International Journal For Recent Developments in Science & Technology
2581-4575
Crossref
A Peer Reviewed Research Journal

TIME SERIES ANALYSIS FOR PUBLIC DECENTRALIZED LEDGER PRICE PREDICTION WITH EDA

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ABSTRACT

A "public decentralized ledger" generally refers to a blockchain, which is a distributed and immutable digital ledger that records transactions across a network of computers in a secure and transparent manner. Blockchain technology underpins cryptocurrencies like Bitcoin, and it is also being explored for various other applications beyond cryptocurrencies. Bitcoin stands out as the most valuable cryptocurrency globally, being traded on numerous exchanges and accepted in various currencies. Its market capitalization currently amounts to a staggering $9 billion, with an impressive daily transaction volume of over 250,000. While traditional financial markets have been extensively studied for prediction purposes, Bitcoin offers a unique challenge due to its status as a time series prediction problem within a rapidly evolving market. Given its unique characteristics, traditional methods struggle to provide accurate predictions. As a result, machine learning emerges as a promising solution due to its proven performance in similar domains. Therefore, this work utilizes time series analysis to identify patterns in Bitcoin's price movement and forecast closing prices for the upcoming days, employing the ARIMA model for this purpose. By applying machine learning techniques to the analysis of financial data, we hope to gain valuable insights into the future of Bitcoin prices, which can have both direct and indirect effects on the global economy.

Keywords: Bitcoin, predictive analytics, time series analysis, ARIMA model,

1. Introduction

Time series analysis for public decentralized ledger price prediction, often focused on cryptocurrencies like Bitcoin, Ethereum, and others, is a crucial and rapidly evolving field with significant implications for investors, traders, businesses, and the broader financial landscape. This analytical approach involves the study of historical price data, transaction volumes, and other relevant metrics to make informed predictions about the future prices of these digital assets. One of the key motivations behind this research is the highly volatile nature of cryptocurrency markets. Cryptocurrencies are known for their price fluctuations, which can be influenced by a myriad of factors, including market sentiment, regulatory changes, technological developments, and macroeconomic events. As a result, accurate price predictions are essential for investors and traders to make informed decisions and manage risks effectively. Time series analysis techniques, such as autoregressive integrated moving average (ARIMA) models, exponential smoothing methods, and machine learning algorithms like recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, are applied to cryptocurrency price data to capture patterns and trends. These models can identify seasonality, cyclicality, and irregularities in the price movements, enabling the creation of predictive models. Furthermore, the decentralized and transparent nature of blockchain technology, which underlies most cryptocurrencies, provides a wealth of data for analysis. Public ledger data, including transaction histories and on-chain metrics, can be integrated into time series models to enhance their predictive accuracy. This comprehensive approach allows analysts to factor in not only market sentiment but also on-chain fundamentals.

The potential applications of time series analysis for decentralized ledger price prediction are diverse. Investors and traders can use these predictions for trading strategies and risk management. Businesses can incorporate price forecasts into financial planning and investment decisions, while policymakers and regulators can gain insights into the market dynamics to make informed decisions regarding regulatory frameworks.

However, it's important to note that the cryptocurrency market is still relatively young and characterized by a high degree of uncertainty. Predicting prices accurately remains a challenging task, and researchers continuously work to refine their models and incorporate new data sources for improved forecasting. Additionally, the market's susceptibility to sudden, unforeseen events underscores the need for a cautious and data-driven approach to cryptocurrency investment and decision-making. Nevertheless, time series analysis for decentralized ledger price prediction represents a valuable tool in navigating the evolving landscape of digital assets and blockchain technology.

2. Literature Survey

The current monetary system is predicated upon the use of fiat currency, which possesses several advantages such as divisibility, transferability, durability, and scarcity [1]. However, this system has several drawbacks, including the absence of a tangible backing for currency and government control over the money supply, which can result in issues such as hyperinflation and income inequality [2]. Furthermore, the current ledgers used to record transactions are susceptible to manipulation and violations, and transactions are often conducted through intermediaries such as financial institutions and credit card companies, leading to high costs and longer transfer times. This can lead to a loss of control and ownership of data by individuals. Despite these limitations, the current financial system is still trusted by the general public due to the backing of government regulations and legal contracts. However, historical instances of trust breaches, such as the dot-com in the 1990s and real estate bubbles in 2008, have resulted in significant financial losses [3]. Thus, it is crucial to develop a new model that can effectively establish trust among all stakeholders in the financial system. In October 2008, an individual or group operating under the pseudonym Satoshi Nakamoto [4] introduced a revolutionary system known as blockchain technology, which was accompanied by the invention of the first digital currency, BTC. This system facilitates peer-to-peer (P2P) monetary transactions over the public internet without the need for intermediaries and has emerged as an important asset class in the international financial landscape [5]. It is now being studied by academic institutions, government agencies, media outlets, and the general public.

