Tesla Stock Forecasting

Time Series Prediction Analysis

Year 2013 to 2023

FINC565 Time Series Modeling

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Table of Contents

1. Project Overview
2. Brief Overview of the Tesla, Inc.
3. Tesla Stock Dataset Overview
4. Data Visualization and Exploratory Analysis
    - Candlestick Plots
    - Stock Splits
    - Percentage Change in Stock
    - Autocorrelation and Partial Autocorrelation
5. About Time Series and its models
6. Data Modeling and prediction analysis
    - ARIMA (Autoregressive Integrated Moving Average)
    - Exponential Smoothing
7. How to use Forecasting in real-life?
8. Conclusion
9. References

Project Overview

In this project, we embark on a journey to explore the dynamics of Tesla's stock market, aiming to uncover insights, identify trends, and make informed predictions about its future trajectory. Our focus is on time series prediction analysis, where we aim to deepen our understanding of Tesla's market dynamics and contribute valuable insights to the discourse on its outlook.

Utilizing historical data spanning from 2013 to 2023, we employ advanced forecasting techniques, including ARIMA and exponential smoothing models, to predict Tesla's future stock price. Through this comprehensive analysis, we aim to unravel potential trends and patterns hidden within the data, providing stakeholders with actionable insights for informed decision-making in the stock market.

About Tesla

Tesla, Inc. is a pioneering American company renowned for its innovative approach to electric vehicles (EVs), renewable energy, and energy storage solutions. Established in 2003 by Martin Eberhard and Marc Tarpenning, Tesla's mission revolves around accelerating the world's transition to sustainable energy. Under the leadership of CEO Elon Musk since 2008, Tesla has spearheaded advancements in electric transportation and renewable energy technologies.

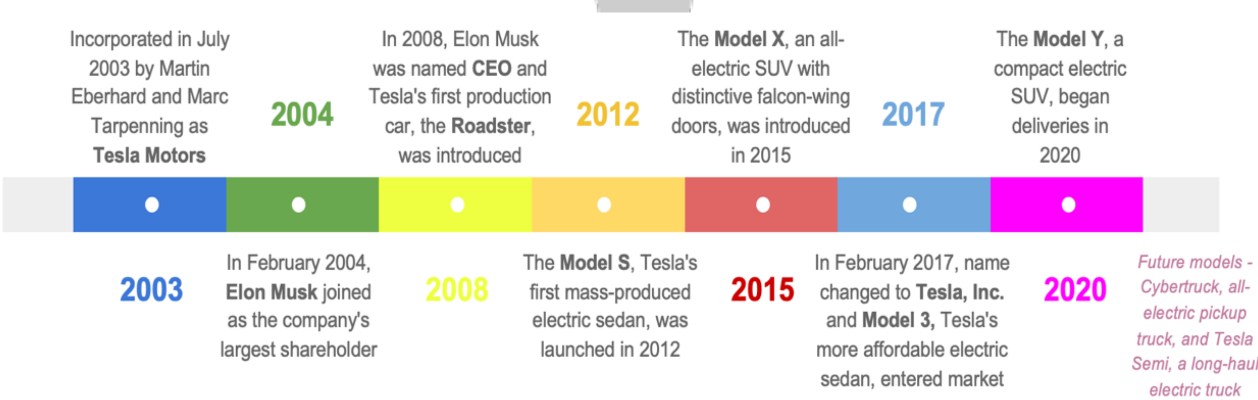

Figure 1: Timeline of Tesla's growth

Tesla's product lineup includes electric vehicles such as the Model S, Model 3, Model X, and Model Y, each offering cutting-edge technology, high performance, and long-range capabilities. Additionally, Tesla is a major player in energy storage and solar energy solutions, with products like the Powerwall and Solar Roof revolutionizing the residential energy market.

With a market capitalization surpassing traditional automakers and a fervent global following, Tesla has established itself as a trailblazer in the automotive industry. Its relentless pursuit of innovation, commitment to sustainability, and ambitious goals for the future continue to drive its influence and shape the future of transportation and energy.

As of December 31, 2023, Tesla reported approximately 129,000 employees worldwide.
Tesla's revenue has grown significantly in recent years, reaching $81.5 billion in 2023.
Tesla has achieved profitability, with a net income of $12.6 billion in 2023.

Tesla Stock Dataset Overview

Tesla's stock (TSLA) is one of the most widely followed and traded stocks in the financial markets.

Key Milestones:

1. 2013: Closing price of $10.03, a significant decrease from the IPO price.
2. 2014-2018: Steady growth with occasional fluctuations.
3. 2019: Significant increase in price, reaching $27.89 by year-end.
4. 2020: Massive surge, reaching $235.22 by year-end, a 743% increase from 2019.
5. 2021: Continued rise, reaching an all-time high of $409.97 on November 4th.
6. 2022: Significant decline, dropping to $123.18 by year-end.
7. 2023: Recovered some losses, closing at $248.48 on December 29th.

Overall Performance:

1. 10,549.3% Increase: Tesla's stock price experienced a phenomenal increase from $10.03 in 2013 to $248.48 by the end of 2023.
2. Volatility: Despite the overall upward trend, Tesla's stock price has been subject to significant fluctuations, particularly in 2022.

I retrieved historical stock data for Tesla (TSLA) from the Yahoo Finance API using the yfinance library in Python.
The dataset comprises daily trading information captured in several key financial metrics:

	open	high	low	close	volume	dividends	stock splits
Date							
2013-01-02 00:00:00-05:00	2.333	2.363	2.314	2.357	17922000	0.000	0.000
2013-01-03 00:00:00-05:00	2.345	2.363	2.317	2.318	11130000	0.000	0.000
2013-01-04 00:00:00-05:00	2.320	2.320	2.261	2.293	10110000	0.000	0.000
2013-01-07 00:00:00-05:00	2.320	2.320	2.260	2.289	6630000	0.000	0.000
2013-01-08 00:00:00-05:00	2.300	2.300	2.207	2.245	19260000	0.000	0.000

Figure 2: First five rows of Tesla stock data from Yahoo Finance library

- **open**: The price at which the stock started trading when the market opened on a given day.
- **high**: The highest price at which the stock traded during the day.

- **low**: The lowest price at which the stock traded during the day.
- **close**: The last price at which the stock traded during the day. This is the figure most reported in the financial news.
- **volume**: The number of shares or contracts traded in a security or an entire market during a given period. It is a measure of the total demand for and supply of the stock.
- **dividends**: The distribution of reward from a portion of the company's earnings and is paid to a class of its shareholders.
- **stock splits**: An action taken by a company to divide its existing shares into multiple shares to boost the liquidity of the shares. Although the number of shares outstanding increases by a specific multiple, the total dollar value of the shares remains the same compared to pre-split amounts, because the split does not add any real value.

Data Visualization

For our analysis, we will be looking closely at Tesla close price and will predict for the future time-period. We will explore various charts to understand patterns and trend of close price.

Candlestick Chart:

Let's first look at the trend of close price from year 2013 to 2023. In order to do so, I have plotted a Candlestick chart, which is a visual tool for market analysis, used to describe price movements of a security, derivative, or currency. Each "candlestick" typically represents one day of trading and is composed of a body and wicks.

