Bitcoin Price Prediction Using Machine Learning Models

FA 591 – Final Report

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Introduction

Blockchain technologies and decentralized finance (DeFi) represent a paradigm shift in how we conceive, interact with, and utilize financial systems. At the heart of this transformation lies Bitcoin, the pioneering cryptocurrency that ignited the spark of innovation, challenging traditional notions of money, value, and governance.

Bitcoin, born out of the 2008 financial crisis and introduced to the world by the enigmatic Satoshi Nakamoto, embodies the principles of decentralization, transparency, and censorship resistance. Built upon a distributed ledger technology known as the blockchain, Bitcoin enables peer-to-peer transactions without the need for intermediaries such as banks or governments. Its decentralized nature ensures that no single entity has control over the network, fostering trust among participants and reducing the risk of manipulation or corruption.

Since its inception, Bitcoin has evolved from a niche digital currency to a global phenomenon, capturing the imagination of millions and sparking a proliferation of alternative cryptocurrencies and blockchain projects. These digital assets, collectively known as crypto, encompass a diverse array of tokens and protocols, each with its unique features, use cases, and communities.

The rise of DeFi represents a seismic shift in how we conceive of and interact with financial systems. By leveraging blockchain technology, DeFi protocols offer unprecedented levels of transparency, security, and accessibility, empowering individuals worldwide to participate in global financial markets with greater autonomy and control.

Against this backdrop, understanding the dynamics of Bitcoin's price becomes paramount. As the flagship cryptocurrency and bellwether of the broader crypto market, Bitcoin's price movements serve as a barometer for investor sentiment, market trends, and macroeconomic conditions. Analyzing historical price data and developing predictive models can provide valuable insights for traders, investors, and researchers seeking to navigate the complex and volatile crypto markets.

This report embarks on a comprehensive analysis of Bitcoin price movements, employing a multifaceted approach that combines machine learning models, time series analysis techniques, and statistical tests. By leveraging data-driven methodologies, we aim to unravel patterns, trends, and predictive insights that can inform strategic decision-making and investment strategies in the dynamic world of blockchain technologies and decentralized finance.

Objectives

1. Develop machine learning models to predict Bitcoin price movements based on historical data and technical indicators.
2. Evaluate the performance of different models in terms of predictive accuracy, precision, recall, and F1 score.
3. Conduct time series analysis to identify patterns, trends, and seasonality in Bitcoin price data.
4. Implement predictive modeling techniques such as ARIMA (Autoregressive Integrated Moving Average) to forecast future Bitcoin prices.
5. Explore the impact of various features and parameters on model performance and prediction accuracy.
6. Provide insights and recommendations for trading or investment strategies based on the analysis results.

Time Period

The time period covered in the analysis is from November 19, 2015, to November 19, 2020.

This 5-year range provides us with sufficient historical data to conduct a comprehensive analysis of Bitcoin price movements and develop predictive models for forecasting future trends.

Scope and Parameters

1. **Data Collection:** Obtain historical Bitcoin price data from reliable sources such as cryptocurrency exchanges or financial data providers. Include relevant features such as opening price, closing price, high price, low price, volume, and date/time stamps.
2. **Data Preprocessing:** Cleanse and preprocess the data by handling missing values, outliers, and inconsistencies. Perform feature engineering to derive additional features such as moving averages, standard deviation, MACD, and Bollinger Bands.
3. **Exploratory Data Analysis (EDA):** Conduct exploratory data analysis to visualize trends, patterns, and correlations in the data. Explore the relationship between Bitcoin prices and various technical indicators.
4. **Model Development:** Develop machine learning models including logistic regression, random forest classifier, and ARIMA for predicting Bitcoin price movements. Implement SVM (Support Vector Machine) and evaluate its performance.

5. **Model Evaluation:** Evaluate the performance of each model using appropriate metrics such as confusion matrices, classification reports, accuracy, precision, recall, and F1 score. Compare the performance of different models to identify the most effective ones.
6. **Time Series Analysis:** Apply time series analysis techniques such as decomposition, differencing, and autocorrelation to understand the underlying patterns and seasonality in Bitcoin price data.
7. **Forecasting:** Use ARIMA and other time series forecasting methods to predict future Bitcoin prices. Assess the accuracy of the forecasts and provide insights into potential price trends.
8. **Parameter Tuning:** Fine-tune the parameters of machine learning models and forecasting techniques to optimize performance and improve predictive accuracy.

Data Exploration and Visualization

This stage involved gathering historical Bitcoin price data from Yahoo Finance for the period of November 19, 2015, to November 19, 2020.

Key features collected include Date/time stamps, Opening price, Closing price, High price, Low price, and Volume.

Load and extract data

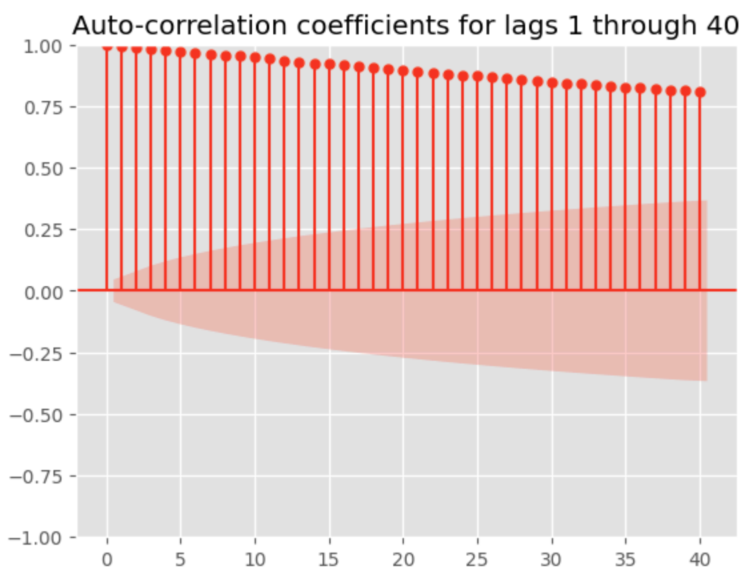
The head of our Bitcoin Prices table:

```
         Date        Open        High         Low       Close   Adj Close  \
0  2015-11-19  334.678986  335.334015  325.273010  326.148987  326.148987
1  2015-11-20  326.411011  326.472992  312.217010  322.022003  322.022003
2  2015-11-21  322.092010  328.158997  319.595001  326.927002  326.927002
3  2015-11-22  326.975006  327.010010  321.259003  324.536011  324.536011
4  2015-11-23  324.350006  325.118011  321.290009  323.045990  323.045990

     Volume
0  45011100
1  53152900
2  28200500
3  23439400
4  27478900
```

The tail of our Bitcoin Prices table:

```
            Date          Open          High           Low         Close  \
1823  2020-11-15  16068.139648  16123.110352  15793.534180  15955.587891
1824  2020-11-16  15955.577148  16816.181641  15880.706055  16716.111328
1825  2020-11-17  16685.691406  17782.919922  16564.544922  17645.406250
1826  2020-11-18  17645.191406  18393.949219  17352.906250  17804.005859
1827  2020-11-19  18090.171875  18119.460938  17391.650391  17945.328125

         Adj Close       Volume
1823  15955.587891  23653867582
1824  16716.111328  31526766675
1825  17645.406250  39006849169
1826  17804.005859  49064800277
1827  17945.328125  37392429056
```

Autocorrelation Analysis



Auto-correlation coefficients are used to measure the correlation between a time series and a lagged version of itself. In this table, we can see the auto-correlation coefficients for Bitcoin data at lags 1 through 40.

