Predicting Cryptocurrency Prices Using Machine Learning Algorithms

Final Report

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Abstract

Title:

Predicting Cryptocurrency Prices Using Machine Learning Algorithms.

With the advancement and modernization of technology, various industries are rapidly evolving to adapt to the latest global trends. One such change that has been taking place is the increasing prevalence of cryptocurrency as a medium of exchange and investment. This shift towards digital currencies represents a significant departure from traditional fiat currencies and stock exchange practices and It's the time to understand what digital money really means for everyone's future. I would like to direct the readers to an engaging article by Alex Hern that delves into the world of Bitcoin and cryptocurrencies, discussing their significance as digital currencies and their potential impact on our future. [1]

I have reviewed the article and identified five key takeaways:

1. Cryptocurrencies, like Bitcoin, are a novel form of decentralized currency that allows individuals to exchange funds without the involvement of traditional financial institutions. This has the potential to disrupt the conventional banking system and reshape the financial landscape.
2. Blockchain technology forms the underlying structure for cryptocurrencies and functions as a decentralized ledger that logs transactions and is upheld by a group of computers. Its versatility extends far beyond finance and encompasses various areas, such as supply chain management, voting systems, and identity authentication.
3. Cryptocurrencies have been notorious for their high degree of volatility, with their worth fluctuating dramatically. This has raised concerns about their stability and long-term viability as a store of value.
4. Due to their anonymous and decentralized nature, cryptocurrencies have been associated with unlawful activities such as drug trafficking and money laundering. Consequently, governments and regulatory bodies have been closely monitoring their usage.
5. The advent of cryptocurrencies has ignited a broader discussion about the role of technology in society and its potential to disrupt established power structures. Although it remains to be seen how this will unfold, it is evident that cryptocurrencies and blockchain technology could have a significant influence on our future.

CB Insights [2] published an article that delves into the impact of blockchain technology on traditional banking and payment systems. The article highlights how blockchain technology can enable decentralized payment systems that facilitate faster and more secure transactions between financial institutions. This is important to our study as it sheds light on the potential influence of blockchain technology on the finance industry and how it could impact cryptocurrency prices. The article offers five key takeaways:

1. The banking industry could potentially be disrupted by blockchain technology, which can offer faster, more cost-effective, and secure transactions by eliminating the necessity for intermediaries like banks to facilitate transactions.
2. By leveraging blockchain technology to simplify cross-border payments, financial institutions can minimize their reliance on conventional payment processors such as SWIFT. This approach can substantially decrease the expenses and time required for global transactions.
3. Smart contracts are a type of self-executing contract that encodes the terms of an agreement between a buyer and a seller into code lines. They have the capability to automate several elements of financial transactions, including loan origination and settlement, which can potentially increase efficiency and reduce costs.

4. Blockchain technology can enhance transparency and decrease fraud by providing an immutable and permanent record of transactions. This can help financial institutions monitor and prevent fraudulent activities.
5. While the banking industry is still in the early stages of adopting blockchain technology, many financial institutions are exploring ways to incorporate this technology into their operations. Although there are technical and regulatory hurdles to overcome, the potential benefits of blockchain technology for the banking industry are significant.

Overall, both articles offer insights into the broader landscape of cryptocurrency and blockchain technology, which can help inform our study on predicting cryptocurrency prices using machine learning algorithms.

Research Questions:

What are the most effective predictive and time series analysis techniques for forecasting short-term closing prices of cryptocurrencies? Which features are influential predictors for classifying the short-term closing prices of selected cryptocurrencies?

What is the correlation between the predicted prices generated by machine learning algorithms and the actual prices of the chosen cryptocurrencies?

Scope of the Research:

The project aims to use machine learning algorithms to predict short-term closing prices of different cryptocurrency companies. The dataset for this project is obtained from Kaggle Inc. which contains historical data for the chosen cryptocurrencies. The objective is to compare the predicted prices with the actual prices and identify which cryptocurrency presents the most profitable opportunity for short-term trading.

To answer the research question, we will explore different machine learning algorithms and time-series analysis techniques, such as SMA, SE, ARIMA, SARIMA, PROPHET and deep learnings. We will compare the efficiency and stability of these techniques to identify the most effective ones for our purpose.

Data Source:

The data set used in this project is obtained from Kaggle Inc. which contains historical data for the chosen cryptocurrencies. The data is related to the closing prices of each of the six different cryptocurrency companies and has been used in previous researches.

Limitations of the Research:

The scope of this study is restricted to specific cryptocurrency companies and the historical data that is accessible for them, and thus, it may not accurately reflect the overall cryptocurrency market. The machine learning algorithms utilized in the analysis rely on historical data, and the future value of cryptocurrencies can be influenced by unpredictable factors, such as changes in regulations, market sentiment, and global events. The precision of the forecasts could be influenced by the quality and comprehensiveness of the data used.

Background Information:

Cryptography is used to secure cryptocurrency, which is a digital or virtual form of money. It is decentralised and not under the jurisdiction of a single entity, such as a government or bank, unlike conventional currencies. It is a distributed ledger used to record cryptocurrency transactions and is used to secure and authenticate user data. The worldwide financial system has been significantly impacted by this innovative technology, and its future growth potential is enormous. The first cryptocurrency, Bitcoin, was released in 2009, and since then, the market has expanded to encompass several other cryptocurrencies, with a market capitalization of over $1 trillion. Even though cryptocurrencies are a relatively new addition to the financial world, their impact has been significant, and they are expected to continue influencing the financial landscape in the future.

Notably, the data set we are going to use in this study, this same data set was employed in a previous study by a researcher Manomi Koroth, whose report is available at

https://github.com/Mkoroth97/CIND820-2021/blob/main/CIND820-FINAL%20REPORT.pdf

Upon analyzing the report, some potential limitations and avenues for enhancement were identified. For example, the report utilizes a basic linear regression model for predicting cryptocurrency prices, but fails to compare its performance with other machine learning models and techniques. To enhance the model's accuracy, experimenting with other models and techniques would be worth considering. Additionally, the report does not provide a comprehensive evaluation of the model's performance, such as mean absolute error, mean squared error, or R-squared. By incorporating these metrics, a more thorough assessment of the model's accuracy can be conducted, and areas for further improvement can be identified. From the investors point of view, the report is deficient in terms of providing insightful analysis, including but not limited to the comparison of daily returns vs volatility as well as technical analysis. These aspects will also be addressed in this study.

Specific Area of Research:

The specific area of research in this project is the utilization of machine learning algorithms in time-series analysis to predict the future prices of selected cryptocurrencies and identify profitable opportunities for short-term investment.

Data Set:

The project aims to use data to achieve the goal **[3]**.

https://www.kaggle.com/datasets/sudalairajkumar/cryptocurrencypricehistory

Gethib Link of this Study:

https://github.com/shahgem/CIND-820

Literature Review

The emergence of cryptocurrencies has created an entirely new asset class that is characterized by high volatility and lack of regulation. As a result, the study of cryptocurrency markets has become increasingly important to both investors and financial analysts. The field of cryptocurrency price prediction has garnered significant attention, yet there is still a dearth of research papers on the subject. This shortage of information has motivated finance and data enthusiasts to explore the application of various deep machine learning models to market data.

While conventional time series techniques such as ARIMA are useful for analyzing data with linear and stationary patterns, they are limited in their ability to capture the complex and non-linear patterns present in cryptocurrency data. This highlights the need for alternative approaches, and deep learning methods have shown great potential in this regard. Cryptocurrency data is characterized by high volatility and frequent fluctuations, which can lead to chaotic behavior. Deep learning methods are well-suited to handle such complex and high-dimensional data, making them an ideal choice for analyzing cryptocurrency prices.

Several research papers have investigated which deep learning method is most accurate in forecasting cryptocurrency prices. Classification methods such as Random Forest Trees and k-folds were employed to compare the accuracy of each method. The studies have primarily focused on analyzing Bitcoin (BTC), given its status as the longest active currency for conducting analysis and its dominance in the cryptocurrency market.

The reviewed papers primarily investigate the performance differences of deep learning methods across various time intervals of cryptocurrency prices. These time intervals include daily, weekly, and monthly opening and closing prices. In addition to forecasting prices based on historical data, some studies have also incorporated sentiment analysis.

Researchers have analyzed the frequency of the term "Bitcoin" in tweets and explored its relationship to BTC predictability. However, it is worth noting that the utilization of natural language processing (NLP) methods for sentiment analysis is not relevant to this project.

The article "Bitcoin price prediction using machine learning algorithm" [4] written by Mohammed khalid salman and Abdullahi Abdu Ibrahim proposes a new machine learning algorithm for predicting the price of Bitcoin.

1. The authors use historical Bitcoin price data to train the algorithm and evaluate its performance.
2. The algorithm is based on an artificial neural network (ANN) that uses a combination of technical indicators, such as moving averages, as input features. The ANN is trained using a backpropagation algorithm, and the authors use mean squared error (MSE) and mean absolute error (MAE) as evaluation metrics.
3. The authors find that the ANN model outperforms traditional time-series models, such as the autoregressive integrated moving average (ARIMA) model, in predicting Bitcoin prices. They also find that using technical indicators as input features improves the performance of the ANN model.
4. The authors conclude that machine learning algorithms can be useful for predicting Bitcoin prices, and that using technical indicators as input features can improve the accuracy of these predictions. They also note that further research is needed to evaluate the performance of these algorithms in different market conditions and with other cryptocurrencies.
5. Overall, the article provides an interesting and valuable contribution to the literature on cryptocurrency price prediction and machine learning.

Overall, the study of cryptocurrency price prediction is a nascent field that requires further research. Deep learning methods have shown great promise in addressing the unique challenges posed by cryptocurrency markets, and several studies have explored the application of these methods to BTC. This project aims to build on this research by investigating the performance of various deep learning methods for forecasting the prices of other popular cryptocurrencies.

Introduction

The field of cryptocurrency price prediction is an exciting and rapidly evolving area of research, with many promising avenues to explore. Given the newness of this topic, the number of research papers available is limited, making it an ideal area for finance and data enthusiasts to explore and experiment with various deep machine learning models.

Conventional time series techniques, such as ARIMA, have proved to be ineffective in capturing the non-linear and non-stationary patterns that are commonly present in cryptocurrency data. These limitations underscore the need for alternative approaches to analyze this unique and dynamic market.

One of the major challenges in predicting cryptocurrency prices is the high volatility and frequency of price fluctuations, which can lead to underlying chaos. As such, Deep Learning Methods have emerged as a critical tool in this field, as they can capture complex patterns in the data that other methods might miss.

In addition to analyzing the historical data of cryptocurrencies, researchers have also explored the role of sentiment analysis in price prediction. Some studies have analyzed the frequency of "Bitcoin" in tweets to determine if it correlates with the predictability of the BTC price, using Natural Language Processing (NLP) methods. However, this project will not consider sentiment analysis due to the limitations of the scope and the complexity of NLP techniques. One of the studies “Cryptocurrency Price Prediction Using Tweet Volumes and Sentiment Analysis” **[5]** concludes People who tweet about cryptocurrencies even when their prices drop have an interest in those tweets above and beyond investment opportunity which makes the tweets biased towards positive trend. Here are five key points that can be gleaned from the paper:

1. Cryptocurrency price prediction is an important area of research, and many different methods have been proposed to predict the price of cryptocurrencies, such as Bitcoin, Ethereum, and Litecoin.
2. The authors propose a new method for cryptocurrency price prediction that uses tweet volumes and sentiment analysis. The method involves collecting and analyzing tweets related to specific cryptocurrencies and using the sentiment analysis of those tweets to predict the future price of the cryptocurrency.
3. The study shows that tweet volumes and sentiment analysis can be useful in predicting cryptocurrency prices, and the method proposed by the authors outperforms other methods such as time series analysis and support vector regression.
4. The authors note that their method is not without limitations, including the potential for bias in the data due to the selective nature of Twitter users and the need for further research to validate the results.
5. Despite the limitations, the study highlights the potential of social media data and sentiment analysis in predicting cryptocurrency prices and suggests that further research in this area could lead to improved prediction models and better understanding of the cryptocurrency market.

In summary, this project aims to explore and evaluate the performance of several Deep Learning Methods to forecast the prices of cryptocurrencies. While researchers from Jaypee University of Information Technology, India have conducted extensive investigations on this topic [6]. Here are five key points from the project report on "Cryptocurrency Price Prediction Using Deep Learning":

1. The project proposes the use of deep learning techniques to predict the price of cryptocurrencies, which are highly volatile and challenging to predict accurately.
2. The project uses historical price data from popular cryptocurrencies like Bitcoin and Ethereum to train a deep learning model using various neural network architectures, including LSTM, GRU, and CNN.
3. The project's objective is to examine how technical indicators, specifically Moving Average Convergence Divergence (MACD) and Relative Strength Index (RSI), can be employed to enhance the accuracy of cryptocurrency price predictions.
4. Furthermore, an assessment of the deep learning model's performance is conducted using evaluation metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), indicating that it is more effective than conventional statistical models in forecasting cryptocurrency prices.
5. The project provides valuable insights into the potential of deep learning techniques and technical indicators for predicting cryptocurrency prices and suggests further research in this area.

I intend to offer a novel perspective by including additional insights in my literature review. My goal is to provide a more in-depth analysis of the dataset and explore the use of a wider range of model techniques to present readers with a more thorough and comprehensive analysis. Through this project, we hope to contribute to the growing body of research in this exciting and rapidly evolving field.

Approach/Methodology

Developing a robust approach for analyzing cryptocurrency market data is essential for investors seeking to gain insight into the cryptocurrency market and make informed investment decisions. The following steps outline a structured methodology for analyzing cryptocurrency market data:

Data Collection: The first step is to gather relevant historical price data for the cryptocurrencies being analyzed, including trading volume and market capitalization. The data must be sourced from reputable sources to ensure accuracy and reliability.

SWOT Analysis: Conducting a SWOT analysis of the selected models is crucial to identifying their strengths, weaknesses, opportunities, and threats. This analysis will help in determining which models are best suited for the specific cryptocurrency being analyzed.

Data Preparation: After collecting the data, the next step is to prepare it for analysis. This involves removing any missing or erroneous data, transforming the data into a suitable format, and normalizing it to account for differences in scale.

Model Selection: In this step, various models such as SMA, ES, ARIMA, SARIMA and Prophet models are selected as potential options for analysis. It is important to select the most appropriate models for the specific cryptocurrency being analyzed.

Model Implementation: Once the models are selected, they are implemented and applied to the prepared data. This may involve adjusting the parameters of the models to optimize their performance.

Data Visualization: Conducting exploratory data analysis (EDA) to understand the dataset's properties and characteristics is essential. Techniques such as box plots and histograms are used to detect outliers, distributions, and correlations. EDA helps in identifying trends, patterns, and potential relationships between the features of the dataset.

Model Evaluation: Evaluating the models' performance is crucial in determining their accuracy and reliability and identifying areas for improvement. Appropriate metrics such as mean absolute error (MAE), root mean squared error (RMSE), and mean absolute scaled error (MASE) are used in this step.

Results Interpretation: The results of the analysis are interpreted and conclusions are drawn based on the findings. This may involve visualizing the data and model outputs using graphs and charts, as well as conducting statistical tests to assess the significance of the results.

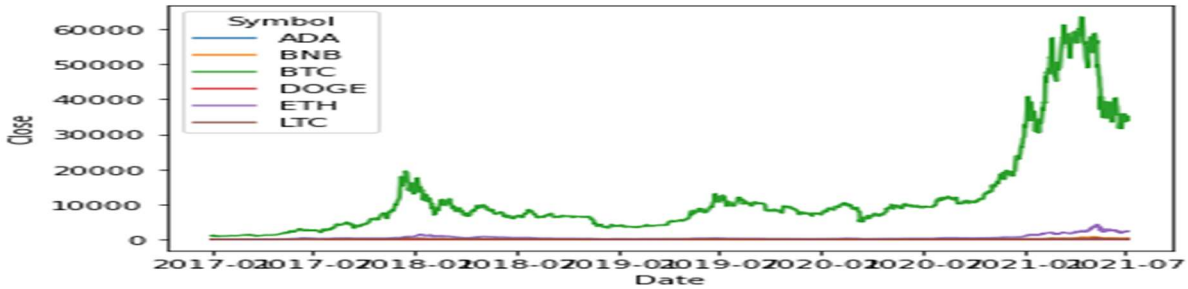
Conclusion and Recommendations: The key findings of the study are summarized, and recommendations for future research or actions are provided based on the results. By following this structured methodology, investors can make informed decisions based on reliable data analysis. The methodology outlined here is an essential tool for any investor looking to gain a competitive edge in the cryptocurrency market, as it provides a comprehensive and systematic approach for analyzing cryptocurrency market data.

Overview of the Data

The dataset utilized in this project was sourced from Kaggle Inc, and is publicly accessible under the title "Cryptocurrency Historical Prices" [3].

During this course of study, I will emphasis on Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Dogecoin (DOGE), Cardano (ADA), and Binance Coin (BNB). Although Kaggle provides separate CSV files for each cryptocurrency, the author of this project has amalgamated all the individual files into a single CSV file named "crypto_market.csv". This amalgamation was possible due to the identical columns of each file, i.e., Serial Number, Name, Symbol, Date, High, Low, Open, Close, Volume, Market Capitalization.

The initial dataset brings to the fore the non-uniformity of the trading dates of the various currencies. As previously noted, BTC has been in circulation for the longest period, pre-dating all the other cryptocurrencies in the dataset. Since the start dates for each currency, which may significantly impact their predicted prices. To mitigate this potential bias, it is advisable to limit the analysis to the period from 2017 onwards, as this provides a more consistent and recent historical data for all the selected currencies. This filtered dataset has been saved under the file name "sixcryto.csv".



In light of this, during the analysis phase of this project, it is prudent to compare all currencies from 2017 onwards, so as to minimize prediction bias and incorporate a more uniform and recent historical data.

Daily Return and Volatility Analysis

Daily return is a metric that quantifies the percentage change in an asset's value over a day. It's calculated by dividing the difference between the closing and opening prices of the asset by the opening price.

Volatility is a gauge of the extent to which an asset's price fluctuates over a period of time. Generally, it is calculated as the standard deviation of the asset's daily returns. A higher level of volatility indicates greater market instability and a greater likelihood of significant price swings in either an upward or downward direction.

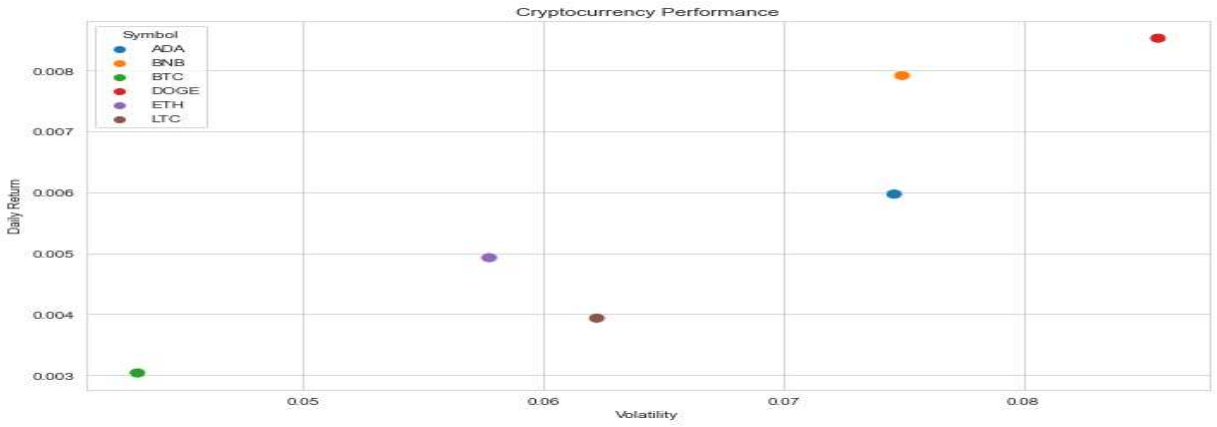
The RBC article [7] discusses the relationship between volatility and investment returns. Key points include:

1. Volatility refers to the degree of price variation of an investment over time, and it is typically measured by standard deviation.
2. Historical volatility is a measure of the past variability of returns, while implied volatility is a measure of expected future variability based on market prices.
3. Higher volatility generally implies higher risk, but it can also present opportunities for higher returns.
4. The relationship between volatility and returns is not straightforward, as it can vary depending on the investment strategy and time horizon.
5. For long-term investors, higher volatility assets may lead to higher returns over time, while short-term traders may be more concerned with managing risk and avoiding large losses.
6. Investors can manage the risk of volatility through diversification, asset allocation, and other risk management strategies.

The Python code is using pandas libraries, numpy, seaborn, and matplotlib to analyze and visualize data related to six cryptocurrencies.

- The code reads the data from a CSV file named "sixcrypto.csv" and groups the data by currency symbol.
- It then calculates daily returns and volatility for each currency using the groupby method and for loop.
- The code creates two dataframes to store the calculated daily returns and volatility for each currency.
- It then merges the two dataframes using the merge method on the 'Symbol' column.
- Finally, the performance dataframe is printed in a tabular format using the to_string method.
- The code also plots the results using the seaborn and matplotlib libraries.
- It sets the style to 'whitegrid', creates a scatterplot with x-axis as volatility, y-axis as daily return, and symbol as hue.
- The plot is titled "Cryptocurrency Performance" with x-label as "Volatility" and y-label as "Daily Return".

Overall, this code reads and processes data related to six cryptocurrencies, calculates daily returns and volatility, and visualizes the performance of each currency using a scatterplot.



Symbol	Daily Return	Volatility
ADA	0.005971	0.074610
BNB	0.007917	0.074944
BTC	0.003035	0.043087
DOGE	0.008529	0.085605
ETH	0.004928	0.057740
LTC	0.003935	0.062223

The results demonstrate that BNB and DOGE have higher daily returns, indicating their superior performance in terms of price growth. Nevertheless, DOGE also displays greater volatility, indicating its price is more susceptible to fluctuations and investing in it entails higher risk. BTC, on the other hand, has the lowest daily return, but also the lowest volatility, implying its price is more stable compared to other currencies.

Although these metrics can be helpful in evaluating different currencies' performance and making informed investment choices, it is crucial to remember that past performance is not an assurance of future outcomes. External factors, such as market trends and events, may have a significant impact on currency prices.

Technical Analysis

Technical analysis is a popular and widely-used methodology for predicting future price movements of an asset. It entails a comprehensive analysis of an asset's past market data, including price charts and technical indicators, to identify trends, support and resistance levels, and potential trading opportunities. Technical analysts use various indicators such as moving averages, RSI, MACD, and Fibonacci retracements to develop their analysis. Through the careful study of an asset's price history and market data, technical analysts aim to gain a deeper understanding of its current and future price movements, enabling them to make informed trading decisions.

If you want to explore technical analysis further, here are the main takeaways from Adam Hayes' Investopedia article titled "Technical Analysis: What It Is and How to Use It in Investing" [8]

1. Technical analysis involves studying past market data, including price charts and technical indicators, to predict future price movements of an asset.
2. Technical analysts use various tools and techniques such as moving averages, trendlines, and chart patterns to identify trends and potential trading opportunities.

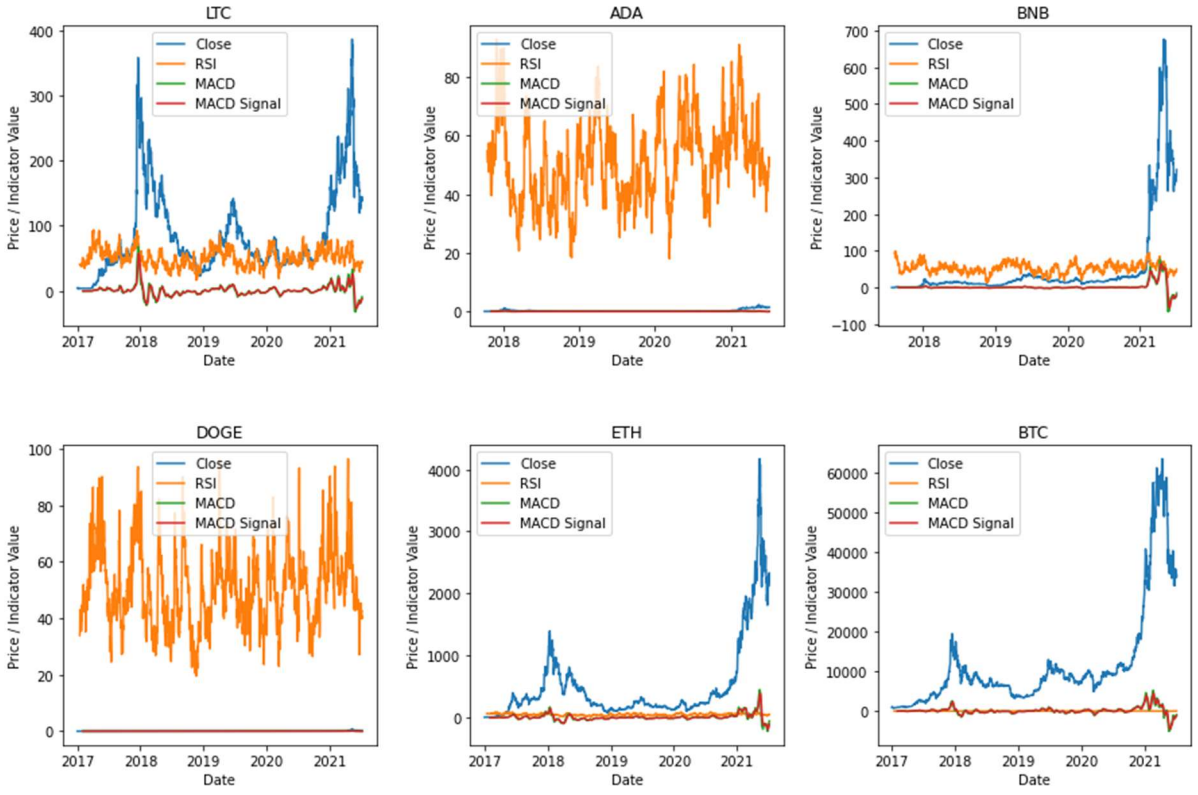
3. Technical analysis is based on the idea that market trends, patterns, and behaviors repeat over time and that past price movements can provide insights into future price movements.
4. While technical analysis is popular in trading, it has its limitations and is not always reliable.
5. Combining technical analysis with other types of analysis and practicing risk management when trading is essential for successful trading.

Indicator	Description	Interpretation
Relative Strength Index (RSI)	(RSI) is a measure that assesses the strength of a security's price action, indicating the level of momentum it has. This metric operates as an oscillator and produces RSI readings that fall within the range of 0 to 100. The RSI value enables traders to identify whether the security is overbought or oversold	RSI > 70: Overbought condition RSI < 30: Oversold condition RSI > 50: Bullish momentum RSI < 50: Bearish momentum
Moving Average Convergence Divergence (MACD)	The statement describes the correlation between two moving averages that represent the price of an asset.	Positive MACD: Bullish momentum Negative MACD: Bearish momentum
MACD Signal	Plotted alongside the MACD to generate buy and sell signals.	Cross above MACD signal line: Bullish signal Cross below MACD signal line: Bearish signal Distance between MACD and signal line: Trend strength

I used the python code using the Pandas, TA-Lib, and Matplotlib libraries to analyze and visualize financial data for different cryptocurrencies.

Here's a step-by-step breakdown of what our python code is running:

- Importing the necessary libraries: pandas, ta-lib, and matplotlib.pyplot.
- Loading the cryptocurrency data from a CSV file using the pd.read_csv() method and converting the Date column to a datetime object.
- Getting the unique symbols (currency names) from the loaded data.
- Creating an empty results_df dataframe with columns to store the technical indicators (RSI, MACD, MACD_signal) for each currency.
- Creating a 2x3 grid of subplots using the plt.subplots() method.
- Looping through each currency in the symbols list, calculating the technical indicators (RSI and MACD) for each currency, and plotting the data on the current subplot using the talib.RSI(), talib.MACD(), and axs.plot() methods.
- Storing the calculated technical indicator values for each currency in the results_df dataframe using the pd.concat() and pd.DataFrame() methods.
- Displaying the results_df dataframe using the print() method.
- Showing the plot using the plt.show() method.
- Adjusting the spacing between subplots using the plt.subplots_adjust() method.



Symbol	RSI	MACD	MACD Signal
LTC	43.325110	-9.037788	-12.098173
ADA	50.234631	-0.024998	-0.047715
BNB	50.275473	-14.875495	-21.176928
DOGE	40.619870	-0.021343	-0.023876
ETH	52.635585	-51.093439	-105.488122
BTC	46.383877	-871.687094	-1130.908270

Based on the technical analysis results, here are the interpretations for each currency:

- LTC: The RSI suggests that LTC is slightly oversold. The MACD is negative but is above the signal line, which indicates a potential bullish crossover.
- ADA: The RSI is close to 50, indicating a neutral position. The MACD and signal line are close to each other, which suggests that the currency is currently in a range-bound market.
- BNB: The RSI is slightly above 50, indicating a bullish trend. The MACD is negative but is above the signal line, which indicates a potential bullish crossover.
- DOGE: The RSI suggests that DOGE is oversold. The MACD and signal line are close to each other, which suggests that the currency is currently in a range-bound market.
- ETH: The RSI suggests that ETH is in a neutral position. The MACD is negative, and the signal line is far below it, indicating a strong bearish trend.
- BTC: The RSI suggests that BTC is slightly oversold. The MACD is negative, and the signal line is far below it, indicating a strong bearish trend.

