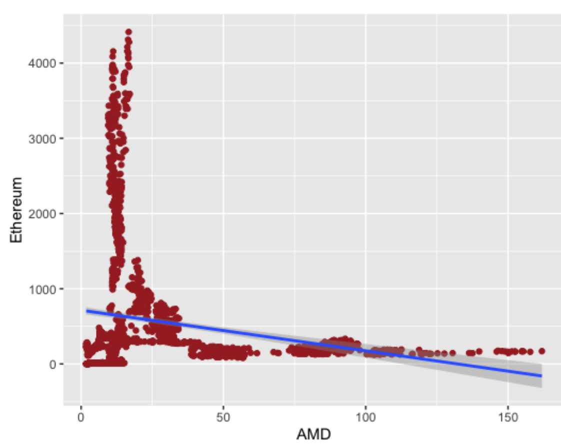
2. Ethe vs NVDA

The below graph shows slight negative linear relation between Ethereum and NVDA



3. Ethe vs AMD

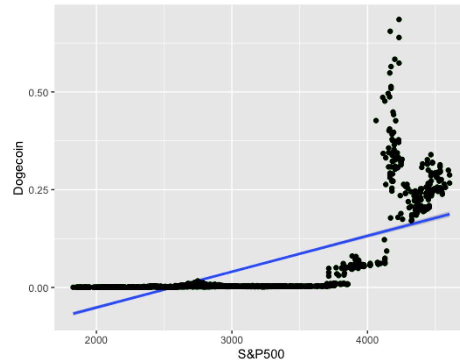
The below graph shows negative linear relation between Ethereum and AMD



Dogecoin

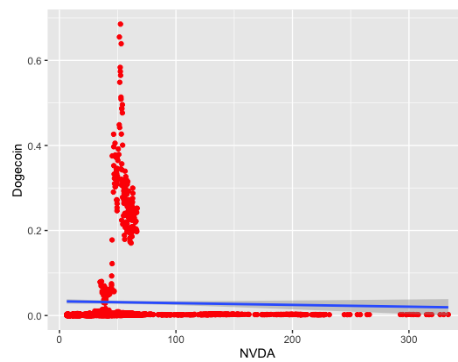
1. Doge vs S&P 500

The below graph shows positive linear relation between Dogecoin and S&P 500



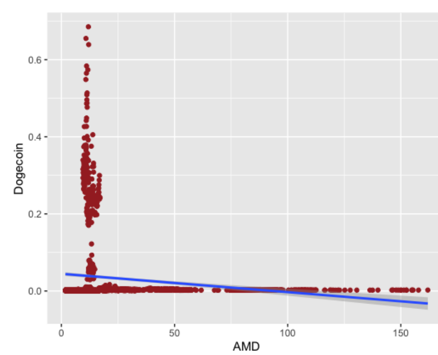
2. Doge vs NVDA

The below graph shows slight negative linear relation between Dogecoin and NVDA



3. Doge vs AMD

The below graph shows negative linear relation between Dogecoin and AMD



We now need to determine whether we have any missing data values in our dataset and check the structure of the data. For which we created a function to check for missing values and used summary as well.

Now we develop the following ML models:

1. Multiple Linear Regression:
2. Boosting
3. Random Forest

We would be using 3 evaluation metrics to determine the performance of all the models when compared to each other.

IV. Result

A. Multiple Linear Regression

Summary of MLR for all three cyrtos:

<u>Bitcoin</u>

```
> multi_reg_bit

Call:
lm(formula = Bitcoin ~ `S&P500` + NVDA + AMD, data = data)

Coefficients:
(Intercept)     `S&P500`         NVDA          AMD
  -43708.54        19.80        45.96      -161.26

> #Summary of the model object!
> summary(multi_reg_bit)

Call:
lm(formula = Bitcoin ~ `S&P500` + NVDA + AMD, data = data)

Residuals:
     Min       1Q   Median       3Q      Max
-15700.4  -2759.5   -420.4   2955.5  27068.5

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -4.371e+04  6.398e+02 -68.314  < 2e-16 ***
`S&P500`     1.980e+01  2.219e-01  89.236  < 2e-16 ***
NVDA         4.596e+01  8.014e+00   5.734 1.12e-08 ***
AMD         -1.613e+02  1.375e+01 -11.726  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 6422 on 2126 degrees of freedom
Multiple R-squared:  0.8172,    Adjusted R-squared:  0.817
F-statistic:  3169 on 3 and 2126 DF,  p-value: < 2.2e-16
```