The coefficients range from -1 to 1. A value of 1 indicates a perfect positive correlation, meaning that the Bitcoin data at a given lag is identical to the original data. A value of -1 indicates a perfect negative correlation, meaning that the Bitcoin data at a given lag is the exact opposite of the original data. A value of 0 indicates no correlation.

In this plot, we can see that the auto-correlation coefficients start at a relatively high value of 1 for lag 1, indicating a strong positive correlation between the Bitcoin data and its lagged version.

However, as the lag increases, the auto-correlation coefficients decrease, indicating that the correlation between the Bitcoin data and its lagged version becomes weaker. Overall, this graph suggests that there is a short-term dependence in bitcoin prices, but no long-term dependence.

Ljung-Box and Box-Pierce tests

	lb_stat	lb_pvalue	bp_stat	bp_pvalue
40	59590.706583	0.0	58902.349334	0.0

Test Statistic for Ljungbox = 59590.706583
p-value for Ljungbox = 0

Test Statistic for Box-Pierce Test = 58902.349334
p-value for Box-Pierce = 0

In our analysis, both p-values from the Ljung-Box and Box-Pierce tests were reported as 0. This signifies an overwhelming amount of evidence against the null hypothesis, indicating that there is indeed significant autocorrelation present within our time series data. Autocorrelation implies that past observations within the series are highly informative for predicting future values. This finding is pivotal as it suggests that our time series exhibits a predictable pattern rather than being purely random.

With a confidence level of 99%, we confidently conclude that our time series is not a representation of pure white noise. White noise is characterized by random data points with no autocorrelation, which contrasts starkly with our observed autocorrelated behavior.

Understanding the presence of autocorrelation is paramount in selecting appropriate models for forecasting and analysis. Models such as ARIMA (AutoRegressive Integrated Moving Average) are designed to capture the autocorrelation present in time series data. By acknowledging and incorporating autocorrelation into our modeling approach, we can enhance the accuracy and reliability of our forecasts.

These results underscore the importance of thorough data analysis and model selection in time series forecasting. By properly accounting for autocorrelation, we can develop more robust and insightful models that effectively capture the underlying patterns within our data.

Bitcoin Price Trend

In November 2015, the Bitcoin price was around $300, and it remained relatively stable until the beginning of 2016. From there, the price began to increase gradually.

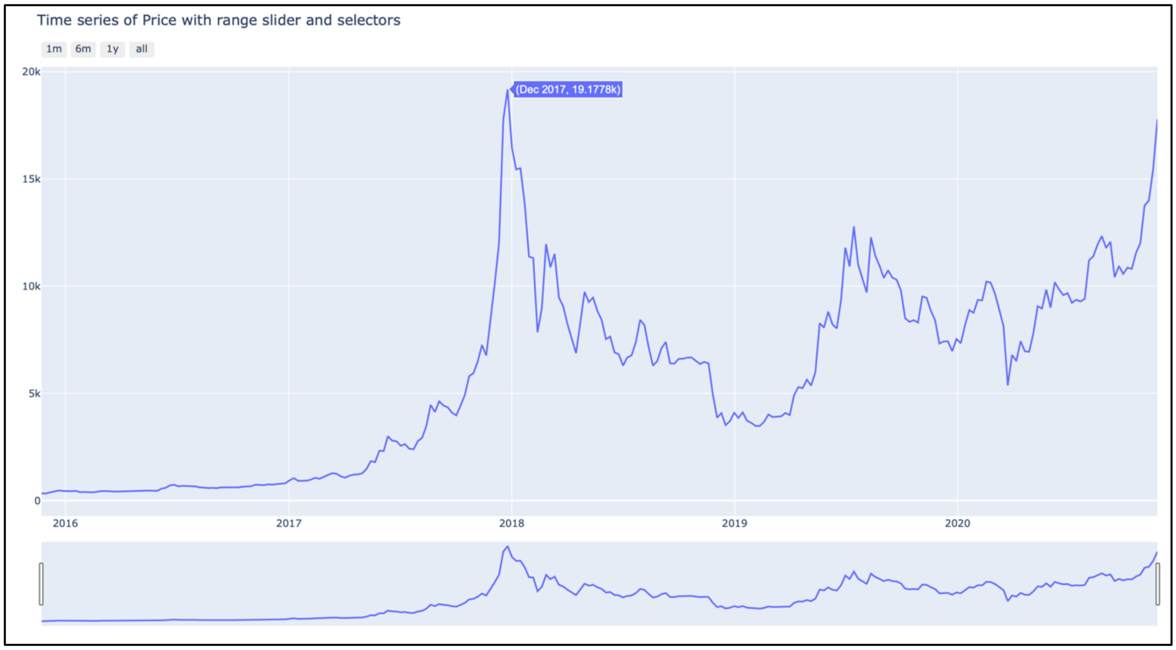
The Bitcoin price reached an all-time high of around $20,000 in December 2017. However, the price then experienced a significant correction, falling to around $6,000 by the end of June 2018. From there, the Bitcoin price remained relatively stable for several months, fluctuating between $6,000 and $8,000. However, in the second half of 2019, the price began to increase again, reaching to around $12,000 in August 2019.