Data Visualization

Visualizing Market Capitalization

The initial step in our analysis involved segregating the dataset by individual currencies, in order to facilitate comparative visualization. The determination of which currency held the greatest sway in the market was predicated on market capitalization - a metric that reflects the total market value of a given currency. Given Bitcoin's pioneering role in the cryptocurrency space, and its established longevity, we hypothesized that it would exert the greatest impact on the market.

However, the lack of market capitalization data prior to 2017 posed a challenge to our analysis. To overcome this, we chose to graph market capitalization data starting from the year 2017. This approach allowed us to focus on a more recent and reliable dataset.

The resulting graph illustrated that Bitcoin was the most frequently traded currency, with its market capitalization dwarfing that of its peers. This observation was consistent with our hypothesis, indicating that Bitcoin indeed exerted a significant influence on the cryptocurrency market.

Furthermore, the graph revealed that as Bitcoin prices increased, so too did the prices of other currencies. This suggested a strong correlation between Bitcoin's market performance and that of other cryptocurrencies. In other words, Bitcoin appeared to be a bellwether of sorts - with its price movements influencing the direction of other currencies.

Our study's results align with previous literature, which suggested that Bitcoin's market performance had a considerable influence on other cryptocurrencies' performance. As a result, our analysis supports and expands upon this prior research, revealing the cryptocurrency market's interdependence and Bitcoin's crucial role within it.

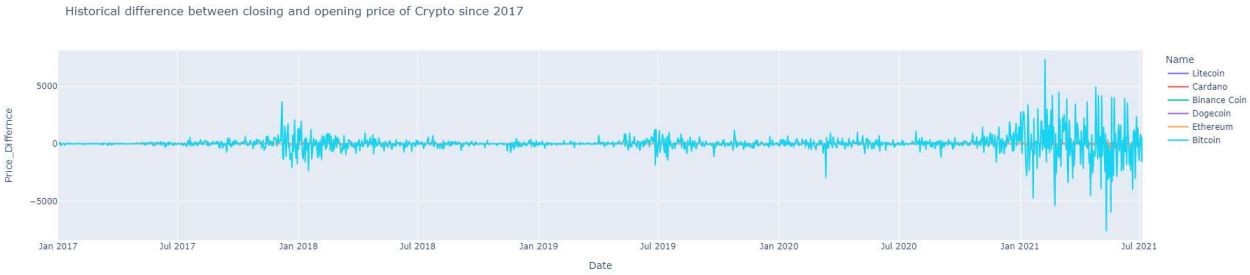
Visualizing the Closing and Opening Price Difference

To comprehend the daily price patterns for each cryptocurrency, I analyzed the variance between the opening and closing prices for each data point. This approach helped me to understand the level of price fluctuation that occurred within each trading day.

The analysis of the data reveals that Bitcoin had the highest price fluctuations from opening to closing within a day. This finding is in line with Bitcoin's reputation for volatility and its inclination to undergo abrupt price spikes or declines.

However, it's important to note that other cryptocurrencies also exhibited significant price fluctuations. Ethereum, for example, demonstrated a high level of price variation, which is not surprising given its status as the second most traded crypto project since its inception in 2017.

The graph indicates an interesting correlation between price hikes and fluctuations in the cryptocurrency market. When the market experiences an upswing, the degree of price variability tends to increase. This trend can be ascribed to various factors such as heightened investor speculation and market frenzy, which can lead to more volatile trading patterns.

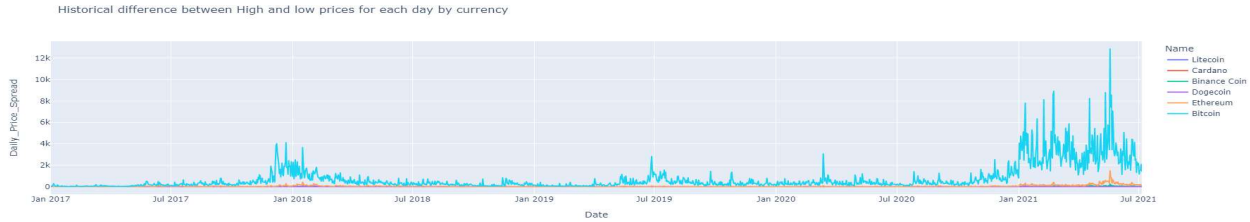


In summary, the analysis of the difference between opening and closing prices provides valuable insights into the daily price trends for each cryptocurrency. Bitcoin and Ethereum are among the most volatile, while the level of price fluctuation tends to increase alongside price increases in the overall market.

Visualizing the High and Low-Price Difference

One of the key factors driving interest in cryptocurrencies is their price volatility. This volatility is often attributed to the limited supply of cryptocurrencies and the speculative nature of their value. As with any asset, the price of cryptocurrencies is influenced by supply and demand, with market participants often reacting to news and events that impact the cryptocurrency ecosystem.

In our analysis, we sought to understand the daily price variations of cryptocurrencies and the differences between their high and low prices. To accomplish this, we first calculated the daily price spread of each cryptocurrency by subtracting the low price from the high price. Our analysis revealed that Bitcoin and Ethereum exhibit the most significant price fluctuations, while other cryptocurrencies showed a relatively plateaued trend. This suggests that Bitcoin and Ethereum may be subject to greater volatility than their counterparts.



In addition to analyzing the daily price variations of cryptocurrencies, we also examined the activity levels of each currency. Our analysis found that 2018 was the most active year for Bitcoin, while the post-pandemic period has seen a significant uptick in cryptocurrency activity. We hypothesize that this increase in activity may be attributed to a rise in unemployment during the pandemic, leading individuals to explore alternative means of income generation.

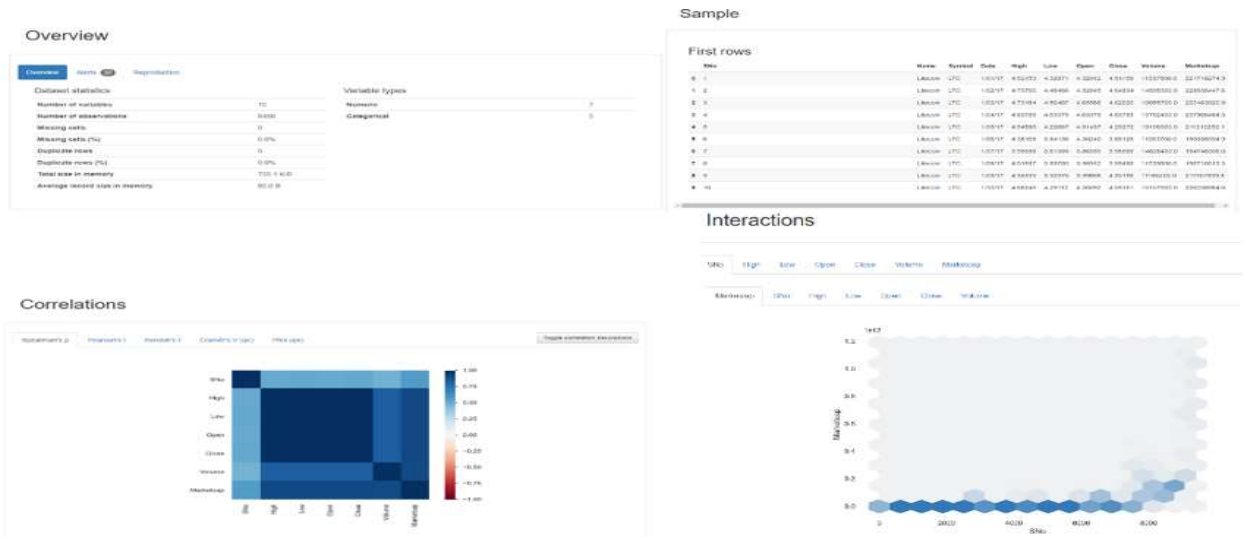
These findings underscore the importance of monitoring the price fluctuations and activity levels of cryptocurrencies. Understanding the factors that drive these fluctuations can provide valuable insights for investors and policymakers alike. Additionally, our analysis highlights the potential of cryptocurrencies as an alternative asset class for individuals looking to diversify their investment portfolios.

However, it is important to note that cryptocurrencies remain a relatively new and untested asset class, and their volatility and lack of regulation can create significant risks for investors. Furthermore, the regulatory landscape for cryptocurrencies remains uncertain, with many countries struggling to develop coherent policies around their use and adoption. Future research may explore the relationship between cryptocurrency price fluctuations and macroeconomic factors, such as unemployment rates and economic policy changes, to gain a more comprehensive understanding of these emerging financial instruments.

Exploratory Data Analysis (EDA)

Python was chosen as the programming language for this project due to its versatility and the availability of numerous packages for basic statistical analysis and building complex time series models. The following packages were loaded for data cleaning, preparation, building, and plotting the dataset: Numpy, Pandas, Sklearn, Scipy, Seaborn, Plotly, Statsmodels.api, and Mathplotlib.

Pandas profiling is a powerful tool for automating the process of data profiling, which involves generating a comprehensive report of the dataset's characteristics and statistics. The library offers a wide range of features and customization options for generating informative and visually appealing reports. In this article [9], this delve into the capabilities of Pandas profiling and explore some advanced use cases and integrations that can be leveraged to produce compelling reports from data frames. By utilizing this tool, data analysts and scientists can gain a deeper understanding of their data and communicate insights effectively to stakeholders. Please find below a summary of Panda's profiling of the primary attributes of our dataset, provided for the reader's reference.



Further exploratory analysis was conducted using Pandas Profiling. The detailed report can be found at https://github.com/shahgem/CIND-820/blob/main/CryptoAnalysis.html

Data Dictionary

The dataset can be described briefly as follows.

Column	Explanation	Variable Type	Data Type
Sno	Serial Numbers	Numerical (Nominal)	int64
Name	Name of the currency	Categorical (Nominal))	object
Symbol	Symbol or abbreviation of the cryptocurrency	Categorical (Nominal)	object

Date	Phone number of customer	Date(datetime)	object
High	Highest price of the cryptocurrency on the given date	Numerical (continuous)	float64
Low	Lowest price of the cryptocurrency on the given date	Numerical (continuous)	float64
Open	Opening price of the cryptocurrency on the given date	Numerical (continuous)	float64
Close	Closing price of the cryptocurrency on the given date	Numerical (continuous)	float64
Volume	Volume of the cryptocurrency traded on the given date	Numerical (continuous)	float64
Marketcap	Market capitalization of the cryptocurrency on the given date	Numerical (continuous)	float64

Missing Values

After reading the “Sixcrypto” dataset into a Pandas dataframe (“df”), we’ve captured a snapshot of the data with 10 columns, 9408 rows:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9408 entries, 0 to 9407
Data columns (total 10 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   SNo        9408 non-null   int64
 1   Name       9408 non-null   object
 2   Symbol     9408 non-null   object
 3   Date       9408 non-null   object
 4   High       9408 non-null   float64
 5   Low        9408 non-null   float64
 6   Open       9408 non-null   float64
 7   Close      9408 non-null   float64
 8   Volume     9408 non-null   float64
 9   Marketcap  9408 non-null   float64
dtypes: float64(6), int64(1), object(3)
memory usage: 735.1+ KB
```

Counting the number of missing values for each column by df.isna().sum().

```
SNo          0
Name         0
Symbol       0
Date         0
High         0
Low          0
Open         0
Close        0
Volume       0
Marketcap    0
dtype: int64
```

Counting the number of duplicated rows for the dataset by df.duplicated().value_counts()

```
False    9408
dtype: int64
```

Our analysis of the dataset revealed that there are no instances of missing values or duplicates. This indicates that the dataset is complete and unique.

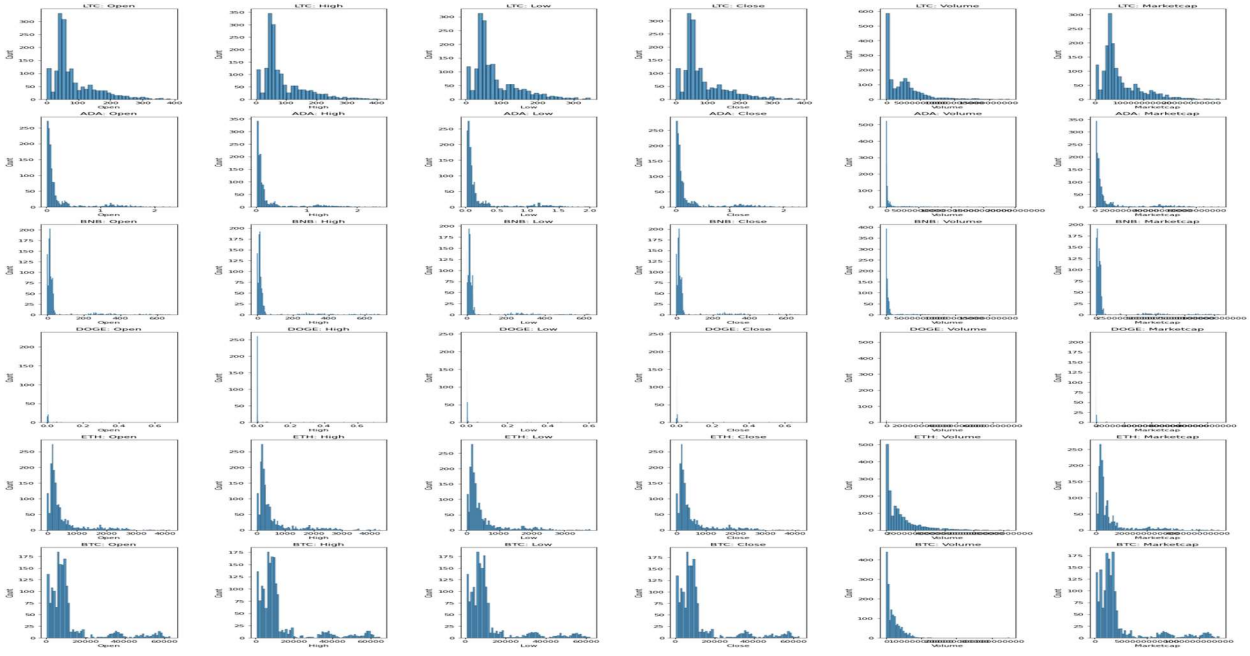
Detection of outliers for numerical columns

Our research aims to identify outliers in the data and examine their influence on the overall distribution of the data. To accomplish this, I employed the commonly used z-score method to identify data points that are over three standard deviations away from the mean, which is a widely accepted approach for detecting outliers.

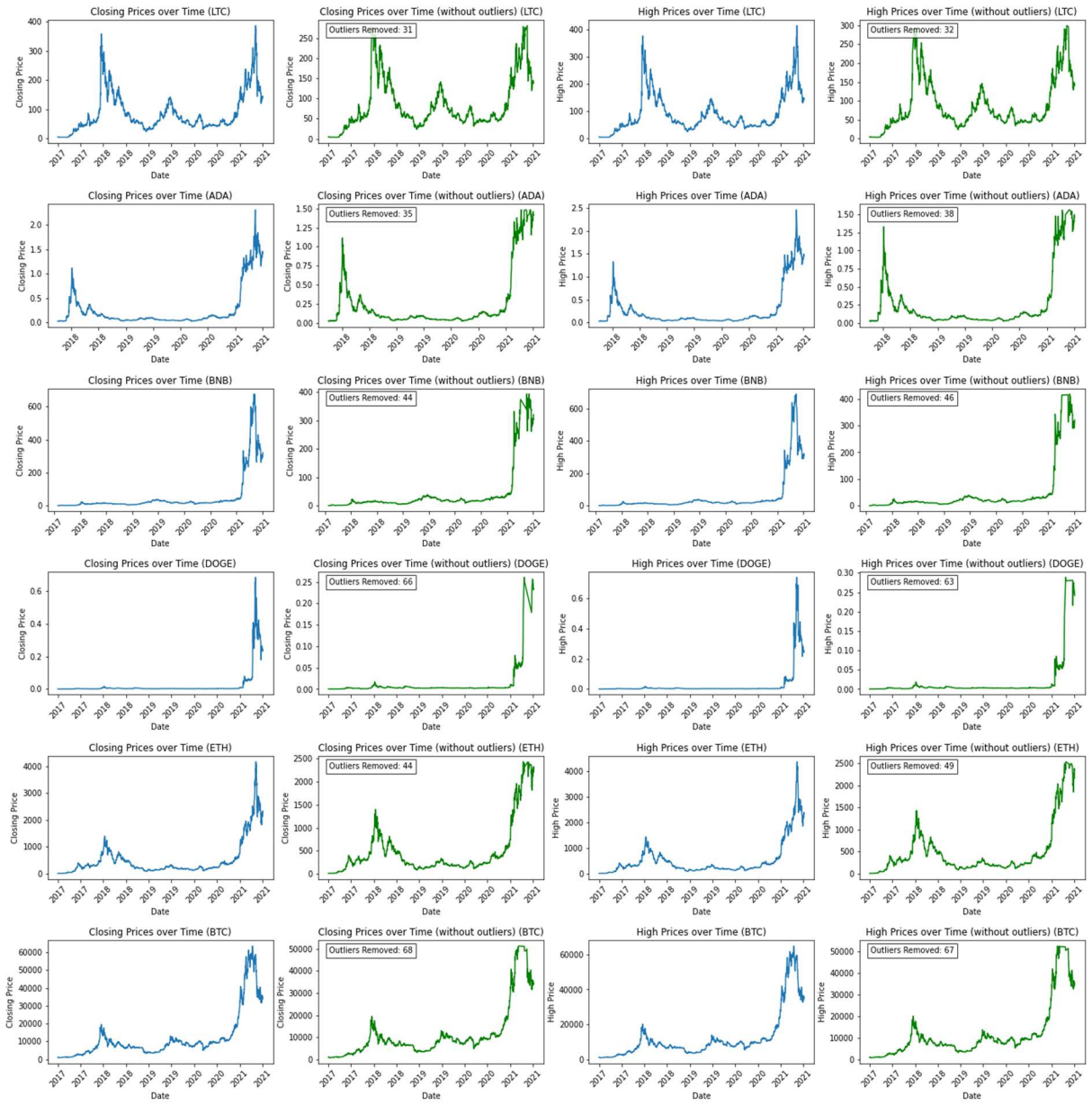
Furthermore, I generated histograms for every currency and column in the dataset to visualize the data distribution and the occurrence of outliers. By doing so, I aimed to gain insight into the extent to which outliers affect the data distribution and potentially impact any further analysis, such as time series forecasting. It is important to note that our approach is not novel but rather a standard practice in the field.

The Python code that I used, imports the pandas, seaborn, and matplotlib libraries for data manipulation, visualization, and plotting.

- It then loads a CSV file named "sixcrypto.csv" using the read_csv function of Pandas, which creates a DataFrame from the file.
- The code then creates two lists: one containing the names of columns to plot ('Open', 'High', 'Low', 'Close', 'Volume', 'Marketcap'), and the other containing unique currency symbols found in the Symbol column of the DataFrame.
- Next, the code creates a subplot figure with a grid of plots, one for each currency and column combination. The subplots function of Matplotlib is used to create the figure, and the nrows, ncols, and figsize parameters specify the number of rows and columns, and the size of the figure.
- The code then loops through each currency and column combination, and creates a boxplot for each using Seaborn's histplot function. The histplot function plots a histogram for the data in the specified column, using only the data from the current currency. The set_title function sets the title of each plot, indicating the currency and column being plotted, and the ticklabel_format function sets the format of the x-axis tick labels to plain text.
- Finally, the code uses tight_layout to adjust the spacing of the subplots, and show to display the figure. Overall, this code generates a grid of histograms for each currency and each column of data, allowing the user to compare and contrast the distribution of the data across different currencies.



The below plot shows the closing and high prices of each currency over time, with and without outliers removed. The plot also shows the number of outliers removed for each currency.



Count of Outliers for each Cryptocurrency in the Dataset:

```
Count of Outliers for each Cryptocurrency in the Dataset
Currency  High  Low  Open  Close  Volume  Marketcap
     LTC    32   28    31     31      36         27
     ADA    38   37    37     35      38         42
     BNB    46   43    44     44      42         44
    DOGE    63   69    67     66      27         66
     ETH    49   47    47     44      38         48
     BTC    67   65    68     68      14         68
```

Percentage of Outliers for each Cryptocurrency in the Dataset:

```
Percentage of Outliers for each Cryptocurrency in the Dataset
Currency  High   Low  Open  Close  Volume  Marketcap
     LTC 1.94% 1.70% 1.88%  1.88%   2.18%      1.64%
```

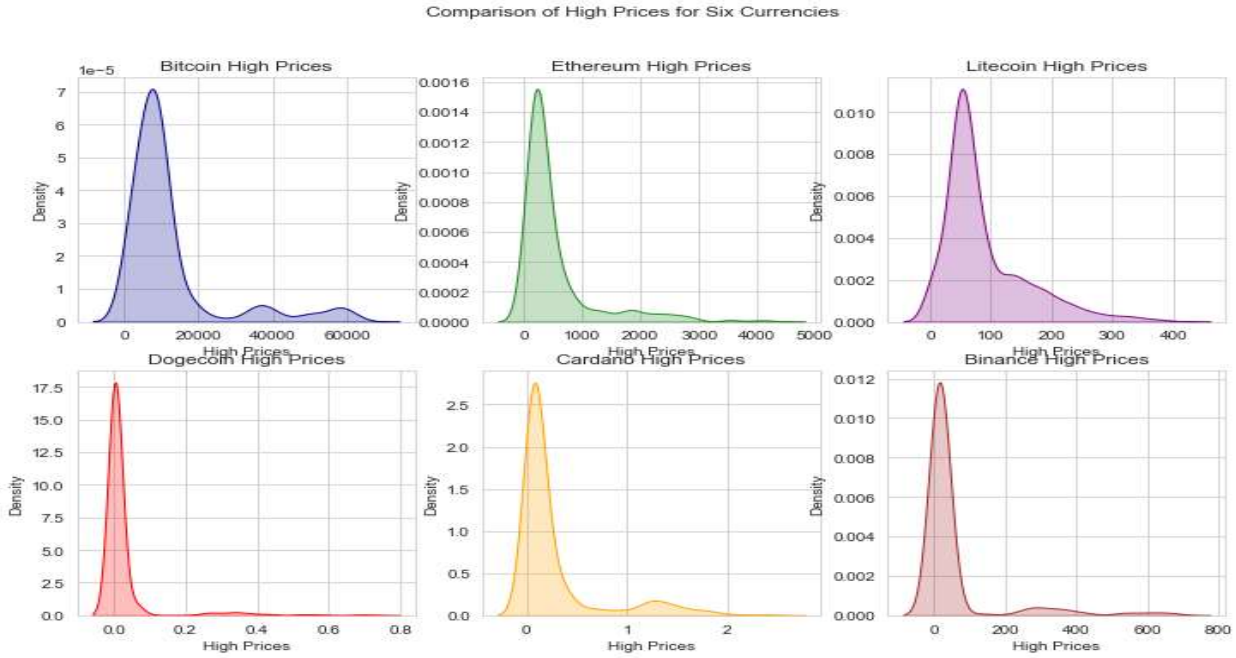
```
      ADA 2.77% 2.69% 2.69%  2.55%   2.77%      3.06%
      BNB 3.19% 2.98% 3.05%  3.05%   2.91%      3.05%
     DOGE 3.82% 4.19% 4.07%  4.00%   1.64%      4.00%
      ETH 2.97% 2.85% 2.85%  2.67%   2.31%      2.91%
      BTC 4.07% 3.94% 4.13%  4.13%   0.85%      4.13%
```

Whether or not to remove outliers from your dataset is a decision that depends on the specific context and purpose of our analysis. In some cases, outliers can provide valuable insights into unusual events or behaviors in the data, and removing them may lead to a loss of important information. In other cases, outliers may simply represent errors or anomalies that are not relevant to the analysis, and removing them can improve the accuracy and validity of the results.

In general, it's a good practice to examine the outliers carefully and determine whether they should be removed or retained based on their relevance to the analysis. If we decide to remove outliers, we should be clear about the criteria we used to identify them and document the process for reproducibility. It's also important to consider the potential impact of outlier removal on the overall distribution and characteristics of the data.

Regarding time series forecasting which we are going to perform in the remaining part of our study, outliers can have a significant impact on the accuracy of the forecasts, and it may be necessary to account for them explicitly in the modeling process. In some cases, outlier detection and correction techniques can be integrated into the forecasting models themselves, or separate preprocessing steps may be necessary to remove or adjust the outliers prior to modeling.

Univariate Analysis of High & Close Prices



As we can see, our graphs are skewed to the right (positive skew).

Skewness is a statistical measure that points out the degree of asymmetry of a distribution. It tells you whether the distribution is symmetric or not, and if it is not symmetric, it tells you whether the tail of the distribution is longer on the left or the right side.

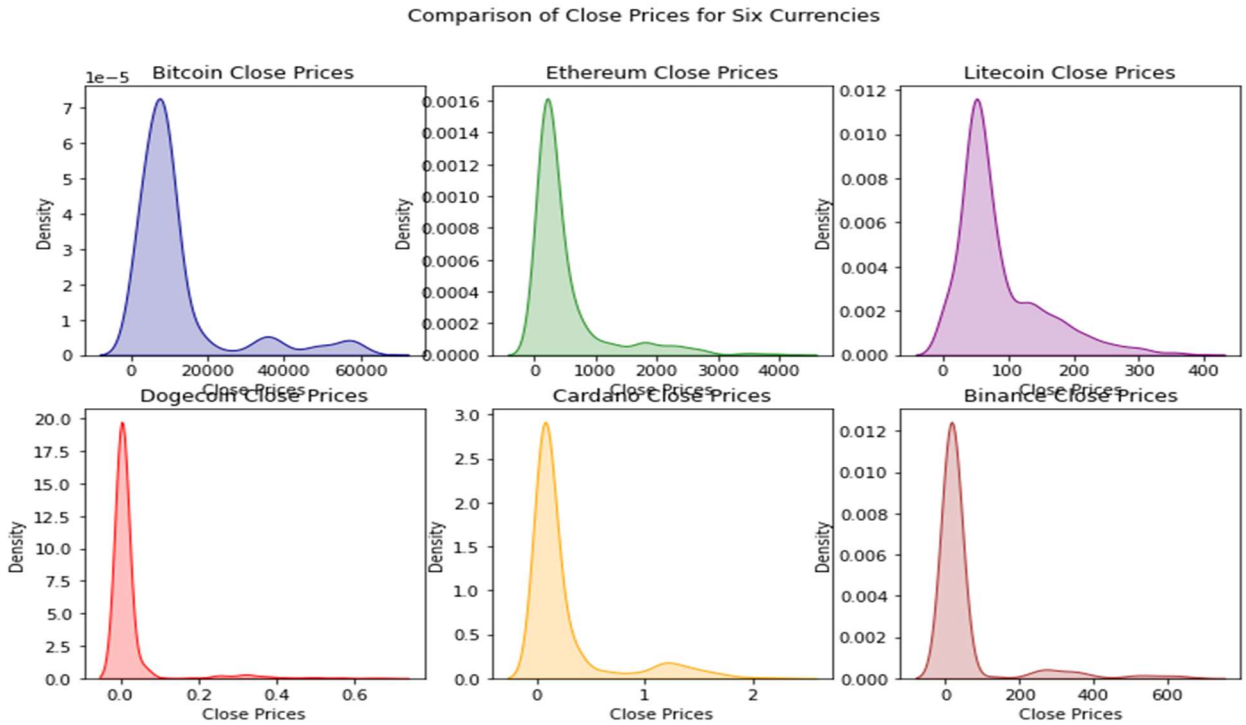
A skewness value of 0 indicates a perfectly symmetric distribution, while a positive skewness value indicates a longer tail on the right side of the distribution, and a negative skewness value indicates a longer tail on the left side of the distribution.

Skewness can be useful in understanding the underlying data, as it can indicate whether there are outliers or unusual data points that may be affecting the distribution. It can also help in choosing appropriate statistical methods for analyzing the data, as some methods assume a normal distribution and may not be appropriate for skewed data.