<u>Ethereum:</u>

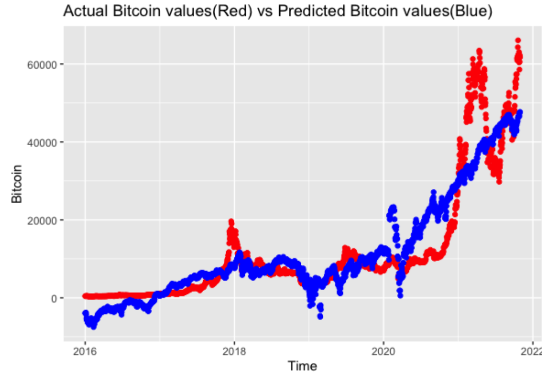
```
> multi_reg_Eth

Call:
lm(formula = Ethereum ~ `S&P500` + NVDA + AMD, data = data)

Coefficients:
(Intercept)     `S&P500`         NVDA          AMD
  -2351.159        1.043        5.898      -16.150

> #Summary of the model object!
> summary(multi_reg_Eth)

Call:
lm(formula = Ethereum ~ `S&P500` + NVDA + AMD, data = data)

Residuals:
    Min      1Q  Median      3Q     Max
-964.37 -184.21    1.53  218.03 2039.14

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -2.351e+03  4.381e+01  -53.66   <2e-16 ***
`S&P500`     1.043e+00  1.519e-02   68.66   <2e-16 ***
NVDA         5.898e+00  5.488e-01   10.75   <2e-16 ***
AMD         -1.615e+01  9.417e-01  -17.15   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 439.8 on 2126 degrees of freedom
Multiple R-squared:  0.7457,    Adjusted R-squared:  0.7454
F-statistic:  2078 on 3 and 2126 DF,  p-value: < 2.2e-16
```

<u>Dogecoin:</u>

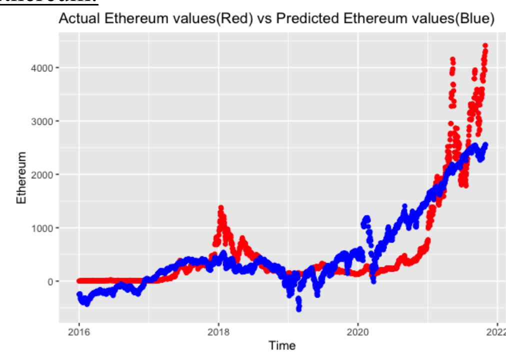
```
> multi_reg_Dog

Call:
lm(formula = Doge_FS ~ `S&P500` + NVDA + AMD, data = data_doge_FS)

Coefficients:
(Intercept)     `S&P500`         NVDA          AMD
  3.316e-15    6.449e-01    5.504e-01   -7.201e-01

> #Summary of the model object!
> summary(multi_reg_Dog)

Call:
lm(formula = Doge_FS ~ `S&P500` + NVDA + AMD, data = data_doge_FS)

Residuals:
    Min      1Q  Median      3Q     Max
-1.3551 -0.3088  0.0202  0.2947  5.8619

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  3.316e-15  1.445e-02    0.00        1
`S&P500`     6.449e-01  1.529e-02   42.17   <2e-16 ***
NVDA         5.504e-01  4.508e-02   12.21   <2e-16 ***
AMD         -7.201e-01  4.458e-02  -16.16   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.6669 on 2126 degrees of freedom
Multiple R-squared:  0.5558,    Adjusted R-squared:  0.5552
F-statistic: 886.8 on 3 and 2126 DF,  p-value: < 2.2e-16
```