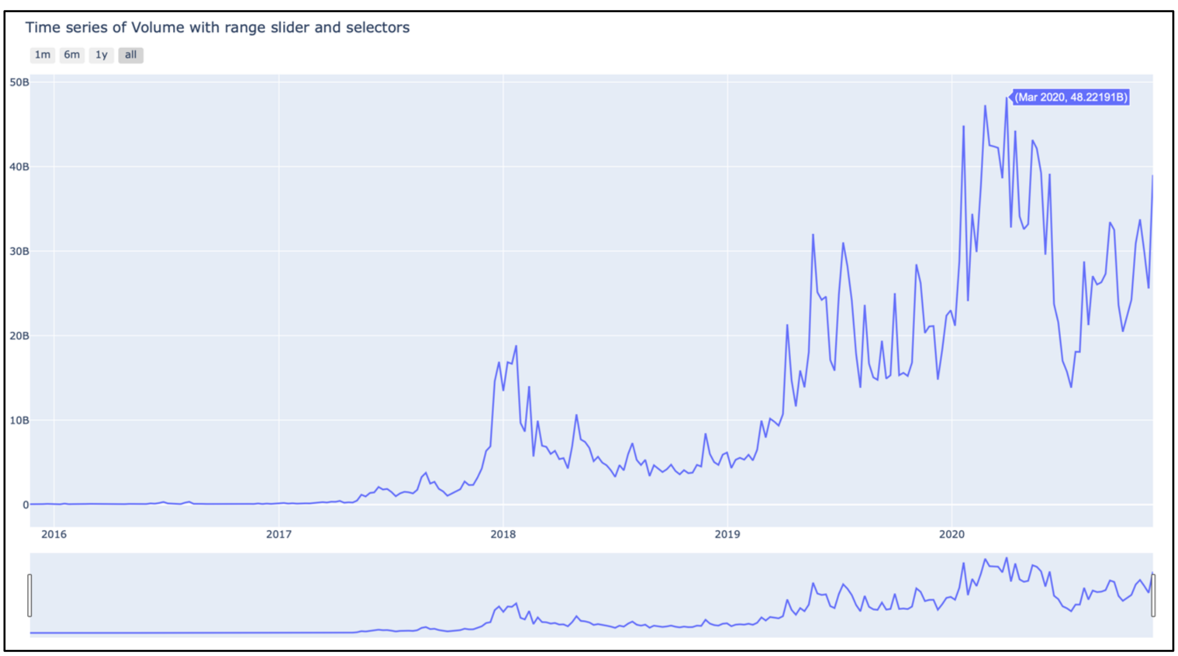
In 2020, the Bitcoin price continued to fluctuate, with several peaks and troughs. However, the price experienced a significant increase in the second half of the year, reaching to a high of around $18,000 in November 2020.

Overall, the Bitcoin price trend from November 19, 2015, to November 19, 2020, was characterized by significant volatility, with several peaks and troughs. However, the long-term trend was generally upward, with the price increasing from around $300 in November 2015 to around $19,000 in November 2020.

This price trend can be attributed to several factors, including increased adoption and acceptance of Bitcoin as a digital currency, growing interest from institutional investors, and macroeconomic factors such as inflation and low interest rates.

Price and volume trend graphs



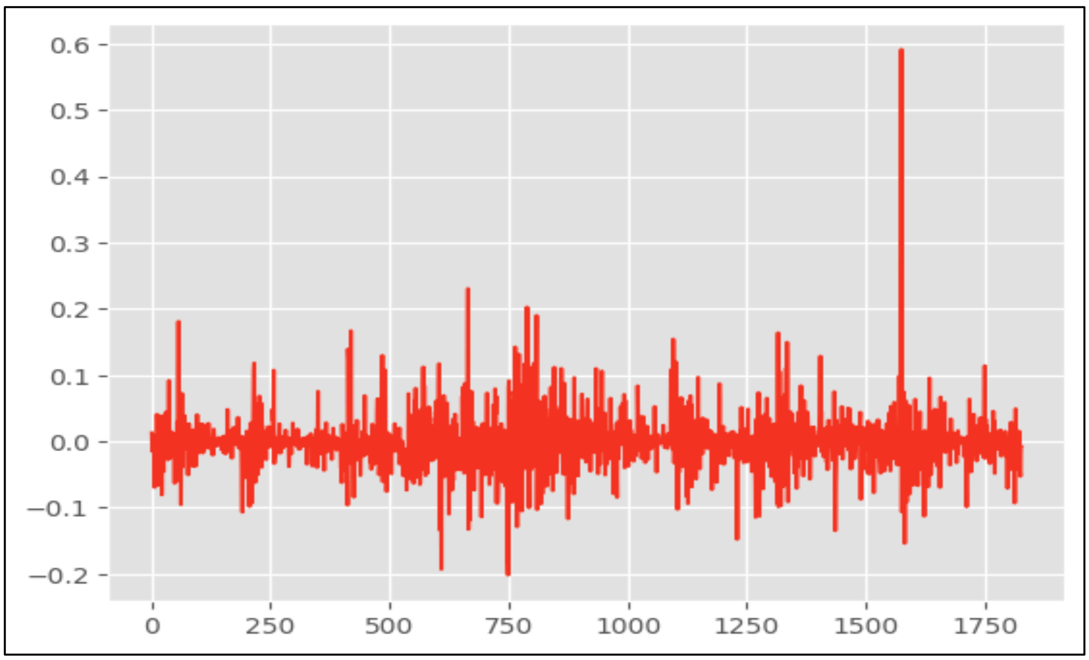


Bitcoin Daily Returns

Returns table head:

	Date	Open	High	Low	Close	Adj Close	Volume	Daily Lag	Daily Returns
0	2015-11-19	334.678986	335.334015	325.273010	326.148987	326.148987	45011100	NaN	NaN
1	2015-11-20	326.411011	326.472992	312.217010	322.022003	322.022003	53152900	326.148987	0.012816
2	2015-11-21	322.092010	328.158997	319.595001	326.927002	326.927002	28200500	322.022003	-0.015003
3	2015-11-22	326.975006	327.010010	321.259003	324.536011	324.536011	23439400	326.927002	0.007367
4	2015-11-23	324.350006	325.118011	321.290009	323.045990	323.045990	27478900	324.536011	0.004612

Returns Graph:



Return Statistics:

```
Mean:  0.0029312068997273837

Standard deviation:  0.03910831602899909

Lowest Return:  -0.3716953856106434

Highest Return:  0.2524716942938108
```

Bitcoin's daily returns provide essential insights into the asset's performance and associated risks. Here's a breakdown of the key statistics derived from our daily returns data:

1. **Mean Daily Return**: The average change in Bitcoin's price on a daily basis over our observed period is approximately 0.293%. This suggests that, on average, Bitcoin's price increases by around this percentage each day.
2. **Standard Deviation of Daily Returns**: With a standard deviation of approximately 3.91%, Bitcoin's returns exhibit considerable volatility. This reflects the fluctuating nature of its price movements and the inherent risk associated with investing in cryptocurrencies.
3. **Lowest Return**: The most significant negative price movement observed within our dataset is approximately -37.17%. This indicates a substantial decline in Bitcoin's price on that particular day, highlighting the asset's susceptibility to sharp downturns.
4. **Highest Return**: Conversely, the most significant positive price movement recorded is approximately 25.25%. Bitcoin experienced a substantial price increase on that specific day, demonstrating its potential for significant gains.