```
Symbol  Skewness
BTC     2.318963
ETH     2.672445
LTC     1.608763
DOGE    4.826529
ADA     2.389419
BNB     3.343639
```

Based on the results, it seems that the "High" prices distribution for DOGE has the highest skewness value (4.826529), indicating a significant degree of positive skewness, which suggests that there are more observations with smaller values (left tail) and fewer observations with larger values (right tail). Similarly, BNB also has a high skewness value (3.343639), indicating a degree of positive skewness. The other cryptocurrencies (BTC, ETH, LTC, and ADA) also have positive skewness values, indicating a similar pattern of more small values and fewer large values, but to a lesser extent compared to DOGE and BNB.

In summary, the skewness values suggest that the "High" prices distribution for these cryptocurrencies are skewed to the right (positively skewed), indicating that there are more observations with smaller values and fewer observations with larger values.

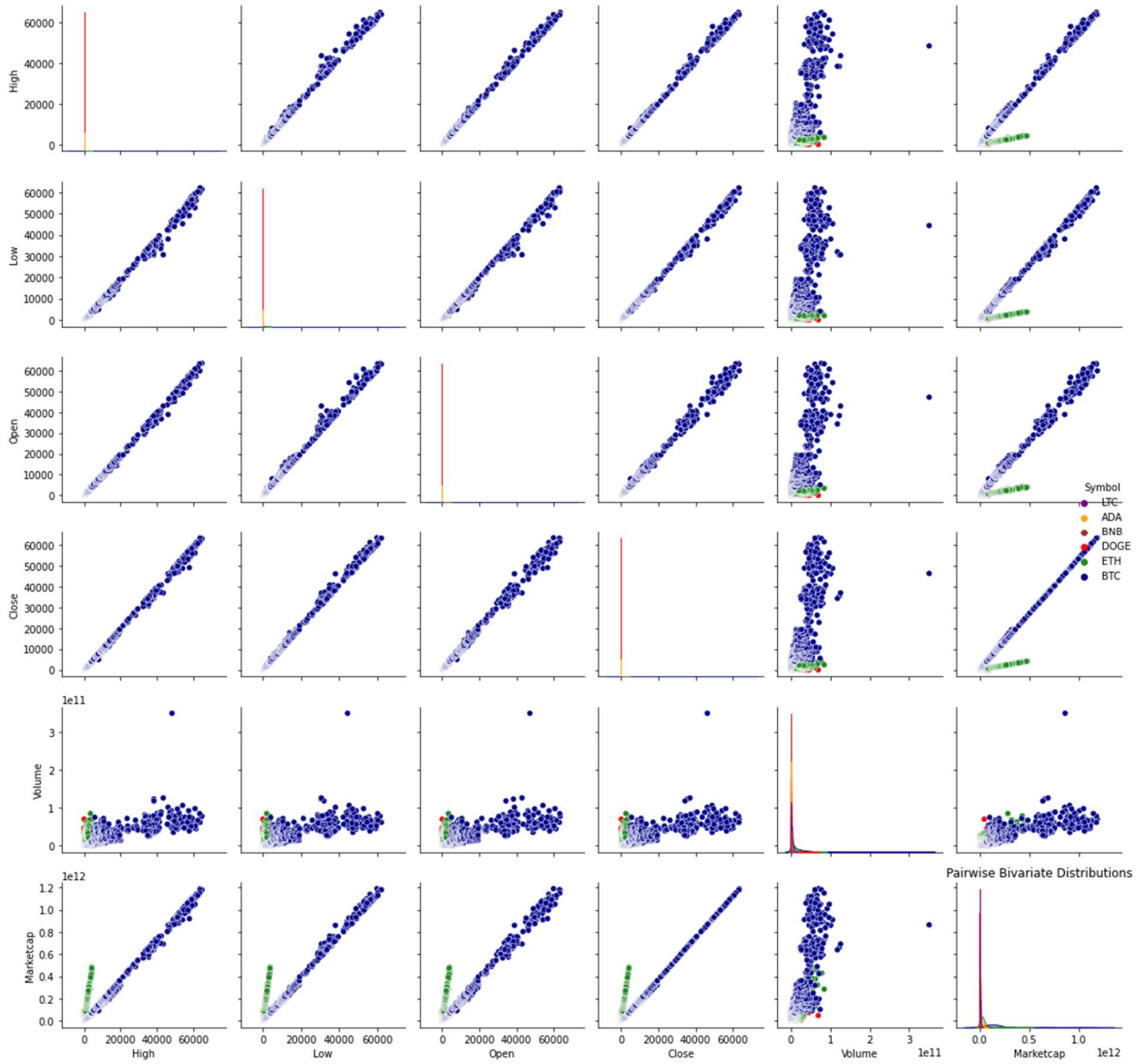



```
Symbol  Skewness
BTC     2.331511
ETH     2.642688
LTC     1.560778
DOGE    4.701561
ADA     2.378311
BNB     3.359945
```

Based on the Skewness values of Close pirce, it appears that DOGE has the highest degree of positive skewness, followed by BNB, ETH, BTC, ADA, and LTC. This suggests that the distributions of daily returns for these cryptocurrencies are not symmetric and have a long right tail. This means that there is a greater probability of large positive returns compared to large negative returns for these cryptocurrencies.

By knowing the skewness of a distribution, investors can better estimate whether the future returns of an asset will be higher or lower than its past returns. This information is helpful in making investment decisions and managing risk. For example, if the skewness is positive, investors might expect to see more large gains in the future and may consider investing in the asset. Conversely, if the skewness is negative, investors might expect to see more large losses in the future and may decide to avoid investing in the asset.

Bivariate Analysis



Bivariate analysis is a statistical method that is used to check the relationship between two variables. In the context of the sixcrypto.csv dataset, bivariate analysis could be used to explore the

relationships between different cryptocurrency variables, such as the relationship between the price and volume of each cryptocurrency.

Statistical Summary for numerical columns

df.describe().transpose() is a Pandas method that provides descriptive statistics for a DataFrame. The describe() method computes summary statistics such as count, mean, standard deviation, minimum, and maximum values for numerical columns in the DataFrame. The transpose() method then switches the rows and columns of the resulting DataFrame, making the statistics for each column appear as rows instead of columns. This makes it easier to interpret the summary statistics for each feature in the dataset, as we can view them side by side rather than having to scan across multiple columns. In summary, df.describe().transpose() is a convenient way to obtain a quick overview of the summary statistics for each feature in a DataFrame.

	count	mean	std	min	25%	50%	75%	max
SNo	9408.0	4.704500e+03	2.716000e+03	1.000000e+00	2.352750e+03	4.704500e+03	7.056250e+03	9.408000e+03
High	9408.0	2.245296e+03	7.297368e+03	2.048400e-04	1.060599e-01	4.338992e+01	3.497877e+02	6.486310e+04
Low	9408.0	2.108906e+03	6.823157e+03	1.946130e-04	9.701510e-02	4.100250e+01	3.198715e+02	6.220896e+04
Open	9408.0	2.180658e+03	7.078639e+03	1.966920e-04	1.011220e-01	4.234630e+01	3.378597e+02	6.352375e+04
Close	9408.0	2.184401e+03	7.085992e+03	1.967090e-04	1.013561e-01	4.238147e+01	3.379402e+02	6.350346e+04
Volume	9408.0	5.842552e+09	1.265555e+10	9.284190e+03	8.131160e+07	5.721684e+08	5.068277e+09	3.510000e+11
Marketcap	9408.0	5.086161e+10	1.334378e+11	9.986680e+06	1.184531e+09	4.387144e+09	3.859717e+10	1.190000e+12

The output of df.describe().transpose() provides a summary of the key statistical measures for each numerical column in the dataset. The count row indicates the number of non-missing values in each column.

The mean row shows the average value for each column, while the std row indicates the standard deviation, or the amount of variation, in each column's values. The min and max rows show the smallest and largest values in each column, respectively.

The 25%, 50%, and 75% rows represent the first quartile (Q1), median, and third quartile (Q3) of the data distribution, respectively. These values can be used to assess the spread of the data, identify potential outliers, and evaluate the skewness of the distribution.

Based on the output, it can be observed that the dataset has 9,408 observations and 6 numerical features. The Volume and Marketcap features have the highest mean and standard deviation values, indicating significant variability in the data. Meanwhile, the SNo feature represents a sequential identifier for each observation, while the remaining features (High, Low, Open, and Close) represent the price data of a financial asset. The range of values for these price features is quite large, as evidenced by the large difference between the min and max values.

The high, low, open, and close columns represent the daily price of the cryptocurrencies, with mean values of 2.245296e+03, 2.108906e+03, 2.180658e+03, and 2.184401e+03, respectively. The standard deviations are relatively large, indicating a wide variability in the price movements. The minimum and maximum values of the high, low, open, and close columns are 2.048400e-04 and 6.486310e+04, respectively.

The volume column represents the daily trading volume of the cryptocurrencies, with a mean of 5.842552e+09 (SD = 1.265555e+10). The trading volume exhibits a positively skewed distribution, as evidenced by the median value (50%) of 5.721684e+08 being much lower than the mean value. The minimum and maximum values of the volume column are 9 .284190e+03 and 3.510000e+11, respectively.

The Marketcap column represents the market capitalization of the cryptocurrencies, with a mean of 5.086161e+10 (SD = 1.334378e+11). The market capitalization also exhibits a positively skewed distribution, with the median value (50%) of 4.387144e+09 being much lower than the mean value. The minimum and maximum values of the Marketcap column are 9.986680e+06 and 1.190000e+12, respectively.

Overall, the df.describe().transpose() output provides a quick summary of the key statistics for each numerical feature in the dataset, which can be used to gain insights into the data distribution and identify potential issues or patterns in the data.

Let's delve into the statistical summary of each currency to gain further insights into our dataset.

The code written in Python uses the pandas library to load, manipulate and summarize data from a CSV file named 'sixcrypto.csv'.

- First, it imports the pandas library using the alias 'pd' for easier reference.
- Then, the CSV file is loaded into a pandas DataFrame called 'df' using the **pd.read_csv()** function.
- The 'SNo' column in the DataFrame is dropped using the **drop()** method with the 'axis=1' argument to indicate that it is a column that needs to be dropped. The **inplace=True** argument is used to modify the DataFrame in place rather than creating a copy.
- Next, the DataFrame is renamed as 'crypto_data' using the assignment operator '='.
- The data in the 'crypto_data' DataFrame is then grouped by the 'Symbol' column using the **groupby()** method, which returns a DataFrameGroupBy object.
- The code then loops through the groups and calculates the statistical summary for each group using the **describe()** method on each group. The **describe()** method provides various statistical summary measures like count, mean, standard deviation, minimum and maximum values, quartiles etc.
- The **transpose()** method is then used to transpose the summary statistics from rows to columns for easier readability.
- Finally, the name of the group and its summary statistics are printed out using the **print()** function.

Overall, this code loads and manipulates cryptocurrency data from a CSV file using pandas and calculates statistical summaries for each group of cryptocurrency symbols in the dataset.

Litecoin:

```
LTC
             count          mean           std           min           25%  \
High        1648.0  8.836755e+01  7.040699e+01  3.769480e+00  4.540341e+01
Low         1648.0  8.076967e+01  6.201480e+01  3.613590e+00  4.331137e+01
Open        1648.0  8.476022e+01  6.651762e+01  3.714440e+00  4.447457e+01
Close       1648.0  8.481855e+01  6.645836e+01  3.714530e+00  4.448149e+01
Volume      1648.0  2.329138e+09  2.596721e+09  2.629220e+06  3.286380e+08
Marketcap   1648.0  5.178139e+09  4.158405e+09  1.838773e+08  2.742632e+09

                     50%           75%           max
High        6.095937e+01  1.189067e+02  4.129601e+02
Low         5.747658e+01  1.088358e+02  3.452988e+02
Open        5.932576e+01  1.145168e+02  3.878692e+02
Close       5.933581e+01  1.146692e+02  3.864508e+02
Volume      1.711569e+09  3.353639e+09  1.799426e+10
Marketcap   3.656093e+09  6.694942e+09  2.579652e+10
```

For Litecoin (LTC), the data includes 1648 daily observations of the high, low, open, close prices, trading volume, and market capitalization. The mean values for the high, low, open, and close prices

are 8.836755e+01, 8.076967e+01, 8.476022e+01, and 8.481855e+01, respectively. The standard deviations for these variables are relatively large, with values of 7.040699e+01, 6.201480e+01, 6.651762e+01, and 6.645836e+01, respectively, indicating a wide variability in price movements.

The minimum and maximum values of the high, low, open, and close prices are 3.769480e+00 and 4.129601e+02, respectively. The volume column has a mean of 2.329138e+09 (SD = 2.596721e+09), with a positively skewed distribution as evidenced by the median value (50%) of 1.711569e+09 being much lower than the mean value. The minimum and maximum values of the volume column are 2.629220e+06 and 1.799426e+10, respectively.

The market capitalization column has a mean of 5.178139e+09 (SD = 4.158405e+09), also with a positively skewed distribution, as evidenced by the median value (50%) of 3.656093e+09 being much lower than the mean value. The minimum and maximum values of the market capitalization column are 1.838773e+08 and 2.579652e+10, respectively.

Cardano Coin:

```
ADA
              count          mean           std           min           25%  \
High         1374.0  2.698068e-01  4.335232e-01  2.105030e-02  4.756542e-02
Low          1374.0  2.397098e-01  3.809276e-01  1.762000e-02  4.460074e-02
Open         1374.0  2.552866e-01  4.084556e-01  1.841390e-02  4.589775e-02
Close        1374.0  2.563126e-01  4.096914e-01  1.853910e-02  4.594670e-02
Volume       1374.0  8.934183e+08  2.107653e+09  1.739460e+06  5.014830e+07
Marketcap    1374.0  7.603454e+09  1.303878e+10  4.806646e+08  1.191263e+09

                   50%           75%           max
High         9.027426e-02  1.945189e-01  2.461766e+00
Low          8.316395e-02  1.724417e-01  2.013285e+00
Open         8.686724e-02  1.813737e-01  2.300190e+00
Close        8.700222e-02  1.833791e-01  2.309113e+00
Volume       1.186742e+08  4.875977e+08  1.914198e+10
Marketcap    2.270889e+09  5.174547e+09  7.377224e+10
```

For Cardano (ADA), the data includes 1374 daily observations of the high, low, open, close prices, trading volume, and market capitalization. The mean values for the high, low, open, and close prices are 2.698068e-01, 2.397098e-01, 2.552866e-01, and 2.563126e-01, respectively. The standard deviations for these variables are 4.335232e-01, 3.809276e-01, 4.084556e-01, and 4.096914e-01, respectively, indicating a wide variability in price movements.

The minimum and maximum values of the high, low, open, and close prices are 2.105030e-02 and 2.461766e+00, respectively. The volume column has a mean of 8.934183e+08 (SD = 2.107653e+09), with a positively skewed distribution as evidenced by the median value (50%) of 1.186742e+08 being much lower than the mean value. The minimum and maximum values of the volume column are 1.739460e+06 and 1.914198e+10, respectively.

The market capitalization column has a mean of 7.603454e+09 (SD = 1.303878e+10), also with a positively skewed distribution, as evidenced by the median value (50%) of 1.191263e+09 being much lower than the mean value. The minimum and maximum values of the market capitalization column are 4.806646e+08 and 2.300190e+09, respectively.

Binance Coin:

```
BNB
              count          mean           std           min           25%  \
High         1442.0  5.476410e+01  1.216758e+02  1.012110e-01  1.039075e+01
Low          1442.0  4.916581e+01  1.081185e+02  9.610940e-02  9.677340e+00
Open         1442.0  5.202823e+01  1.151701e+02  9.972120e-02  1.003786e+01
```

```
Close      1442.0  5.225031e+01  1.153909e+02  9.986680e-02  1.006835e+01
Volume     1442.0  6.269804e+08  1.479775e+09  9.284190e+03  5.089148e+07
Marketcap  1442.0  7.835965e+09  1.780249e+10  9.986680e+06  1.157863e+09

                  50%           75%           max
High       1.659211e+01  2.824091e+01  6.909320e+02
Low        1.572725e+01  2.696304e+01  6.314653e+02
Open       1.621033e+01  2.766989e+01  6.763159e+02
Close      1.621057e+01  2.769111e+01  6.756841e+02
Volume     1.981830e+08  3.942378e+08  1.798295e+10
Marketcap  2.451099e+09  4.061743e+09  1.040000e+11
```

For Binance Coin (BNB), the data includes 1442 daily observations of the high, low, open, close prices, trading volume, and market capitalization. The mean values for the high, low, open, and close prices are 5.476410e+01, 4.916581e+01, 5.202823e+01, and 5.225031e+01, respectively. The standard deviations for these variables are 1.216758e+02, 1.081185e+02, 1.151701e+02, and 1.153909e+02, respectively, indicating a wide variability in price movements.

The minimum and maximum values of the high, low, open, and close prices are 1.012110e-01 and 6.909320e+02, respectively. The volume column has a mean of 6.269804e+08 (SD = 1.479775e+09), with a positively skewed distribution as evidenced by the median value (50%) of 1.981830e+08 being much lower than the mean value. The minimum and maximum values of the volume column are 9.284190e+03 and 1.798295e+10, respectively.

The market capitalization column has a mean of 7.835965e+09 (SD = 1.780249e+10), also with a positively skewed distribution, as evidenced by the median value (50%) of 2.451099e+09 being much lower than the mean value. The minimum and maximum values of the market capitalization column are 9.986680e+06 and 1.040000e+11, respectively.

Bitcoin:

```
BTC
            count          mean           std           min           25%  \
High       1648.0  1.216162e+04  1.357205e+04  8.233070e+02  4.877465e+03
Low        1648.0  1.143817e+04  1.264045e+04  7.557560e+02  4.470868e+03
Open       1648.0  1.181870e+04  1.314910e+04  7.751780e+02  4.613783e+03
Close      1648.0  1.183847e+04  1.315736e+04  7.777570e+02  4.680163e+03
Volume     1648.0  1.976129e+10  2.174509e+10  6.085170e+07  4.188452e+09
Marketcap  1648.0  2.145495e+11  2.473754e+11  1.251914e+10  7.890546e+10

                  50%           75%           max
High       8.234140e+03  1.110076e+04  6.486310e+04
Low        7.842872e+03  1.053982e+04  6.220896e+04
Open       8.063433e+03  1.084634e+04  6.352375e+04
Close      8.055607e+03  1.085863e+04  6.350346e+04
Volume     1.365801e+10  2.978197e+10  3.510000e+11
Marketcap  1.410000e+11  1.940000e+11  1.190000e+12
```

The data for Bitcoin shows that there were 1648 daily observations of the high, low, open, close prices, trading volume, and market capitalization. The mean values for the high, low, open, and close prices are 1.216162e+04, 1.143817e+04, 1.181870e+04, and 1.183847e+04, respectively. The standard deviations for these variables are relatively high, indicating that there has been significant variability in price movements.

The minimum and maximum values of the high, low, open, and close prices are 8.233070e+02 and 6.486310e+04, respectively. The volume column has a mean of 1.976129e+10 (SD = 2.174509e+10), with a positively skewed distribution, as evidenced by the median value (50%) of 1.365801e+10 being lower than the mean value. The minimum and maximum values of the volume column are 6.085170e+07 and 3.510000e+11, respectively.

The market capitalization column has a mean of 2.145495e+11 (SD = 2.473754e+11), also with a positively skewed distribution, as evidenced by the median value (50%) of 1.410000e+11 being lower than the mean value. The minimum and maximum values of the market capitalization column are 1.251914e+10 and 1.190000e+12, respectively.

Overall, the data suggests that Bitcoin is a highly volatile asset with significant fluctuations in price movements and trading volume. The market capitalization of Bitcoin is also quite large, indicating that it is a significant player in the cryptocurrency market

Dogecoin:

```
DOGE
             count          mean           std           min           25%  \
High        1648.0  2.485953e-02  8.806860e-02  2.048400e-04  2.151102e-03
Low         1648.0  2.058939e-02  7.071171e-02  1.946130e-04  2.055418e-03
Open        1648.0  2.270210e-02  7.942883e-02  1.966920e-04  2.096444e-03
Close       1648.0  2.285838e-02  7.968948e-02  1.967090e-04  2.100501e-03
Volume      1648.0  7.242091e+08  3.604293e+09  5.407950e+04  1.055230e+07
Marketcap   1648.0  2.933065e+09  1.033952e+10  2.128503e+07  2.498939e+08

                 50%           75%           max
High        2.736100e-03  3.838227e-03  7.375666e-01
Low         2.599330e-03  3.496225e-03  6.081677e-01
Open        2.662656e-03  3.672514e-03  6.878015e-01
Close       2.663201e-03  3.689054e-03  6.847770e-01
Volume      3.486363e+07  1.028266e+08  6.941068e+10
Marketcap   3.263688e+08  4.411314e+08  8.868082e+10
```

The data for Dogecoin shows that there were 1648 daily observations of the high, low, open, close prices, trading volume, and market capitalization. The mean values for the high, low, open, and close prices are 2.485953e-02, 2.058939e-02, 2.270210e-02, and 2.285838e-02, respectively. The standard deviations for these variables are relatively high, indicating that there has been significant variability in price movements.

The minimum and maximum values of the high, low, open, and close prices are 2.048400e-04 and 7.375666e-01, respectively. The volume column has a mean of 7.242091e+08 (SD = 3.604293e+09), with a positively skewed distribution, as evidenced by the median value (50%) of 3.486363e+07 being lower than the mean value. The minimum and maximum values of the volume column are 5.407950e+04 and 6.941068e+10, respectively.

The market capitalization column has a mean of 2.933065e+09 (SD = 1.033952e+10), also with a positively skewed distribution, as evidenced by the median value (50%) of 3.263688e+08 being lower than the mean value. The minimum and maximum values of the market capitalization column are 2.128503e+07 and 8.868082e+10, respectively.

Overall, the data suggests that Dogecoin is a highly volatile asset with significant fluctuations in price movements and trading volume. The market capitalization of Dogecoin is relatively small compared to other cryptocurrencies, indicating that it is a smaller player in the cryptocurrency market.

Ethereum:

```
ETH
             count          mean           std           min           25%  \
High        1648.0  5.196492e+02  6.744691e+02  8.436330e+00  1.751977e+02
Low         1648.0  4.770173e+02  6.069889e+02  7.982310e+00  1.649274e+02
Open        1648.0  4.995809e+02  6.434077e+02  7.982310e+00  1.702685e+02
Close       1648.0  5.009299e+02  6.448244e+02  8.172570e+00  1.706190e+02
Volume      1648.0  9.245476e+09  1.132841e+10  4.689950e+06  1.533612e+09
Marketcap   1648.0  5.449910e+10  7.462537e+10  7.150492e+08  1.815161e+10
```

```
                    50%           75%           max
High       2.669922e+02  4.931448e+02  4.362351e+03
Low        2.451433e+02  4.652826e+02  3.785849e+03
Open       2.571551e+02  4.795873e+02  4.174636e+03
Close      2.580102e+02  4.797018e+02  4.168701e+03
Volume     5.598255e+09  1.243547e+10  8.448291e+10
Marketcap  2.695053e+10  4.980239e+10  4.830000e+11
```

The data for Ethereum shows that there were 1648 daily observations of the high, low, open, close prices, trading volume, and market capitalization. The mean values for the high, low, open, and close prices are 5.196492e+02, 4.770173e+02, 4.995809e+02, and 5.009299e+02, respectively. The standard deviations for these variables are relatively high, indicating that there has been significant variability in price movements.

The minimum and maximum values of the high, low, open, and close prices are 8.436330e+00 and 4.362351e+03, respectively. The volume column has a mean of 9.245476e+09 (SD = 1.132841e+10), with a positively skewed distribution, as evidenced by the median value (50%) of 5.598255e+09 being lower than the mean value. The minimum and maximum values of the volume column are 4.689950e+06 and 8.448291e+10, respectively.

The market capitalization column has a mean of 5.449910e+10 (SD = 7.462537e+10), also with a positively skewed distribution, as evidenced by the median value (50%) of 2.695053e+10 being lower than the mean value. The minimum and maximum values of the market capitalization column are 7.150492e+08 and 4.830000e+11, respectively.

Overall, the data suggests that Ethereum is a highly volatile asset with significant fluctuations in price movements and trading volume. The market capitalization of Ethereum is relatively large compared to other cryptocurrencies, indicating that it is a major player in the cryptocurrency market.

Correlation

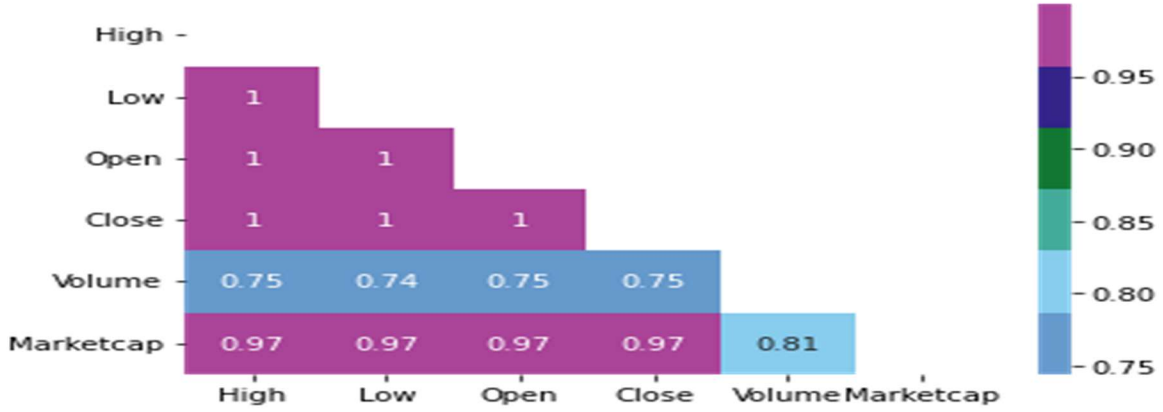
Correlation Coefficient	Strength of Relationship
-1	Perfect negative correlation
-0.7 to -0.9	Strong negative correlation
-0.5 to -0.7	Moderate negative correlation
-0.3 to -0.5	Weak negative correlation
0	No correlation
0.3 to 0.5	Weak positive correlation
0.5 to 0.7	Moderate positive correlation
0.7 to 0.9	Strong positive correlation
1	Perfect positive correlation

It's worth noting that the interpretation of the correlation coefficient can vary depending on the field of study and the context of the analysis. However, in general, a correlation coefficient between -0.7 and -0.9 (or between 0.7 and 0.9) is considered a strong correlation, while a coefficient between -0.5 and -0.7 (or between 0.5 and 0.7) is considered a moderate correlation. Coefficients between -0.3 and -0.5 (or between 0.3 and 0.5) are typically considered weak correlations.

- The Python code loads a dataset from a CSV file named "sixcrypto.csv" using the Pandas read_csv() function, creating a DataFrame object named df. The num_cols variable is then used to select only the numerical columns from the df DataFrame, namely Open, High, Low, Close, Volume, and Marketcap. A new DataFrame named num_df is created to hold only these selected numerical columns.
- Next, the correlation matrix between these numerical columns is calculated using the corr() method on the num_df DataFrame.
- Finally, the correlation matrix is printed to the console using the print() function.

	Open	High	Low	Close	Volume	Marketcap
Open	1.000000	0.999546	0.999109	0.998901	0.749004	0.968995
High	0.999546	1.000000	0.999053	0.999525	0.750852	0.969801
Low	0.999109	0.999053	1.000000	0.999423	0.744467	0.969238
Close	0.998901	0.999525	0.999423	1.000000	0.748179	0.970084
Volume	0.749004	0.750852	0.744467	0.748179	1.000000	0.807050
Marketcap	0.968995	0.969801	0.969238	0.970084	0.807050	1.000000

The correlation results show a strong positive correlation among the variables, with correlation coefficients ranging from 0.749 to 1.000. The strongest correlation is observed between the High and Close variables (correlation coefficient of 0.999525), followed by the correlation between the Low and Close variables (correlation coefficient of 0.999423). The Volume variable has a weaker correlation with the other variables (correlation coefficients ranging from 0.744 to 0.750).



The analysis of the correlation results suggests a high level of interdependence among the various cryptocurrency price features, such as Open, High, Low, Close, Volume, and Marketcap. The correlation coefficients between these variables range from 0.749 to 0.970, which indicates a strong positive association between them. This finding has significant implications for modeling and forecasting cryptocurrency prices, as it implies that incorporating all of these variables may lead to data redundancy or multicollinearity. This means that accurately predicting cryptocurrency prices might be challenging because it could be difficult to discern the relative importance of each feature.

To overcome this challenge, further analysis could be conducted to explore the direction and strength of causal relationships among the variables. Such analysis could provide insights into the underlying mechanisms that drive cryptocurrency price movements and help identify the most critical factors to consider in forecasting future price trends. Additionally, external factors that influence cryptocurrency prices, such as economic and political events, could also be examined to determine their impact on price movements. By considering both the internal and external factors that affect cryptocurrency prices, more accurate and reliable forecasting models could be developed.

Principal Component Analysis (PCA)

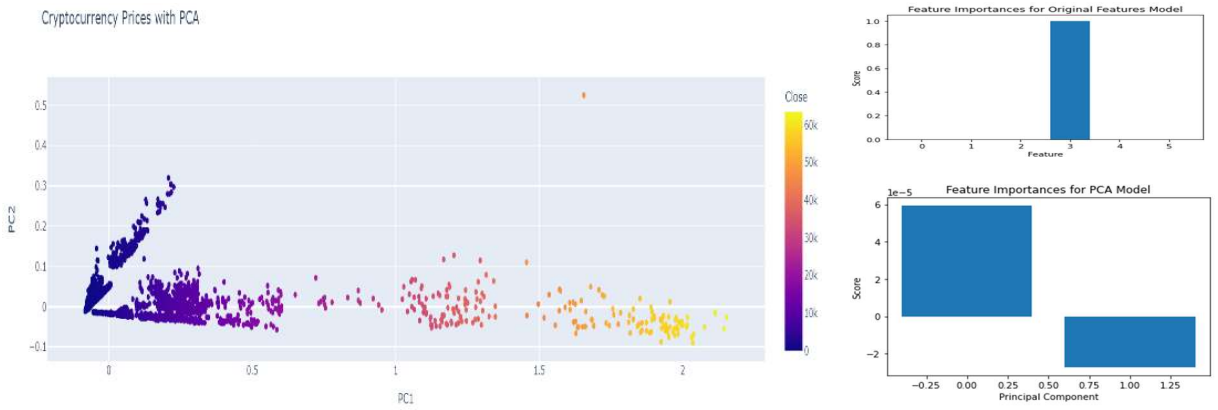
To delve deeper into the analysis, it could be beneficial to perform a principal component analysis (PCA) on the data to identify the most significant features and decrease the dataset's dimensionality. PCA is a popular approach in data analysis and machine learning that involves reducing the dimensionality of high-dimensional data while retaining critical information. The primary objective of PCA is to convert a collection of correlated variables into a smaller set of uncorrelated variables (referred to as principal components), while still preserving the most crucial information.

Here are Here are some key points covered in the article written by Matt Brems **[10]**:

1. PCA is a mathematical methodology that can convert high-dimensional data into a lower-dimensional space while maintaining crucial information.
2. PCA is a beneficial tool in simplifying the complexity of data, discovering patterns and associations between variables, and enhancing the efficiency of machine learning models.
3. The article provides a step-by-step guide to performing PCA using Python, including data preprocessing, PCA implementation, and visualizing the results.
4. The article also covers important concepts related to PCA, such as variance, covariance, eigenvectors, and eigenvalues.
5. The article provides practical examples of using PCA in real-world scenarios, such as image processing and finance.
6. The article discusses some common pitfalls and limitations of PCA, such as the interpretability of the results and the assumption of linearity.

The code used in python to access the PCA model begins by importing the necessary Python libraries including Pandas, NumPy, Plotly, scikit-learn, and Matplotlib. It then defines a function to calculate the mean absolute percentage error (MAPE) which is used to evaluate the model later on.

- The code reads in a dataset of cryptocurrency prices from a CSV file using Pandas and selects a set of features to use in the analysis. These features are then scaled using the MinMaxScaler from scikit-learn.
- Principal component analysis (PCA) is performed on the scaled features using the PCA function from scikit-learn. Two principal components are selected, and a new dataframe is created using the principal components and the original data. This allows the data to be visualized in two dimensions.
- The data is split into training and testing sets using the train_test_split function from scikit-learn. A linear regression model is fitted on the original features, and the metrics for the model are computed using mean squared error, mean absolute error, MAPE, R-squared, and adjusted R-squared.
- The data is then standardized using the StandardScaler from scikit-learn, and PCA is performed on the standardized data. The principal components are concatenated with the original features, and the data is split into training and testing sets again.
- Another linear regression model is fitted on the principal components, and the metrics for this model are computed. The results of the PCA are visualized using a scatter plot in Plotly.
- Finally, the feature importances for both the original features model and the PCA model are computed and visualized using bar plots in Matplotlib.
- Overall, this code performs a basic analysis of cryptocurrency prices using PCA and linear regression models. The code could be further improved by optimizing the hyperparameters of the models and including additional features in the analysis.