<u>Comparing the predicted values vs the actual values</u>

<u>Bitcoin:</u>

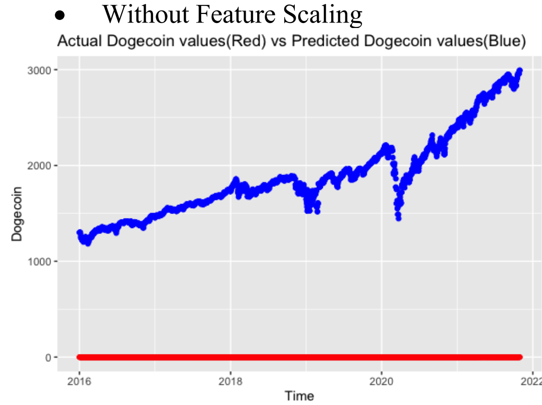


<u>Ethereum:</u>

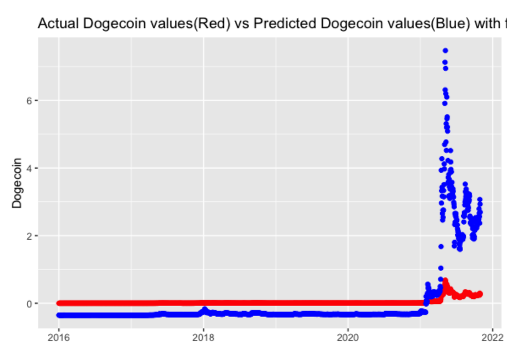


<u>Dogecoin:</u>

- Without Feature Scaling



- With Feature Scaling



B. **Boosting**

Summary of Boosting for all three cryptos

<u>Bitcoin:</u>

```
> boost_model_bitcoin
Stochastic Gradient Boosting

1598 samples
   3 predictor

No pre-processing
Resampling: Bootstrapped (25 reps)
Summary of sample sizes: 1598, 1598, 1598, 1598, 1598, 1598, ...
Resampling results across tuning parameters:

  interaction.depth  n.trees  RMSE      Rsquared   MAE
  1                   50      3858.891  0.9371731  2385.859
  1                  100      3481.235  0.9481987  2137.956
  1                  150      3285.902  0.9535726  2004.803
  2                   50      3158.292  0.9574395  1958.444
  2                  100      2680.087  0.9688725  1580.870
  2                  150      2545.746  0.9719432  1469.668
  3                   50      2726.893  0.9679014  1668.179
  3                  100      2413.581  0.9747407  1379.943
  3                  150      2284.235  0.9774265  1290.942

Tuning parameter 'shrinkage' was held constant at a value of 0.1
Tuning
 parameter 'n.minobsinnode' was held constant at a value of 10
RMSE was used to select the optimal model using the smallest value.
The final values used for the model were n.trees = 150, interaction.depth =
 3, shrinkage = 0.1 and n.minobsinnode = 10.
> boost_model_bitcoin$finalModel
A gradient boosted model with gaussian loss function.
150 iterations were performed.
There were 3 predictors of which 3 had non-zero influence.
```

<u>Ethereum:</u>

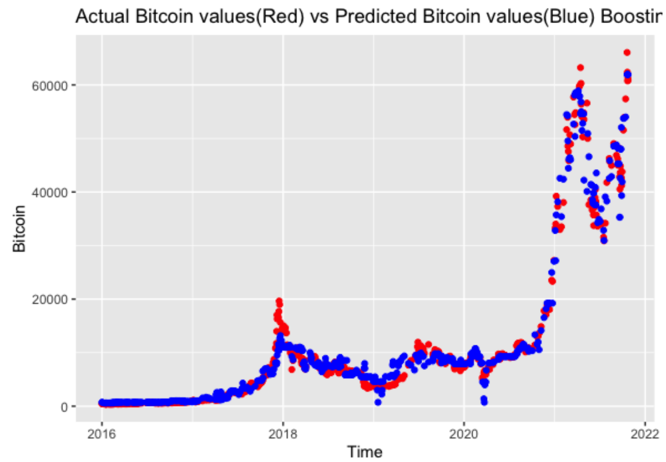
```
> boost_model_ethereum
Stochastic Gradient Boosting

1598 samples
   3 predictor

No pre-processing
Resampling: Bootstrapped (25 reps)
Summary of sample sizes: 1598, 1598, 1598, 1598, 1598, 1598, ...
Resampling results across tuning parameters:

  interaction.depth  n.trees  RMSE      Rsquared   MAE
  1                   50      236.1029  0.9292177  149.50466
  1                  100      203.9513  0.9461749  117.95800
  1                  150      192.2483  0.9518581  108.85921
  2                   50      185.3110  0.9559821  108.97049
  2                  100      154.9647  0.9683879   87.61238
  2                  150      147.7794  0.9712710   83.13489
  3                   50      157.8131  0.9677382   90.50035
  3                  100      135.4865  0.9758173   75.69104
  3                  150      129.6779  0.9779055   71.40809

Tuning parameter 'shrinkage' was held constant at a value of 0.1
Tuning
 parameter 'n.minobsinnode' was held constant at a value of 10
RMSE was used to select the optimal model using the smallest value.
The final values used for the model were n.trees = 150, interaction.depth =
 3, shrinkage = 0.1 and n.minobsinnode = 10.
> boost_model_ethereum$finalModel
A gradient boosted model with gaussian loss function.
150 iterations were performed.
There were 3 predictors of which 3 had non-zero influence.
```