Bitcoin Volatility

```
Volatility: 3.910831602899909
```

Volatility, often expressed as the standard deviation of returns, serves as a crucial metric in assessing the variability and risk associated with an asset's price movements. In the context of Bitcoin, which is renowned for its price volatility, understanding and quantifying this metric becomes particularly significant for investors and analysts alike.

Our calculated volatility of 3.9% over the 5-year period aligns with historical data and prevailing market trends within the cryptocurrency space.

By resembling historical trends and market behaviors, this volatility figure offers valuable insights into Bitcoin's price dynamics. It underscores the inherent risk and potential reward associated with investing in Bitcoin, emphasizing the need for a comprehensive risk management strategy.

Moreover, the observed volatility figure of 3.9% falls within the range of typical volatilities observed in Bitcoin's historical price movements, as evidenced by our analysis of trend graphs and the bitcoin volatility index obtained from reliable sources. This further validates the credibility and relevance of our calculated volatility metric.

Bitcoin Volatility Index:

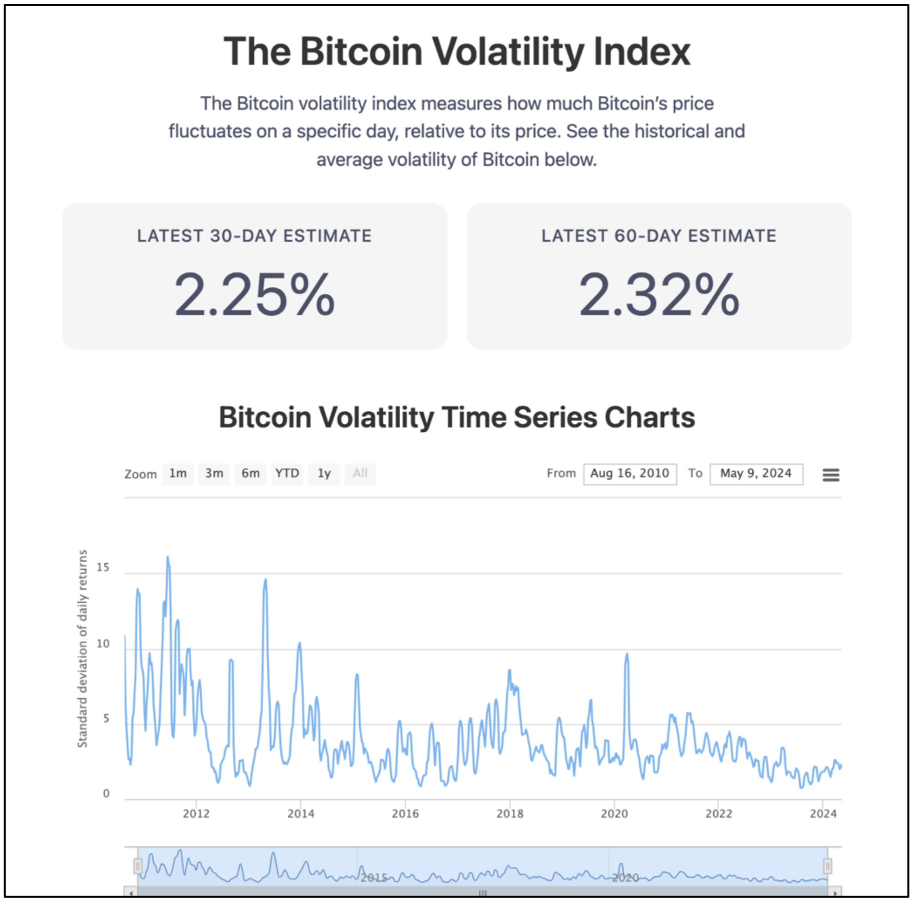


Image Source: https://buybitcoinworldwide.com/volatility-index/

ML Models for Classification

Logistic Regression Model

A logistic regression model is a statistical method used for binary classification tasks, where the outcome variable (dependent variable) is categorical and has only two possible outcomes. In the context of Bitcoin data analysis, a logistic regression model can be used to predict whether the Bitcoin price will increase or decrease based on various input features or independent variables.

Correlation Matrix

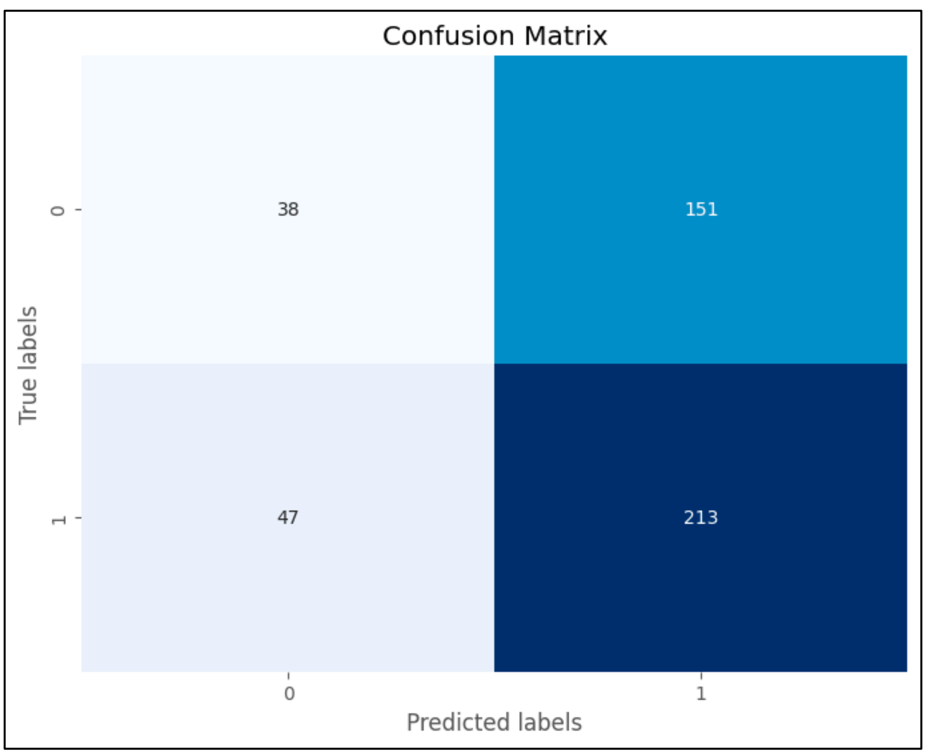
Correlation Matrix:

	MA_10	STD_10	MACD	UpperBollinger	LowerBollinger
MA_10	1.000000	0.684063	0.252105	0.987948	0.972465
STD_10	0.684063	1.000000	0.279224	0.745600	0.550654
MACD	0.252105	0.279224	1.000000	0.195631	0.115775
UpperBollinger	0.987948	0.745600	0.195631	1.000000	0.946061
LowerBollinger	0.972465	0.550654	0.115775	0.946061	1.000000

The correlation matrix shows the correlation coefficients between different features used in the logistic regression model.