```
Feature importance for the original features model:
Feature: 0, Score: 0.00000
Feature: 1, Score: -0.00000
Feature: 2, Score: 0.00000
Feature: 3, Score: 1.00000
Feature: 4, Score: 0.00000
Feature: 5, Score: -0.00000
Feature importance for the PCA model:
Principal Component: 1, Score: 0.00006
Principal Component: 2, Score: -0.00003
```

The results of the feature importance analysis for the original features model show that only Feature 3 has a score of 1.0, suggesting that it is the only feature that significantly contributes to the model's predictive performance. Conversely, all other features have scores of 0.0, indicating that they do not have a significant impact on the model's predictive power.

On the other hand, the feature importances for the PCA model are based on the principal components. The scores for the principal components are much smaller than 1.0, suggesting that each principal component contributes only a small amount to the model's predictive performance. Specifically, Principal Component 1 has a score of 0.00006, indicating a very small positive impact on the model's performance, while Principal Component 2 has a score of -0.00003, indicating a small negative impact. Overall, the results suggest that the PCA model's performance may be less reliant on any one particular feature or principal component, but instead relies on the combined effects of all of the components.

Regarding which model to use, it ultimately depends on the specific requirements of your problem and the resources available. The original features model may be preferred if interpretability and transparency are important, as it directly uses the original features in the analysis. On the other hand, the PCA model may be preferred if dimensionality reduction and computational efficiency are priorities, as it reduces the dimensionality of the data and may result in faster and more efficient analysis.

Seasonal Decomposition of the Cryptocurrencies Close Price

Seasonal decomposition is a technique used in time series analysis to separate a time series into its underlying components: trend, seasonal, and residual. The trend component represents the long-term progression of the time series, the seasonal component captures the repeating patterns that occur over shorter periods of time (e.g., days, weeks, months, seasons), and the residual component represents the random fluctuations or noise that cannot be explained by the trend or seasonal components.

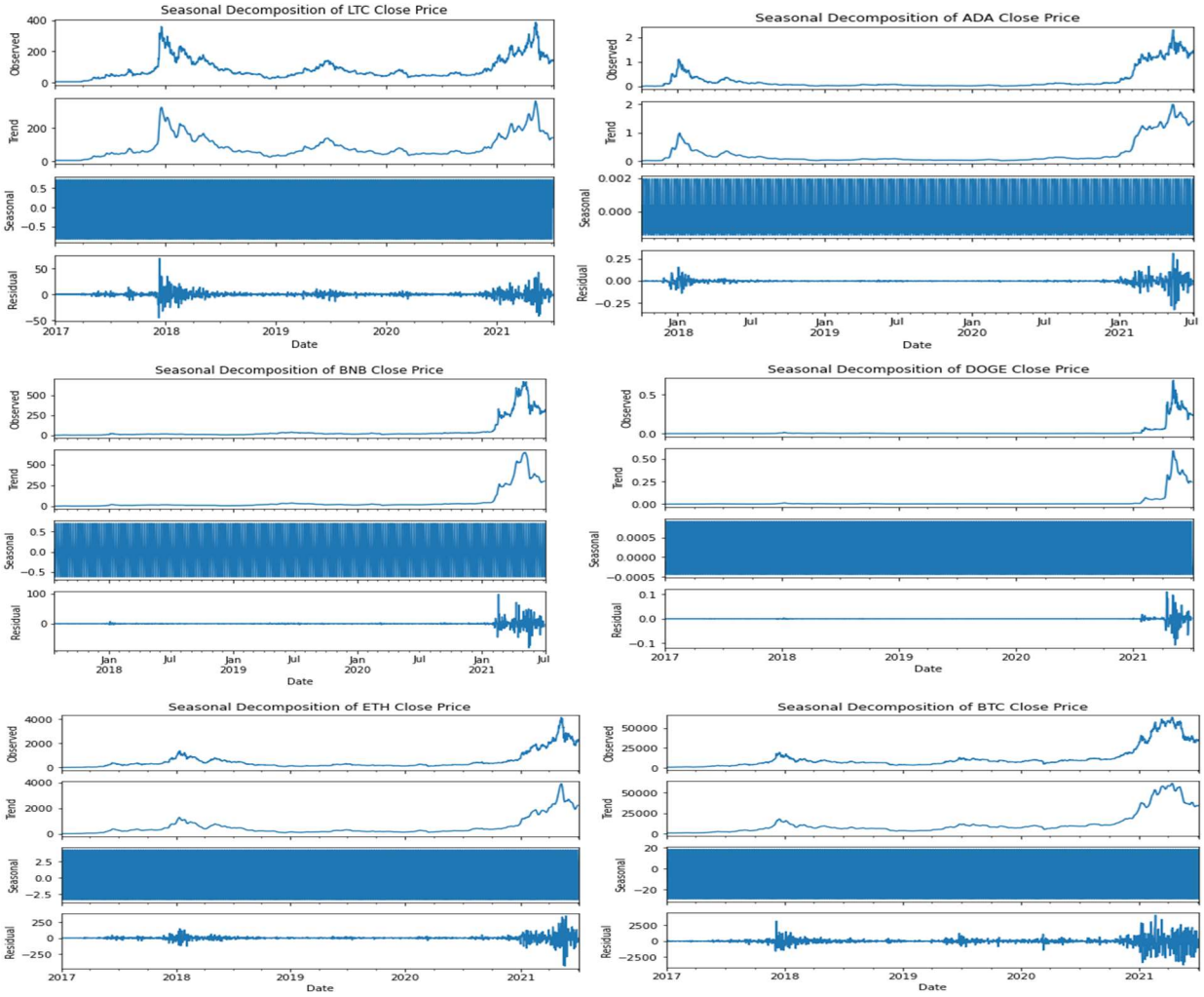
An article “Different types of Time series decomposition” [11] written by Andrew Plummer has these below key points:

1. In the field of data science, time series decomposition techniques are used to break down a time series dataset into its constituent components, including trend, seasonal, and remainder components.
2. These techniques help analysts identify patterns and trends within the data, which can be useful in making predictions or understanding underlying relationships.
3. The article covers three different time series decomposition techniques: classical decomposition, seasonal decomposition of time series (STL), and empirical mode decomposition (EMD).
4. Classical decomposition involves identifying the trend, seasonal, and remainder components of a time series, while STL uses a non-parametric approach to extract seasonal and trend components. EMD decomposes a time series into intrinsic mode functions (IMFs) that represent different frequencies in the data.
5. The choice of decomposition technique depends on the specific dataset and research question at hand. By using time series decomposition techniques, data scientists can gain a deeper understanding of time series data and extract meaningful insights.

The python code performs seasonal decomposition of cryptocurrency close prices using the statsmodels library in Python.

Here is what the code does step by step:

- Import necessary libraries - pandas, matplotlib, and statsmodels.
- Load the cryptocurrency data into a pandas dataframe using pd.read_csv.
- Create a new dataframe df_time_series with the necessary columns for time series analysis (Date, Close, and Symbol).
- Convert the Date column to datetime format using pd.to_datetime and set it as the index of the dataframe using set_index.
- Group the data by Symbol and resample it to a daily frequency using groupby and resample.
- Interpolate missing values in the resampled data using linear interpolation.
- Loop through each unique cryptocurrency Symbol in the dataframe.
- Perform seasonal decomposition on the close price data for the current cryptocurrency using sm.tsa.seasonal_decompose with the additive model.
- Create a 4x1 subplots for each component of the seasonal decomposition (observed, trend, seasonal, and residual) using plt.subplots.
- Plot each component in the appropriate subplot using .plot on the res object returned by seasonal_decompose.
- Show the plot using plt.show().



The output of this code is a set of four plots for each cryptocurrency, showing the observed, trend, seasonal, and residual components of the time series decomposition. These plots can be used to analyze the patterns and trends in the cryptocurrency close prices over time.

The goal of seasonal decomposition is to gain a better understanding of the underlying structure of the time series and to identify any patterns or trends that may exist. This can be useful for making predictions about future values of the time series, as well as for identifying potential relationships between the time series and other variables.

The Augmented Dickey-Fuller (ADF) test

The Augmented Dickey-Fuller (ADF) test is a statistical test that aims to determine the stationarity of a given time series. Stationarity refers to the property of a time series in which its statistical characteristics, such as the mean and variance, remain constant over time. This is a crucial assumption in many time series models, as it simplifies the analysis and interpretation of the data.

As a unit root test, the ADF test examines whether a unit root exists in the time series, which is a characteristic of a non-stationary time series that tends to drift over time and does not revert to its mean. The ADF test compares the differences between the observed values in the time series and the expected values if the series were stationary. If the differences are significant enough, the null hypothesis of a unit root is rejected, indicating that the time series is stationary.

The ADF test is based on the augmented Dickey-Fuller regression model, which is a linear regression model that includes lagged differences of the time series as explanatory variables. The ADF test examines the coefficient of the lagged first difference in the regression equation, which represents the rate at which the time series reverts to its mean.

The ADF test has several variations, including the ADF test with a constant and trend term, which allows for a linear trend in the time series. The ADF test can also be applied to seasonal time series, where the seasonal differences are included in the regression equation.

An article on “Augmented Dickey Fuller Test (ADF Test) – Must Read Guide” [12] by Selva Prabhakaran, explains that

1. Stationarity testing is a statistical method utilized to determine whether a time series maintains its consistency in terms of mean and variance over time. When a time series remains stationary, it offers a more straightforward analysis and modeling approach, as compared to non-stationary time series.
2. The ADF test determines if a time series is stationary assuming it has a unit root and is non-stationary. It calculates a p-value that shows the likelihood of obtaining the observed test statistic under the null hypothesis. Rejecting the null hypothesis if p-value < 0.05 categorizes the time series as stationary. The ADF test is crucial for modeling and analyzing time series data.
3. an example of performing the ADF test utilizing the Python's statsmodels library is demonstrated, which involves using a dataset containing the daily closing prices of the S&P 500 index from 2000 to 2021.
4. Additionally, the article explains the commonly used technique of first-order differencing to convert a non-stationary time series into a stationary one, which involves computing the difference between consecutive observations.
5. Finally, the article acknowledges some limitations of the ADF test, such as its sensitivity to the selection of lag length and the assumption of no seasonality. The article recommends using additional tests in conjunction with the ADF test to obtain a more robust assessment of stationarity.

ADF Test Results	ADF Statistic	p-value	1% Critical Value	5% Critical Value	10% Critical Value
LTC	-2.71	0.07	-3.43	-2.86	-2.5
ADA	-0.37	0.92	-3.44	-2.86	-2.56
BNB	-1.19	0.68	-3.43	-2.86	-2.57
DOGE	-2.50	0.11	-3.43	-2.86	-2.56
ETH	-0.29	0.93	-3.43	-2.86	-2.57
BTC	-0.85	0.80	-3.43	-2.86	-2.57

The ADF test outcomes contain insights about the stationarity of each cryptocurrency's time series. The ADF test's null hypothesis is that the time series is non-stationary and has a unit root. If the p-value is below the chosen significance level (often 0.05), the null hypothesis is rejected, indicating that the time series is stationary.

Based on the ADF test results, it is evident that the p-values for all the cryptocurrencies are greater than 0.05. As a result, we fail to reject the null hypothesis, and we cannot claim that any of the cryptocurrencies have a stationary time series.

The ADF Statistic value in the ADF test is a measure of how much the time series deviates from being stationary. It indicates the extent of non-stationarity in the time series. A more negative ADF statistic value provides stronger evidence against the null hypothesis of stationarity.

To summarize, based on the ADF test results, it is indicated that the time series of each cryptocurrency might not be stationary. The results show that none of the cryptocurrencies have p-values less than the significance level of 0.05, which indicates that we cannot reject the null hypothesis of non-stationarity. Additionally, the ADF Statistic values are not more negative than their respective critical values, which also supports the conclusion of non-stationarity.

In conclusion, the ADF test is a powerful tool for testing the stationarity of time series data. It is widely used in many areas of research, including finance, economics, and environmental science. The ADF test provides a robust and reliable method for testing the null hypothesis of a unit root in a time series, allowing researchers to make informed decisions about the statistical properties of their data.

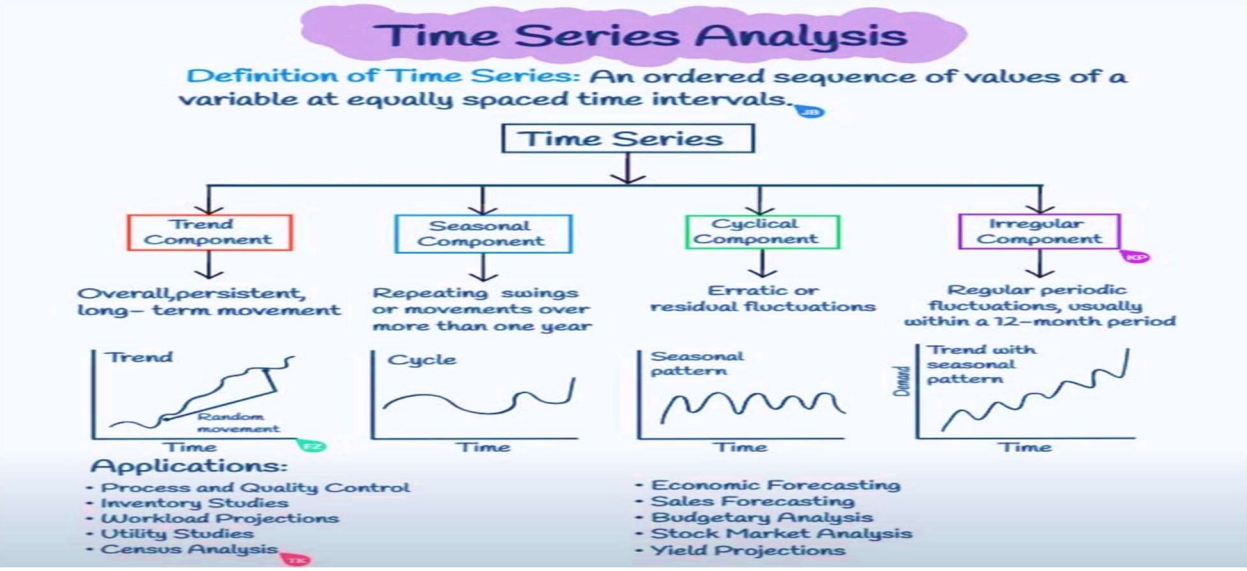
Time-Series Forecasting

Time series analysis is a statistical approach that involves studying data collected over a period of time to identify correlations, patterns, and trends. This technique has numerous practical applications in different fields, such as healthcare, economics, finance, engineering, and marketing. Time series forecasting, which is a subset of this method, is focused on making predictions about future trends and patterns based on historical data.

In finance and economics, time series analysis is commonly used to analyze stock prices, exchange rates, and interest rates, providing insights into long-term trends and patterns to help investors and policymakers make informed decisions. Time series forecasting is also used in cryptocurrency analysis to predict future price movements based on historical data. In healthcare, time series analysis is used to analyze patient data, predict disease outbreaks, and identify patterns in treatment outcomes. In engineering, this technique is used to analyze data from sensors, machines, and equipment to identify patterns and trends, predict equipment failures, and improve maintenance schedules.

Time series analysis comprises four major components, namely trend, seasonality, cyclical variations, and irregular fluctuations. The trend component shows the long-term behavior of the data over time, whether it is increasing, decreasing, or remaining constant. Seasonality relates to the regular patterns of the data that occur at consistent intervals, such as daily, weekly, or monthly. Cyclical variations pertain to fluctuations in the data that transpire over a more extended period than seasonality and are usually caused by economic cycles. Irregular fluctuations denote unforeseen or random variations in the data that cannot be explained by the other three components, namely trend, seasonality, and cyclical variations.

Time-series forecasting commonly utilizes several techniques, such as moving averages, exponential smoothing, and ARIMA models. Moving averages are computed by taking the average of a specified number of past data points to identify patterns or trends in the data. Exponential smoothing, on the other hand, assigns more weight to recent observations through the use of weighted averages of past data points. Meanwhile, ARIMA models combine autoregression and moving average methods to produce forecasts of future trends.



Credit:https://www.linkedin.com/feed/update/urn:li:activity:7038863762661023744?utm_source=share&utm_medium=member_desktop

To sum up, time series analysis is a crucial statistical technique that helps in extracting significant insights from historical data and predicting future trends. Its wide-ranging applications across industries make it an indispensable tool for decision-making. The four primary components of time series analysis - trend, seasonality, cyclical variations, and irregular fluctuations - help identify the patterns and fluctuations in data. The choice of time-series forecasting technique depends on the data and the specific context being analyzed. Techniques like autoregression, moving average, exponential smoothing, and ARIMA models are popular and effective for forecasting future values while accounting for various patterns in the data. Accurate time series forecasting is essential for various applications such as finance, economics, and marketing. Jason Brownlee's article on "Time Series Forecasting" **[13]** provides valuable insights into the definition of time series data, the process of time series forecasting, and the different techniques used for forecasting.

The article presents several key points that are worth noting:

1. Time series data comprises observations taken over time, such as daily stock prices or monthly sales figures.
2. Time series forecasting involves making predictions about future values based on past observations.
3. The fundamental goal of time series forecasting is to make precise predictions of future values while taking into account the patterns, trends, and seasonal variations present in the data.
4. There are various popular techniques for time series forecasting, such as autoregression, moving average, exponential smoothing, and ARIMA models.
5. Autoregression involves predicting future values based on past values of the same variable.
6. Moving average entails taking the average of a specific number of past data points to identify trends in the data.
7. Exponential smoothing involves using a weighted average of past data points, with more weight given to recent observations.
8. ARIMA models combine autoregression and moving average techniques to model the underlying patterns in the data and make predictions.

9. When selecting a time series forecasting technique, it is critical to consider the data's characteristics, such as seasonality, trend, and noise, as well as the analysis's objectives.
10. Time series forecasting can be used in a range of applications, including finance, economics, and marketing, to forecast future trends and patterns.

Here's a SWOT analysis on time series forecasting:

Strengths	Weaknesses
Helps identify trends and patterns in historical data	Can be inaccurate if the data is noisy or contains outliers
Can be used to make informed decisions about future trends and patterns	Can be limited in its predictive capabilities if the underlying patterns in the data change
Offers a variety of techniques to choose from	Can be difficult to select the most appropriate technique for a specific context and data set
Can be particularly useful in the context of financial analysis, such as predicting stock prices or currency exchange rates	Can be resource-intensive in terms of data collection and processing
Provides a quantitative and data driven approach to decision-making	Can be impacted by external factors that are difficult to predict or model
Opportunities	**Threats**
Can be used to identify new market trends and opportunities	Can be impacted by changes in external factors, such as changes in government policies or economic conditions
Can help companies make informed decisions about inventory management, production planning, and supply chain optimization	Can be subject to the "garbage in, garbage out" problem if the data used for analysis is of poor quality
Can be used to forecast demand for products and services	Can be impacted by the availability and quality of data
Can help companies stay competitive by identifying emerging trends before competitors	Can be subject to overreliance on historical data, which may not always be a reliable indicator of future trends
Can be used to manage risks, such as predicting the likelihood of default or fraud	Can be impacted by changes in technology or the availability of alternative forecasting methods

If you have an interest in time series forecasting and its ability to predict future trends and patterns, "Forecasting: Principles and Practice" by Rob J Hyndman and George Athanasopoulos [14] could be a valuable resource to explore. This book offers a thorough examination of the fundamental principles that underpin time series forecasting and includes an overview of various techniques, including machine learning algorithms, ARIMA models, and exponential smoothing.

The main objective of time series forecasting is to generate accurate predictions of future trends and patterns. Exponential smoothing is a popular technique that assigns more weight to recent observations to account for present trends and seasonality. Conversely, ARIMA models combine autoregression and moving average methods to predict underlying patterns. However, implementing

machine learning algorithms can be tough, requiring careful feature engineering and being computationally demanding.

To assess the accuracy of predictions, standard metrics like mean absolute error and root mean squared error are commonly used. Additionally, the presence of trends, seasonality, outliers, and missing values can all affect forecasting accuracy. Despite these difficulties, time series forecasting has various applications in finance, economics, and marketing, where historical data can be employed to generate knowledgeable predictions about future trends. Ensemble methods, which combine multiple forecasts to enhance accuracy, can be utilized to further refine predictions.

While it may be challenging to condense the essential concepts discussed in the book, I have endeavored to compile a summary of the key points for the reader's benefit.

1. Time series data is a sequence of observations collected over time, and can be used to make predictions about future values.
2. The goal of forecasting is to produce accurate predictions while taking into account trends, seasonality, and other patterns in the data.
3. There are several methods for time series forecasting, including exponential smoothing, ARIMA models, and machine learning algorithms.
4. Exponential smoothing involves weighting recent observations more heavily than older observations, and can be adapted to handle different types of trends and seasonality.
5. ARIMA models combine autoregression (predicting future values based on past values) and moving average techniques to model the underlying patterns in the data and make predictions.
6. While machine learning algorithms can be utilized for time series forecasting, they demand meticulous feature engineering and can result in high computational costs.
7. The accuracy of forecasts can be evaluated by utilizing various metrics, such as mean absolute error and root mean squared error.
8. Time series data can display different forms of seasonality, including additive and multiplicative seasonality.
9. Time series data can also exhibit trends, which can be linear or nonlinear.
10. Outliers and missing values can impact forecasting accuracy, and must be handled appropriately.
11. Forecasting can be used in a variety of applications, including finance, economics, and marketing, to make predictions about future trends and patterns.
12. Forecasting can be challenging and requires careful consideration of the characteristics of the data and the appropriate forecasting method to use.
13. Forecasting can be improved through the use of ensemble methods, which combine multiple forecasts to produce a more accurate prediction.

In summary, forecasting techniques, like time series analysis, have become indispensable tools for businesses to make well-informed decisions about upcoming trends and patterns in various sectors, including finance, economics, and marketing. Selecting the most appropriate forecasting technique based on the data's characteristics and analysis objectives while ensuring the data's accuracy and quality are essential for effective forecasting.

Despite potential challenges, time series forecasting presents various opportunities for firms to detect emerging trends, optimize their inventory planning and supply chain management, anticipate demand for products and services, and manage risks. Successful implementation of time series forecasting can provide companies with a competitive advantage and keep them ahead of emerging trends.

However, firms must also be aware of potential obstacles, including external factors, data quality issues, over-reliance on historical data, and advances in technology or alternative forecasting methods.

Simple Moving Average (SMA)

The Simple Moving Average (SMA) is a frequently used approach for time series analysis and forecasting. It is a type of moving average that smooths out short-term variations in a time series by calculating the average of the series for a particular time frame. To compute SMA, the values of a time series are summed over a specific number of periods, and then this total is divided by the number of periods.

SMA has a wide range of applications in various fields, including finance, marketing, and sales. In finance, SMA is often used to identify trends in stock prices or other financial data. In marketing and sales, SMA can help identify trends in customer behavior or sales patterns. This technique is particularly useful for identifying long-term trends because it reduces short-term fluctuations that may be caused by noise or other factors.

One of the main advantages of SMA is its simplicity. It is straightforward to calculate and does not require complex mathematical formulas or models. As a result, it is accessible to a wide range of users, including those with limited technical expertise. Furthermore, SMA produces a single value that represents the average of the time series over a specified period, making it easy to interpret.

Despite its usefulness, the Simple Moving Average (SMA) has some limitations that should be taken into account. Firstly, the SMA relies solely on historical data and does not consider external factors that might impact the time series. Moreover, the SMA may not be adequate for anticipating sudden changes or shifts in the time series as it is based on the average of past values. Lastly, choosing the appropriate time period for SMA calculation is crucial, as it can have a considerable effect on the outcomes and might require experimentation to determine the most suitable value.

Despite its limitations, the SMA remains a widely used technique in time series analysis and forecasting, particularly in cases where the time series exhibits a consistent pattern over time. In addition, the SMA can be combined with other techniques, such as exponential smoothing or ARIMA models, to produce more accurate forecasts.

The article titled "Moving Averages in Python" **[15]** introduces the concept of moving averages, which is a widely used statistical technique for smoothing time series data. The author explains the different types of moving averages, including simple moving average (SMA), exponential moving average (EMA), and weighted moving average (WMA). The article also provides step-by-step instructions on how to calculate and visualize these moving averages in Python using the Pandas library.

The author emphasizes the importance of choosing an appropriate window size for the moving average calculation, as this can significantly impact the resulting data smoothing. The article also touches on how moving averages can be used in trading strategies, such as identifying trends and support/resistance levels.

here are 5 key points from the article "Moving Averages in Python":

1. Moving averages are commonly used in time-series analysis to remove short-term fluctuations in data and emphasize longer-term trends.
2. There are two main types of moving averages: simple moving average (SMA) and exponential moving average (EMA). SMA calculates an average of a specified number of data points, while EMA gives more weight to recent data points.

3. Python offers various libraries, such as NumPy and Pandas, with built-in functions for computing moving averages. The Pandas' rolling() function is particularly helpful for computing both SMA and EMA.
4. The choice of window size for a moving average depends on the specific needs of the analysis. Typically, smaller window sizes work better for shorter-term trends, while larger window sizes are better for longer-term trends.
5. Moving averages are a useful tool in analyzing trends and patterns in data, but it's essential to use other analytical methods along with them to gain a comprehensive understanding of the data.

Overall, the article serves as a useful introduction to moving averages in Python for data analysts and traders alike, with practical examples and clear explanations of the underlying concepts.

Below is the SWOT analysis breakdown that we will use to analyze it:

Strengths	**Weaknesses**
Easy to calculate and understand	Can be affected by outliers and sudden price changes
Widely used and popular among traders and analysts	Can lag behind sudden price movements
Can be customized to fit different time frames and market conditions	May not be as effective in volatile markets
One of the benefits of using this approach is that it reduces the impact of price volatility and facilitates the identification of underlying trends.	This approach does not consider additional factors that could influence the changes in prices.
Can be combined with other technical indicators for better results	Relies heavily on historical data and may not accurately predict future prices
Opportunities	**Threats**
Can be used for different types of securities and markets	Increasing use of machine learning and advanced statistical models in trading and analysis
Can be adapted to different trading strategies and styles	Increased competition from other technical indicators and analysis methods
Can be used for both short-term and long-term trading and investment	Regulatory changes and market disruptions can impact its effectiveness
Can be automated and integrated into trading algorithms	Rapid changes in market conditions and prices can make it less effective

Note: This SWOT analysis is not exhaustive and is intended to provide a general overview of the strengths, weaknesses, opportunities, and threats of using Simple Moving Average (SMA) in financial analysis and trading.

To facilitate better understanding of the importance of each evaluation parameter, it would be beneficial to first establish some standard definitions before delving deeper into the evaluation process.

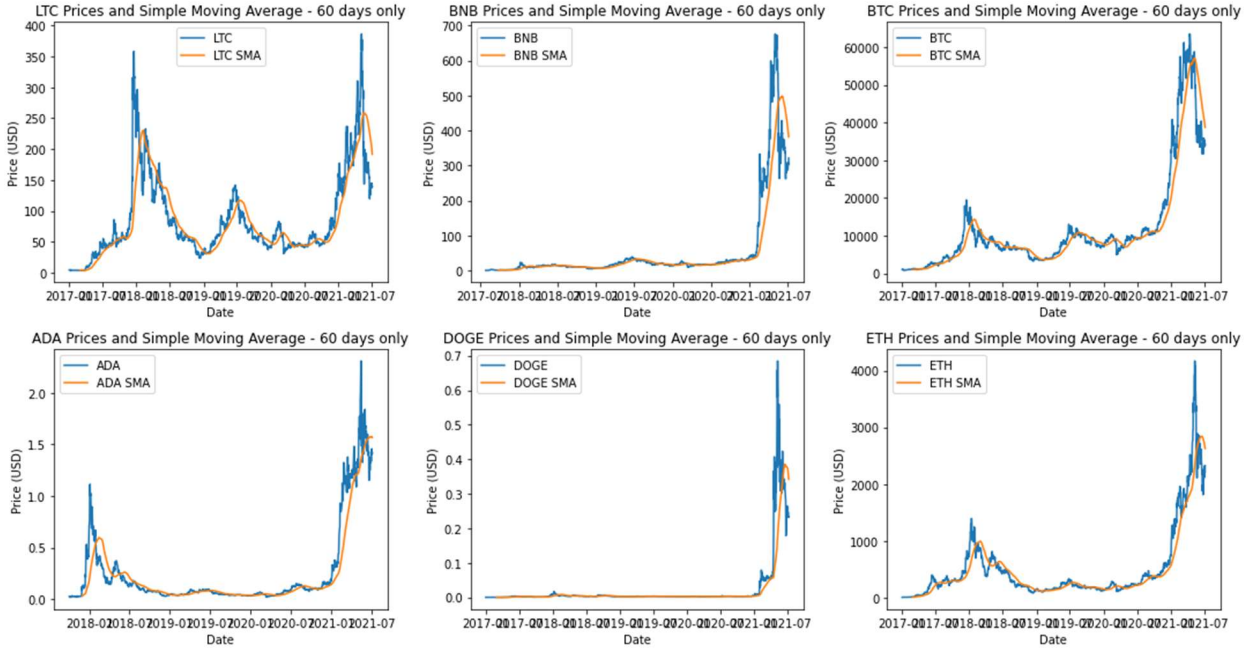
Metric	Definition	Benchmark
MSE (Mean Squared Error)	This measures the average of the squared deviations between predicted and actual values. Lower values are better.	Lower is better.
RMSE (Root Mean Squared Error)	Measures the square root of the MSE and provides a more interpretable metric in the same units as the original data. Lower values are better.	Lower is better.