Figure 3: Trendline of Tesla close price

This chart comprises of two parts:

Body: The wider section of the candlestick which indicates the opening and closing prices. If the body is filled or dark, the security closed lower than it opened. If the body is empty or light, it closed higher than it opened.

Wicks: Lines that extend from the top and bottom of the body representing the high and low prices during the period.

Tesla Stock Split:

The company declared the second 3-for-1 stock split in early August 2022. Tesla shares closed on August 24 at $891.29 and began trading on a split-adjusted basis at around $297 per share. Tesla implemented the split by paying a stock dividend of two shares for each share held after the close of trading. The stock split makes the shares less expensive, and more accessible for a wider base of retail investors. It also makes trading options in the stock less expensive.

When Tesla first proposed the stock split, it said the move was primarily intended to help the company "offer every employee the option of receiving equity" in Tesla, and that increasing employee satisfaction would help to maximize stockholder value.

The first time Tesla split its stock 5-for-1 in August 2020, shares had gained 81% between the split announcement and the day the stock split. In the month following the split, Tesla shares dropped about 14%, but recovered in less than two months, and were up about 36% six months after the split.

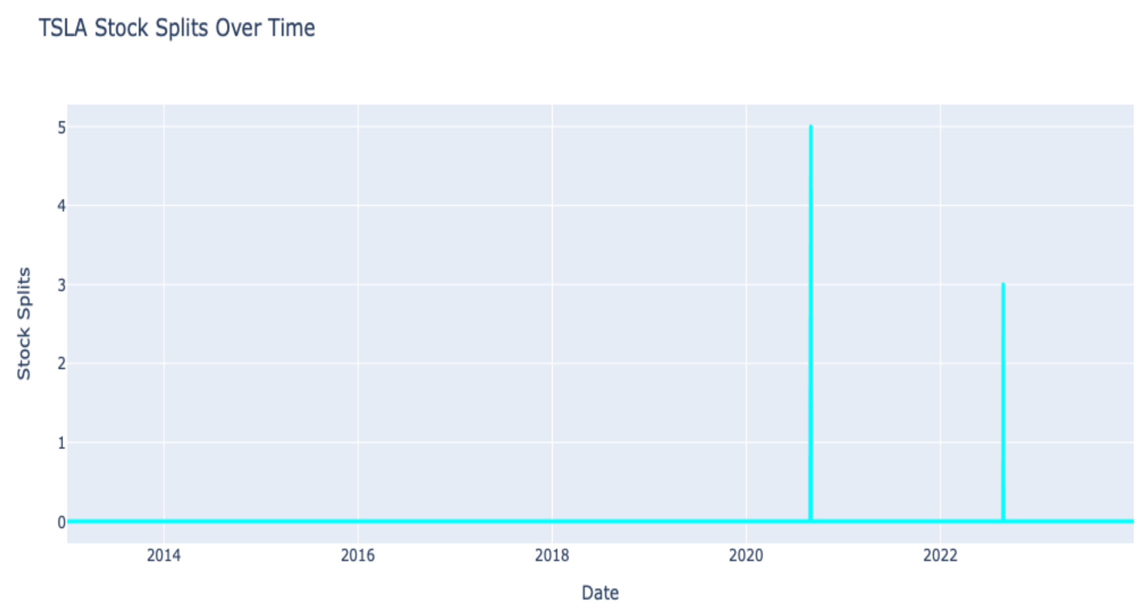

Figure 4: Tesla Stock Split in year 2020 and 2022

Percent Change in Tesla Stock:

Percentage change in stock prices serves as a valuable metric for gauging price fluctuations over time relative to the preceding price. This measure facilitates comparisons of stock performance across various time periods or against other stocks, aiding in the assessment of relative performance and trends. The formula to calculate the daily percentage change is:

$$\text{Percentage Change} = \left(\frac{\text{Current Price} - \text{Previous Price}}{\text{Previous Price}} \right) \times 100$$

The "Current Price" refers to the stock price recorded at the conclusion of the current period, such as the end of the trading day. Conversely, the "Previous Price" denotes the stock price at the end of the preceding period. In instances where the time series begins and there is no prior data point for comparison, the percentage change is typically undefined. To address this, it's customary to either designate the percentage change as zero or exclude the value altogether. This method is commonly employed in financial analysis to evaluate stock volatility and performance, aiding investors in their decision-making process regarding buying or selling securities.

The Tesla Percent Change over Time plot depicts the daily percentage fluctuations in Tesla's stock price, highlighting the volatility observed throughout the period under review. Sharp spikes and dips in the graph indicate days with significant price movements, potentially influenced by market reactions to news events, corporate earnings reports, or broader economic conditions.

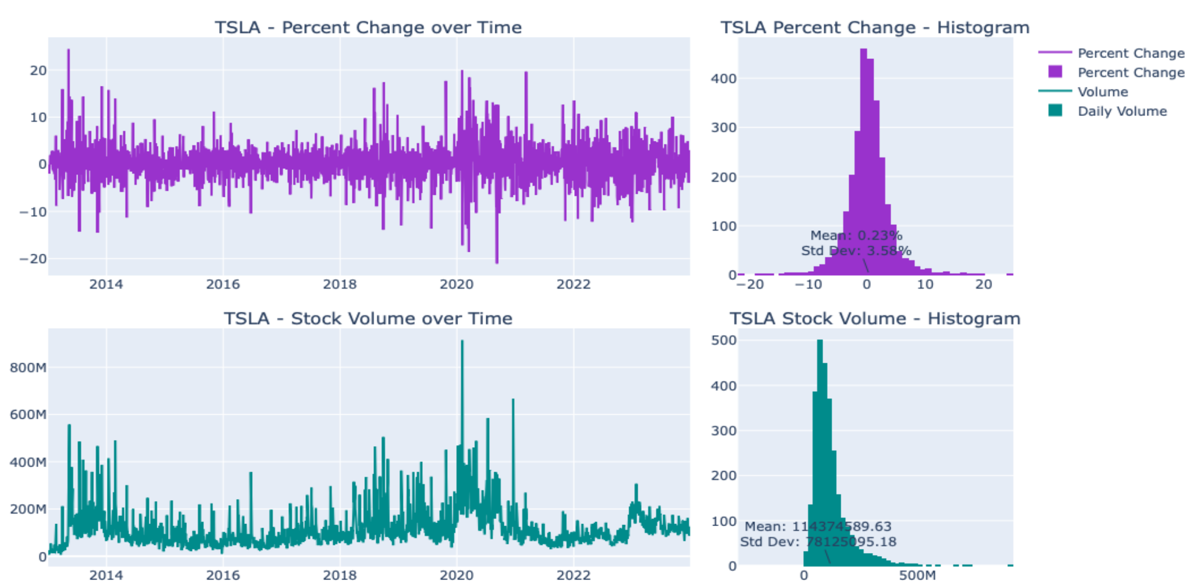

Figure 5: Percent change in close price and stock volume

The Tesla Percent Change Histogram, located in the top right corner, showcases the distribution of these daily percentage changes. Most changes cluster around the mean, suggesting a normal distribution of returns, a common occurrence in stock prices over time. The proximity of the mean to zero implies stable average growth, while the standard deviation measures the extent of variation from this average.