Cryptocurrencies are a new type of digital currency that uses cryptography to safeguard the transaction process and prevent counterfeiting [6]. One important fact about cryptocurrencies is that they are independent of traditional banks, as they are not issued by any central authority, which makes them distinguishable from the traditional centralized currencies. Since the blockchain is essential to cryptocurrencies, it is stated that cryptocurrencies share all the characteristics of the blockchain. For instance, BTC provides people with a secure way to conduct digital transactions pseudo-anonymously, which makes it easy to know the patron and recipient in its transactions.

The blockchain technology has gained attention from governments worldwide, leading to calls for regulation in the cryptocurrency sector. The motivation behind this governmental interest stems from concerns related to crime, sovereignty, and opportunities. However, the BTC network operates on Proof-of-Work (PoW) and Proof-of-Stake (PoS) hybrid schemes, which demand high energy consumption in their computational processes to secure the network [7]. Proof-of-work is a consensus algorithm used in some blockchain systems, such as BTC that requires users to perform a certain amount of computational work to validate transactions and add them to the blockchain.[8].

Among the numerous cryptocurrencies available, BTC stands out as the most well-known and widely used. This is due to its early arrival in the market and its status as the first decentralized cryptocurrency, which helped it gain a significant amount of attention and popularity. Over time, this has established BTC as the leading currency in the crypto-market. Other popular cryptocurrencies include ETH, LTC, and Ripple (XRP). Ethereum is considered the second largest blockchain platform after BTC, and it enables the creation of smart contracts, decentralized apps, and decentralized organizations (DAOs). The primary goal of LTC's introduction to the blockchain was to prioritize transaction speed, making it a popular choice for time-sensitive mining processes.

Ref. [9] highlights that the competition between Bitcoin and other cryptocurrencies is a positive development, as it drives technological and security advancements within the industry. The relationship and interaction between big data and cryptocurrency have been studied in [10]. Big data refer to the vast amounts of data generated by various sources such as social media, sensors, and mobile devices. These data are typically unstructured and challenging to process using traditional methods. The digitization and high-end technology of the past decade have undergone significant changes in computing and communication platforms.

This progression has resulted in the widespread collection and implementation of big data analytics into various aspects of daily life, as stated in [11]. The Internet of Things (IoT) and the use of big data analytics are transforming communication infrastructure and shaping the way data are processed and analyzed. They both rely on advanced technology, including Artificial Intelligence (AI) and machine learning, to manage large amounts of data. The connection between big data and cryptocurrencies is close, as blockchain technology, which is used in cryptocurrency management, to leverage big data techniques for secure and decentralized data storage and processing.

Additionally, big data analytics can be used to study cryptocurrency market trends and detect fraudulent activities, thereby strengthening the cryptocurrency market. The interdependence between big data and cryptocurrencies creates growth opportunities for both.

Machine learning is an artificial intelligence tool that uses past data to predict the future. From this aspect, by training a machine learning model on historical cryptocurrency price data, it may be possible to predict future price movements with some degree of accuracy. Prior research has shown that machine learning based techniques have a number of advantages over traditional forecasting models, including the ability to give results that is nearly or exactly the same as the actual result while also improving the accuracy of the results [12]. There are a number of different machine learning techniques that can be used for this purpose, including decision trees, support vector machines (SVM), and neural networks (NN). The authors of [13] reveal that inclusion of cryptocurrencies in multi-asset portfolios improves the effectiveness of the portfolio in different ways. First, it enhances the minimum variance of the portfolio and also moves the efficient frontier into a better position. Furthermore, the standard deviation of the portfolio decreases and the Sharpe ratio increases by including cryptocurrency assets into the portfolios.