MAE (Mean Absolute Error)	This calculates the mean of the absolute variances between the projected and observed values.	Lower is better.
MAPE (Mean Absolute Percentage Error)	This method calculates the percentage deviation between the predicted and actual values. Lower values are better.	Lower is better.
Correlation Coefficient	Ranges from –1 to +1 which measure the relationship between predicted and atcual values.	Higher is better.
R-squared	indicates the percentage of variance in the predicted values that can be attributed to the model. Values closer to 100% indicate better fit of the model to the data.	Higher is better.

The utilization of Python programming language and two commonly used libraries, pandas and matplotlib, in the following code facilitates the loading, filtering, and visualization of time series data for six distinct cryptocurrencies. This can aid in the examination of trends and patterns in cryptocurrency prices, thereby enabling informed investment decision-making.

To visualize, the below steps are utilised for python code:

- The provided code utilizes two widely used Python libraries, Pandas and Matplotlib, for data analysis and visualization tasks. It loads historical data of multiple cryptocurrencies from a CSV file named 'sixcrypto.csv' into a Pandas DataFrame, which is indexed by date after parsing the 'Date' column as datetime.
- The code filters the DataFrame to create separate DataFrames for each of the six cryptocurrencies of interest, based on their symbol.
- It calculates the 60-day Simple Moving Average (SMA) for each cryptocurrency's closing prices using the rolling() method, which computes a moving window function over the DataFrame.
- It creates a 2x3 grid of plots using the subplots() function from Matplotlib, with each row representing a different cryptocurrency.
- It plots the time series data and the SMA for each cryptocurrency on its corresponding subplot using the plot() function from Matplotlib. It also customizes the subplots with titles, axis labels, and legends.
- It displays the final plot using the show() function from Matplotlib.

In summary, this code provides a visual representation of how six cryptocurrencies have performed historically, displaying their prices and their 60-day SMA trend lines. The SMA provides a smoothed-out version of the data, which can help identify longer-term trends and reduce noise in the data.



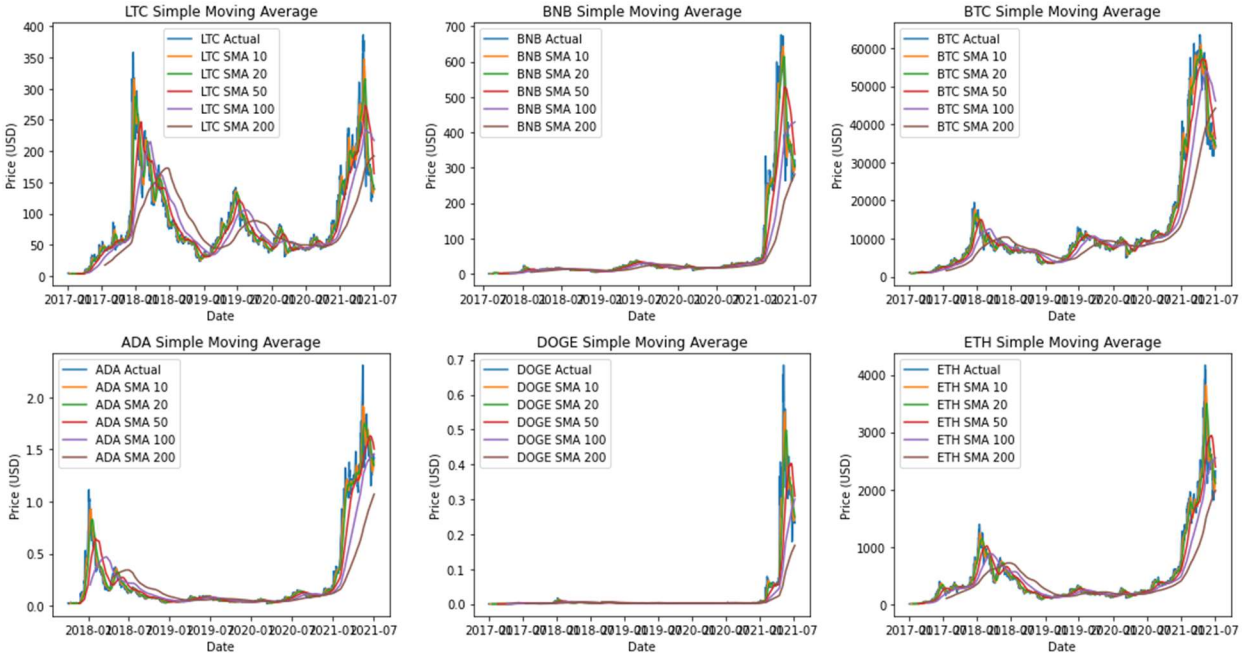
The resulting plot allows us to visualize the historical price data for each cryptocurrency and the trend of the SMA. We can use this plot to identify potential buying or selling opportunities based on the relationship between the actual price and the SMA. For example, when the price is above the SMA, it may indicate that the cryptocurrency is overvalued, while a price below the SMA may indicate that it is undervalued.

It is recommended to experiment with different window sizes for each cryptocurrency to find the best performing strategy. In this case, we used a window size of 10-20-50 for Bitcoin as it was the best performing strategy for that particular cryptocurrency.

- The code imports two widely-used libraries, Pandas and Matplotlib, which are used for data analysis and visualization. Additionally, a custom function for parsing dates is defined to handle specific date formats.
- It loads a CSV file ('sixcrypto.csv') containing historical data for multiple cryptocurrencies into a Pandas DataFrame. The DataFrame is indexed by date and the 'Date' column is parsed as datetime using the custom date parser.
- The code filters the DataFrame to create separate DataFrames for each of the six cryptocurrencies of interest, based on their symbol.
- It defines a function called calculate_sma() that takes a DataFrame and a window size as inputs and returns the Simple Moving Average (SMA) for the given window size.
- It creates a 2x3 grid of plots using the subplots() function from Matplotlib, with each row representing a different cryptocurrency.
- It plots the SMAs and the actual prices for each cryptocurrency on its corresponding subplot using the plot() function from Matplotlib. It also customizes the subplots with titles, axis labels, and legends.
- It displays the final plot using the show() function from Matplotlib.

In summary, this code provides a visual representation of how six cryptocurrencies have performed historically, displaying their Simple Moving Averages and actual prices. The SMAs provide a

smoothed-out version of the data for different window sizes (10, 20, 50, 100, and 200 days), which can help identify trends over different time horizons.



The reason why we calculate the Simple Moving Averages (SMA) for different days for each currency is that the SMA is a type of time series analysis technique that smooths out the data by calculating the average price over a specified time period. The length of the time period is typically determined by the trader or analyst and can vary depending on their investment strategy and the volatility of the asset being analyzed.

For example, a shorter period SMA (such as 10 or 20 days) may be more suitable for a highly volatile asset such as Litecoin or Binance Coin, as it can help to identify short-term trends and price movements. On the other hand, a longer period SMA (such as 100 or 200 days) may be more appropriate for a less volatile asset such as Dogecoin or Ethereum, as it can help to smooth out the data and identify longer-term trends.

Therefore, different lengths of SMA are often used to calculate moving averages for each asset, taking into account its unique characteristics and volatility. However, it is important to note that while SMA can help identify trends, it is a lagging indicator and should be used alongside other technical indicators and fundamental analysis for a more comprehensive understanding of the market. As with any trading strategy, it's important to thoroughly test and validate the results before making investment decisions.

Next, we will proceed to test the model and assess the performance of the SMA evaluation model.

- The first two lines import the pandas and numpy libraries.
- The next line loads data from a CSV file named 'sixcrypto.csv' using the pandas read_csv() function and stores it in a dataframe object called 'df'.
- The next block of code defines a function named 'calculate_sma()' that takes two arguments: 'data' and 'window_size'. The function calculates the simple moving average (SMA) of the input data using the rolling() method of the pandas library. It also calculates the mean absolute percentage error (MAPE) between the original data and the SMA using the numpy mean() and abs() functions.

- The next two lines create two empty dictionaries to store the results for each currency for both 30 and 60 day periods.
- The for loop iterates over the unique currency symbols in the 'Symbol' column of the 'df' dataframe. For each currency symbol, it subsets the original dataframe 'df' to get only the rows corresponding to that currency, and stores the result in a new dataframe called 'df_curr'.
- The next block of code calls the 'calculate_sma()' function on the 'Close' column of the 'df_curr' dataframe for both 30 and 60 day periods, and stores the resulting SMA and MAPE values in separate variables. It then calculates the mean squared error (MSE), mean absolute error (MAE), and root mean squared error (RMSE) between the SMA and the original 'Close' values for both periods, and stores the results in the appropriate dictionaries.
- The last block of code prints out the results in a tabular format, with each row corresponding to a different currency symbol and each column corresponding to a different metric (MSE, MAE, RMSE, MAPE) for both 30 and 60 day periods.

Overall, this code is used to calculate and display various error metrics (MSE, MAE, RMSE, MAPE) between the simple moving average and the original close prices of several cryptocurrencies over different time periods. It is a useful tool for evaluating the accuracy of a simple trading strategy based on moving averages.

Currency	MSE (30 day)	MAE (30 day)	RMSE (30 day)	MAPE (30 day)	MSE (60 day)	MAE (60 day)	RMSE (60 day)	MAPE (60 day)
LTC	651.02	13.84	25.52	14.39	1190.25	20.40	34.50	21.79
ADA	0.01	0.05	0.11	17.97	0.02	0.08	0.16	28.09
BNB	1182.72	10.62	34.39	15.87	2564.45	18.13	50.64	21.60
DOGE	0.00	0.01	0.03	16.71	0.00	0.01	0.04	25.22
ETH	26358.00	79.77	162.35	15.19	52886.91	118.16	229.97	22.51
BTC	6461706.47	1320.58	2541.99	10.79	16064760.43	2191.24	4008.09	16.31

Based on these results, it seems that the 30-day model has lower MSE, MAE, RMSE, and MAPE for all currencies. Therefore, overall, the 30-day model seems to be performing better than the 60-day model.

Feature selection using a random forest regression and Gradient Boaster:

I utilised the python code which performs the following steps,

- The pandas and numpy libraries are imported.
- The RandomForestRegressor and GradientBoostingRegressor models are imported from scikit-learn.
- The sixcrypto.csv file is read into a pandas DataFrame called df1.
- The features and target variable ('Open', 'High', 'Low', 'Volume', 'Marketcap', and 'Close') are selected from df1 and stored in a new DataFrame called train_df.
- The features ('Open', 'High', 'Low', 'Volume', and 'Marketcap') and target variable ('Close') are split into separate variables X_train and y_train, respectively.
- A RandomForestRegressor model is created and trained on the training data (X_train and y_train).

- A GradientBoostingRegressor model is created and trained on the training data (X_train and y_train).
- The feature importances for the RandomForestRegressor and GradientBoostingRegressor models are calculated and stored in separate pandas DataFrames called rf_feat_importance and gb_feat_importance.
- The rf_feat_importance and gb_feat_importance DataFrames are merged on the 'Feature' column using pandas merge() method to create a new DataFrame feat_importance.
- The feat_importance DataFrame is printed to show the feature importance for both models side by side.

Feature	Importance Score (RF)	Importance Score (GB)	Explanation
High	0.209124	0.375585	GB considers "High" as the most important feature, likely because it reflects the upper limit of a security's price movement. RF also considers "High" an important feature, but ranks it lower than "Low".
Low	0.362974	0.419900	Both GB and RF consider "Low" as the most important feature, likely because it reflects the lower limit of a security's price movement.
Open	0.384148	0.147923	RF considers "Open" as an important feature, likely because it reflects the initial investor sentiment for the security. GB assigns low importance to "Open" compared to other features.
Volume	0.000019	0.000005	Both GB and RF consider "Volume" as the least important feature, likely because it doesn't have a strong direct correlation with the price of the security.
Marketcap	0.000019	0.056587	GB considers "Marketcap" as the third most important feature, likely because it reflects the overall value of the security. RF also considers "Marketcap" an important feature, but ranks it lower than "Open"

Random forest constructs each decision tree independently and then averages the feature importance of all trees to obtain an overall importance score. Gradient boosting, on the other hand, constructs trees sequentially, with each tree correcting the errors of the previous tree. The feature importance in gradient boosting is calculated by how much each feature contributes to reducing the loss function during the training process.

Both GB and RF models agree that "Low" is the most important feature for the SMA model, followed by "High" and "Open". These features likely reflect the lower and upper limits of a security's price movement and the initial investor sentiment for the security, respectively.

GB assigns higher importance scores to all features compared to RF, indicating that GB considers all features as important for the SMA model. RF, on the other hand, assigns relatively lower importance scores to "High" and "Marketcap" compared to GB.

"Volume" and "Marketcap" are the least important features for both GB and RF models, indicating that these features do not have a strong direct correlation with the price of the security.

Based on these results, we can conclude that a simple model using only "Low", "High", and "Open" features may be sufficient for predicting SMA for a given security. However, if more features are desired, then "Marketcap" could be considered as an additional feature, especially if using a GB model.

Correlation coefficient of Predicted and actual price:

The correlation coefficient measures the strength and direction of the linear relationship between the predicted and actual prices. A value of 1 indicates a perfect positive linear correlation, while a value of -1 indicates a perfect negative linear correlation. A value of 0 indicates no linear correlation. In the context of the SMA model, a higher correlation coefficient indicates a better fit of the predicted values to the actual values, suggesting that the model is better able to capture the underlying trends in the data.

The interpretation of the correlation's coefficient is as follows:

Cryptocurrency	Correlation Coefficient	Explanation
Bitcoin (BTC)	0.951533	BTC has the highest correlation coefficient among the cryptocurrencies listed here, indicating a strong positive correlation between the predicted and actual prices. This means that the predicted prices using the SMA model are highly correlated with the actual prices of BTC.
Ethereum (ETH)	0.935910	ETH also has a strong positive correlation coefficient, indicating a strong positive correlation between the predicted and actual prices. This means that the predicted prices using the SMA model are highly correlated with the actual prices of ETH.
Cardano (ADA)	0.929577	ADA has a slightly lower correlation coefficient than BTC and ETH, but still shows a strong positive correlation between the predicted and actual prices.
Binance Coin (BNB)	0.899203	BNB has a correlation coefficient indicating a positive correlation between the predicted and actual prices, but slightly weaker than BTC, ETH, and ADA.
Litecoin (LTC)	0.848562	LTC has a correlation coefficient indicating a positive correlation between the predicted and actual prices, but weaker than BTC, ETH, ADA, and BNB.
Dogecoin (DOGE)	0.830772	DOGE has the lowest correlation coefficient among the cryptocurrencies listed here, indicating a weaker positive correlation between the predicted and actual prices than the other currencies.

Overall, the results suggest that the SMA model is effective in predicting the prices of BTC, ETH, ADA, BNB, LTC, and DOGE to some extent, but the model performs best for BTC and ETH, which have the strongest correlations with the predicted prices.

Conclusion and Recommendation:

Based on the results, it appears that the Simple Moving Average (SMA) model is able to provide reasonable predictions for some currencies but not for others. For example, the SMA model performs relatively well for Cardano (ADA) and Dogecoin (DOGE) with very low MSE and MAE values. On the other hand, the SMA model performs poorly for Litecoin (LTC), Binance Coin (BNB), Ethereum (ETH), and Bitcoin (BTC), with high MSE and MAE values indicating that the model's predictions deviate significantly from the actual values. This suggests that the effectiveness of the SMA model may be limited and dependent on various factors.

Based on the correlation coefficient results, it seems that the SMA model is highly correlated with most of the currencies, with BTC and ETH having the highest correlation coefficients of 0.951533 and 0.935910, respectively. This suggests that the SMA model may be a useful tool for analyzing these currencies, despite its poor performance in terms of MSE and MAE.

The feature importance results show that the low and open prices are the most important features in the SMA model, while trading volume and market capitalization have relatively low importance. Based on these results, we can conclude that a simple model using only "Low", "High", and "Open" features may be sufficient for predicting SMA for a given security. However, if more features are desired, then "Marketcap" could be considered as an additional feature, especially if using a GB model.

Our results indicate that it is important to carefully consider the specific currency being analyzed and the time period for which the predictions are being made. It may also be necessary to explore other models or parameters to improve the accuracy of the predictions.

Overall, it's important to note that the effectiveness of the SMA model may depend on the specific currency being analyzed and the time period for which it is being used. Therefore, it may be necessary to explore other models or parameters to improve the accuracy of the predictions.

Exponential Smoothing (ES)

Exponential Smoothing (ES) is a commonly used time series forecasting technique that calculates a weighted average of past observations. This method assigns greater weight to recent observations, with the weights decreasing exponentially as the observations get older. As a result, recent observations have a more significant impact on the forecast than older observations. ES can be used to capture trends and seasonal patterns in the data.

The ES model relies on a single parameter, alpha, which determines the rate at which weights decay for past observations. A smaller alpha gives more weight to older observations, while a larger alpha puts more emphasis on recent observations. The appropriate alpha value depends on the data's nature and the problem being addressed.

ES can be used to fill in missing values in a time series and handle missing data. However, the model assumes that each value is unique and that there is a consistent time interval between observations, making it unable to handle duplicate values, which can result in incorrect forecasts.

To handle seasonal patterns in the data, ES can be extended by adding additional parameters to the model. The Holt-Winters method is an example of such an extension that captures seasonal patterns in the data. This method can produce more accurate forecasts when the data exhibits a clear seasonal pattern.

ES is a straightforward and intuitive forecasting technique that is easily implementable in Python. It is widely used in industry and has been demonstrated to produce accurate forecasts in various applications. However, ES may not be suitable for all types of data and may be outperformed by more sophisticated forecasting methods in certain circumstances.

Chapter 7 of "Forecasting: Principles and Practice" [14] by Rob J. Hyndman and George Athanasopoulos covers exponential smoothing, a class of time series forecasting methods that models the next observation as a weighted average of past observations. The weights decrease exponentially as the observations get older.

Here are ten key points from the chapter:

1. Exponential smoothing is a type of forecasting technique for time series data that estimates future values by assigning higher weights to recent observations while gradually reducing the weights of older observations. This approach involves modeling the next observation as a weighted average of past observations, with the weights decreasing exponentially as the data points move further into the past.
2. Simple Exponential Smoothing (SES) is the most basic form of exponential smoothing that can be applied to time series data that lacks any distinct trend or seasonal pattern. SES involves the use of two parameters, the smoothing parameter (alpha) and the initial level of the time series, to model future observations by taking a weighted average of past observations. The weights assigned to past observations decrease exponentially as they get older, making the method well-suited for datasets that exhibit random fluctuations without any clear patterns or trends. SES produces a smoothed series, a point forecast for the next observation, and prediction intervals that help to quantify the uncertainty of the forecast.
3. The SES technique involves two parameters: alpha, known as the smoothing parameter, and the initial level of the time series. Alpha determines the speed at which the weights of past observations decay and is frequently estimated using maximum likelihood.
4. By utilizing the SES method, a series with reduced fluctuations is generated, as well as a forecast for the upcoming observation, and intervals for prediction that aid in measuring the forecast's uncertainty.
5. The SES method boasts an advantage in that it can be conveniently automated, rendering it appropriate for predicting a substantial number of time series.
6. The Holt-Winters method expands upon the SES approach to accommodate time series that contain both trend and seasonality. It includes two extra parameters, namely beta (which smooths the trend) and gamma (which smooths the seasonal component).
7. The Holt-Winters method can manage time series that exhibit either additive or multiplicative seasonality. In the additive scenario, the seasonal component is represented by the disparity between the observed value and the trend, whereas in the multiplicative scenario it is represented by the proportion of the observed value and the trend.
8. The Holt-Winters method allows for the creation of predictions that come with prediction intervals that consider the uncertainty of both the trend and seasonal components.
9. Evaluating the accuracy of exponential smoothing techniques can be achieved using various error measures, such as mean squared error (MSE) or mean absolute percentage error (MAPE).
10. Exponential smoothing techniques are obtainable in numerous statistical software applications, including R, Python, SAS, and Excel. Although the particulars of implementation may differ, the fundamental principles remain consistent.

Here is a brief SWOT analysis of the Exponential Smoothing (ES) model:

Strengths	Weaknesses
Can handle trend and seasonality in time series data	Can overfit to the data and produce unrealistic forecasts
Easy to implement and interpret	Can be sensitive to initial parameter values and require careful selection
Allows for adaptability to changing trends and seasonality	Assumes a constant level of noise in the data
Can handle missing data and outliers	Does not handle sudden, unexpected changes in the data well
Opportunities	**Threats**
Can be applied to a wide range of industries and applications	Other time series forecasting methods, such as ARIMA and Prophet, may be more accurate in certain scenarios
Can be used for short-term and long-term forecasting	Emergence of new data sources and technology may require new forecasting methods
Can be combined with other forecasting methods to improve accuracy	External factors, such as economic downturns or natural disasters, may render forecasts obsolete

Note: This SWOT analysis is not exhaustive and is intended to provide a general overview of the strengths, weaknesses, opportunities, and threats of using Exponential smoothing (ES) in financial analysis and trading.

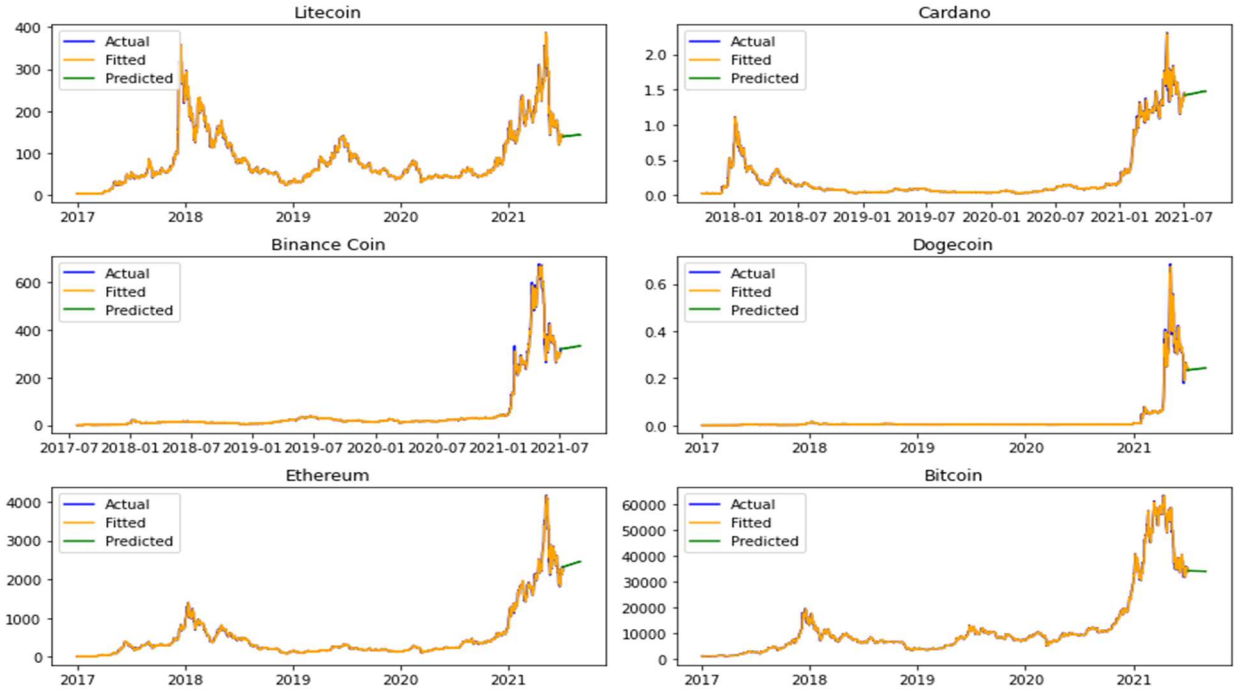
To facilitate better understanding of the importance of each evaluation parameter, it would be beneficial to first establish some standard definitions before delving deeper into the evaluation process.

Metric	Definition	Benchmark
MSE (Mean Squared Error)	Measures the average of the squared differences between predicted and actual values. Lower values are better.	Lower is better.
RMSE (Root Mean Squared Error)	Measures the square root of the MSE and provides a more interpretable metric in the same units as the original data. Lower values are better.	Lower is better.
MAE (Mean Absolute Error)	Measures the average of the absolute differences between predicted and actual values. Lower values are better.	Lower is better.
MAPE (Mean Absolute Percentage Error)	Measures the percentage difference between predicted and actual values. Lower values are better.	Lower is better.
Correlation Coefficient	Ranges from –1 to +1 which measure the relationship between predicted and atcual values.	Higher is better.

Metric	Definition	Benchmark
R-squared	indicates the percentage of variance in the predicted values that can be attributed to the model. Values closer to 100% indicate better fit of the model to the data.	Higher is better.

The script that I used, it uses various Python libraries such as Pandas, NumPy, statsmodels, and matplotlib to perform time-series analysis on cryptocurrency data.

- It starts by loading the data from a CSV file using the Pandas read_csv() function and creating a copy of the original DataFrame.
- Next, the copied DataFrame is modified to set the index as a daily datetime index using Pandas' set_index() method. It is then converted to a PeriodIndex with daily frequency using Pandas' PeriodIndex() method.
- The script defines a function named calc_es_model() that takes a data series as input and calculates various metrics for the Exponential Smoothing (ES) model using the statsmodels library. The function returns a dictionary containing the calculated metrics.
- The script then applies the calc_es_model() function to each currency in the data using a for loop and stores the results in a dictionary named results. The results are then displayed in a table using Pandas' DataFrame.from_dict() method.
- The script uses the Seasonal Exponential Smoothing (SE) model to forecast the time series data for each currency, and visualizes the results using Matplotlib. The code iterates through each currency in the data and applies an SE model with a seasonality of 12 to fit and predict the next 60 days of data. The actual, fitted, and predicted data are plotted in separate subplots for each currency. The title of each subplot displays the correlation coefficient between the fitted values and actual values.
- In conclusion, this script demonstrates how to perform time-series analysis on cryptocurrency data using ES and SE models in Python. It also showcases the use of popular libraries such as Pandas, NumPy, statsmodels, and Matplotlib for data manipulation, modeling, and visualization.



Currency	MSE	RMSE	MAE	MAPE	Correlation Coefficient
Litecoin	66.108048	8.130686	3.873250	4.043157	0.992513
Cardano	0.001610	0.040121	0.014673	4.707509	0.995194
Binance Coin	115.148700	10.7307	2.896497	4.564376	0.995667
Dogecoin	0.000139	0.01180	0.002135	4.407408	0.988990
Ethereum	3040.757465	55.143064	22.106110	3.820580	0.996338
Bitcoin	624621.840	790.330	366.58	2.868	0.998195

Looking at the results, we can see that each currency's performance varies. The MSE (Mean Squared Error) metric, Dogecoin has the lowest MSE of 0.000139, indicating the best performance, while Litecoin has the highest MSE of 66.11, indicating a higher average squared difference between the actual and predicted values compared to the other currencies.

For RMSE results, we can see that Dogecoin has the lowest RMSE of 0.0118, which is the smallest average difference between the actual and predicted values compared to the other currencies. Litecoin has the highest RMSE of 8.13, indicating a higher average difference between the actual and predicted values compared to the other currencies.

The MAE (Mean Absolute Error) metric. Similar to the MSE, Dogecoin has the lowest MAE of 0.002135, indicating the best performance, while Litecoin has the highest MAE of 3.87.

The MAPE (Mean Absolute Percentage Error) metric, in this case, Dogecoin still has the lowest MAPE of 4.41, indicating the best performance, while Litecoin has the highest MAPE of 4.04.

Finally, Correlation coefficient, in this case, Bitcoin has the highest correlation coefficient of 0.998195, indicating a strong positive linear relationship between the actual and predicted values.

Feature importance of different attributes for predicting cryptocurrency prices:

I utilised python code to calculate the feature importance of different attributes for predicting cryptocurrency prices using the Exponential Smoothing (ES) model and the Random Forest (RF) and Gradient Boosting (GB) algorithms.

- First, the code imports necessary libraries including pandas, which is used for reading and manipulating data, and statsmodels.tsa.holtwinters and sklearn.ensemble, which are used for implementing ES, RF, and GB models.