Additionally, the Tesla Stock Volume over Time plot illustrates the trading volume of Tesla's stock over the observed period, with peaks potentially corresponding to specific events or significant news releases that impact investor sentiment and trading activity. Lastly, the Tesla Stock Volume Histogram displays the distribution of trading volume occurrences, providing insights into the frequency of different volume levels. The concentration of data towards the lower end suggests that while high-volume days are less frequent, they may coincide with crucial market or company-specific events.

Q-Q Plot:

A QQ plot or Quantile-Quantile plot, is a graphical tool used in statistics to assess whether a given data set follows a specific probability distribution, typically the normal distribution. It compares the quantiles of the data set against the quantiles of a theoretical distribution, such as the normal distribution.

In a QQ plot, when data points closely align with the diagonal line, it indicates that the data is well-fitted to the assumed distribution, typically the normal distribution. Conversely, deviations from this line suggest departures from normality, indicating that the data may not conform to the expected distribution.

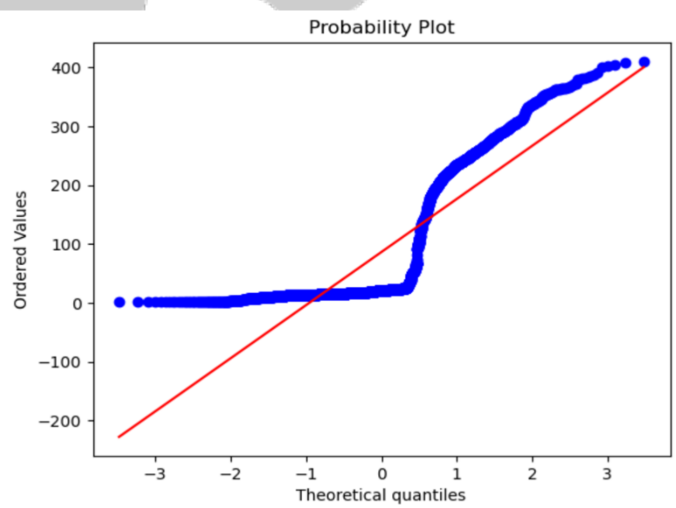

Figure 6: Q-Q plot of Tesla close price

Specifically, if data points veer upwards or downwards from the diagonal, it signals skewness in the data, revealing asymmetry around the mean. Additionally, an S-shaped curve formed by data points (as below) implies heavy-tailedness or leptokurtosis, indicating thicker tails compared to the normal distribution.

Autocorrelation and Partial Autocorrelation:

Autocorrelation checks how much a time series is related to itself at different points in the past. High values at a specific lag indicate a strong connection between the current value and the value at that past point.

Partial autocorrelation, on the other hand, isolates the unique correlation between a value and its past at a specific lag, removing the influence of earlier lags. This helps identify the direct impact of past values on the present, independent of any indirect influences.

When analyzing these plots, look for spikes beyond the confidence interval. Significant spikes in the:

- Autocorrelation plots suggest strong overall relationships at specific lags.
- Partial autocorrelation plot pinpoints the direct influence of specific past values, helping identify the order of moving average terms in forecasting models.

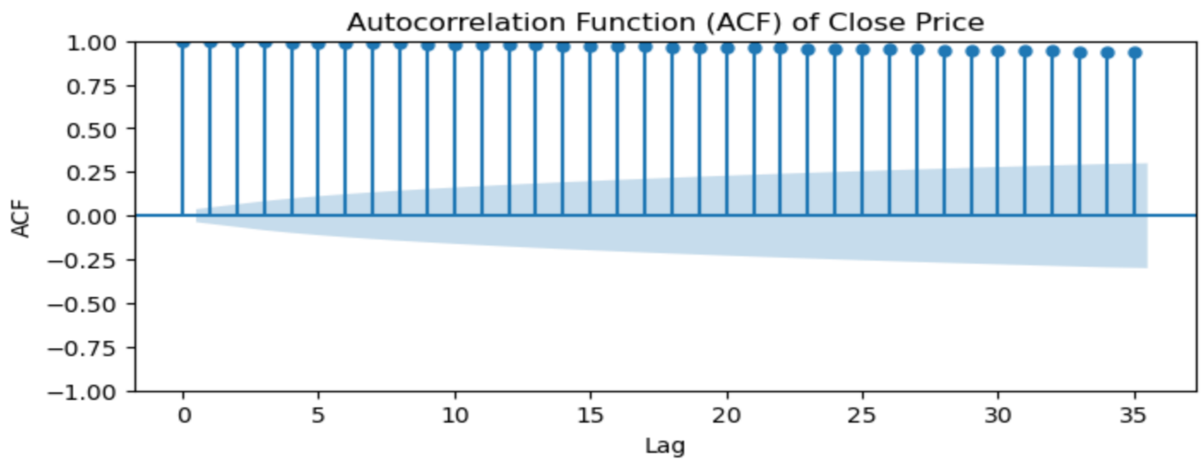

Figure 7: Autocorrelation Function of close price

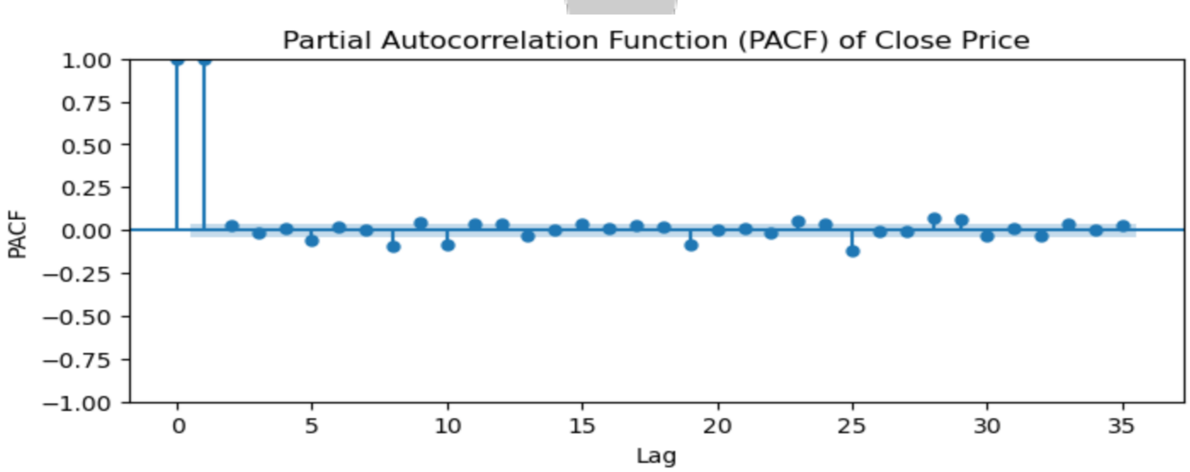

Figure 8: Partial Autocorrelation Function of close price

Time series and its models

Time series data is a sequence of measurements taken over regular intervals, like stock prices or weather patterns. It allows us to analyze how things change over time, revealing trends, seasonality, and patterns. By analyzing this data, we can make informed predictions about the future, such as forecasting sales figures or predicting stock market movements. This makes time series analysis crucial in various fields like finance, business, science, and weather forecasting, helping us understand the dynamic nature of the world around us.

In this project, we will explore the application of ARIMA (Autoregressive Integrated Moving Average) and Exponential Smoothing, for forecasting Tesla's stock prices.

For **ARIMA modeling,** the time series must be stationary, meaning it lacks trend and has a consistent mean and variance. If not stationary, it can be done by differencing the series.