3. EXISTING SYSTEM

3.1 STL Analysis

Seasonal Decomposition of Time Series (STL) is a powerful and widely used method for decomposing time series data into its underlying components, which typically include seasonal, trend, and remainder (or residual) components. This decomposition helps analysts and researchers understand the underlying patterns and structures within the time series data. Let's break down the key components and steps of STL in detail:

1. **Seasonal Component**: This component represents the repetitive patterns or fluctuations in the data that occur at regular intervals. These intervals could be daily, monthly, quarterly, or any other regular time unit. The seasonal component is often the result of factors like weather, holidays, or other recurring events. STL aims to extract this component from the data.
2. **Trend Component**: The trend component represents the long-term direction or overall tendency in the data. It helps identify whether the data is increasing, decreasing, or remaining relatively constant over time. Trends can be linear or nonlinear, and STL is designed to capture them accurately.
3. **Remainder (Residual) Component**: The remainder component accounts for the noise or irregularities in the data that cannot be explained by the seasonal and trend components. It includes random fluctuations, measurement errors, and other sources of variation.

The key steps involved in Seasonal Decomposition of Time Series (STL) are as follows:

Data Smoothing: STL begins by applying a smoothing process to the original time series data. Smoothing helps to reduce the impact of noise and highlight the underlying patterns. Various smoothing techniques can be used, such as moving averages or exponential smoothing.

Seasonal Component Extraction: After smoothing the data, STL identifies and extracts the seasonal component. This is typically done using a seasonal decomposition algorithm like LOESS (Locally Weighted Scatterplot Smoothing) or other robust methods. These algorithms adapt to the local patterns in the data, making them suitable for capturing complex seasonal variations.

Trend Component Extraction: Once the seasonal component is separated, STL proceeds to extract the trend component. It does this by removing the seasonal component from the smoothed data. The resulting data should primarily represent the long-term trend.

Remainder Calculation: After extracting the seasonal and trend components, the remainder component is calculated by subtracting the seasonal and trend components from the original data. This residual component should ideally represent the random and unpredictable fluctuations in the data.

Visualization and Analysis: The decomposed components—seasonal, trend, and remainder—are usually visualized separately to gain insights into the time series data. Analysts can examine each component's characteristics, detect anomalies, and make forecasts or predictions based on the decomposed components.

3.2 Drawbacks

While Seasonal Decomposition of Time Series (STL) is a powerful method for extracting underlying components from time series data, it also has some drawbacks and limitations that researchers and analysts should be aware of:

- **Complexity of Parameters**: STL requires the selection of various parameters, such as the degree of smoothing and the robustness parameter for seasonal decomposition. Choosing

2581-4575

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appropriate values for these parameters can be challenging and may require experimentation. Poor parameter choices can lead to inaccurate results.

- **Sensitivity to Outliers**: STL can be sensitive to outliers in the data. Outliers can disproportionately affect the smoothing and decomposition processes, potentially leading to inaccurate results, especially in data with extreme values.
- **Handling Missing Data**: STL assumes that time series data is complete and evenly spaced. Handling missing data can be challenging, and the method may require data imputation or interpolation, which can introduce additional uncertainties.
- **Difficulty in Modeling Complex Trends**: While STL is effective at capturing linear and relatively simple trends, it may struggle to model complex nonlinear trends accurately. In such cases, alternative decomposition methods or more sophisticated time series modeling techniques may be more appropriate.
- **Lack of Causality**: STL is a descriptive method that decomposes time series data into components but does not offer insights into causality or underlying processes driving the observed patterns. It can help identify correlations but not causation.
- **Inability to Capture Structural Changes**: If there are significant structural changes in the data over time (e.g., regime shifts or abrupt changes in trends), STL may not handle them well, as it assumes that the seasonal and trend components are relatively stable over the entire time series.
- **Data Stationarity Assumption**: STL assumes that the data is stationary, meaning that the statistical properties (e.g., mean and variance) do not change over time. In practice, many real-world time series data are non-stationary, requiring preprocessing or transformations before applying STL.
- **Computational Resources**: STL can be computationally intensive, particularly for large datasets or high-frequency time series. This may limit its applicability in real-time or resource-constrained environments.
- **Subjectivity in Parameter Tuning**: Parameter tuning in STL can be somewhat subjective and dependent on the analyst's judgment. This subjectivity can introduce variability in the results, particularly when different analysts choose different parameter values.