<u>Dogecoin</u>**:**

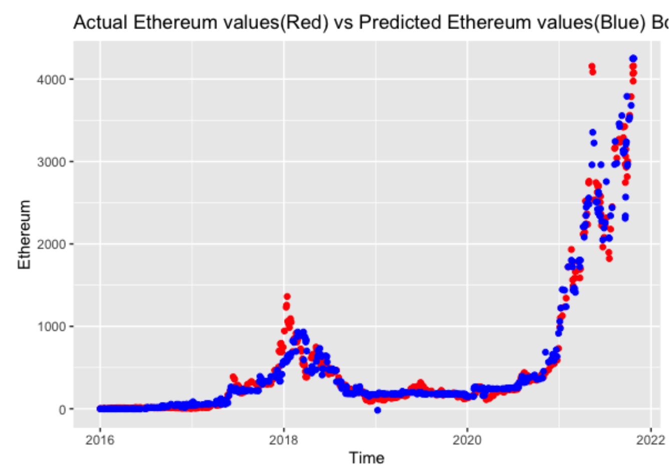
```
> boost_model_dogecoin
Stochastic Gradient Boosting

1598 samples
   3 predictor

No pre-processing
Resampling: Bootstrapped (25 reps)
Summary of sample sizes: 1598, 1598, 1598, 1598, 1598, 1598, ...
Resampling results across tuning parameters:

  interaction.depth  n.trees  RMSE        Rsquared   MAE
  1                   50      0.03104948  0.8760268  0.008812771
  1                  100      0.02928872  0.8891406  0.007975144
  1                  150      0.02867403  0.8936551  0.007743919
  2                   50      0.02516281  0.9181749  0.006777646
  2                  100      0.02330667  0.9292454  0.006242237
  2                  150      0.02275596  0.9328336  0.006027341
  3                   50      0.02196240  0.9372272  0.005952373
  3                  100      0.02131304  0.9410324  0.005541217
  3                  150      0.02130982  0.9411003  0.005468001

Tuning parameter 'shrinkage' was held constant at a value of 0.1
Tuning
 parameter 'n.minobsinnode' was held constant at a value of 10
RMSE was used to select the optimal model using the smallest value.
The final values used for the model were n.trees = 150, interaction.depth =
 3, shrinkage = 0.1 and n.minobsinnode = 10.
> boost_model_dogecoin$finalModel
A gradient boosted model with gaussian loss function.
150 iterations were performed.
There were 3 predictors of which 3 had non-zero influence.
```