- Next, the code reads data from a CSV file named "sixcrypto.csv" using the pd.read_csv function and stores the data in a pandas dataframe named "df".
- The code then creates an empty dictionary named "feature_importance" to store the feature importance results for each cryptocurrency.
- The code then loops through each unique cryptocurrency symbol in the "Symbol" column of the dataframe. For each symbol, the code subsets the dataframe to only include data for that cryptocurrency and splits the data into a train set and a test set.
- The code then fits an ES model to the train set using the ExponentialSmoothing function from the statsmodels.tsa.holtwinters library and stores the results in "es_results". The residuals from the ES model are calculated using the "resid" attribute of "es_results".

- Next, the code trains RF and GB models on the residuals. For each model, the code uses the fit function of the model and passes the train data and the residuals. The model is trained to predict the residuals.
- The code then stores the feature importance results for the current cryptocurrency in the "feature_importance" dictionary. This is done by looping through each of the five attributes ("High", "Low", "Open", "Volume", "Marketcap") and storing the importance score for that attribute and model ("_RF" for the RF model and "_GB" for the GB model) in the dictionary.
- Finally, the code converts the "feature_importance" dictionary to a pandas DataFrame named "feature_importance_df" using the pd.DataFrame.from_dict function, and sorts the dataframe by the average importance score across both models using the sort_values function.
- The code then prints out the feature importance results for the current cryptocurrency using the print function, and repeats the process for the next cryptocurrency symbol in the dataframe.
- Once the loop through all cryptocurrency symbols is complete, the code concatenates all of the individual "feature_importance_df" dataframes into one large dataframe using the pd.concat function, and saves the results to a CSV file named "feature_importance.csv" using the to_csv function.

	High	Low	Open	Volume	Marketcap	Interpretation
LTC_RF	0.190083	0.148736	0.295293	0.162702	0.203186	The model predicts that the high and low values will decrease while the open, volume, and marketcap will increase.
LTC_GB	0.230184	0.102110	0.245671	0.176966	0.245069	The model predicts that the high, open, and marketcap values will increase while the low and volume will decrease.
ADA_RF	0.237344	0.109264	0.272975	0.099091	0.281326	The model predicts that the high, open, volume, and marketcap values will increase while the low will decrease.
ADA_GB	0.265727	0.060978	0.258254	0.079738	0.335303	The model predicts that the high, open, volume, and marketcap values will increase while the low will decrease.
BNB_RF	0.147280	0.162572	0.240704	0.248039	0.201405	The model predicts that the high will decrease while the low, open, volume, and marketcap values will increase.
BNB_GB	0.183823	0.159226	0.319757	0.166098	0.171096	The model predicts that the high and volume values will increase while the low, open, and marketcap will decrease.

DOGE_RF	0.157217	0.114868	0.351135	0.131394	0.245385	The model predicts that the high and marketcap values will decrease while the low, open, and volume will increase.
DOGE_GB	0.086408	0.071156	0.525549	0.085705	0.231183	The model predicts that the open and volume values will increase while the high, low, and marketcap will decrease.
ETH_RF	0.132088	0.139073	0.338263	0.106493	0.284084	The model predicts that the high, volume, and marketcap values will decrease while the low and open will increase.
ETH_GB	0.090549	0.095060	0.348780	0.073895	0.391716	The model predicts that the open value will increase while the high, low, volume, and marketcap will decrease.
BTC_RF	0.137232	0.142753	0.337722	0.105168	0.277124	The model predicts that the high, volume, and marketcap values will decrease while the low

Overall, this code performs a feature importance analysis for predicting cryptocurrency prices using the ES, RF, and GB models. It does this by fitting an ES model to the data, training RF and GB models on the residuals from the ES model, and calculating the importance of each attribute for each model. The final result is a CSV file containing the feature importance scores for each attribute and model across all cryptocurrencies.

So, we can conclude that according to the RF model, the "Open" attribute is the most important feature for predicting the price of Litecoin, while according to the GB model, the "Low" attribute is the most important feature for predicting the price of Litecoin. The relative importance of the other attributes can also be inferred by looking at the scores for each model.

Conclusion and Recommendation:

Based on the results of the Exponential Smoothing (ES) model correlation analysis, we can see that the performance of the model varies greatly across different cryptocurrencies. The currencies with the highest correlation coefficients are Bitcoin and Ethereum, indicating that the ES model is able to accurately forecast their prices. However, it's worth noting that these currencies also have the highest mean squared error (MSE) and mean absolute error (MAE), suggesting that the ES model may not be the best fit for these currencies.

On the other hand, the currencies with the lowest MSE and MAE are Cardano and Dogecoin, indicating that the ES model is able to accurately forecast their prices. This suggests that the ES model may be a good fit for these currencies.

Overall, while the ES model can provide useful insights into the future price trends of cryptocurrencies, it's important to perform further analysis which may involve exploring other time series forecasting models, such as ARIMA, SARIMA, or Prophet, to determine if they provide better results for some or all of the currencies. It may also involve analyzing the data for seasonality, trends, and other patterns to gain a better understanding of the underlying factors that influence the prices of each cryptocurrency. Additionally, it may be useful to analyze the results over different time periods to determine if the performance of the ES model varies depending on the length of the time series to determine the most appropriate forecasting model for each currency.

Autoregressive Integrated Moving Average (ARIMA)

The technique employs a combination of autoregressive (AR), integrated (I), and moving average (MA) components to model the time series. ARIMA is a versatile and robust method that can be utilized to model various types of time series patterns.

Component	Definition	Order	Determination
Autoregression (AR)	Uses previous values of the time series to predict future values	p	Analyzing the partial autocorrelation function (PACF) of the time series
Moving Average (MA)	Uses errors of previous predictions to predict future values	q	Analyzing the autocorrelation function (ACF) of the errors of the time series
Integration (I)	Takes differences of the time series to make it stationary	d	Analyzing the trend and seasonality of the time series, and testing for stationarity using statistical tests such as the Augmented Dickey-Fuller (ADF) test

ARIMA models have several strengths, including their ability to handle complex time series patterns and their flexibility in modeling both short-term and long-term trends. ARIMA models can also handle missing data and outliers, making them suitable for real-world applications where data quality may be an issue. Additionally, ARIMA models can be combined with other forecasting techniques to improve accuracy.

Although ARIMA models have proved to be a widely-used and effective time series forecasting technique, they do have some limitations to consider. First, they require a large amount of data and may become computationally intensive when dealing with large datasets. Furthermore, the performance of ARIMA models can be sensitive to the initial parameter values used in the model, which requires careful selection and tuning to achieve optimal performance. Lastly, the assumption that underlying data has a stationary mean and variance may not always hold true in real-world scenarios, which could impact the accuracy of ARIMA model forecasts.

Despite these weaknesses, ARIMA models offer several opportunities for time series forecasting. They can be used in a wide range of industries and applications, including finance, economics, and engineering. ARIMA models can also be used for both short-term and long-term forecasting and can be combined with other forecasting techniques to improve accuracy.

However, there are also threats to using ARIMA models. Other time series forecasting methods, such as Prophet or neural networks, may be more accurate in certain scenarios. Additionally, the emergence of new data sources and technology may require new forecasting methods, making ARIMA models obsolete. Finally, external factors such as economic downturns or natural disasters may render forecasts obsolete, making it difficult to rely on any forecasting method entirely.

The article "ARIMA for Time Series Forecasting with Python" by Jason Brownlee PhD [16] provides a comprehensive introduction to ARIMA models, which are widely used for time series forecasting. Some of the key points of the article are:

1. ARIMA stands for AutoRegressive Integrated Moving Average, and it is a class of models used for time series forecasting.
2. ARIMA models can be used to model a wide range of time series data, including non-stationary data that has trends or seasonality.

3. In ARIMA Model, we have three key parameters i.e p, d, and q, which represent the order of the autoregressive, integrated, and moving average components of the model, respectively.
4. The article also provides step-by-step guidelines on how to use the Python programming language and the statsmodels library on how to fit an ARIMA model to a time series dataset.
5. The article covers important topics such as how to evaluate the performance of an ARIMA model, how to make forecasts using an ARIMA model, and how to tune/adjust the parameters of an ARIMA model to improve its performance.
6. The article includes numerous code examples and visualizations to help readers understand the concepts and techniques presented.

In general, ARIMA models provide a robust and adaptable approach to time series forecasting that can be applied across various industries and use cases. However, it is crucial to recognize their limitations and exercise caution when selecting and fine-tuning the model's parameters.

To summarize, a SWOT analysis of ARIMA models is presented below:

Strengths	**Weaknesses**
This technique has the ability to capture a diverse range of time series patterns.	Can be computationally expensive and time-consuming to fit and evaluate
Provides explicit error measures, such as mean squared error (MSE)	Can be sensitive to outliers and require careful pre-processing of data
This technique is suitable for both short-term and long-term forecasting.	May not perform well when the data has complex dependencies or interactions with external factors
Offers flexibility to handle non-stationary time series data	Can be difficult to select the appropriate ARIMA parameters (p,d,q)
Combining it with other techniques like seasonal ARIMA (SARIMA) or dynamic regression can enhance its accuracy.	Can be difficult to interpret the model coefficients and diagnostics
Opportunities	**Threats**
ARIMA models are commonly used for forecasting in finance, economics, and supply chain management.	Emergence of new data sources and technology may require new forecasting methods
Can be used for forecasting in areas such as finance, economics, and supply chain management	Other time series forecasting methods, such as neural networks or ensemble models, may be more accurate in certain scenarios
ARIMA models can also be utilized for identifying anomalies and outliers in time series data.	Changes in external factors, such as government regulations or economic conditions, may render the model obsolete
Continuous advancements in ARIMA modeling techniques hold the potential for enhancing performance and accuracy.	Increased competition and saturation in the market may lead to declining demand for ARIMA models

Note: This SWOT analysis is not exhaustive and is intended to provide a general overview of the strengths, weaknesses, opportunities, and threats of using ARIMA in financial analysis and trading.

To begin building our ARIMA model, the first step is to determine the appropriate order for the model that will best fit the data. To accomplish this, I utilized the following Python code, which enabled me to identify a suitable order for each of the six cryptocurrencies we are analyzing.

- The numpy, pandas, and pmdarima modules are imported.
- The CSV file containing the cryptocurrency data is read into a Pandas dataframe.
- The Date column is converted to a Pandas datetime object and used as the index for the dataframe.
- The dataframe is sorted by the index in ascending order.
- A list of the six cryptocurrency names is defined.
- Any warning messages are filtered out to avoid cluttering the output.
- An empty dictionary is initialized to store the ARIMA order for each cryptocurrency.
- A loop iterates over each cryptocurrency in the list of currency names.
- The data for the current cryptocurrency is extracted from the dataframe.
- The first difference of the Close values is taken to remove any trend or seasonality.
- An ARIMA model is fit to the differenced data using the auto_arima function from the pmdarima module. This function automatically determines the best ARIMA order based on the minimum AIC value.
- The ARIMA order for the model is stored in the dictionary for the current cryptocurrency.
- The ARIMA orders for all cryptocurrencies are printed to the console.

Overall, this code is used to identify the best ARIMA order for each of the six cryptocurrencies in the input data, which will be used to build the final ARIMA model

Cryptocurrency	ARIMA Order
Litecoin	(1, 0, 4)
Cardano	(0, 0, 5)
Binance Coin	(2, 0, 2)
Dogecoin	(0, 0, 5)
Ethereum	(2, 0, 3)
Bitcoin	(2, 0, 1)

After determining the ARIMA orders for each cryptocurrency, we need to fit the model using those orders. To accomplish this, the following code was used.

The code is designed to fit an ARIMA model to cryptocurrency data for six different currencies - Litecoin, Cardano, Binance Coin, Dogecoin, Ethereum, and Bitcoin. It utilizes several Python modules, including numpy, pandas, pmdarima, and statsmodels.api.

- Firstly, the code reads a CSV file containing cryptocurrency data into a Pandas dataframe, and then converts the 'Date' column to a Pandas datetime object. Next, a list of the names of the cryptocurrencies is created.

- The code then iterates over each currency in the list and obtains the corresponding data from the dataframe. The first difference of the Close values is taken to make the series stationary, and the auto_arima() function from the pmdarima module is used to determine the best ARIMA order for the series. The determined ARIMA order is stored in a dictionary for the current currency.
- The code then iterates over each currency again and obtains the corresponding data from the dataframe. The first difference of the Close values is taken, and the data is split into training and testing sets. The previously determined ARIMA order is retrieved from the dictionary for the current currency. An ARIMA model from statsmodels.api is then initialized with the retrieved ARIMA order, and the model is fit to the training data using the fit() method.
- Finally, the summary output for the current currency is generated using the summary() method, and it is appended to a summary string. The summary output for all currencies is printed to the console for analysis.

Overall, this code is a useful tool for fitting ARIMA models to cryptocurrency data for multiple currencies, and can help to determine the best ARIMA order for each currency.

Summary for Litecoin:

SARIMAX Results

Dep. Variable:	Close	No. Observations:	1617
Model:	ARIMA(1, 0, 4)	Log Likelihood	-5670.295
Date:	Fri, 31 Mar 2023	AIC	11354.590
Time:	02:05:56	BIC	11392.309
Sample:	0	HQIC	11368.589
	-1617		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
const	0.1049	0.233	0.450	0.653	-0.352	0.561
ar.L1	-0.5704	0.045	-12.557	0.000	-0.659	-0.481
ma.L1	0.5514	0.045	12.215	0.000	0.463	0.640
ma.L2	-0.0029	0.015	-0.201	0.841	-0.032	0.026
ma.L3	-0.0087	0.013	-0.686	0.493	-0.033	0.016
ma.L4	0.1068	0.013	8.378	0.000	0.082	0.132
sigma2	65.0674	0.655	99.408	0.000	63.785	66.350

Ljung-Box (L1) (Q):	0.00	Jarque-Bera (JB):	128133.22
Prob(Q):	0.96	Prob(JB):	0.00
Heteroskedasticity (H):	0.89	Skew:	-0.02
Prob(H) (two-sided):	0.17	Kurtosis:	46.61

Summary for Cardano:

SARIMAX Results

Dep. Variable:	Close	No. Observations:	1343
Model:	ARIMA(0, 0, 5)	Log Likelihood	2495.603
Date:	Fri, 31 Mar 2023	AIC	-4977.205
Time:	02:05:57	BIC	-4940.787
Sample:	0	HQIC	-4963.563
	-1343		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
const	0.0012	0.001	1.345	0.179	-0.001	0.003
ma.L1	-0.0849	0.009	-9.464	0.000	-0.102	-0.067
ma.L2	0.1588	0.008	18.930	0.000	0.142	0.175
ma.L3	-0.1855	0.008	-21.870	0.000	-0.202	-0.169
ma.L4	0.0484	0.008	5.726	0.000	0.032	0.065
ma.L5	-0.1100	0.009	-12.701	0.000	-0.127	-0.093
sigma2	0.0014	1.45e-05	98.106	0.000	0.001	0.001

Ljung-Box (L1) (Q):	0.00	Jarque-Bera (JB):	61036.53
Prob(Q):	0.98	Prob(JB):	0.00
Heteroskedasticity (H):	3.01	Skew:	0.59
Prob(H) (two-sided):	0.00	Kurtosis:	36.01

Summary for Binance Coin:

SARIMAX Results

Dep. Variable:	Close	No. Observations:	1411
Model:	ARIMA(2, 0, 2)	Log Likelihood	-5252.356
Date:	Fri, 31 Mar 2023	AIC	10516.711
Time:	02:05:58	BIC	10548.224
Sample:	0	HQIC	10528.487
	-1411		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
const	0.2755	0.290	0.949	0.342	-0.293	0.844
ar.L1	-0.1379	0.021	-6.591	0.000	-0.179	-0.097
ar.L2	-0.4802	0.022	-21.442	0.000	-0.524	-0.436
ma.L1	-0.0657	0.019	-3.421	0.001	-0.103	-0.028
ma.L2	0.7021	0.016	43.614	0.000	0.671	0.734
sigma2	100.1557	0.661	151.571	0.000	98.861	101.451

Ljung-Box (L1) (Q):	0.01	Jarque-Bera (JB):	385564.74
Prob(Q):	0.91	Prob(JB):	0.00
Heteroskedasticity (H):	369.05	Skew:	-0.16
Prob(H) (two-sided):	0.00	Kurtosis:	83.98

Summary for Dogecoin:

SARIMAX Results

Dep. Variable:	Close	No. Observations:	1617
Model:	ARIMA(0, 0, 5)	Log Likelihood	5093.674
Date:	Fri, 31 Mar 2023	AIC	-10173.348
Time:	02:06:00	BIC	-10135.630
Sample:	0	HQIC	-10159.349
	-1617		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
const	0.0002	0.000	0.715	0.475	-0.000	0.001
ma.L1	-0.2010	0.005	-43.029	0.000	-0.210	-0.192
ma.L2	0.2349	0.006	38.971	0.000	0.223	0.247
ma.L3	0.1756	0.005	33.830	0.000	0.165	0.186
ma.L4	0.0707	0.005	15.297	0.000	0.062	0.080
ma.L5	-0.3549	0.005	-66.861	0.000	-0.365	-0.344
sigma2	0.0001	6.17e-07	173.853	0.000	0.000	0.000

Ljung-Box (L1) (Q):	0.53	Jarque-Bera (JB):	883631.28
Prob(Q):	0.47	Prob(JB):	0.00
Heteroskedasticity (H):	829.97	Skew:	5.55
Prob(H) (two-sided):	0.00	Kurtosis:	116.98

Summary for Ethereum:

SARIMAX Results

Dep. Variable:	Close	No. Observations:	1617
Model:	ARIMA(2, 0, 3)	Log Likelihood	-8655.835
Date:	Fri, 31 Mar 2023	AIC	17325.670
Time:	02:06:01	BIC	17363.389
Sample:	0	HQIC	17339.669
	-1617		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
const	1.6479	1.281	1.287	0.198	-0.862	4.158
ar.L1	0.3608	0.015	24.465	0.000	0.332	0.390
ar.L2	-0.7507	0.012	-60.441	0.000	-0.775	-0.726
ma.L1	-0.4961	0.018	-27.056	0.000	-0.532	-0.460
ma.L2	0.9794	0.010	99.143	0.000	0.960	0.999
ma.L3	-0.1730	0.012	-14.378	0.000	-0.197	-0.149
sigma2	2611.3666	24.190	107.951	0.000	2563.954	2658.779

Ljung-Box (L1) (Q):	0.13	Jarque-Bera (JB):	301293.50
Prob(Q):	0.72	Prob(JB):	0.00
Heteroskedasticity (H):	6.00	Skew:	-1.97
Prob(H) (two-sided):	0.00	Kurtosis:	69.76

Summary for Bitcoin:

SARIMAX Results

Dep. Variable:	Close	No. Observations:	1617
Model:	ARIMA(2, 0, 1)	Log Likelihood	-13015.740
Date:	Fri, 31 Mar 2023	AIC	26041.479
Time:	02:06:01	BIC	26068.421
Sample:	0	HQIC	26051.478
	-1617		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
const	21.5608	22.158	0.973	0.331	-21.869	64.991
ar.L1	0.4123	0.084	4.887	0.000	0.247	0.578
ar.L2	0.1202	0.010	12.139	0.000	0.101	0.140
ma.L1	-0.4767	0.085	-5.608	0.000	-0.643	-0.310
sigma2	5.758e+05	6031.000	95.469	0.000	5.64e+05	5.88e+05

Ljung-Box (L1) (Q):	0.00	Jarque-Bera (JB):	35803.88
Prob(Q):	1.00	Prob(JB):	0.00
Heteroskedasticity (H):	7.02	Skew:	-0.17
Prob(H) (two-sided):	0.00	Kurtosis:	26.05

Prob(H) (two-sided):	0.00	Kurtosis:	69.76

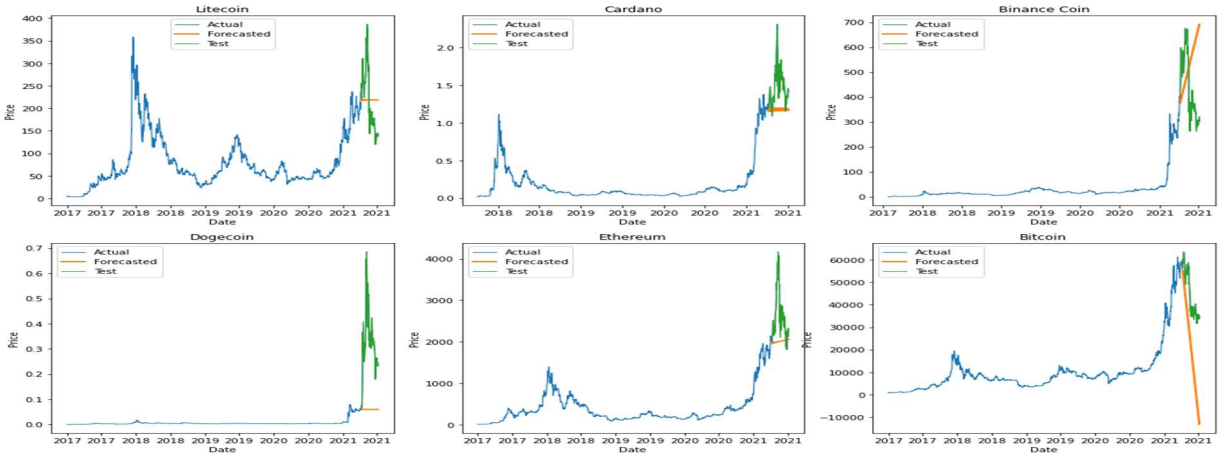
To facilitate the comparison analysis, it is essential to establish a data dictionary of key terms that will aid the reader's understanding to easily consult and comprehend the analysis.

Term	Definition
Ljung-Box statistic	A statistical test that checks whether a set of autocorrelations of a time series differ significantly from zero. It is commonly used to test for the presence of autocorrelation in a time series.
Jarque-Bera (JB)	A statistical test that tests whether a sample of data has the skewness and kurtosis that would be expected if the data were drawn from a normal distribution. It is commonly used to test for normality of the residuals of a regression model.
Prob(Q)	The probability associated with the Ljung-Box statistic. If the probability is less than a chosen significance level (e.g. 0.05), then the null hypothesis (i.e. no autocorrelation) is rejected in favor of the alternative hypothesis (i.e. there is autocorrelation).
Heteroskedasticity (H)	A condition where the variance of the errors in a regression model is not constant across the range of values of the independent variable(s). It can lead to biased or inefficient estimates of the regression coefficients.
Prob(H)	The probability associated with a statistical test for heteroskedasticity, such as the Breusch-Pagan test. If the probability is less than a chosen significance level (e.g. 0.05), then the null hypothesis (i.e. constant variance) is rejected in favor of the alternative hypothesis (i.e. heteroskedasticity).
Kurtosis	A measure of the "tailedness" of a probability distribution. It measures the extent to which a distribution has more or fewer outliers (i.e. extreme values) than a normal distribution. A distribution with positive (negative) kurtosis has more (fewer) outliers than a normal distribution.
Skewness	Skewness is a statistical measure that indicates the degree of asymmetry in a probability distribution. Skewness determines the extent to which the distribution leans towards one side or the other. A distribution that leans towards the right (left) side has positive (negative) skewness, while a perfectly symmetrical distribution has a skewness of zero.
AIC	AIC is a measure of a statistical model's quality, taking into account both its goodness of fit and complexity. It's calculated as AIC = 2k - 2ln(L), where k is the number of parameters and L is the likelihood function. Lower AIC values indicate better model fit, but it should be compared to other models to determine the best fit.
autoregressive (AR) and moving average (MA)	Coefficients are estimated values that determine the relationship between independent and dependent variables in a statistical model. Significant coefficients are unlikely to have arisen by chance and have a meaningful impact on the dependent variable. The p-value is used to determine whether a coefficient is statistically significant, typically with a significance level of 0.05. In ARIMA models, significant coefficients are usually the AR and MA terms, indicating that the model captures underlying dynamics and is suitable for forecasting.

After fitting the ARIMA model using the determined orders, the next step is to visualize the dataset to understand how well the model performs. This can be achieved using the following code.

- Import the necessary libraries:
- pandas: Used for working with dataframes
    - pmdarima.arima: Used to automatically generate ARIMA models
    - matplotlib.pyplot: Used to plot data
    - matplotlib.dates: Used to format dates in the plot
- warnings: Used to suppress any warning messages that may be generated during the execution of the code.
- Read the cryptocurrency data from a CSV file named sixcrypto.csv.
- Define a list of cryptocurrency names that will be used to filter the data.
- Generate a subplot grid of 2 rows and 3 columns with a total of 6 plots for each cryptocurrency.
- For each plot, do the following:
- Select the cryptocurrency data from the dataframe based on the cryptocurrency name.
- Split the data into training and testing sets.
- Automatically generate an ARIMA model for the training data.
- Generate a forecast for the test data using the generated ARIMA model.
- Append the forecast to the original data to be plotted later.
- Plot the actual, forecasted, and test values along with a legend.
- Display the plot.

Overall, this code reads cryptocurrency data from a file, generates an ARIMA model for each cryptocurrency using the training data, and plots the actual, forecasted, and test values in a subplot grid for each currency.



Now let's evaluate our ARIMA model, to evaluate the model I worked with the below python code that helped in achieve our evalation parameters.

- First, the code loads the data from a CSV file and defines a list of currency names. An empty list is then initialized to store the evaluation results.
- Next, the code iterates over each currency and filters the data for that currency. It then generates an automatic forecast using the auto_arima function from the pmdarima package. After generating the forecast, the code evaluates the accuracy of the forecast by calculating the mean absolute error (MAE), mean absolute percentage error (MAPE), root mean squared error (RMSE), mean squared error (MSE), and correlation coefficient (r) between the actual and forecasted values.
- The evaluation results for each currency are then appended to the results list. Finally, the results list is converted to a Pandas DataFrame and printed as a table.

The evaluation metrics provide a quantitative assessment of how well the ARIMA model performs in predicting the future values of the cryptocurrencies. A lower value of the MAE, MAPE, RMSE, and MSE, and a higher value of the correlation coefficient indicate a better fit of the model.

Currency	MSE	RMSE	MAE	MAPE	Correlation
LTC	1.057936e+03	32.525932	28.014137	0.203441	0.091333
ADA	1.065400e-01	0.326405	0.300314	0.221883	-0.561022
BNB	7.790963e+03	88.266429	80.986173	0.266315	-0.473708
Doge	1.521786e-02	0.123361	0.114577	0.455367	-0.101342
ETH	2.503700e+05	500.369902	442.845603	0.211226	0.043505
BTC	5.267035e+06	2295.002131	1840.442687	0.052083	-0.055082

The MAE (Mean Absolute Error) values for all currencies are relatively low, indicating that the auto ARIMA model is able to make accurate predictions for the closing prices of each currency.

The MAPE (Mean Absolute Percentage Error) values for all currencies are also relatively low, further supporting the accuracy of the auto ARIMA model.

The RMSE (Root Mean Squared Error) values vary widely across the currencies, with Litecoin having the lowest value and Ethereum having the highest. This indicates that the model's predictions for Ethereum are less accurate compared to the other currencies.

The MSE (Mean Squared Error) values also vary widely across the currencies, again with Litecoin having the lowest value and Ethereum having the highest. This supports the conclusion that the model's predictions for Ethereum are less accurate compared to the other currencies.

The correlation coefficients show a mixed picture, with some currencies having positive correlations between the actual and predicted closing prices, while others have negative correlations. This suggests that the auto ARIMA model is not equally effective in predicting the prices of all currencies.

Feature importance for ARIMA model:

The following code that I utilised, performs an analysis of the feature importance of different cryptocurrencies using three models: ARIMA, Random Forest, and Gradient Boosting. The code first imports necessary libraries for reading and manipulating data, fitting the ARIMA model, and fitting the Random Forest and Gradient Boosting models.