4. PROPOSED SYSTEM

4.1 Overview

In summary, this research work involves a systematic analysis of time series data, including preprocessing, trend and seasonality analysis, model selection (ARIMA), and forecasting. The goal is to provide predictions for the future price of the public decentralized ledger, which can be valuable for investment decisions and market analysis in the context of cryptocurrencies. Figure 1 shows the proposed system model. The detailed operation illustrated as follows:

Step 1: EDA and Preprocessing: The research starts with Exploratory Data Analysis (EDA) and preprocessing. This involves cleaning the dataset, handling missing values, and possibly converting data into a suitable time series format. EDA is conducted to understand the data's characteristics, visualize trends and patterns, and identify potential outliers.

Step 2: Trend & Seasonality: After preprocessing, the next step is to analyze the time series for trends and seasonality. Trend analysis helps identify long-term patterns in the data, such as upward or downward trends. Seasonality analysis helps identify recurring patterns or cycles within the data, which may be daily, weekly, or annual.

Step 3: Moving Average: Moving averages are calculated to smooth out short-term fluctuations and highlight underlying trends. Different types of moving averages, such as simple moving averages (SMA) and exponential moving averages (EMA), may be used to analyze and visualize the data.

Step 4: Rolling Mean & Standard Deviation: Rolling mean and standard deviation are calculated to assess how the statistical properties of the time series change over time. This helps in understanding whether the data exhibits volatility or stability.

Step 5: Dickey-Fuller Test: The Dickey-Fuller test is employed to check the stationarity of the time series data. Stationarity is a critical assumption for many time series models. If the data is non-stationary, transformations or differencing may be applied to make it stationary.

Step 6: ACF & PACF Test: The AutoCorrelation Function (ACF) and Partial AutoCorrelation Function (PACF) are used to identify potential lag values for autoregressive (AR) and moving average (MA) components in an ARIMA model. These functions provide insights into the data's autocorrelation structure.

Step 7: ARIMA Model: Based on the results of the ACF and PACF tests, an ARIMA (AutoRegressive Integrated Moving Average) model is selected and fitted to the time series data. The ARIMA model combines autoregressive (AR), differencing (I), and moving average (MA) components to capture the underlying patterns in the data.

Step 8: Forecasting Results: Finally, the ARIMA model is used to make predictions for future values of the public decentralized ledger price in Satoshi. The forecasting results are evaluated for accuracy, and measures such as Mean Absolute Error (MAE) or Root Mean Squared Error (RMSE) may be used to assess the model's performance.

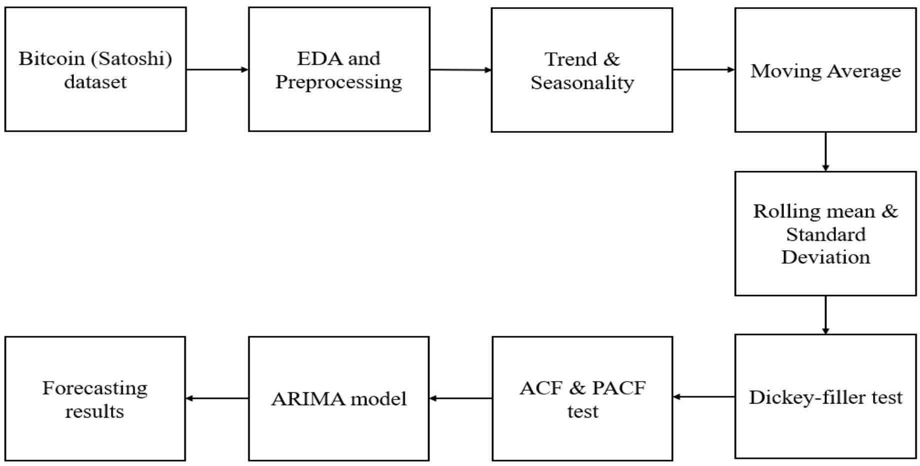

Fig. 1: Block diagram of proposed system.