Figure 9: Components of ARIMA model

Intuitive Explanation:
Imagine predicting tomorrow's stock price based on a combination of:

- Recent price trends (AutoRegressive): "If it went up yesterday, it might go up again today."
- Removing overall trends (Integrated): "Is the price consistently increasing or decreasing over time?"
- Averaging out random fluctuations (Moving Average): "Smoothing out short-term bumps and noise."

Mathematical Explanation:
ARIMA uses a statistical model with three components:

- p: AutoRegressive (AR) - considers the impact of past p values on the current prediction.
- d: Integrated (I) - applies differencing to remove trends and make the data stationary (constant mean and variance).
- q: Moving Average (MA) - averages past q errors to account for random fluctuations.

An **exponential smoothing** of time series data allocates the exponentially decaying weights from newest to oldest observations.

$$F_t = F_{t-1} + \alpha(A_{t-1} - F_{t-1})$$

where: F_t = new forecast
F_{t-1} = previous period forecast
A_{t-1} = previous period *actual* demand
α = smoothing (weighting) constant

Figure 10: Formula of Exponential Smoothing

Intuitive Explanation:

- Picture giving more weight to recent stock prices and gradually decreasing the influence of older prices.
- Think of it like a weighted average, where recent days have a bigger say in the forecast, and older days have less impact.

Mathematical Explanation:

- This method uses a smoothing parameter (α) to exponentially decrease the weight of past observations.
- The forecast for the next period is a weighted average of the previous forecast and the current observation, with more weight given to the current observation due to the smoothing factor.

ARIMA (Autoregressive Integrated Moving Average) and Exponential Smoothing stand out as effective methods for forecasting Tesla's stock price due to their ability to capture complex patterns, handle non-stationarity, and incorporate lagged observations. ARIMA models excel in modeling both linear and nonlinear trends, as well as seasonality, making them suitable for capturing the intricate dynamics of stock prices. They are flexible and adaptable, allowing for fine-tuning to capture various patterns and behaviors in the data. On the other hand, Exponential Smoothing models offer simplicity and interpretability while effectively handling trends, seasonality, and outliers. They provide intuitive forecasts by assigning exponentially decreasing weights to past observations, making them versatile for forecasting purposes.

Data Modeling and prediction analysis

ARIMA

ADF Statistic: The ADF test checks if a time series is stationary (stable over time). ARIMA models require stationarity, so the ADF helps:

- Identify non-stationarity (trends or fluctuations).
- Guide the process of differencing (transforming the data) to achieve stationarity if needed.

A low p-value (e.g., 0.05), from the ADF suggests the data is already stationary, while a high p-value indicates the need for differencing before using ARIMA for accurate forecasting.

The ADF test results suggest that we cannot reject the possibility of a unit root at a 5% significance level. This indicates the data may be non-stationary, potentially containing trends or fluctuations.

```
ADF Statistic: -0.9272724690026403
p-value: 0.7788585955294782
Critial Values:
   1%, -3.4327397185476918
Critial Values:
   5%, -2.8625958054606793
Critial Values:
   10%, -2.5673320392686283
```

Figure 11: ADF and p-value of close price

How to find p, d and q values?

Check Stationarity: Augmented Dickey-Fuller (ADF) test suggested that the time series is not stationary, so we will difference the series and find the value of d until stationarity is achieved.

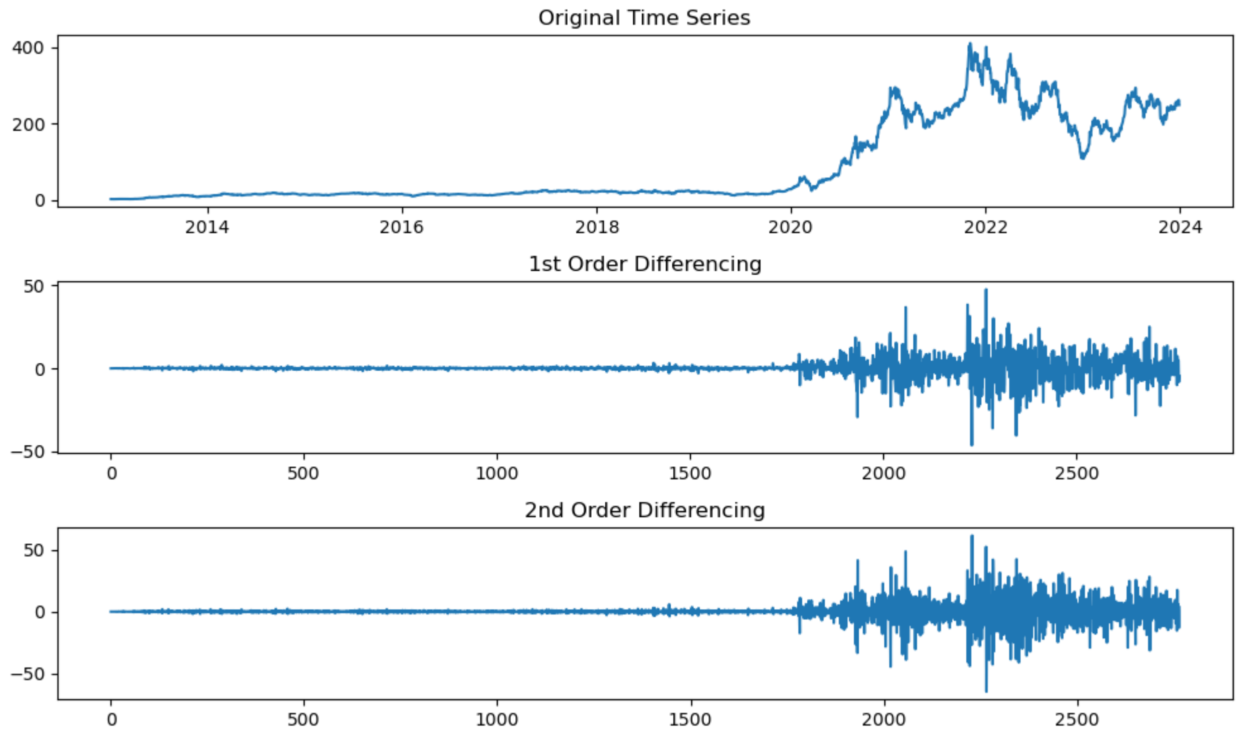

Figure 12: Original and differenced series of close price (d=1)

Partial Autocorrelation Function (PACF): Plot the PACF of first differenced series to identify the potential value of p (the number of lag observations). Significant spikes at certain lags suggest the number of AR terms needed in the model.