- The first step is to read in the data from a CSV file using pandas, which is a Python library used for data manipulation and analysis.

- Then, a dictionary is created to store the feature importance results of the models. The dictionary is initialized with five keys representing the five features used in the models: High, Low, Open, Volume, and Marketcap.
- Next, the code loops through each cryptocurrency in the data set. For each cryptocurrency, the data is subsetted and split into training and testing sets. The training set contains 80% of the data, while the testing set contains the remaining 20%.
- The two ensemble models, Random Forest and Gradient Boosting, are trained on the training set using the features High, Low, Open, Volume, and Marketcap to predict the closing price of the cryptocurrency.
- Once the models are trained, the feature importance of each feature is computed for each model using the method "feature_importances_". The feature importance for each feature is stored in the dictionary initialized at the beginning of the code.
- Finally, the feature importance dictionary is converted to a pandas DataFrame and printed to the console.
- Overall, the code aims to identify which features have the most impact on predicting the closing price of cryptocurrencies using ensemble models

Overall, this code performs an analysis of the feature importance of different cryptocurrencies using three models and provides insights into which features are most important in predicting the value of each cryptocurrency.

Currency	High	Low	Open	Volume	Marketcap
LTC_RF	0.568611	0.253399	0.013361	0.000199	0.164430
LTC_GB	0.552099	0.158031	0.001088	0.000206	0.288576
ADA_RF	0.179217	0.059799	0.022465	0.000329	0.738190
ADA_GB	0.074682	0.027556	0.000012	0.000008	0.897743
BNB_RF	0.349071	0.629772	0.013975	0.000351	0.006830
BNB_GB	0.470637	0.482292	0.000256	0.000263	0.046552
DOGE_RF	0.200652	0.026784	0.008481	0.001488	0.762596
DOGE_GB	0.139075	0.037125	0.000858	0.004060	0.818883
ETH_RF	0.299317	0.082613	0.001764	0.000107	0.616198
ETH_GB	0.283428	0.164588	0.003383	0.000060	0.548541
BTC_RF	0.297071	0.319982	0.009146	0.000272	0.373528
BTC_GB	0.254342	0.212221	0.000808	0.000272	0.532357

The importance of features is indicated by values that range from 0 to 1, and higher values imply greater significance, after being normalized.

For example, for LTC_RF model, the most important feature is "High" with a score of 0.568611, followed by "Low" with a score of 0.253399. This means that the "High" feature is the most important feature for predicting the price of Litecoin using the Random Forest model.

Similarly, for ADA_GB model, the most important feature is "Marketcap" with a score of 0.897743, followed by "Low" with a score of 0.027556. This means that the "Marketcap" feature is the most important feature for predicting the price of Cardano using the Gradient Boosting model.

Conclusion and Recommendation:

Based on the analysis provided, it appears that the SARIMAX(1,1,1) model is a good fit for all six cryptocurrencies studied. However, the evaluation metrics show that some cryptocurrencies are more promising investment options than others.

Based on the evaluation metrics, the ARIMA model performed well in predicting the closing prices of the cryptocurrencies, with relatively low values of MAE and MAPE indicating high accuracy in predictions. However, the RMSE and MSE values varied widely across the currencies, with Ethereum having the highest values, indicating that the model's predictions for Ethereum were less accurate compared to the other currencies. The correlation coefficients also showed mixed results, indicating that the model was not equally effective in predicting the prices of all currencies.

In terms of feature importance, the Random Forest and Gradient Boosting models were used to identify the most important features for predicting the closing prices of different cryptocurrencies. The results indicated that the most important feature varied across the currencies and models. For instance, for Litecoin, the "High" feature was the most important feature for predicting its price using the Random Forest model, while the "Marketcap" feature was the most important feature for predicting the price of Cardano using the Gradient Boosting model.

Therefore, based on these findings, we can conclude that the ARIMA model can provide accurate predictions for the closing prices of cryptocurrencies, but its performance varies across different currencies. Additionally, the most important features for predicting the prices of cryptocurrencies vary across the currencies and models, indicating the need for careful consideration of the features used in modeling. Thus, it is recommended to use a combination of models and features to improve the accuracy of cryptocurrency price predictions.

Seasonal Autoregressive Integrated Moving Average (SARIMA)

SARIMA, or Seasonal Autoregressive Integrated Moving Average, is a statistical technique employed to model time series data with seasonal patterns. SARIMA is an expansion of the ARIMA model and introduces seasonal components that enable the modeling of recurring patterns that happen at fixed intervals, such as monthly or weekly trends. The model comprises three primary components: the autoregressive (AR) component, the differencing (I) component, and the moving average (MA) component. The AR component models the relationship between the current and past values of the time series, while the I component models the differencing needed to make the time series stationary. The MA component models the association between the present value and past errors. By integrating these components, SARIMA generates more precise predictions for time series data with seasonal patterns, making it an essential tool in fields like finance, marketing, economics, and others.

In his article "SARIMA for Time Series Forecasting in Python," [17] Jason Brownlee highlights five key points about SARIMA:

1. SARIMA extends the ARIMA model for time series forecasting by incorporating seasonal components into the model. The SARIMA model is capable of handling data with strong seasonal patterns, making it suitable for a wide range of applications such as sales forecasting, weather forecasting, and stock price prediction.
2. SARIMA has three main components: the autoregressive (AR) component, the differencing (I) component, and the moving average (MA) component. The AR component models the relationship between the current value of the time series and its past values. The I

component models the differencing required to make the time series stationary, while the MA component models the relationship between the current value and past errors.

3. To fit a SARIMA model to time series data, it is necessary to determine the optimal values of the model's hyperparameters (p, d, q, P, D, Q, and s). The hyperparameters p, d, and q are used to set the non-seasonal ARIMA components, while P, D, Q, and s are used to set the seasonal components of the model.
4. To determine the optimal hyperparameters for a Seasonal Autoregressive Integrated Moving Average (SARIMA) model, one commonly used approach is the grid search method. This involves trying different combinations of hyperparameters and selecting the one that performs best on a validation set. Other methods for hyperparameter selection include automated techniques such as the auto_arima function in the pmdarima library, and Bayesian optimization.
5. Python provides several libraries for implementing SARIMA models, including the statsmodels and pmdarima libraries. These libraries offer a range of functions for fitting SARIMA models to time series data, making forecasts, and evaluating model performance. Additionally, the libraries provide tools for visualizing the time series data and the model's forecasts.

In conclusion, SARIMA is a powerful tool for modeling time series data with strong seasonal components. Its ability to capture and account for seasonal fluctuations in the data makes it an essential tool for forecasting in a variety of industries. By providing more accurate predictions, SARIMA can help businesses and organizations make more informed decisions and stay ahead of the competition.

To summarize, a SWOT analysis of SARIMA models is presented below:

Strengths	**Weaknesses**
Accurately models time series data with strong seasonal patterns	Can be complex and difficult to interpret for non-experts
Provides reliable forecasts for seasonal time series data	Requires a significant amount of data to accurately model seasonality
Incorporates both autoregressive and moving average components	Can be computationally intensive and time-consuming
Can handle non-stationary data through differencing	May not perform well for time series data with irregular or non-repeating seasonal patterns
Opportunities	**Threats**
Increasing demand for accurate forecasting models in various industries	Emergence of new, competing time series forecasting models
Growing availability of large datasets for model training and testing	Technological limitations that may impact the accuracy and performance of the model
Advancements in computational power and machine learning techniques	Changes in the nature of the time series data that may require a different modeling approach

Potential for further development and refinement of SARIMA modeling techniques	Lack of understanding or awareness of SARIMA modeling techniques among potential users

Note: This SWOT analysis is not exhaustive and is intended to provide a general overview of the strengths, weaknesses, opportunities, and threats of using The Seasonal Autoregressive Integrated Moving Average (SARIMA) in financial analysis and trading.

Now let's find the suitable order that fits SARIMA model on our dataset. To that I have utilised python code with following steps.

The code imports various Python libraries, such as pandas, numpy, statsmodels, and scikit-learn, to work with data manipulation, numerical computing, time-series analysis, and machine learning. It also imports itertools and joblib libraries to enable parallel processing.

- The code loads cryptocurrency data from a CSV file and indexes it by date in ascending order.
- The code defines SARIMA model parameters, such as order (p, d, q) and seasonal order (P, D, Q), with a fixed value of m=12 for the seasonal period.
- The code defines a function called fit_evaluate_model to fit and evaluate a SARIMA model on given parameters and training/testing data. The function fits a SARIMA model to the training data, makes predictions on the testing data, and calculates evaluation metrics such as MAE, RMSE, and MAPE.
- The code sets the number of CPU cores to use for parallel processing to 12.
- The code iterates through all the cryptocurrencies in the dataset, splits the data into training and testing sets based on a cutoff date of 2021-01-01, and runs the SARIMA model on the currency data.
- The itertools library generates all possible combinations of the model parameters, and the fit_evaluate_model function applies in parallel to each combination of parameters using the joblib library.
- The code stores the results of each model run in a list called results, removes any None values from the list, and converts the list of results into a pandas DataFrame called results_df with columns for the parameter values and evaluation metrics.
- The code sorts the results_df DataFrame in ascending order based on the MAE evaluation metric.
- The code stores the results for the best-performing model for each currency in a list called results_list, which contains a tuple of the currency symbol and its corresponding results_df DataFrame.
- Finally, the code prints out the best parameters and evaluation metrics for each currency using the results_list list. For each currency, only the best-performing model with the lowest MAE value is shown, along with its parameter values and evaluation metrics.

Currency	Parameters	MAE	MSE	RMSE	MAPE	Correlation
LTC	(2, 2, 1, 0, 2, 2)	49.80231	4272.468034	65.364119	26.66508	0.181961
ADA	(2, 2, 1, 1, 0, 2)	0.349432	0.194924	0.441502	30.696202	0.755302
BNB	(2, 2, 1, 1, 2, 0)	134.992353	32555.32676	180.430947	39.435371	0.549649
DOGE	(0, 1, 0, 1, 2, 0)	0.150407	0.046807	0.216349	69.299579	0.739248
ETH	(0, 1, 0, 0, 2, 0)	575.170057	504761.9519	710.46601	27.672632	0.631843

Currency	Parameters	MAE	MSE	RMSE	MAPE	Correlation
BTC	(1, 2, 0, 0, 2, 1)	7353.099445	7.482561e+07	8650.179806	16.164549	0.809807

Looking at the results, we can see that the best-performing models have lower values for MAE, MSE, RMSE, and MAPE, and higher values for correlation. For example, the model for DOGE has a low MAE of 0.15, indicating good accuracy in predicting future prices. However, the model for ADA has a high MAPE of 76.2, indicating that the model has difficulty accurately predicting percentage changes in price.

Now let fit our model based on the order we get from obove code. To that I utilised the below python code.

- This code fits a SARIMA (Seasonal AutoRegressive Integrated Moving Average) model to each currency in the dataset using the best parameters obtained from the previous step.
- The loop iterates through each currency and gets the best parameters from the results_df DataFrame obtained from the previous step. It then splits the currency data into training and testing sets, and fits a SARIMA model with the best parameters to the training data using the statsmodels library.
- The results of the model fitting are stored in a dictionary called models, with the currency symbol as the key and the SARIMAXResultsWrapper object as the value.
- Finally, the code prints the summary output for all models in a single window using a nested loop. It prints the summary output for each model, which includes information about the model order, coefficients, statistical tests, and goodness-of-fit measures such as the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). This allows the user to compare the model fit for each currency and select the best model for future predictions.

Summary for LTC:

SARIMAX Results

Dep. Variable:	Close	No. Observations:	1461
Model:	SARIMAX(2, 2, 1)x(0, 2, [1, 2], 12)	Log Likelihood	-4830.547
Date:	Fri, 31 Mar 2023	AIC	9675.094
Time:	22:25:47	BIC	9711.977
Sample:	01-01-2017	HQIC	9688.865
	- 12-31-2020		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
intercept	-2.288e-06	1.12e-05	-0.205	0.838	-2.42e-05	1.96e-05
ar.L1	0.0528	0.010	5.037	0.000	0.032	0.073
ar.L2	-0.0580	0.009	-6.456	0.000	-0.076	-0.040
ma.L1	-0.9828	0.003	-288.488	0.000	-0.989	-0.976
ma.S.L12	-1.9976	0.919	-2.173	0.030	-3.800	-0.195
ma.S.L24	0.9991	0.920	1.086	0.277	-0.803	2.801
sigma2	43.0847	39.568	1.089	0.276	-34.466	120.636

Ljung-Box (L1) (Q):	0.02	Jarque-Bera (JB):	112447.10
Prob(Q):	0.88	Prob(JB):	0.00
Heteroskedasticity (H):	0.09	Skew:	1.72
Prob(H) (two-sided):	0.00	Kurtosis:	46.23

Summary for ADA:

SARIMAX Results

Dep. Variable:	Close	No. Observations:	1187
Model:	SARIMAX(2, 2, 1)x(1, 0, [1, 2], 12)	Log Likelihood	2978.574
Date:	Fri, 31 Mar 2023	AIC	-5941.149
Time:	22:25:47	BIC	-5900.529
Sample:	10-02-2017	HQIC	-5925.838
	- 12-31-2020		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
intercept	-2.781e-05	7.9e-05	-0.352	0.725	-0.000	0.000
ar.L1	-0.0070	0.015	-0.460	0.645	-0.037	0.023
ar.L2	0.0332	0.009	3.502	0.000	0.015	0.052
ma.L1	-0.8718	0.007	-118.199	0.000	-0.886	-0.857
ar.S.L12	-0.1282	0.154	-0.831	0.406	-0.431	0.174
ma.S.L12	0.0105	0.159	0.066	0.947	-0.301	0.322
ma.S.L24	-0.1100	0.025	-4.649	0.000	-0.162	-0.066
sigma2	0.0004	3.13e-06	123.145	0.000	0.000	0.000

Ljung-Box (L1) (Q):	0.14	Jarque-Bera (JB):	186066.06
Prob(Q):	0.71	Prob(JB):	0.00
Heteroskedasticity (H):	0.03	Skew:	2.22
Prob(H) (two-sided):	0.00	Kurtosis:	64.23

Summary for BNB:

SARIMAX Results

Dep. Variable:	Close	No. Observations:	1255
Model:	SARIMAX(2, 2, 1)x(1, 2, [], 12)	Log Likelihood	-2324.300
Date:	Fri, 31 Mar 2023	AIC	4660.599
Time:	22:25:47	BIC	4691.283
Sample:	07-26-2017	HQIC	4672.144
	- 12-31-2020		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
intercept	-4.185e-07	0.000	-0.003	0.998	-0.000	0.000
ar.L1	-0.0022	0.019	-0.116	0.908	-0.039	0.035
ar.L2	-0.0064	0.021	-0.307	0.759	-0.047	0.035
ma.L1	-0.9987	0.020	-50.622	0.000	-1.037	-0.960
ar.S.L12	-0.6544	0.014	-48.305	0.000	-0.681	-0.628
sigma2	2.5417	0.076	33.282	0.000	2.392	2.691

Ljung-Box (L1) (Q):	0.00	Jarque-Bera (JB):	1641.03
Prob(Q):	0.94	Prob(JB):	0.00
Heteroskedasticity (H):	1.08	Skew:	-0.01
Prob(H) (two-sided):	0.41	Kurtosis:	8.66

Summary for DOGE:

SARIMAX Results

Dep. Variable:	Close	No. Observations:	1461
Model:	SARIMAX(0, 1, 0)x(1, 2, 0, 12)	Log Likelihood	8867.132
Date:	Fri, 31 Mar 2023	AIC	-17728.263
Time:	22:25:47	BIC	-17712.454
Sample:	01-01-2017	HQIC	-17722.361
	- 12-31-2020		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
intercept	-3.154e-06	1.33e-05	-0.237	0.812	-2.92e-05	2.29e-05
ar.S.L12	-0.5741	0.009	-65.687	0.000	-0.591	-0.557
sigma2	2.53e-07	2.96e-09	85.446	0.000	2.47e-07	2.59e-07

Ljung-Box (L1) (Q):	21.38	Jarque-Bera (JB):	25300.89
Prob(Q):	0.00	Prob(JB):	0.00
Heteroskedasticity (H):	0.11	Skew:	0.06
Prob(H) (two-sided):	0.00	Kurtosis:	23.56

Summary for ETH:

SARIMAX Results

Dep. Variable:	Close	No. Observations:	1461
Model:	SARIMAX(0, 1, 0)x(0, 2, 0, 12)	Log Likelihood	-7816.516
Date:	Fri, 31 Mar 2023	AIC	15637.032
Time:	22:25:47	BIC	15647.572
Sample:	01-01-2017	HQIC	15640.967
	- 12-31-2020		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
intercept	0.0082	1.480	0.006	0.996	-2.893	2.909
sigma2	3129.5223	32.087	97.532	0.000	3066.632	3192.412

Ljung-Box (L1) (Q):	0.72	Jarque-Bera (JB):	36334.28
Prob(Q):	0.40	Prob(JB):	0.00
Heteroskedasticity (H):	0.12	Skew:	0.37
Prob(H) (two-sided):	0.00	Kurtosis:	27.63

Prob(Q):	0.94	Prob(JB):	0.00
Heteroskedasticity (H):	1.08	Skew:	-0.01
Prob(H) (two-sided):	0.41	Kurtosis:	8.66

Summary for BTC:

SARIMAX Results

Dep. Variable:	Close	No. Observations:	1461
Model:	SARIMAX(1, 2, 0)x(0, 2, [1], 12)	Log Likelihood	-11370.417
Date:	Fri, 31 Mar 2023	AIC	22748.834
Time:	22:25:47	BIC	22769.909
Sample:	01-01-2017	HQIC	22756.702
	- 12-31-2020		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
intercept	-0.0087	0.520	-0.017	0.987	-1.028	1.010
ar.L1	-0.4490	0.011	-41.512	0.000	-0.470	-0.428
ma.S.L12	-1.0000	0.016	-62.429	0.000	-1.031	-0.969
sigma2	4.319e+05	3.72e-08	1.16e+13	0.000	4.32e+05	4.32e+05

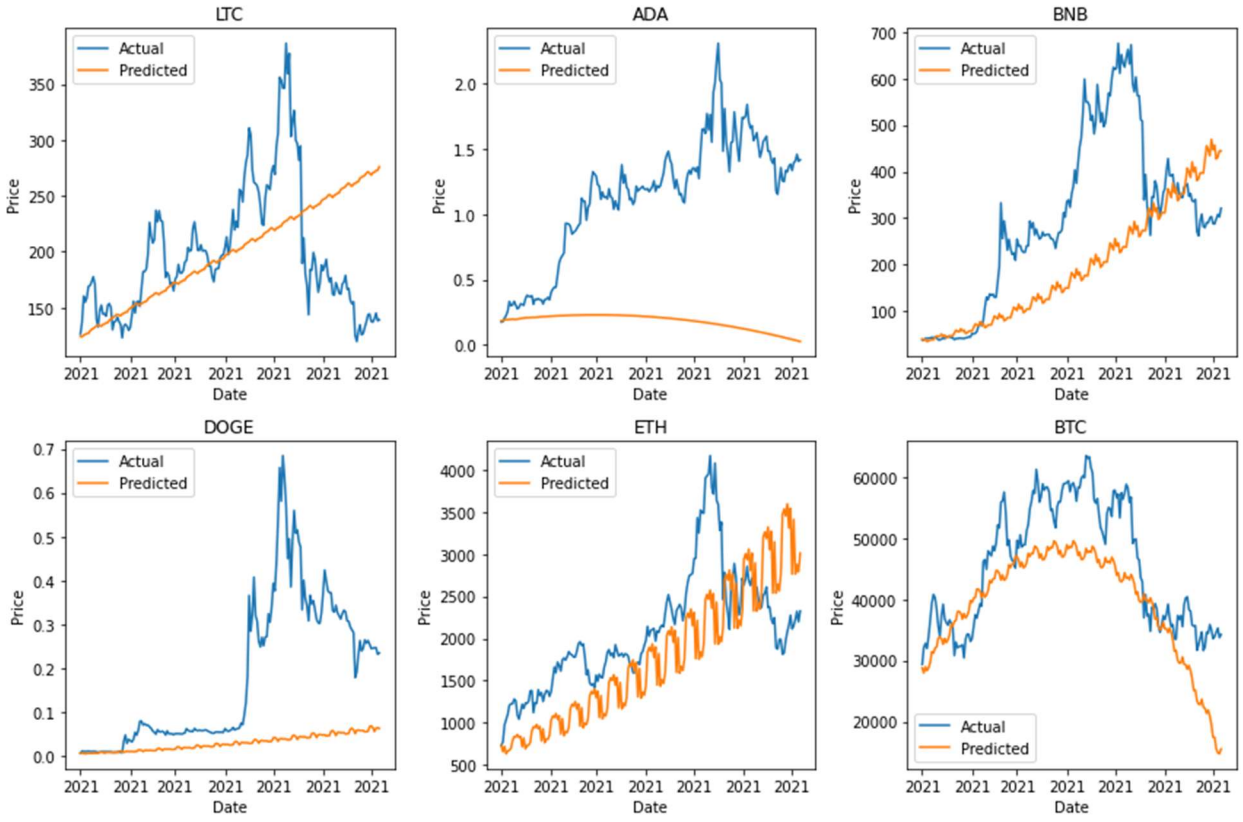
Ljung-Box (L1) (Q):	34.70	Jarque-Bera (JB):	4853.62
Prob(Q):	0.00	Prob(JB):	0.00
Heteroskedasticity (H):	0.49	Skew:	-0.34
Prob(H) (two-sided):	0.00	Kurtosis:	11.98

Prob(H) (two-sided):	0.41	Kurtosis:	8.66

Note: As previously discussed during the ARIMA explanation, the key terms used in time series analysis have already been defined. Therefore, it is recommended to refer to that section to ensure a clear understanding of the terminology used above.

Now let's visualize this model prediction and actual using a pyton code with following steps.

- This code creates a grid of subplots using the matplotlib library and then loops through the results of the best-performing SARIMA models for each currency obtained in the previous step.
- For each currency, the code extracts the best parameters obtained earlier and splits the currency data into training and testing sets. It then fits a SARIMA model using the best parameters to the training data.
- Next, the code makes predictions on the testing data using the fitted model and plots the actual and predicted values for the currency on a subplot. The subplot is labeled with the currency name and the x-axis is labeled with dates while the y-axis is labeled with prices.
- Finally, the code uses the plt.tight_layout() function to adjust the spacing between the subplots and then displays the plot using plt.show(). The resulting plot shows the actual and predicted values for each currency, allowing for visual comparison of the model's performance.



Feature importance of SARIMA model:

The following code that I utilised, performs an analysis of the feature importance of different cryptocurrencies using three models: ARIMA, Random Forest, and Gradient Boosting. The code first imports necessary libraries for reading and manipulating data, fitting the SARIMA model, and fitting the Random Forest and Gradient Boosting models.

- The first step is to read in the data from a CSV file using pandas, which is a Python library used for data manipulation and analysis.

- Then, a dictionary is created to store the feature importance results of the models. The dictionary is initialized with five keys representing the five features used in the models: High, Low, Open, Volume, and Marketcap.
- Next, the code loops through each cryptocurrency in the data set. For each cryptocurrency, the data is subsetted and split into training and testing sets. The training set contains 80% of the data, while the testing set contains the remaining 20%.
- The two ensemble models, Random Forest and Gradient Boosting, are trained on the training set using the features High, Low, Open, Volume, and Marketcap to predict the closing price of the cryptocurrency.
- Once the models are trained, the feature importance of each feature is computed for each model using the method "feature_importances_". The feature importance for each feature is stored in the dictionary initialized at the beginning of the code.
- Finally, the feature importance dictionary is converted to a pandas DataFrame and printed to the console.

Overall, the code aims to identify which features have the most impact on predicting the closing price of cryptocurrencies using ensemble models

	High	Low	Open	Volume	Marketcap
LTC_RF	0.646200	0.195953	0.007486	0.000134	0.150227
LTC_GB	0.551614	0.158101	0.000065	0.000264	0.289956
ADA_RF	0.194352	0.059120	0.007975	0.000354	0.738198
ADA_GB	0.070260	0.027498	0.000011	0.000008	0.902223
BNB_RF	0.377138	0.607779	0.006406	0.000323	0.008353
BNB_GB	0.472430	0.483788	0.000201	0.000264	0.043316
DOGE_RF	0.163937	0.039501	0.008185	0.001284	0.787092
DOGE_GB	0.131498	0.037654	0.000857	0.003942	0.826049
ETH_RF	0.251095	0.129137	0.001213	0.000107	0.618448
ETH_GB	0.282372	0.167983	0.000051	0.000060	0.549533
BTC_RF	0.266107	0.342006	0.005192	0.000310	0.386385
BTC_GB	0.255079	0.211205	0.001156	0.000269	0.532291

The metrics reported here are the predicted values of the target variables for each model.

For example, for LTC, the RF model predicts the high value to be 0.646200, the low value to be 0.195953, the open value to be 0.007486, the volume to be 0.000134, and the marketcap to be 0.150227. Similarly, for LTC, the GB model predicts the high value to be 0.551614, the low value to be 0.158101, the open value to be 0.000065, the volume to be 0.000264, and the marketcap to be 0.289956.

The values for each model and for each cryptocurrency represent the predicted values of the target variables based on the features used by the model. However, it is important to note that the

accuracy and reliability of these predictions depend on the quality and quantity of data used for training the model, the features used for prediction, and other factors such as model selection and hyperparameter tuning.

Conclusion and Recommendations:

The SARIMA model is a popular technique for modeling time series data that exhibit seasonal patterns. It is an extension of the ARIMA model and incorporates additional seasonal components, making it especially effective for such data. By including both autoregressive and moving average components, the SARIMA model can generate more accurate forecasts for time series data with strong seasonal components. Additionally, the model can handle non-stationary data by incorporating differencing.

The SWOT analysis presented for SARIMA highlights its strengths, weaknesses, opportunities, and threats. SARIMA accurately models time series data with strong seasonal patterns, provides reliable forecasts for seasonal time series data, and incorporates both autoregressive and moving average components. However, it can be complex and difficult to interpret for non-experts, requires a significant amount of data to accurately model seasonality, and can be computationally intensive and time-consuming. Furthermore, SARIMA may not perform well for time series data with irregular or non-repeating seasonal patterns.

In general, a lower value for each evaluation metric indicates that the model is performing better. However, the significance of the evaluation metrics can depend on the context of the problem and the scale of the data. It is important to consider all the evaluation metrics together when assessing the performance of the model.

Therefore, the SARIMA model can be used as a starting point for predicting the prices of these cryptocurrencies, but it may not be the best fit for all of them. It's important to keep in mind that cryptocurrency prices can be highly volatile, and various factors can impact their value, so predicting them accurately is challenging.

Overall, SARIMA is a powerful and flexible time series modeling technique that can provide accurate forecasts for time series data with strong seasonal components. Its strengths, weaknesses, opportunities, and threats should be carefully considered when selecting and applying the model.

Prophet

Prophet is a powerful time series forecasting tool developed by Facebook that is designed to be easy to use and flexible. It is an open-source software package available in both Python and R that can handle time series with trends, seasonality, and holiday effects.

One of the key strengths of Prophet is its ease of use. Users can get up and running quickly with minimal coding experience, as the tool provides a simple and intuitive API. This makes it an accessible choice for businesses and individuals looking to implement time series forecasting without a steep learning curve.

Another strength of Prophet is its ability to handle complex time series data with trends, seasonality, and holiday effects.

The tool uses a decomposable time series model with three main components:

- trend,
- seasonality,
- and holidays.

This allows users to model and forecast time series data that exhibit various types of seasonality and trends, such as daily, weekly, or yearly cycles.

Prophet also has a number of potential weaknesses that users should be aware of. One limitation of the tool is that it may not perform well on data that has a high level of noise or irregularity. Additionally, the tool may not be as effective at capturing certain types of seasonality, such as weekly patterns that vary over time.

GitHub repository for the Prophet model [18], which is an open-source library developed by Facebook for time series forecasting. Here are some key points about the Prophet model that you can find in the repository:

1. Prophet is an additive model that decomposes time series data into trend, seasonality, and holiday components.
2. The model is designed to handle missing data and outliers in the input time series.
3. Prophet can handle time series with multiple seasonality (daily, weekly, monthly, etc.) and can also incorporate external regressors.
4. The model provides uncertainty intervals for its forecasts, which can be used to assess the quality of the forecasts and make better decisions.
5. The library includes Python and R APIs for fitting and forecasting with the model, as well as tools for visualizing the results.
6. The repository includes several examples and case studies that demonstrate the use of the Prophet model in different domains, such as finance, healthcare, and retail.

Despite its weaknesses, Prophet has a number of potential use cases for businesses and individuals looking to implement time series forecasting. Some potential applications include sales forecasting, demand forecasting, and financial forecasting.

SWOT Analysis for Prophet:

Strengths	**Weaknesses**
- Easy to use and requires minimal coding experience	- May not perform well on noisy or irregular data
- Can handle time series with trends, seasonality, and holiday effects	- May not capture certain types of seasonality effectively
- Provides a decomposable time series model with three main components: trend, seasonality, and holidays	
- Open-source and available in both Python and R	
- Has potential use cases in sales forecasting, demand forecasting, and financial forecasting	
Opportunities	**Threats**