4.3 Data Preprocessing

Data pre-processing is a process of preparing the raw data and making it suitable for a machine learning model. It is the first and crucial step while creating a machine learning model. When creating a machine learning project, it is not always a case that we come across the clean and formatted data. And while doing any operation with data, it is mandatory to clean it and put in a formatted way. So, for this, we use data pre-processing task. A real-world data generally contains noises, missing values, and maybe in an unusable format which cannot be directly used for machine learning models. Data pre-processing is required tasks for cleaning the data and making it suitable for a machine learning model which also increases the accuracy and efficiency of a machine learning model.

The dataset is filtered to include data from January 1, 2001, to January 1, 2017, using date comparisons. The dataset is reset to have a new index and the 'index' column is dropped. The cleaned dataset is saved to a new CSV file named 'Rainfall.csv'. The cleaned dataset 'Rainfall.csv' is loaded into a DataFrame named 'Rainfall'. Missing values in the dataset are filled with the mean value of the respective columns.

4.3 EDA

This work provides a step-by-step walkthrough of a time series analysis, from data cleaning and visualization to ARIMA modeling and forecasting. It is used to forecast annual rainfall based on historical data, with a focus on visualizing trends and uncertainties in the predictions.

Creating a Time Series: A time series is created using the 'ANNUAL' column from the 'Rainfall' DataFrame. A plot is generated to visualize the annual rainfall data over time using plt.plot().

Applying Moving Averages: Four different moving averages are applied to the time series: 4-month, 12-month, 16-month, and 60-month rolling means. These moving average time series are plotted to analyze trends in the data.

Augmented Dickey-Fuller Test: The Augmented Dickey-Fuller test is applied to test the stationarity of the time series data. The results are printed, including the test statistic, p-value, number of lags used, and the number of observations used.

ACF and PACF Plots: Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots are created to identify potential parameters for an ARIMA model. These plots help in determining the orders (p, d, q) for the ARIMA model.

ARIMA Model Selection: Different combinations of p, d, and q parameters are tested using nested loops. The loop iterates through all possible combinations of seasonal orders to find the best-fitting ARIMA model based on the lowest Akaike Information Criterion (AIC). The selected ARIMA model parameters are printed.

Fitting the ARIMA Model: The best-fitting ARIMA model is created and fitted to the time series data using the sm.tsa.statespace.SARIMAX() function.

Dynamic Forecasting: Dynamic forecasting is performed using the best-fitting ARIMA model. The model is set to predict future values beyond the observed data. Confidence intervals for the forecasts are calculated.

Visualization of Forecasts: The code generates plots to visualize the dynamic forecasts, including confidence intervals. The Mean Squared Error (MSE) of the forecasts is calculated and printed.

Forecasting for Future Periods: The code forecasts annual rainfall for future periods (36 months) using the best-fitting ARIMA model. Confidence intervals (95% and 99%) for the forecasts are calculated.

Plotting the Forecast: The code plots the observed data (annual rainfall) along with the forecasted values and their confidence intervals for future periods.

5. RESULTS AND DISCUSSIONS

Figure 2 represents a sample dataset used for predicting the price of Satoshi. It likely includes columns like Date, Open, High, Low, Close, Volume, and Market Cap, providing historical data points for analysis. Figure 3 displays the mean Bitcoin price for each quarter. It likely shows a line plot or bar graph illustrating the average price of Bitcoin over distinct quarters of time. Figure 4 shows the image demonstrates a time series plot with three overlaid lines. The blue line represents the original data, the red line indicates the rolling mean, and the green line represents the rolling standard deviation. This visualization helps assess the stationarity of the time series data.

	Date	Open	High	Low	Close	Volume	Market Cap
0	Jul 31, 2017	2763.24	2889.62	2720.61	2875.34	860,575,000	45,535,800,000
1	Jul 30, 2017	2724.39	2758.53	2644.85	2757.18	705,943,000	44,890,700,000
2	Jul 29, 2017	2807.02	2808.76	2692.80	2726.45	803,746,000	46,246,700,000
3	Jul 28, 2017	2679.73	2897.45	2679.73	2809.01	1,380,100,000	44,144,400,000
4	Jul 27, 2017	2538.71	2693.32	2529.34	2671.78	789,104,000	41,816,500,000
...	...	...	...	...	...	...	...
1551	May 02, 2013	116.38	125.60	92.28	105.21	-	1,292,190,000
1552	May 01, 2013	139.00	139.89	107.72	116.99	-	1,542,820,000
1553	Apr 30, 2013	144.00	146.93	134.05	139.00	-	1,597,780,000
1554	Apr 29, 2013	134.44	147.49	134.00	144.54	-	1,491,160,000
1555	Apr 28, 2013	135.30	135.98	132.10	134.21	-	1,500,520,000

1556 rows × 7 columns

Figure 2: sample dataset used for Satoshi price prediction.