<u>Comparing the predicted values vs the actual values</u>

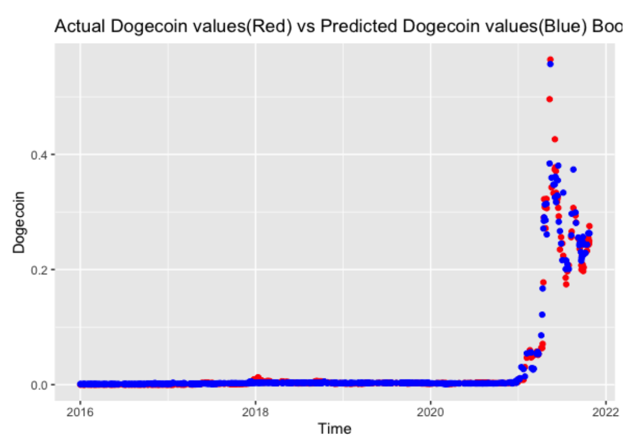
<u>Bitcoin:</u>



<u>Ethereum:</u>



<u>Dogecoin:</u>



C. Random Forest

Summary of Random Forest for all three cryptos

Bitcoin:

```
> RF_model_bitcoin
Random Forest

1598 samples
   3 predictor

No pre-processing
Resampling: Bootstrapped (25 reps)
Summary of sample sizes: 1598, 1598, 1598, 1598, 1598, 1598, ...
Resampling results across tuning parameters:

  mtry  RMSE      Rsquared   MAE
  2     1812.409  0.9857222  833.9701
  3     1880.613  0.9846596  847.0182

RMSE was used to select the optimal model using the smallest value.
The final value used for the model was mtry = 2.
> RF_model_bitcoin$finalModel

Call:
 randomForest(x = x, y = y, mtry = min(param$mtry, ncol(x)), proximity = TR
               Type of random forest: regression
                     Number of trees: 500
No. of variables tried at each split: 2

          Mean of squared residuals: 2724977
                    % Var explained: 98.79
>
```

Ethereum:

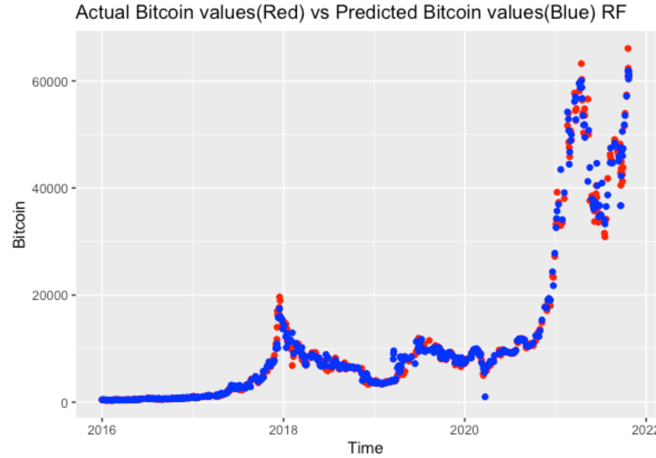
```
> RF_model_ethe
Random Forest

1598 samples
   3 predictor

No pre-processing
Resampling: Bootstrapped (25 reps)
Summary of sample sizes: 1598, 1598, 1598, 1598, 1598, 1598, ...
Resampling results across tuning parameters:

  mtry  RMSE      Rsquared   MAE
  2     105.8296  0.9854026  42.16559
  3     109.8475  0.9842925  42.91649

RMSE was used to select the optimal model using the smallest value.
The final value used for the model was mtry = 2.
> RF_model_ethe$finalModel

Call:
 randomForest(x = x, y = y, mtry = min(param$mtry, ncol(x)), proximity = TR
               Type of random forest: regression
                     Number of trees: 500
No. of variables tried at each split: 2

          Mean of squared residuals: 9448.161
                    % Var explained: 98.74
>
```

Dogecoin:

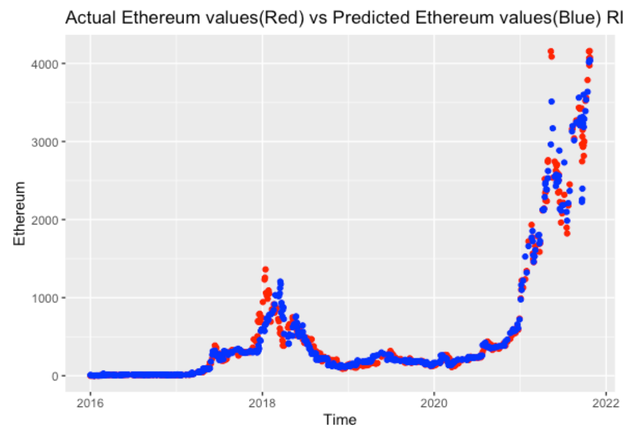
```
> RF_model_doge
Random Forest

1598 samples
   3 predictor

No pre-processing
Resampling: Bootstrapped (25 reps)
Summary of sample sizes: 1598, 1598, 1598, 1598, 1598, 1598, ...
Resampling results across tuning parameters:

  mtry  RMSE        Rsquared   MAE
  2     0.01989426  0.9481562  0.004121097
  3     0.02118793  0.9408087  0.004276084

RMSE was used to select the optimal model using the smallest value.
The final value used for the model was mtry = 2.
> RF_model_doge$finalModel

Call:
 randomForest(x = x, y = y, mtry = min(param$mtry, ncol(x)), proximity = TR
               Type of random forest: regression
                     Number of trees: 500
No. of variables tried at each split: 2

          Mean of squared residuals: 0.0003560781
                    % Var explained: 95.38
>
```