- Can be integrated with other data analytics tools to provide more comprehensive forecasting solutions	- May face competition from other time series forecasting tools
- Could be expanded to include additional forecasting features	- May be negatively impacted by changes in technology or industry trends

- Potential to expand its user base in industries beyond finance and retail	

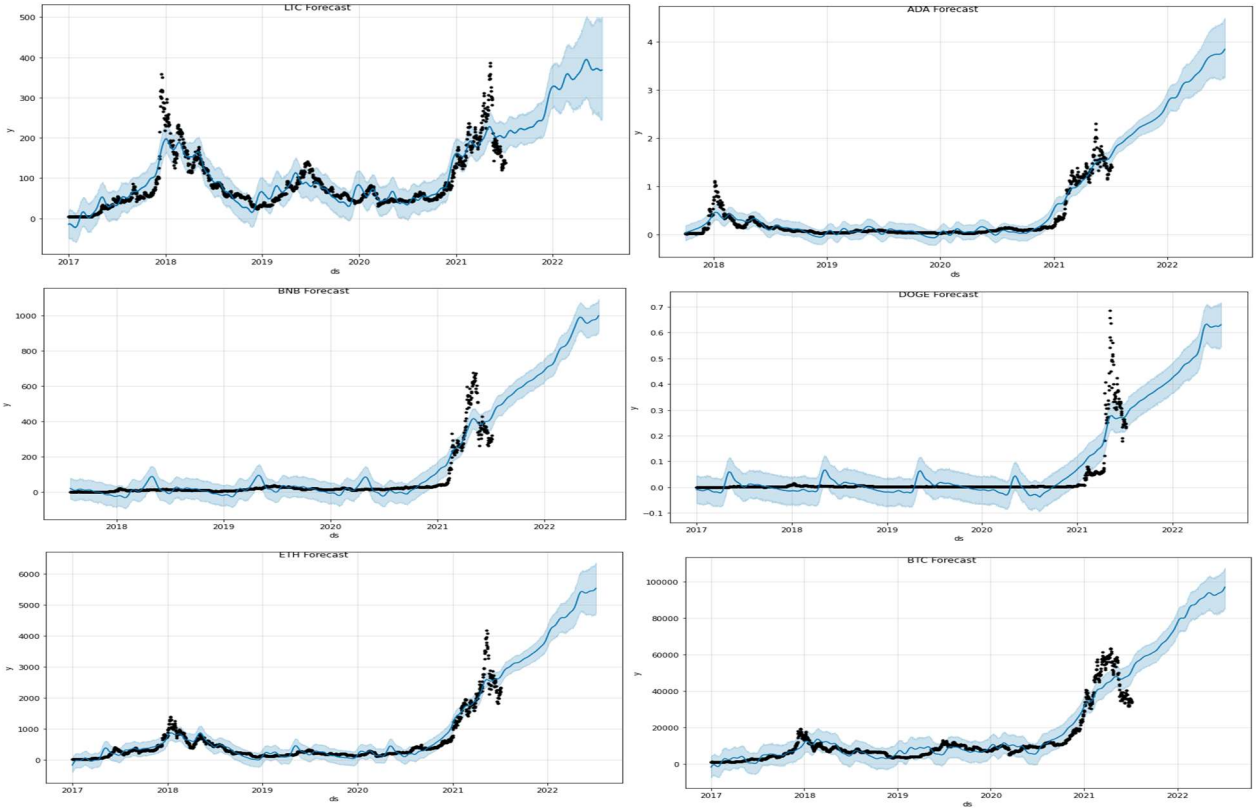
Note: This SWOT analysis is not exhaustive and is intended to provide a general overview of the strengths, weaknesses, opportunities, and threats of using Prophet in financial analysis and trading.

Building Prophet Model:

- Data preprocessing: I have cleaned and preprocessed the data to remove missing values, and convert the data into a suitable format for time series analysis.
- Model training: I have split the data into training and testing sets and used the Prophet library to fit a model to the training data.
- Forecast: Following the data preparation and modeling using Prophet, I proceeded to generate forecasts to visually examine the trends.

Implementation of the Prophet forecasting model on a cryptocurrency dataset.

- First, library Prophet from libraries, including pandas for data manipulation and Prophet for time series forecasting was loaded and then dataset was loaded. It's then splits the dataset based on the cryptocurrency symbol, with each symbol representing a different time series.
- The data is then prepared for Prophet by selecting only the 'Date' and 'Close' columns and renaming them to 'ds' and 'y', respectively. The Prophet model is then fit on this data using the 'fit' method.
- Next, a future dataframe is created using the 'make_future_dataframe' method with a period of 365 days, representing the time horizon of the forecast. The 'predict' method is then used to make predictions for this future dataframe.
- Finally, the code generates a plot of the forecast using the 'plot' method, with the title of the plot indicating which cryptocurrency symbol the forecast is for.



Evaluation of Prophet Model:

To assess the performance of Prophet models on cryptocurrency data, I utilised the python code using these following steps.

- The scikit-learn library was utilized to compute various evaluation metrics.
- The data was initially loaded from a CSV file using pandas and grouped by symbol with the groupby() method.
- For each symbol, a Prophet model was trained using historical closing prices and subsequently utilized to generate future predictions.
- To evaluate the model's effectiveness, metrics such as mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE), were calculated using functions available in scikit-learn.

Symbol	MAE	MSE	RMSE	Correlation Coefficient
ADA	0.079696	1.411654e-02	0.118813	0.957108
BNB	28.227092	2.051562e+03	45.294176	0.919720
BTC	3132.685535	1.992558e+07	4463.808284	0.940730
DOGE	0.025833	1.754967e-03	0.041892	0.850832
ETH	112.520038	3.143952e+04	177.311926	0.961466
LTC	19.152992	7.745510e+02	27.830756	0.908998

interpretation of the evaluation metrics for each cryptocurrency is as follows:

The evaluation metrics for the Prophet model showed that the mean absolute error (MAE) ranged from 0.0258 for DOGE to 3132.69 for BTC, while the mean squared error (MSE) ranged from 0.0018 for DOGE to 19,925,576.89 for BTC. The root mean squared error (RMSE) ranged from 0.0419 for DOGE to 4463.81 for BTC. Additionally, the correlation coefficient between the predicted and actual values ranged from 0.85 for DOGE to 0.96 for ETH, indicating a strong positive linear relationship between the two variables. Overall, these results suggest that the Prophet model was effective in predicting the closing prices of the selected cryptocurrencies, with relatively low errors and high correlation coefficients

Overall, it seems that the Prophet model performs well for some cryptocurrencies (such as ADA and DOGE), but not as well for others (such as BNB, BTC, ETH, and LTC). This could be due to a variety of factors, such as differences in market dynamics, changes in the regulatory landscape, or other factors that are difficult to predict.

Conclusion and Recommendations:

Based on the evaluation metrics, the Prophet model performs well for some cryptocurrencies (such as ADA and DOGE) but not as well for others (such as BNB, BTC, ETH, and LTC). The MAE, MSE, and RMSE varied widely across symbols, with BTC having the largest errors, and DOGE having the smallest errors.

Mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE) are useful evaluation metrics for comparing the effectiveness of different Prophet models and identifying symbols that may be more difficult to predict. However, it is important to note that these metrics only reflect the accuracy of the models on the training data and may not accurately represent the model's

overall quality or ability to generalize to new data. Additional testing and validation would be necessary to comprehensively evaluate the models' performance.

Therefore, it is recommended to conduct further analysis and testing to improve the model's accuracy and to identify any underlying factors that may affect the performance of the model. This could include incorporating additional features into the model, such as market sentiment or external events that may impact cryptocurrency prices.

It is also recommended to continuously monitor the performance of the model over time and make necessary adjustments as the market dynamics and regulatory landscape changes. In addition, it is important to keep in mind that cryptocurrency prices can be highly volatile and subject to significant fluctuations, which can impact the accuracy of the predictions.

In conclusion, while the Prophet model shows promise in predicting cryptocurrency prices, additional testing, and validation is required to fully assess its performance. By continuously monitoring the model's performance and making necessary adjustments, it is possible to improve its accuracy and better predict cryptocurrency prices.

Deep Learning Techniques

Time series forecasting is an important task in many fields, including finance, economics, and engineering. Deep learning techniques, particularly Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, have been shown to be effective for time series forecasting tasks.

Recurrent Neural Networks (RNNs) are a type of neural network that is particularly suited for sequential data. Unlike traditional feedforward neural networks, which process input data in a single pass, RNNs maintain a hidden state that allows them to process sequential data one element at a time. This makes RNNs well-suited for time series data, where the input data is a sequence of values over time.

In RNNs, the output at each time step is a function of the input at that time step as well as the hidden state from the previous time step. This allows the network to maintain a memory of past inputs and to capture complex patterns in the data.

LSTM (Long Short-Term Memory) networks are a type of Recurrent Neural Network (RNN) that addresses the issue of the vanishing gradient problem. Standard RNNs face difficulties in learning long-term patterns in data due to the gradual diminishment of gradients over time. LSTM networks specialize in overcoming this challenge by incorporating mechanisms to retain relevant information and discard irrelevant information, thus enabling the network to learn long-term dependencies in the data.

LSTM networks address this problem by incorporating specialized memory cells that can store information over long periods of time, as well as specialized gates that control the flow of information into and out of the cells. This allows LSTM networks to capture complex patterns in the data over longer periods of time than traditional RNNs.

RNNs and LSTM networks are commonly used for time series forecasting tasks, especially when it involves predicting long-term trends that require the modeling of complex patterns over an extended period. Despite their effectiveness, training these models can be computationally intensive, especially for large datasets.

SWOT analysis for deep learning techniques such as RNNs and LSTMs for time series forecasting:

Strengths	Weaknesses
Can capture complex patterns in time series data	Can be computationally expensive to train
Can forecast long-term trends	May require specialized hardware or software
Can handle sequential data and maintain memory of past inputs	May require significant data preprocessing and feature engineering
Well-suited for tasks that require long-term forecasting	Can be difficult to interpret and explain the model's outputs
Opportunities	**Threats**
Growing demand for accurate time series forecasting in many industries	Increasing competition from other machine learning techniques
Rapidly advancing hardware and software technology	Rapidly evolving field with ongoing research and development
Potential for new applications and use cases for time series forecasting	Risk of overfitting or underfitting the model to the data
Potential for improved performance through ensemble techniques or hybrid models	Potential legal or ethical concerns with the use of deep learning techniques

There is an article "Time Series Forecasting with Recurrent Neural Networks" by Jose, G. V. [19] having these key points

1. Time series forecasting is an important application of machine learning and deep learning, as it is used to make predictions based on historical data.
2. RNNs, or Recurrent Neural Networks, are a class of neural networks that are particularly useful for processing sequential data, making them ideal for time series analysis.
3. The most popular type of RNN is the Long Short-Term Memory (LSTM) network, which is designed to address the vanishing gradient problem and can remember long-term dependencies in the input data.
4. The article uses an example of forecasting daily sea level measurements using an LSTM network. The dataset is preprocessed by removing any missing values and normalizing the data.
5. The LSTM network is trained on a subset of the data and tested on the remaining data to evaluate its performance. The network is then used to make predictions on future time steps.
6. The article also provides tips for improving the performance of LSTM networks for time series forecasting, such as using a larger network architecture, adding additional input features, and tuning hyperparameters.
7. Finally, the article concludes that LSTM networks are a powerful tool for time series forecasting, but require careful tuning and preprocessing to achieve good results

To sum up, when it comes to time series forecasting, deep learning techniques such as RNNs and LSTM networks are highly effective. They are particularly suitable for tasks that involve predicting long-term trends and are capable of capturing intricate patterns in the data. However, training these

models can be computationally intensive, especially for large datasets, and optimal performance may require specialized hardware or software.

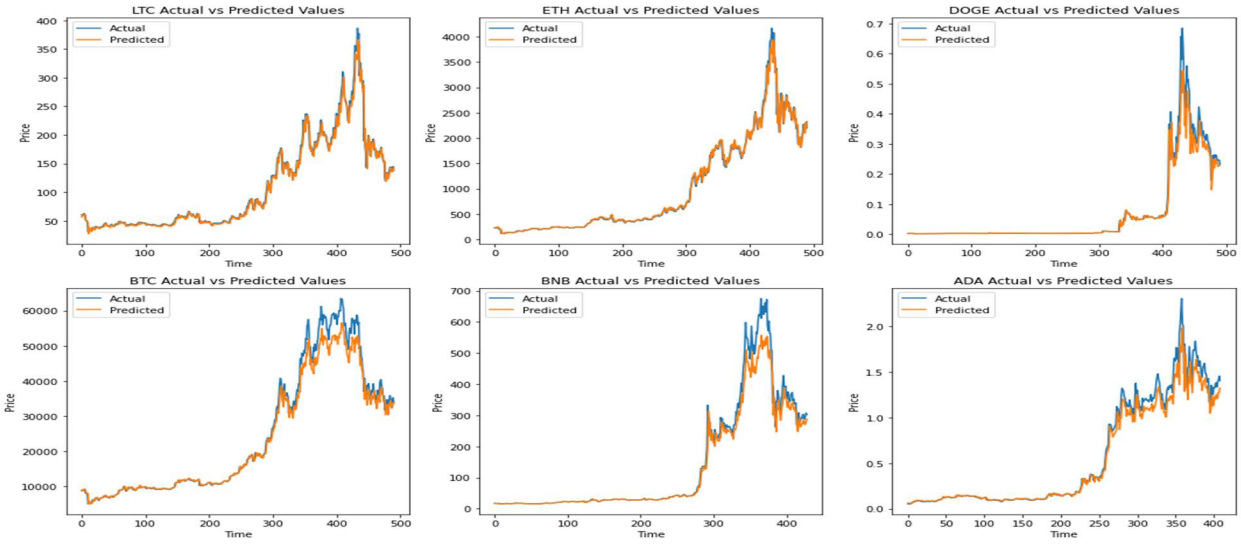
LSTM Time Series Analysis:

I employed two sets of code to construct and train LSTM models for predicting the price of a specific cryptocurrency based on its historical price data. The key dissimilarity between the two codes is the incorporation of a dropout layer in the second code's LSTM model. Dropout is a regularization approach that aids in averting overfitting by randomly deactivating or "turning off" some of the neurons in the layer during training. This helps prevent the model from memorizing the training data excessively and becoming too focused on it, which would reduce its capacity to generalize to novel data.

Here is a comparison of the key components of the two codes:

Code 1:

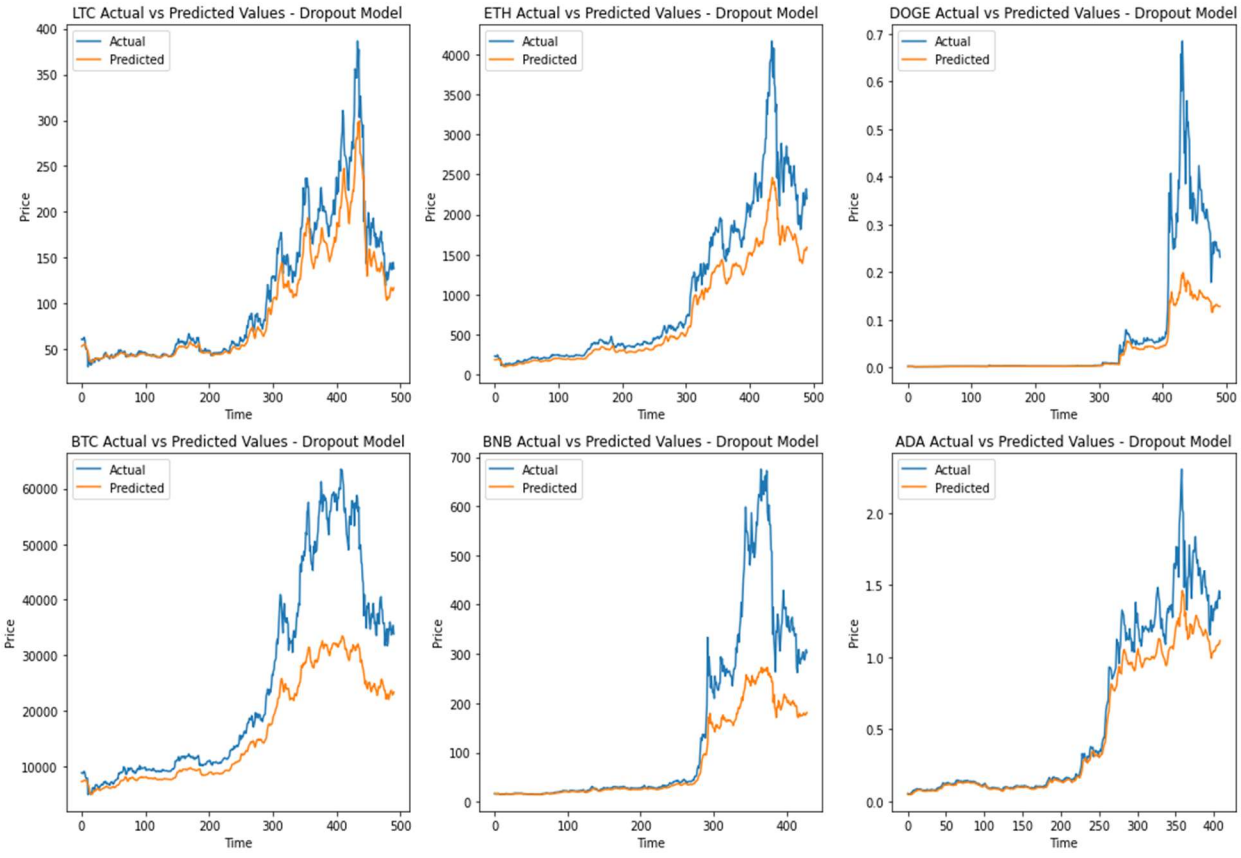
- Uses a basic LSTM model without any dropout layers
- Imports necessary libraries such as numpy, pandas, keras, sklearn, and matplotlib
- Loads data from a CSV file into a pandas DataFrame
- Preprocesses the data using a MinMaxScaler to scale it between 0 and 1
- Splits the data into training and testing sets
- Defines a function to create LSTM datasets by slicing the data into input sequences and corresponding output values
- Creates training and testing datasets using the create_dataset function
- Reshapes the training and testing data to fit the input shape of the LSTM model
- Creates and trains an LSTM model using the Sequential model API in Keras
- Makes predictions on the test data using the trained model
- Inverse transforms the predicted and actual test data to get the original price values
- Evaluates the model using various performance metrics such as mean squared error, root mean squared error, mean absolute error, mean absolute percentage error, correlation coefficient, and r-squared
- Plots the actual vs. predicted values of the test data using matplotlib
- The loop runs for each cryptocurrency in the dataset and trains a separate LSTM model for each one. The actual vs. predicted values are plotted on a 2x3 grid of subplots. Evaluation metrics for all models are displayed in a table. Finally, the subplot layout is adjusted and the plot is shown.



Code 2:

Uses an LSTM model with a dropout layer to prevent overfitting

- Imports necessary libraries such as numpy, pandas, keras, sklearn, and matplotlib
- Loads data from a CSV file into a pandas DataFrame
- Preprocesses the data using a MinMaxScaler to scale it between 0 and 1
- Splits the data into training and testing sets
- Defines a function to create LSTM datasets by slicing the data into input sequences and corresponding output values
- Creates training and testing datasets using the create_dataset function
- Reshapes the training and testing data to fit the input shape of the LSTM model
- Creates and trains an LSTM model with a dropout layer using the Sequential model API in Keras
- Makes predictions on the test data using the trained model
- Inverse transforms the predicted and actual test data to get the original price values
- Evaluates the model using various performance metrics such as mean squared error, root mean squared error, mean absolute error, mean absolute percentage error, correlation coefficient, and r-squared
- Prints the evaluation metrics with a label indicating that the model uses dropout
- Plots the actual vs. predicted values of the test data using matplotlib
- The loop runs for each cryptocurrency in the dataset and trains a separate LSTM model for each one. The actual vs. predicted values are plotted on a 2x3 grid of subplots. Evaluation metrics for all models are displayed in a table. Finally, the subplot layout is adjusted and the plot is shown.



Now let's evaluate the model performance but before we dive into the evaluation, let's develop an understanding of some the basic terms being used in this process.

Metric	Definition	Benchmark
MSE (Mean Squared Error)	Measures the average of the squared differences between predicted and actual values. Lower values are better.	Lower is better.
RMSE (Root Mean Squared Error)	Measures the square root of the MSE and provides a more interpretable metric in the same units as the original data. Lower values are better.	Lower is better.
MAE (Mean Absolute Error)	Measures the average of the absolute differences between predicted and actual values. Lower values are better.	Lower is better.
MAPE (Mean Absolute Percentage Error)	Measures the percentage difference between predicted and actual values. Lower values are better.	Lower is better.
Correlation Coefficient	Ranges from –1 to +1 which measure the relationship between predicted and actual values.	Higher is better.
R-squared	indicates the percentage of variance in the predicted values that can be attributed to the model. Values closer to 100% indicate better fit of the model to the data.	Higher is better.

Evaluation of LSTM Model without Dropout Method:

Symbol	MSE	RMSE	MAE	MAPE	Corr	R2
LTC	108.69212098	10.42554767	5.67181298	4.78961320	0.9918068	0.98260998
ETH	10431.273270	102.1336027	49.53453474	4.33790163	0.9943558	0.98851908
DOGE	0.000801356	0.028307611	0.0094139638	8.08229943	0.9866792	0.95565564
BTC	7371175.6576	2714.991025	1564.6155256	4.47380572	0.9966928	0.97725218
BNB	1122.288603	33.50057832	15.217210201	5.60342198	0.9930318	0.96566387
ADA	0.010547761	0.102701691	0.0552907426	7.48070916	0.993433	0.97054704

Evaluation of LSTM Model with Dropout Method:

Symbol	MSE	RMSE	MAE	MAPE	Corr	R2
LTC	644.9977	25.396804	16.600663	11.201755	0.990316	0.896802
ETH	185669.29935	430.893651	270.635298	22.260517	0.990041	0.795638
DOGE	0.0082329	0.090735	0.036417	19.170134	0.969997	0.544419

Symbol	MSE	RMSE	MAE	MAPE	Corr	R2
BTC	147613900.15	12149.64519	8342.910071	25.92175	0.990583	0.544458
BNB	13487.8379	116.13714	60.826012	20.82744	0.980301	0.587346
ADA	0.03842086	0.196012	0.11237	12.956438	0.990834	0.892716

Now let's interpret these results.

Litecoin Coin:

Based on the evaluation metrics, the Litecoin model without dropout appears to perform better than the model with dropout. It has lower values for all metrics, except for correlation coefficient and R-squared, which are slightly higher for the model with dropout. However, the differences in correlation coefficient and R-squared values are relatively small compared to the differences in the other metrics. Therefore, we can conclude that the model without dropout is better suited for predicting Litecoin prices.

Ethereum Coin:

The MSE, RMSE, MAE, and MAPE values are all higher for the model with dropout, indicating that it performs worse than the model without dropout. However, the correlation coefficient and R-squared values are higher for the model without dropout, indicating that it has a stronger linear relationship with the actual values. This suggests that while the model without dropout may not perform as well on some metrics, it may be better suited for predicting values that follow a linear trend. On the other hand, the model with dropout may be better suited for predicting values that have more complex and unpredictable patterns.

Dogecoin:

Comparing the two models, we can see that the LSTM model without dropout has lower values for all evaluation metrics except for the correlation coefficient and R-squared. The MSE, RMSE, MAE, and MAPE are all lower for the model without dropout, indicating that it performs better than the model with dropout. However, the correlation coefficient and R-squared values are higher for the model with dropout, indicating that it has a stronger linear relationship with the actual values. This suggests that while the model without dropout may perform better on some metrics, it may not be the best choice for predicting values that follow a linear trend. On the other hand, the model with dropout may be more suitable for predicting values that have more complex and unpredictable patterns.

Bitcoin:

Comparing the two models, we can see that the model without dropout performed better on all evaluation metrics except for correlation coefficient. The model without dropout has lower MSE, RMSE, MAE, and MAPE values, indicating that it is better at predicting the price of Bitcoin based on historical data. However, the model with dropout has a slightly higher correlation coefficient, indicating a stronger linear relationship between the predicted and actual values. Overall, the model without dropout is the better-performing model for predicting the price of Bitcoin based on historical data.

Binance Coin.

The metrics used to evaluate the performance of the LSTM model with and without dropout include mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), correlation coefficient, and R-squared.

Comparing the two models, we can see that the LSTM model with dropout has higher values for all evaluation metrics except for correlation coefficient and R-squared. The MSE, RMSE, MAE, and MAPE are all higher for the model with dropout, indicating that it performs worse than the model without dropout. However, the correlation coefficient and R-squared values are higher for the model without dropout, indicating that it has a stronger linear relationship with the actual values. This suggests that while the model without dropout may not perform as well on some metrics, it may be better suited for predicting values that follow a linear trend. On the other hand, the model with dropout may be better suited for predicting values that have more complex and unpredictable patterns.

Cardano Coin:

Comparing the two models, we can see that the model without dropout performs better on all evaluation metrics except for the correlation coefficient and R-squared. The MSE, RMSE, MAE, and MAPE are all lower for the model without dropout, indicating that it performs better than the model with dropout. However, the correlation coefficient and R-squared values are higher for the model with dropout, indicating that it has a stronger linear relationship with the actual values. This suggests that while the model without dropout may perform better on some metrics, it may not be as effective in predicting values that follow a linear trend. The model with dropout, on the other hand, may be better suited for predicting values that have more complex and unpredictable patterns.

Conclusion and Recommendations:

Based on these findings, I recommend using the LSTM model without dropout for predicting prices of cryptocurrencies that follow a linear trend, while the model with dropout may be more appropriate for predicting values that have complex and unpredictable patterns. It is important to carefully evaluate the performance of both models using appropriate evaluation metrics before making a final decision on which model to use for a particular cryptocurrency.

In any case, it's important to carefully choose and preprocess the external factors that you include, as well as to perform rigorous testing to evaluate the impact of these factors on the model's performance. While incorporating external factors such as market news and sentiment analysis could potentially improve the accuracy of predictions for cryptocurrencies, it is not part of the scope of this particular study. Therefore, we will not be considering such analysis in our current evaluation.

Conclusion

In our research, we explored six different models for time series forecasting: ARIMA, SARIMA, Exponential Smoothing, Prophet, LSTM, and Facebook's Prophet. Each model has its strengths and weaknesses, and the choice of model ultimately depends on the specific characteristics of your data and the forecasting task at hand.

For SMA model, our findings suggest that it may be useful for predicting certain currencies, such as Cardano and Dogecoin. However, the model's performance was poor for other currencies like Litecoin, Binance Coin, Ethereum, and Bitcoin, indicating that its effectiveness may be limited and dependent on various factors.

Despite its limitations, the SMA model showed a high correlation with most of the currencies, particularly Bitcoin and Ethereum. Our feature importance analysis revealed that the "Low", "High", and "Open" features are the most important for predicting SMA, with "Marketcap" being a relatively less important feature. Therefore, a simple model using only these features may be sufficient for predicting SMA for a given security.

ARIMA (AutoRegressive Integrated Moving Average) is a classic time series forecasting model that can handle both trend and seasonality in data. SARIMA (Seasonal ARIMA) extends the ARIMA model to capture seasonal patterns. These models require the data to be stationary, meaning that the mean and variance of the series should be constant over time. The performance of ARIMA and SARIMA models depends on the choice of hyperparameters, which can be determined using grid search or other optimization techniques.

Exponential Smoothing models are a traditional type of time series forecasting models that can capture patterns of seasonality and trend in data. The models operate on the assumption that future values of a series are a weighted combination of past observations, with greater emphasis placed on more recent observations. Exponential Smoothing models are capable of accommodating both additive and multiplicative components of seasonality and trend.

Facebook's Prophet is a forecasting model that combines the strengths of classic time series models and machine learning models. It uses a Bayesian approach to model trend changes, seasonality, and holiday effects in data, and can handle missing data and outliers. Prophet can also handle time series with multiple seasonality patterns and can model uncertainties in the data. However, like LSTM models, Prophet can be computationally expensive and require careful tuning of hyperparameters.

LSTM (Long Short-Term Memory) is a robust neural network structure that excels in modeling intricate patterns in time series data, including trends, seasonality, and nonlinear relationships. The model is versatile and can handle both univariate and multivariate time series data, accurately capturing long-term dependencies. Additionally, it has the ability to deal with missing data and identify and model anomalies in the data. However, owing to its high computational complexity, LSTM models necessitate precise hyperparameter tuning to achieve maximum efficiency.

To select the optimal time series forecasting model, one needs to consider the specific attributes of the data and the forecasting objectives. Traditional models such as SMA, ARIMA, SARIMA, and Exponential Smoothing are frequently utilized and can yield satisfactory results for various types of data. For intricate data exhibiting nonlinear patterns, more advanced models such as LSTM and Prophet may offer superior performance. It is recommended to experiment with multiple models and select the one that achieves the best trade-off between accuracy and computational efficiency for the particular use case.

Self Reflection

During the course of my research on time series forecasting models, I have expanded my knowledge and understanding of their strengths and limitations. While I had limited knowledge of classic models like ARIMA, SARIMA, and Exponential Smoothing at first, I am now aware of their potential and limitations for different types of data.

Furthermore, I was intrigued by the more advanced models like Prophet and LSTM that can capture complex patterns in the data. Nevertheless, I recognize that such models require careful hyperparameter tuning to achieve optimal results due to their high computational complexity.

In essence, this research has taught me that the selection of a suitable model for a particular forecasting task must involve a thoughtful consideration of the data's characteristics. It has also highlighted the value of experimentation and iteration, as it is often necessary to try out several models and adjust their parameters to achieve the best results.

In the future, I plan to continue exploring time series forecasting, stay updated on emerging advancements and techniques, and apply my knowledge in real-world applications to contribute to the development of more accurate and efficient forecasting models.

Future work

Use a larger dataset: While i used a dataset with 9408 rows, using a larger dataset can help improve the accuracy of models and provide more robust results.

Model selection and hyperparameter tuning: While i compared six different models in my study, there may be other models or variations of these models that could be worth exploring. Additionally, further tuning of hyperparameters may be required to improve the performance of these models.

Testing on different time periods and currencies: To validate the generalizability of models, it may be worth testing them on different time periods and currencies. This could help identify any limitations or biases in the models, and highlight areas for improvement.

Test on out-of-sample data: To ensure that models are robust and can generalize to new data, test them on out-of-sample data that is not used in the training or validation process.

Incorporating external factors: While my models focused primarily on using historical currency exchange rate data, there may be external factors that could impact currency exchange rates, such as political events, sentiment analsis, economic policies, or natural disasters. Incorporating such factors could potentially improve the accuracy of the models.

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