Figure 3: Mean Bitcoin price for each quarter

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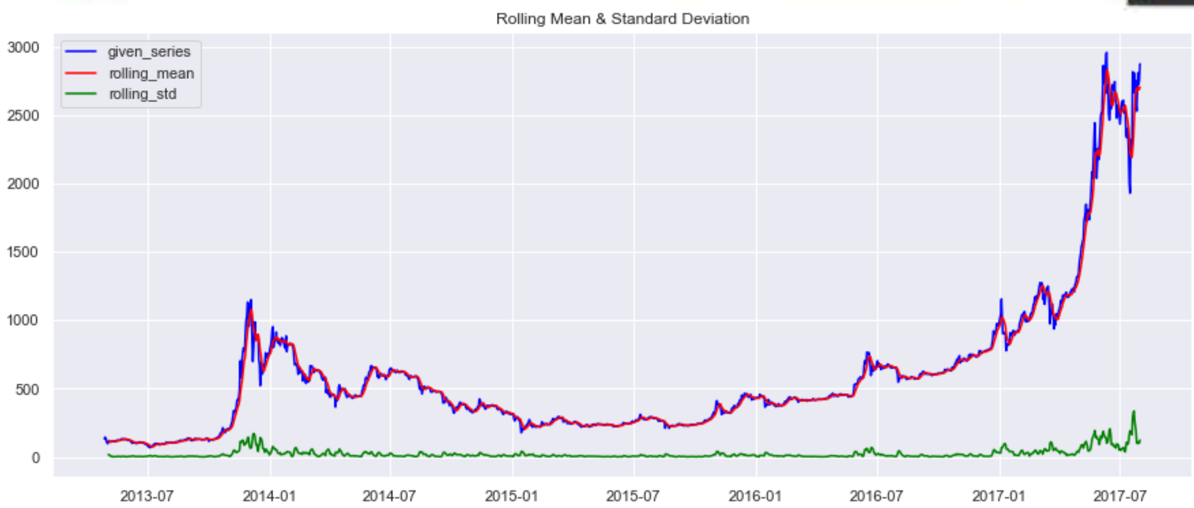

Figure 3: Rolling Mean and Standard Deviation

Figure 4 shows the image displays a time series plot with three overlaid lines: one representing the original data in blue, a red line depicting the rolling mean, and a green line representing the rolling standard deviation.

Figure 5: The plot displays a time series data (in blue) after applying a rolling average (in red) with a window size of 7, providing a smoothed representation of the original data.