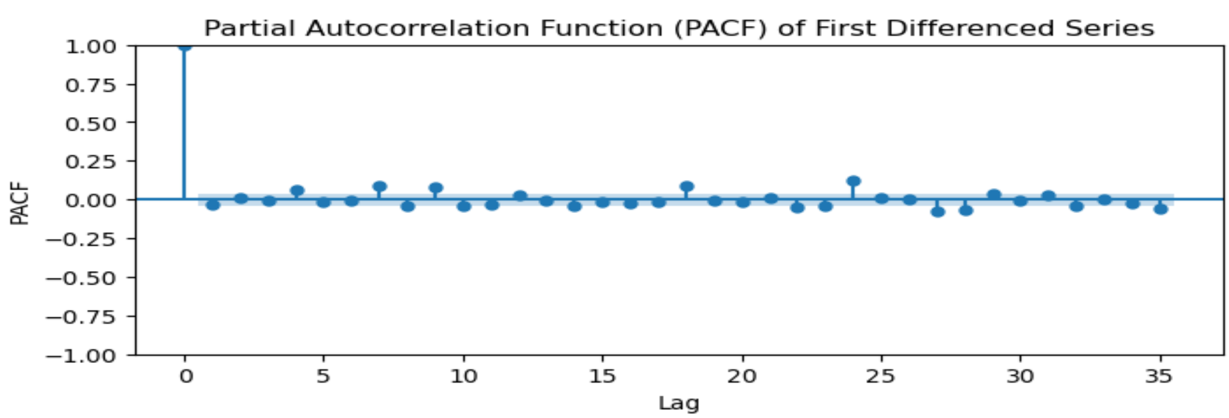

Figure 13: PACF of first differenced series of close price (p=1)

Autocorrelation Function (ACF): Plot the ACF of first differenced series to identify the potential value of q (the number of lagged forecast errors). Significant spikes at certain lags suggest the number of MA terms needed in the model.

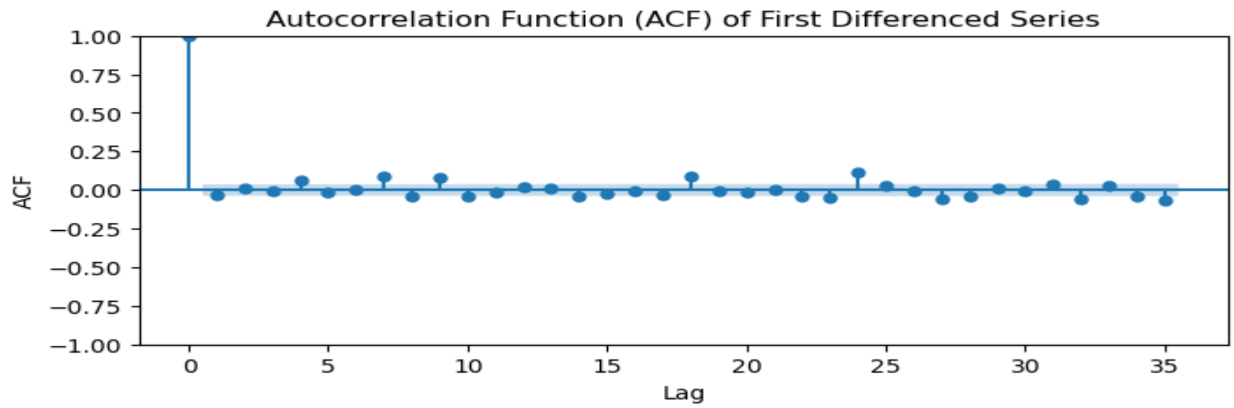

Figure 14: ACF of first differenced series of close price (q=1)

Hence, from the charts above, p=1, d=1 and q=1 to predict close price using ARIMA model.

<u>Model Results:</u>

Coefficients:
Past value (lag 1) has a negative influence on the current value (AR coefficient).
Past forecast error has a positive influence on the current value (MA coefficient).

Fit:
The model seems to fit the data decently based on the provided metrics.

Statistical Significance:
Both AR and MA terms are statistically significant, meaning they likely have a real impact on the data.

Residual Analysis:
No significant autocorrelation detected in the residuals, indicating the model captures the patterns well. Residuals are not perfectly normal, but this might not be a major concern.

Dep. Variable:	close	**No. Observations:**	2768
Model:	ARIMA(1, 1, 1)	**Log Likelihood**	-8468.362
Date:	Sun, 05 May 2024	**AIC**	16942.724
Time:	17:06:44	**BIC**	16960.500
Sample:	0	**HQIC**	16949.144
	- 2768		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-0.5961	0.158	-3.767	0.000	-0.906	-0.286
ma.L1	0.5637	0.163	3.450	0.001	0.243	0.884
sigma2	26.6569	0.245	108.962	0.000	26.177	27.136

Ljung-Box (L1) (Q):	0.03	**Jarque-Bera (JB):**	26898.17
Prob(Q):	0.87	**Prob(JB):**	0.00
Heteroskedasticity (H):	554.03	**Skew:**	-0.15
Prob(H) (two-sided):	0.00	**Kurtosis:**	18.27

Figure 15: ARIMA(1,1,1) model results

The presence of heteroskedasticity (unequal variance) in the residuals needs further investigation.

Overall:
The ARIMA(1, 1, 1) model seems reasonable, with statistically significant coefficients and mostly acceptable diagnostics.

While the model provides a good starting point, further analysis of the heteroskedasticity and potentially comparing it to other ARIMA models might be beneficial for the best possible forecasting accuracy.

Residual plots:

Commonly used in statistical model assessment, the standardized residual plot, histogram with estimated density, normal Q-Q plot, and correlogram aid in evaluating model performance, especially in time series analysis.

The standardized residual plot compares residuals to fitted values, highlighting outliers and assessing homoscedasticity. The histogram with density estimation shows the distribution of standardized residuals, aiding in assessing normality assumptions. The normal Q-Q plot compares residuals to a theoretical normal distribution, detecting departures from normality. Lastly, the correlogram illustrates autocorrelation in residuals, helping identify remaining temporal patterns. Analyzing these plots collectively aids in evaluating model fit, identifying assumption violations, and diagnosing residual patterns for model refinement.