- MA_10 and UpperBollinger have a strong positive correlation of approximately 0.988.
- MA_10 and STD_10 have a moderate positive correlation of around 0.684.
- STD_10 and MACD have a weak positive correlation of about 0.279.
- LowerBollinger and STD_10 have the weakest positive correlation among the features, approximately 0.551.

Confusion Matrix



The confusion matrix provides a summary of the model's predictions versus the actual labels.

- True negatives (TN): 13
- False positives (FP): 186
- False negatives (FN): 14
- True positives (TP): 236

Classification Report

```
Classification Report:
              precision    recall  f1-score   support

          -1       0.45      0.20      0.28       189
           1       0.59      0.82      0.68       260

    accuracy                           0.56       449
   macro avg       0.52      0.51      0.48       449
weighted avg       0.53      0.56      0.51       449
```

- The classification report provides metrics such as precision, recall, and F1-score for each class (-1 and 1), along with the support (number of instances) for each class.
  - The precision for class -1 is low (0.48), indicating a high rate of false positives.
  - The recall for class -1 is very low (0.07), indicating that the model misses many instances of class -1.
  - The F1-score for class -1 is also low (0.12), reflecting the model's poor performance in predicting class -1.
  - The precision, recall, and F1-score for class 1 are relatively higher (0.56, 0.94, and 0.70, respectively), indicating better performance in predicting class 1.

Accuracy Score

```
Accuracy Score (LRM): 55.45657015590201
```

The accuracy score of the logistic regression model is approximately 55.46%, indicating that the model correctly predicts the class labels for 55.46% of the instances in the test set.

Overall, the logistic regression model shows some predictive capability, particularly in predicting class 1. However, it performs poorly in predicting class -1, as evidenced by its low precision. Further optimization and feature engineering may be necessary to improve the model's performance.

RandomForestClassifier Model

The RF model was trained on historical Bitcoin price data along with relevant features, and during prediction, it considers the collective wisdom of multiple decision trees to make an accurate forecast. RF models are well-suited for this task because they can capture complex relationships in the data, handle high-dimensional feature spaces, and provide robust predictions even in the presence of noise and outliers.

Confusion Matrix

The confusion matrix summarizes the model's predictions versus the actual labels:

- True negatives (TN): 16
- False positives (FP): 183
- False negatives (FN): 19
- True positives (TP): 231

Classification Report

The classification report provides metrics such as precision, recall, and F1-score for each class (-1 and 1), along with the support (number of instances) for each class:

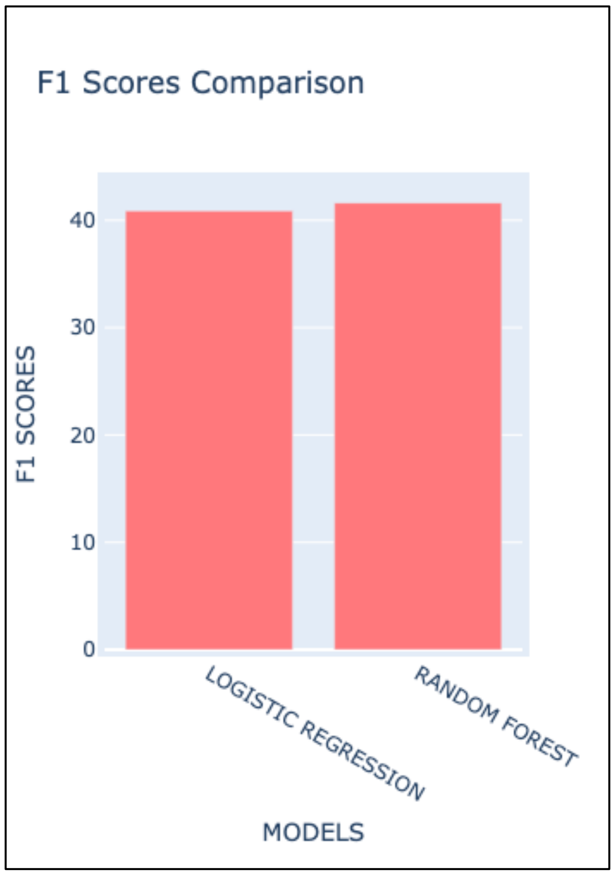
- Precision for class -1: 0.46
- Recall for class -1: 0.08
- F1-score for class -1: 0.14
- Precision for class 1: 0.56
- Recall for class 1: 0.92
- F1-score for class 1: 0.70

Accuracy Score

The accuracy score of the RandomForestClassifier model is approximately 55.01%.

The model demonstrates some predictive capability, particularly in predicting class 1. However, it performs poorly in predicting class -1, as evidenced by its low precision, recall, and F1-score for that class. Further optimization and feature engineering may be necessary to improve the model's performance.

Comparison of LRM and RF



Accuracy Score:

- RF: Approximately 55.01%
- LRM: Approximately 55.46%

Summary:

- Both models show similar accuracy scores, around 55%, indicating that they correctly predict class labels for about half of the instances in the test set.

- The Logistic Regression Model performs slightly better in terms of precision, recall, and F1-score for class -1 compared to the Random Forest Model.
- However, both models exhibit poor performance in predicting class -1, as evidenced by their low precision, recall, and F1-score for that class. Further optimization and feature engineering may be necessary to improve the models' performance, particularly in predicting class -1.

Time Series Analysis of Bitcoin Price Data

Head of the time series data of Bitcoin closing prices:

```
          Date       Close
14 2015-12-03  361.045990
15 2015-12-04  363.183014
16 2015-12-05  388.949005
17 2015-12-06  388.782990
18 2015-12-07  395.536011
```

Testing and training datasets:

```
Train Data Head:
          Date       Close
14 2015-12-03  361.045990
15 2015-12-04  363.183014
16 2015-12-05  388.949005
17 2015-12-06  388.782990
18 2015-12-07  395.536011

Train Data Tail:
            Date         Close
1380 2019-08-30   9598.173828
1381 2019-08-31   9630.664063
1382 2019-09-01   9757.970703
1383 2019-09-02  10346.760742
1384 2019-09-03  10623.540039
```

```
Test Data Head:
            Date         Close
1385 2019-09-04  10594.493164
1386 2019-09-05  10575.533203
1387 2019-09-06  10353.302734
1388 2019-09-07  10517.254883
1389 2019-09-08  10441.276367
```