Comparing the predicted values vs the actual values

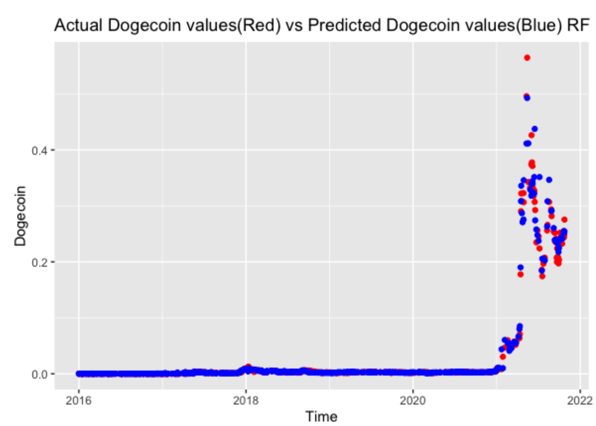
Bitcoin:



Ethereum:



Dogecoin:



Values of Evaluation metrics:

Bitcoin

Evaluation metrics	MLR	Boosting	Random Forest
R^2	81.72	97.74	98.46
MAE	4471.638	1290.942	847.01
MSE	41167282	4695461	2459460

Ethereum

Evaluation metrics	MLR	Boosting	Random Forest
R^2	74.57	97.79	98.42
MAE	315.4053	71.4	42.91
MSE	193031.7	-1106817	-1098089

Dogecoin

Evaluation metrics	MLR	Boosting	Random Forest
R^2	55.58	94.11	94.81
MAE	0.5445672	0.0054	0.0041
MSE	0.8331208	0.00017	0.00015

V. Conclusion

Cryptocurrencies are digital currencies that have garnered significant investor attention in the financial markets. The aim of this project is to predict the price of the cryptocurrencies (Bitcoin, Ethereum and Dogecoin). This plays a vital role in making investment decisions. There exist various factors which affect the price of these cryptocurrencies.
For evaluating our models, we have taken three metrics, namely R-Squared (R^2), Mean square error (MSE) and mean absolute error (MAE).

As observed from the results table, the value of R^2 is highest in Random Forest and the other two metrics, MSE and MAE are minimum for Random Forest, hence it is our best predicting model.

Future findings

In the future when all the Bitcoins would be mined it would be risky to invest in it. As there exist various factors which affect the price of Bitcoin, thereby making price prediction a complex and technically challenging task.
Currently Bitcoins are being traded in micro bitcoins and it would be divided further in future as the demand increases. By that time its value will become so infinitesimal that it stops making sense (think 10^-20) due to the limited number of bitcoin availability. So, investing in other cryptos can be considered a better option as Bitcoin might be risky.
Ethereum can be considered as an alternate investment option. Reason being, Ethereum was built as a general purpose blockchain unlike Bitcoin which was built to do one thing well that is to provide a way for people to transfer value from one to another without a central bank. As a result, it can do many things well instead of serving solely as a store of value.

Demand in the market

While the number of merchants who accept cryptocurrencies has steadily increased, they are still very much in the minority. For cryptocurrencies to become more widely used, they must first gain widespread acceptance among consumers. However, their relative complexity compared to conventional currencies will likely deter most people, except for the technologically adept. What will be harder to surmount is the basic paradox that torments cryptocurrencies – the more popular they become, the more regulation and government scrutiny they are likely to attract, which erodes the fundamental premise for their existence.

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[4] *https://www.crunchbase.com/organization/coin-metrics-6fa3*

[5] *Studies [25], [26] have shown that the price pattern recognition for cryptocurrency has many causes and is difficult to forecast. For potential investors and government agencies it is necessary to establish a cryptocurrency price prediction mechanism*

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