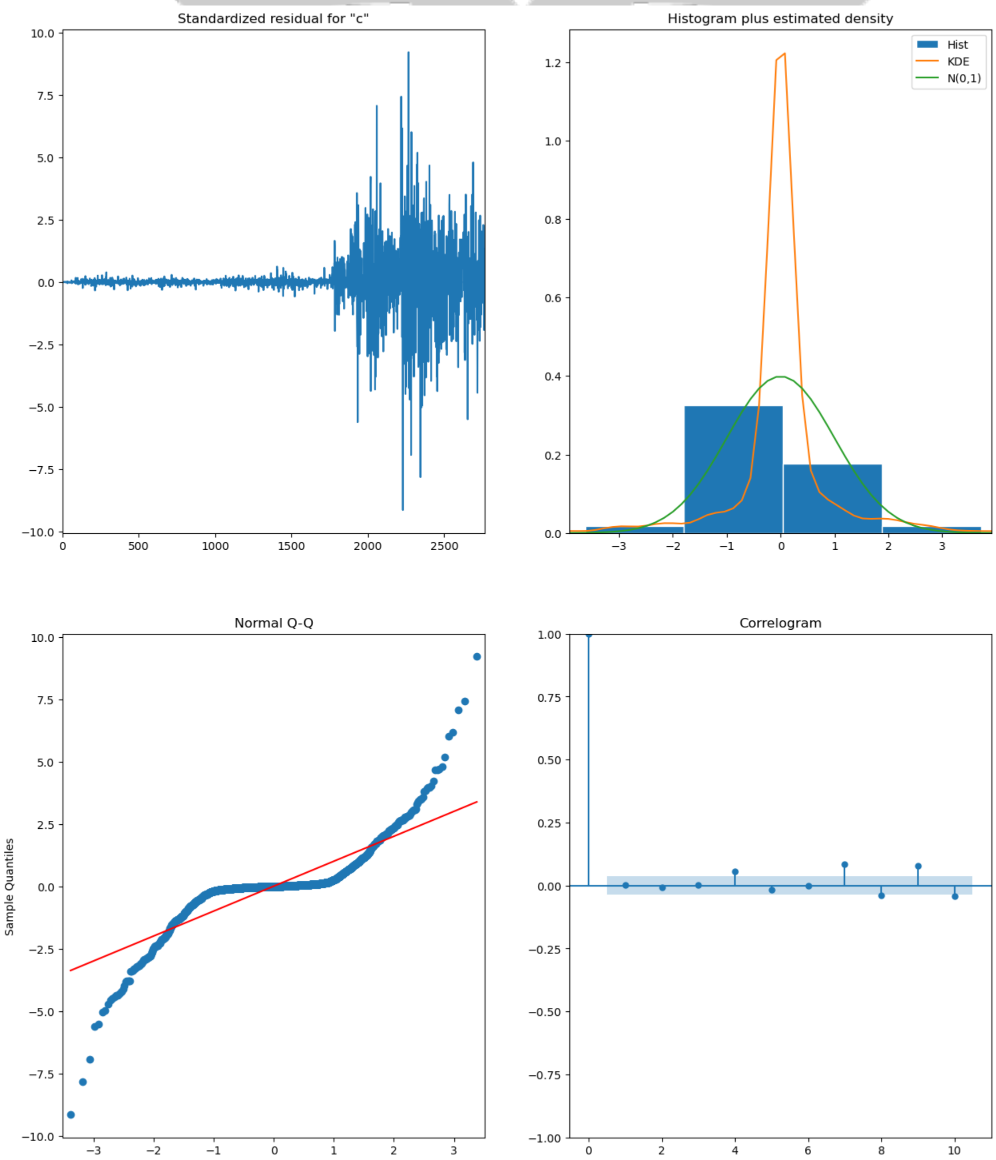

Figure 16: Residual plots of ARIMA(1,1,1) on close price

Prediction for next 365 days:

Based on the model results from ARIMA(1,1,1) I have predicted the close price for next 365 days in year 2024 with 95% confidence interval band. From the prediction it seems that the stock price will be close to ~248.485.

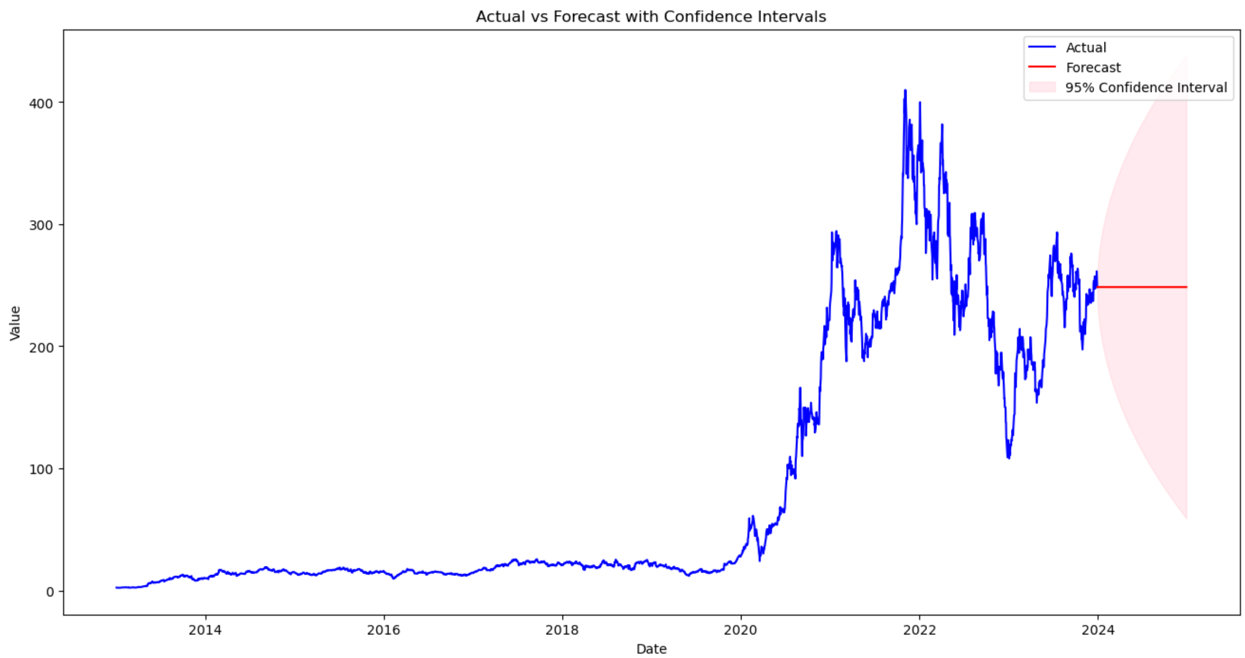

Figure 17: Predicted close price for next 365 days and 95% confidence interval range

I also split the data into test and train, ran my model on training data and predict it on test data. The following chart shows the actuals vs predictions for the test data.

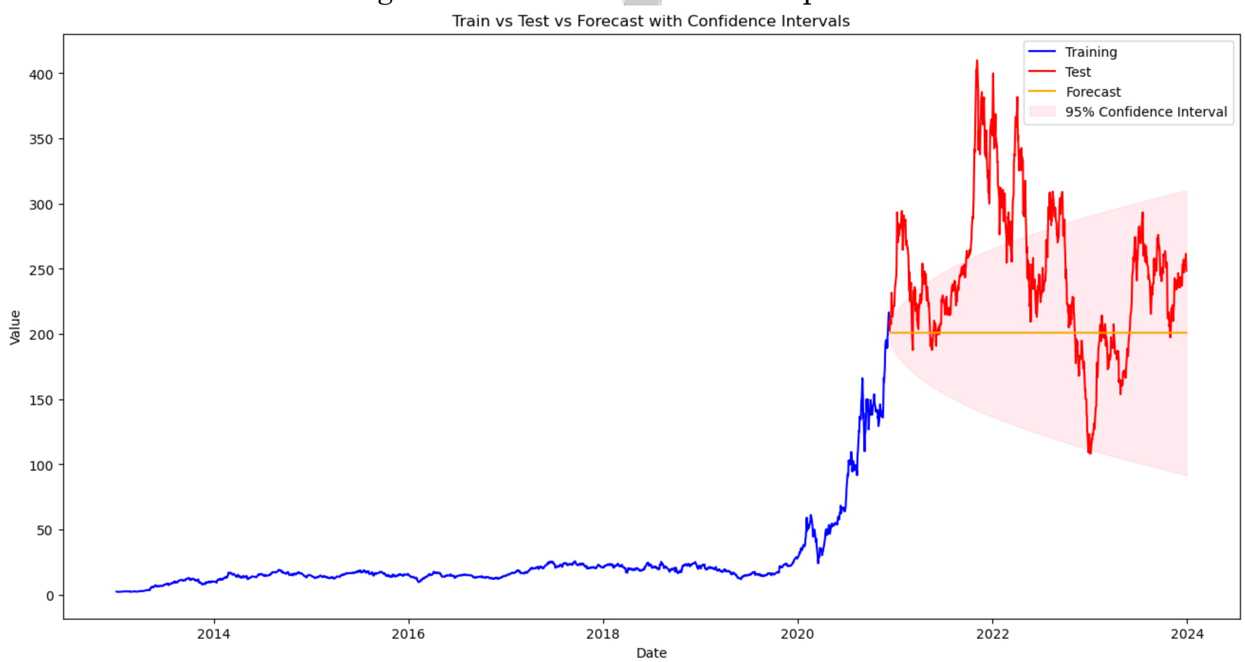

Figure 18: Train and Test split on close price with forecasted test values and 95% confidence intervals

Overall, the model performed well on the series but could be improved further with different iterations of the p, d and q values.