Simple Moving Average Method

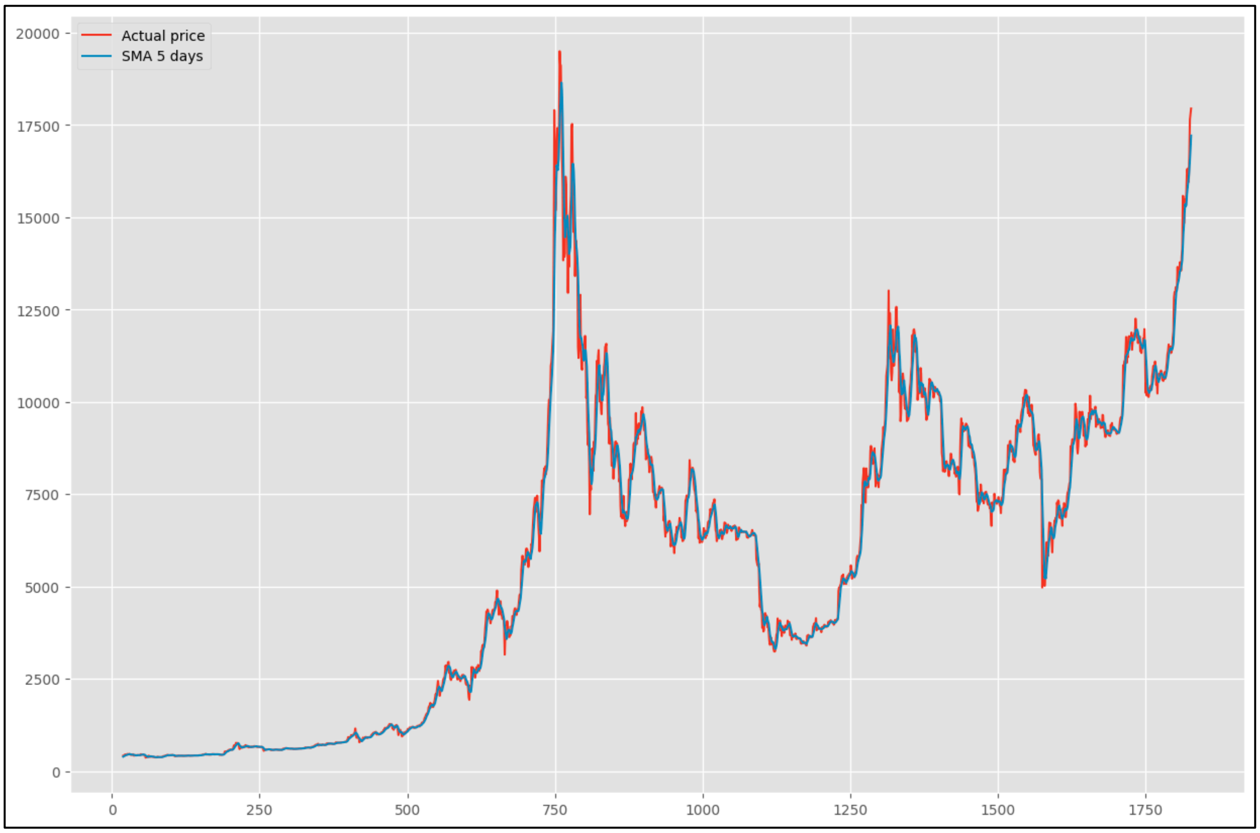
The Simple Moving Average (SMA) method is a commonly used technique in time series analysis for smoothing out fluctuations in data and identifying trends over a specific period. It calculates the average of a specified number of data points over that period and updates this average as new data becomes available.

Here we are taking the average of the closing prices for the past five days.

Head of the time series table with the SMA_5 calculations:

	Date	Close	SMA_5
19	2015-12-08	415.562988	390.4
20	2015-12-09	417.562988	401.3
21	2015-12-10	415.479004	406.6
22	2015-12-11	451.937988	419.2
23	2015-12-12	434.997009	427.1

Plot of SMA price predictions vs. the actual bitcoin prices



In the graph, the price of Bitcoin is represented by the blue line, and the 5-day SMA is represented by the orange line. Here are some observations we can make from the graph:

- The plot exhibits the highly volatile nature of Bitcoin prices during this period. The actual price (red line) fluctuates rapidly, with multiple sharp spikes and troughs.
- The 5-day SMA (blue line) helps smooth out some of these short-term fluctuations, providing a clearer view of the overall trend.

- Over the entire time period shown, both the actual price and the SMA demonstrate an overall upward trend, with a few notable sharp rises and subsequent declines.
- The most prominent spike occurred around the end of 2017/early 2018, where the actual price reached exceptionally high levels before plummeting shortly after.

Root Mean Square Error

```
Root Mean Square Error (SMA):  338.67514051732445
```

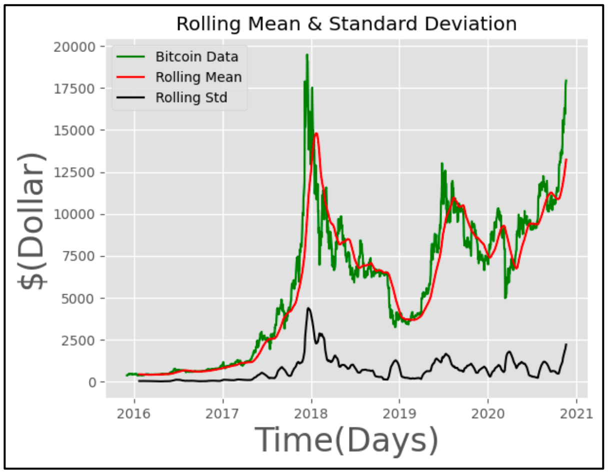
The Root Mean Square Error (RMSE) for the Simple Moving Average (SMA) is a measure of the differences between values predicted by the SMA model and the actual values observed in the data.

Our RMSE value of approximately 338.68 suggests that, on average, the SMA model's predictions deviate from the actual Bitcoin prices by around $338.68. Lower RMSE values indicate better model performance in accurately predicting the observed data.

Augmented Dicky Fuller (ADF) Test

In the context of Bitcoin time series data analysis, the Dickey-Fuller Test is used to assess whether the data is stationary or not. Stationarity implies that the statistical properties of the time series, such as mean and variance, remain constant over time. If the time series is non-stationary, it may exhibit trends or seasonality, making it challenging to model accurately.