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                              ARIMA Model Results
==============================================================================
Dep. Variable:                D.Close   No. Observations:                 1555
Model:                 ARIMA(2, 1, 0)   Log Likelihood                2704.690
Method:                       css-mle   S.D. of innovations              0.042
Date:                Mon, 28 Aug 2023   AIC                          -5401.380
Time:                        13:59:58   BIC                          -5379.984
Sample:                    04-29-2013   HQIC                         -5393.424
                         - 07-31-2017
================================================================================
                  coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
const           0.0020      0.001      1.908      0.056   -5.37e-05       0.004
ar.L1.D.Close  -0.0011      0.025     -0.044      0.965      -0.051       0.049
ar.L2.D.Close  -0.0435      0.025     -1.715      0.086      -0.093       0.006
                                    Roots
=============================================================================
                  Real          Imaginary           Modulus         Frequency
-----------------------------------------------------------------------------
AR.1           -0.0127           -4.7948j            4.7948           -0.2504
AR.2           -0.0127           +4.7948j            4.7948            0.2504
-----------------------------------------------------------------------------
```

Figure 6: ARIMA Model results

Figure 5 illustrates a time series dataset (in blue) after applying a rolling average (in red) with a window size of 7. The rolling average provides a smoothed representation of the original data, aiding in visualizing trends while reducing short-term fluctuations. Figure 6 showcases the results of an ARIMA model. It may include plots of the observed data, the fitted values from the ARIMA model, and potentially the forecasted values for future time points. Figure 7 displays the Residual Sum of Squares (RSS), which is a metric used to evaluate the performance of a predictive model. A lower RSS indicates a better fit of the model to the data, signifying its effectiveness in capturing underlying patterns or trends.

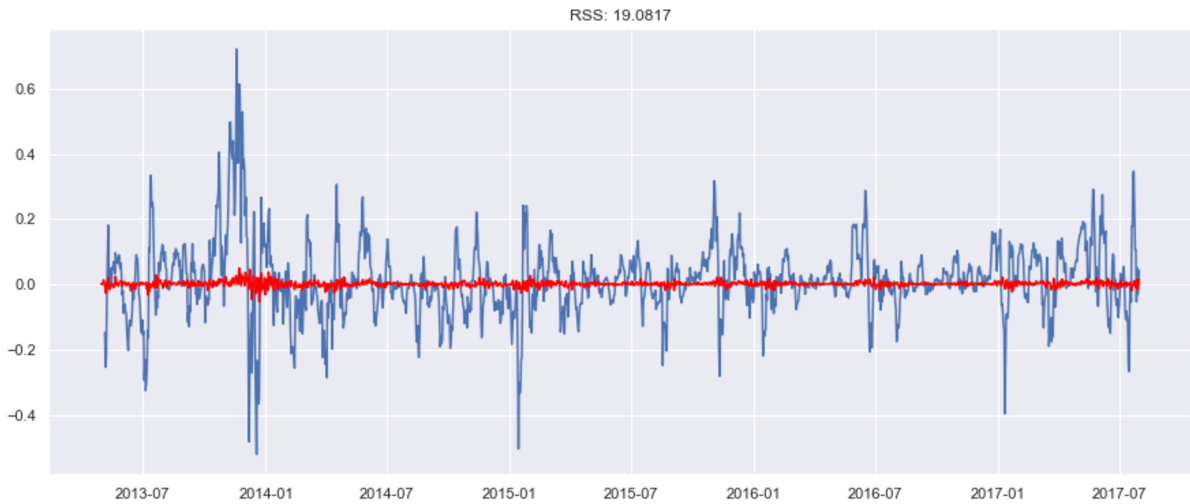

Figure 7: displays the Residual Sum of Squares (RSS) to evaluate model performance.

6. CONCLUSION AND FUTURE SCOPE

In conclusion, this study embarked on the challenging task of predicting the price of Bitcoin, a highly volatile and rapidly evolving cryptocurrency, by employing time series analysis with an ARIMA model. Traditional financial prediction methods often fall short when applied to Bitcoin due to its unique characteristics and lack of seasonality. However, through the application of machine learning techniques, we have explored patterns and trends within Bitcoin's price data, striving to gain insights into its future price movements. While the results may not always provide perfect predictions, they underscore the potential of machine learning models in understanding and forecasting cryptocurrency markets.

The future scope of this research holds several exciting possibilities. Firstly, the incorporation of more advanced machine learning algorithms and deep learning models could enhance the accuracy of Bitcoin price predictions. Additionally, incorporating sentiment analysis of news, social media, and market sentiment could provide valuable insights into market dynamics and help improve forecasting accuracy. Furthermore, expanding the analysis to consider other cryptocurrencies and their interrelationships with Bitcoin could provide a more comprehensive view of the cryptocurrency market. Another avenue for future exploration is the development of real-time prediction models that adapt to changing market conditions, as cryptocurrency markets are highly influenced by breaking news and events. Moreover, the integration of blockchain analytics and on-chain data into the prediction process could offer unique insights into Bitcoin's price movements. Lastly, this research can extend its focus to explore the broader economic and regulatory implications of Bitcoin price predictions. As Bitcoin continues to gain prominence in global financial markets, accurate forecasting becomes not only a financial asset but also a tool for policy-makers and investors. In summary, the future scope of this study lies in the refinement of prediction models, the incorporation of additional data sources, and the exploration of the broader implications of Bitcoin price forecasts in the context of the global economy and financial markets.

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