Exponential Smoothing

Exponential smoothing is a time series method for forecasting univariate time series data. Time series methods work on the principle that a prediction is a weighted linear sum of past observations or lags. The Exponential Smoothing time series method works by assigning exponentially decreasing weights for past observations. It is called so because the weight assigned to each demand observation is exponentially decreased.

The model assumes that the future will be somewhat the same as the recent past. The only pattern that Exponential Smoothing learns from demand history is its level - the average value around which the demand varies over time.

Exponential smoothing is generally used to make forecasts of time-series data based on prior assumptions by the user, such as seasonality or systematic trends.

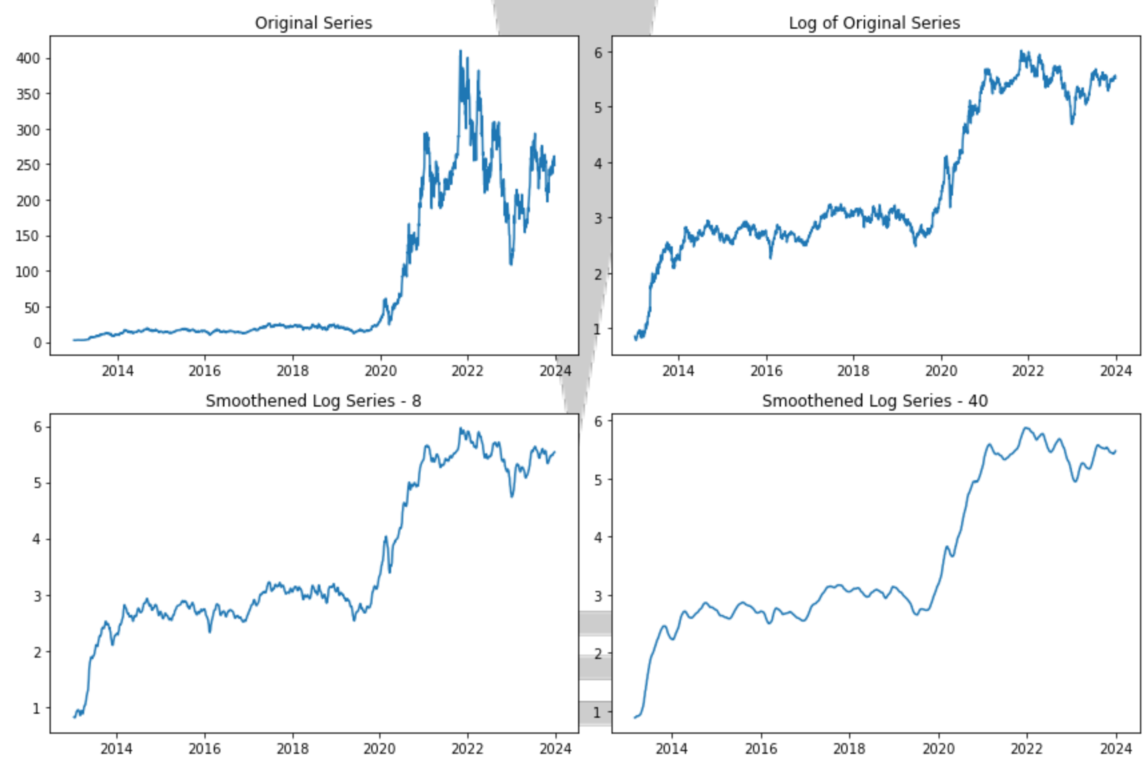

Figure 19: Original, log and smoothened close price series

Single Exponential Smoothing

Simple or single exponential smoothing (SES) is the method of time series forecasting used with univariate data with no trend and no seasonal pattern. It needs a single parameter called alpha (a), also known as the smoothing factor. Alpha controls the rate at which the influence of past observations decreases exponentially. The parameter is often set to a value between 0 and 1.

Figure 20: Close price prediction for next 365 days using Single Exponential Smoothing with different values of alpha

<u>Model Results and Residual Plots</u> of Single Exponential Smoothing model with alpha=0.1

The model employed is a Simple Exponential Smoothing (SES) model, aimed at forecasting the closing prices of a financial asset over time. However, it's noteworthy that the model hasn't been optimized, with manual specification of the alpha parameter and initial level. The evaluation of the model is based on metrics such as the Sum of Squared Errors (SSE), Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and corrected AIC (AICC). Despite its simplicity, SES may not capture complex trends or seasonality in the data, as indicated by the absence of trend and seasonal components. The alpha parameter, set at 0.1, governs the smoothing level, influencing the weighting of past

Dep. Variable:	close	**No. Observations:**	2768
Model:	SimpleExpSmoothing	**SSE**	412631.300
Optimized:	False	**AIC**	13856.261
Trend:	None	**BIC**	13868.112
Seasonal:	None	**AICC**	13856.275
Seasonal Periods:	None	**Date:**	Sun, 05 May 2024
Box-Cox:	False	**Time:**	15:55:57
Box-Cox Coeff.:	None		

	coeff	code	optimized
smoothing_level	0.1000000	alpha	False
initial_level	2.3399998	l.0	False

Figure 21: SES model results with alpha=0.1

observations. Overall, while SES provides a straightforward forecast, its suitability hinges on comparing its performance with other models and considering the inherent characteristics of the data.