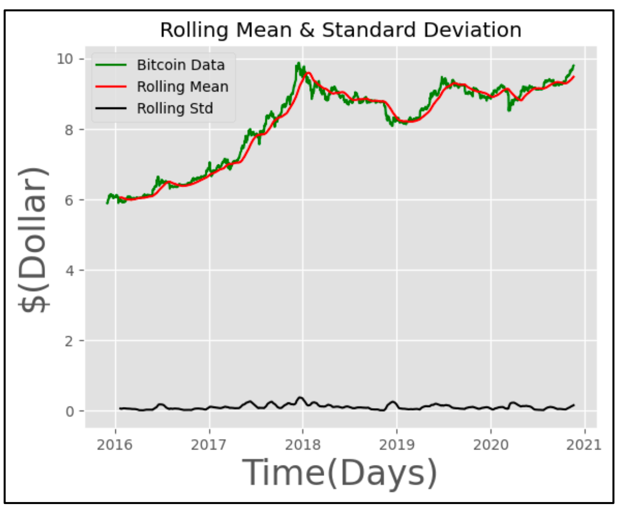
Original Time Series




```
Results of Dickey-Fuller Test:
Test Statistic                   -1.027795
p-value                           0.742992
#Lags Used                       20.000000
Number of Observations Used    1793.000000
Critical Value (1%)              -3.434002
Critical Value (5%)              -2.863153
Critical Value (10%)             -2.567629
```

- The Dickey-Fuller Test results for the original Bitcoin daily price data showed a high p-value (0.743), indicating that the series is likely non-stationary. Consequently, the null hypothesis of the test, which assumes non-stationarity, cannot be rejected.
- As the series is non-stationary, it is unsuitable for modeling using certain techniques like ARIMA (AutoRegressive Integrated Moving Average).

Logarithmic Transformation

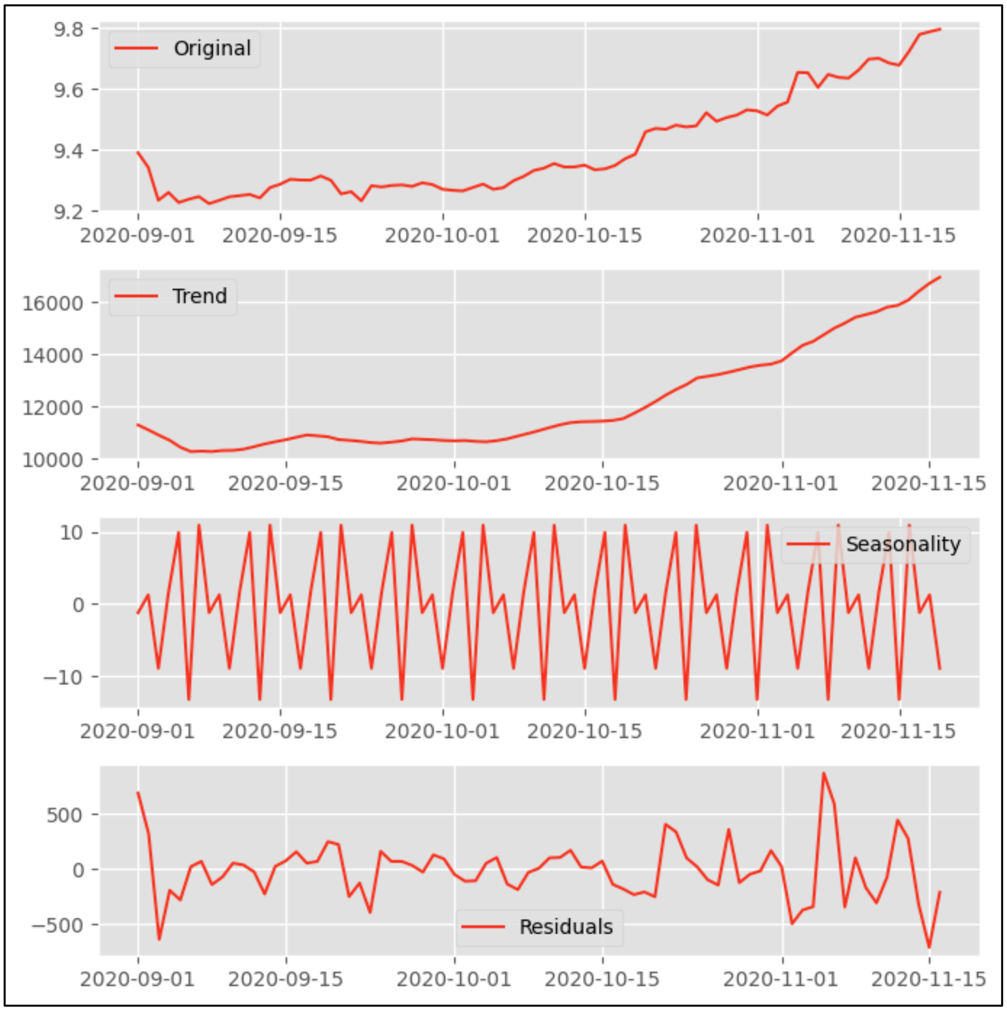


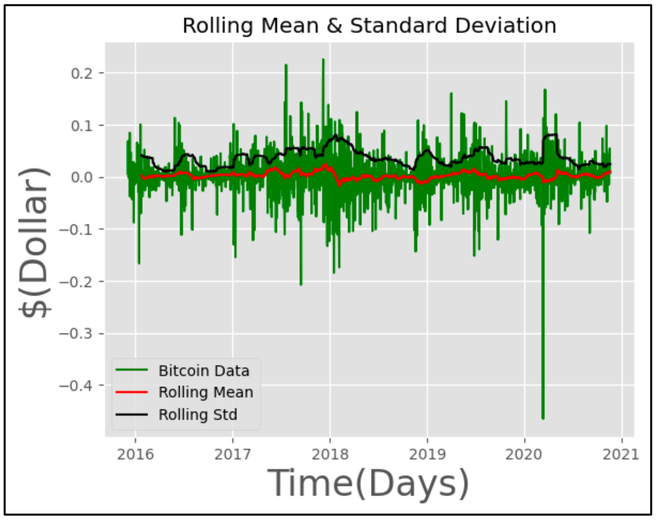

```
Results of Dickey-Fuller Test:
Test Statistic                   -1.360976
p-value                           0.600835
#Lags Used                        0.000000
Number of Observations Used    1813.000000
Critical Value (1%)              -3.433962
Critical Value (5%)              -2.863136
Critical Value (10%)             -2.567619
```

- To address the non-stationarity, the original time series data was logarithmically transformed.
- However, even after transformation, the p-value remained high (0.601), suggesting that the series is still non-stationary.

Differencing

Decomposition of the Time Series data:



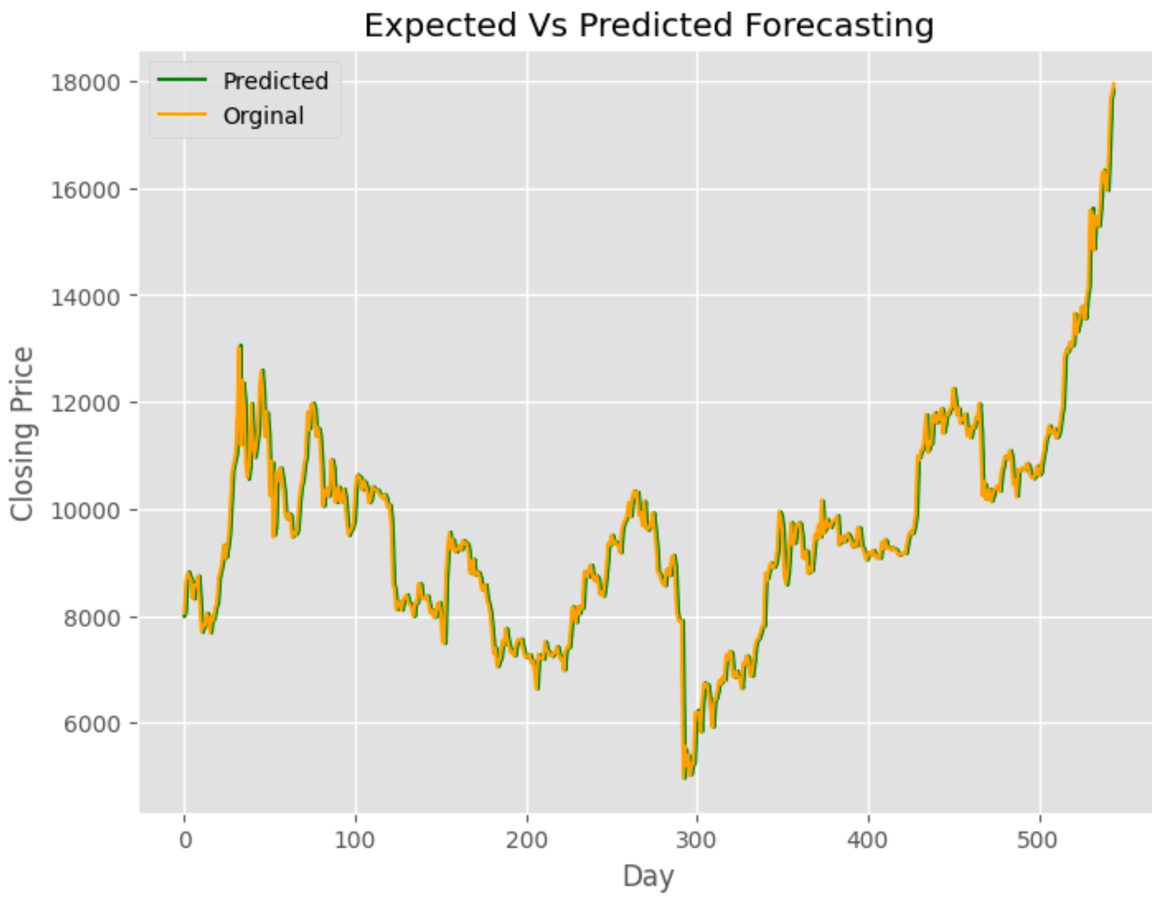



```
Results of Dickey-Fuller Test:
Test Statistic                  -29.564591
p-value                           0.000000
#Lags Used                        1.000000
Number of Observations Used    1811.000000
Critical Value (1%)              -3.433966
Critical Value (5%)              -2.863137
Critical Value (10%)             -2.567620
```

- To make the series stationary, differencing was applied to the logarithmically transformed data.
- By computing the difference between each observation and its lagged value, the trend component was effectively removed from the time series.
- The Dickey-Fuller Test conducted on the differenced series yielded a significantly lower p-value (0.000), indicating stationarity.
- The decomposition of the time series further confirmed the removal of trend and seasonality, making it suitable for modeling, such as with the ARIMA model.

In summary, the process involved transforming the original Bitcoin daily price data to achieve stationarity, which is essential for accurate modeling and forecasting using techniques like ARIMA. The final differenced series exhibited stationarity, making it suitable for further analysis and modeling.

Auto Regressive Integrated Moving Average (ARIMA) Model




```
Mean Error in Predicting Test Case Articles : 2.394227  %
```

The plot compares the predicted values from the ARIMA model with the original or expected values, for Bitcoin prices.

The y-axis represents the closing price, while the x-axis represents the number of days. The red line depicts the predicted values from the ARIMA model, and the yellow line represents the original or expected values.

The ARIMA model used has an order of (2, 1, 0), which means it has two autoregressive terms, one order of differencing, and no moving average terms.

The mean squared error (MSE) of the model is given as 2.394227%, which indicates the average squared difference between the predicted and expected values. A lower MSE generally indicates a better fit of the model to the data. The MSE for our model appears reasonably good.

From the plot, it can be observed that the predicted values from the ARIMA model generally follow the overall trend of the original data, capturing the major fluctuations and patterns.

However, there are some deviations between the two lines, particularly during periods of high volatility or sharp changes in the original data.

Overall, the plot allows for a visual comparison between the ARIMA model's predictions and the actual expected values, providing insight into the performance and accuracy of the model in forecasting Bitcoin prices.

Conclusions

1. Bitcoin price prediction using machine learning models remains a challenging task due to the high volatility and unpredictable nature of cryptocurrency markets.
2. The logistic regression and random forest classification models demonstrated modest predictive capabilities, correctly classifying around 55% of the instances in the test set. However, their performance in predicting price decreases (class -1) was poor, with low precision, recall, and F1-scores.
3. Time series analysis techniques, such as simple moving averages (SMA) and the ARIMA model, can capture the overall trend and patterns in Bitcoin prices, but may struggle with accurately predicting sharp fluctuations or sudden price movements.
4. The ARIMA (2, 1, 0) model achieved a reasonably good mean squared error (MSE) of 2.394227%, indicating a reasonable fit for forecasting Bitcoin prices, given the asset's volatility.
5. Feature engineering and the selection of relevant technical indicators played a crucial role in the performance of the machine learning models, as evidenced by the correlation analysis and feature importance scores.
6. Continuous monitoring and updating of the models with the latest data is necessary to maintain accurate predictions, as the cryptocurrency market is highly dynamic and influenced by various external factors.
7. Future work could explore ensemble models, incorporating additional data sources (e.g., sentiment analysis, news, economic indicators), and advanced deep learning techniques to improve the predictive accuracy of Bitcoin price movements.

In summary, our project highlights the challenges and potential approaches for Bitcoin price prediction, while also acknowledging the limitations and the need for continued research and model refinement in this rapidly evolving domain.

References

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