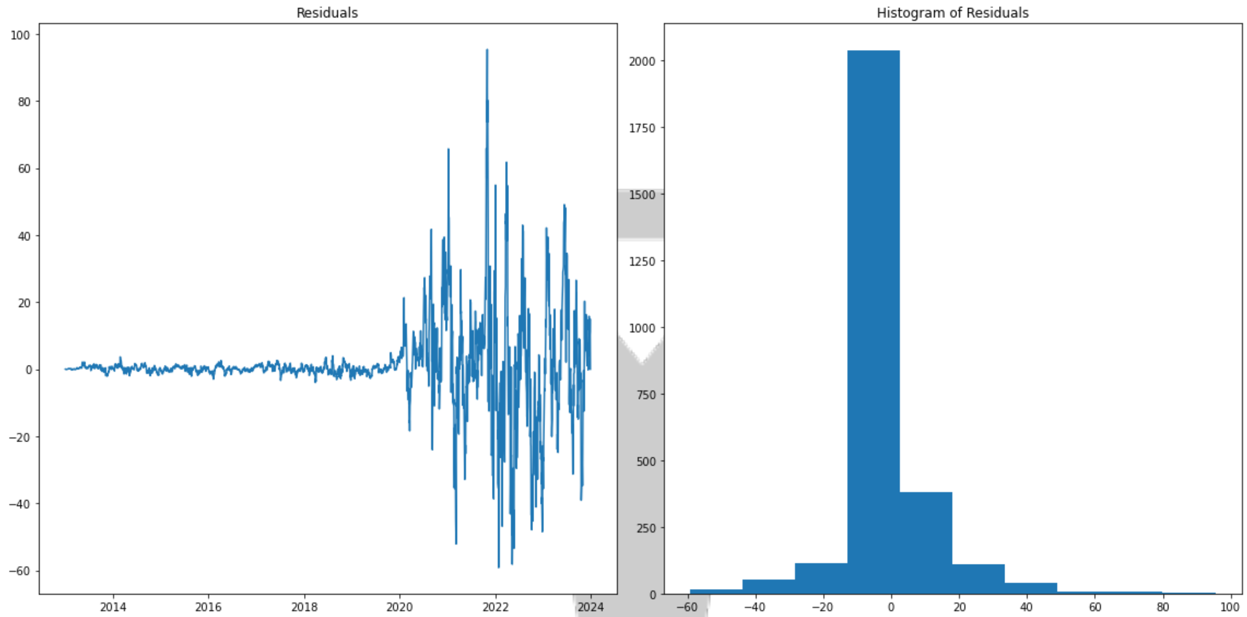

Figure 22: Residual plots for SES with alpha=0.1

<u>Holt Exponential Smoothing</u>

Holt's Exponential Smoothing is a more advanced version of simple exponential smoothing. Here's the key difference:

- Simple Exponential Smoothing: Only considers the level (average value) of the data and is not suitable for data with trends.
- Holt's Smoothing: Accounts for both the level (average value) and the trend (slope) of the data. This makes it useful for forecasting data that exhibits increasing or decreasing patterns over time.

Holt's method uses two smoothing parameters:

- Alpha (α): Controls how much weight is given to recent data points compared to past values when estimating the level.
- Beta (β): Controls how much weight is given to the previous trend estimate when updating the current trend.

By adjusting these parameters, Holt's smoothing can adapt to different types of trends in the data, making it a more flexible forecasting tool compared to simple exponential smoothing.

Figure 23: Close price prediction for next 365 days using Holt Exponential Smoothing with different values of alpha and beta

Model Results and Residual Plots of Single Exponential Smoothing model with alpha=0.9 and beta=0.2

The Holt Exponential Smoothing model presented employs an additive trend component but does not incorporate seasonality. With manually set parameters of alpha=0.9 for the smoothing level and beta=0.2 for the smoothing trend, the model lacks optimization. Evaluation metrics, including a relatively high Sum of Squared Errors (SSE) and corresponding Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values, indicate suboptimal performance in capturing underlying data patterns. Moreover, the absence of seasonality consideration limits its ability to forecast data with recurring patterns effectively. While the model can capture level and trend components, its suboptimal performance suggests the need for further refinement and optimization to enhance forecasting accuracy.

Dep. Variable:	close	**No. Observations:**	2768
Model:	Holt	**SSE**	80232.567
Optimized:	False	**AIC**	9327.315
Trend:	Additive	**BIC**	9351.018
Seasonal:	None	**AICC**	9327.345
Seasonal Periods:	None	**Date:**	Sun, 05 May 2024
Box-Cox:	False	**Time:**	18:29:32
Box-Cox Coeff.:	None		

	coeff	code	optimized
smoothing_level	0.9000000	alpha	False
smoothing_trend	0.2000000	beta	False
initial_level	2.3399998	l.0	False
initial_trend	-0.0135879	b.0	False

Figure 24: Holt Linear Trend model results with alpha=0.9 and beta=0.2

Compared to SSE model, Holt performed better on Tesla close price and the model performance metrics improved.

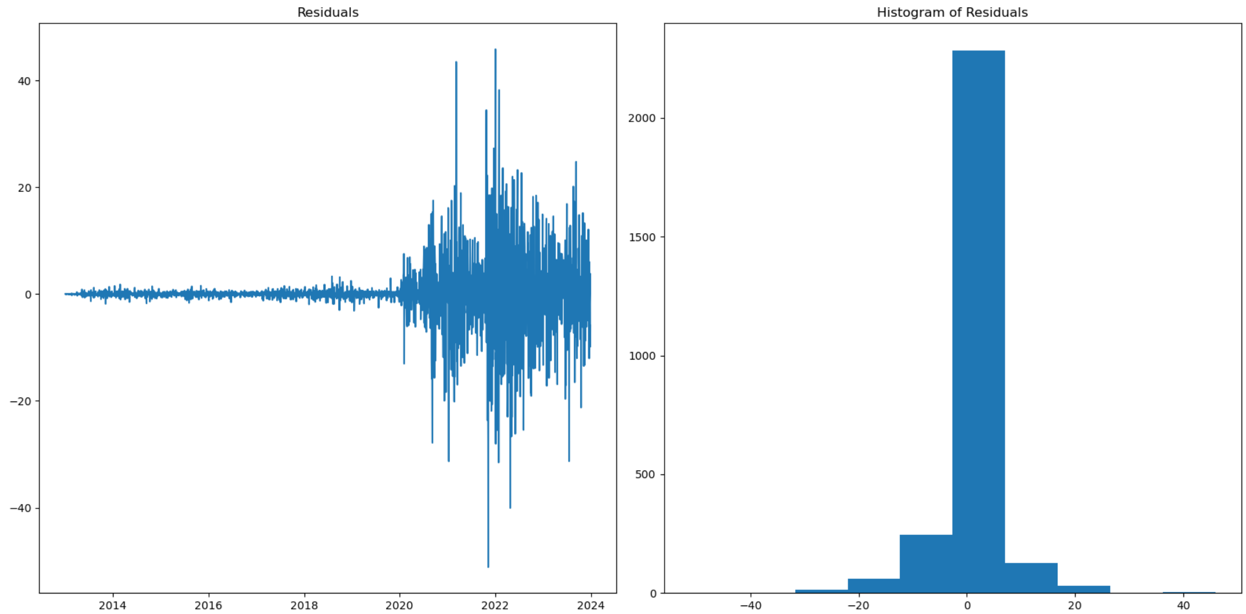

Figure 25: Residual plots for Holt with alpha=0.9 and beta=0.2

How to use Forecasting in real-life?

Time series forecasting for Tesla stock holds significant value for investors, traders, financial analysts, and Tesla itself. Stakeholders can leverage forecasts to inform investment decisions, optimize portfolio management, manage risk, plan finances, develop trading strategies, and enhance supply chain management. These forecasts enable stakeholders to identify profit opportunities, mitigate risks, and make informed decisions amidst the dynamic financial landscape.

Overall, time series forecasting for Tesla stock can provide valuable insights and support decision-making across various domains, helping stakeholders navigate the dynamic and complex financial markets more effectively.

Conclusion

After conducting an analysis of Tesla's closing prices, I applied ARIMA and exponential smoothing models to forecast future trends. While both approaches yielded satisfactory results, the performance of the Holt smoothing method stood out as notably superior. Despite this, the overall performance scores of the models remained suboptimal. To enhance forecasting accuracy, it would be prudent to explore alternative time series models that are adept at capturing nuanced trends, seasonality, and patterns, particularly those models tailored for handling increasing or decreasing trends. Additionally, fine-tuning the parameters of the selected models could further refine their predictive capabilities and contribute to more accurate forecasts in the future.

References

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