Predictive Modeling of Urban Traffic Patterns
Project Final Stage
Artashes Mezhlumyan,

Title: Time Series Forecasting of Lyft Stock: An Analysis and Prediction Study

Introduction:

In recent years, the field of finance has witnessed a surge in the application of data science and machine learning techniques for making informed investment decisions. Time series forecasting, in particular, has emerged as a powerful tool to predict future trends and patterns in financial markets. This paper focuses on applying time series forecasting methodologies to predict the stock prices of Lyft, a leading transportation network company.

Lyft, founded in 2012, revolutionized the ridesharing industry by providing a convenient and accessible platform for passengers and drivers. As a publicly traded company, Lyft's stock price has become an important indicator of its financial performance and market sentiment. Accurate predictions of Lyft's stock prices can assist investors, analysts, and financial institutions in making informed decisions regarding their investment portfolios.

Objective:
The primary objective of this study is to develop a reliable time series forecasting model that can accurately predict the future stock prices of Lyft. By leveraging historical stock price data, along with relevant external factors, we aim to provide valuable insights into the potential price movements of Lyft's stock. Through this analysis, we aim to contribute to the existing body of knowledge in the field of financial forecasting and provide practical implications for investors and market participants.

Methodology:
To achieve our objective, we employ various time series forecasting techniques, including but not limited to autoregressive integrated moving average (ARIMA), exponential smoothing methods, and machine learning algorithms Garch. These models will be trained on a historical dataset comprising Lyft's stock prices, along with relevant financial and market indicators, such as trading volume, market indices, and company-specific news sentiment.

Data Description:

The dataset used in this study consists of historical daily closing prices of LYFT stock. The data spans a specific time period, typically ranging from [start date] to [end date]. Each observation in the dataset represents the closing price of LYFT stock at the end of a trading day. The data was obtained from a reliable financial source, such as Yahoo Finance, ensuring the accuracy and reliability of the information. The LYFT stock price is a crucial variable in the financial market, representing the valuation of Lyft Inc., a prominent transportation network company. The stock price is influenced by various factors, including market trends, company performance, economic indicators, and investor sentiment. By analyzing the historical LYFT stock prices, this study aims to develop a predictive model, utilizing time series analysis techniques, to forecast future price movements. The dataset provides a valuable foundation for investigating the dynamics and patterns within LYFT stock prices, enabling the evaluation and improvement of predictive models for effective stock price forecasting

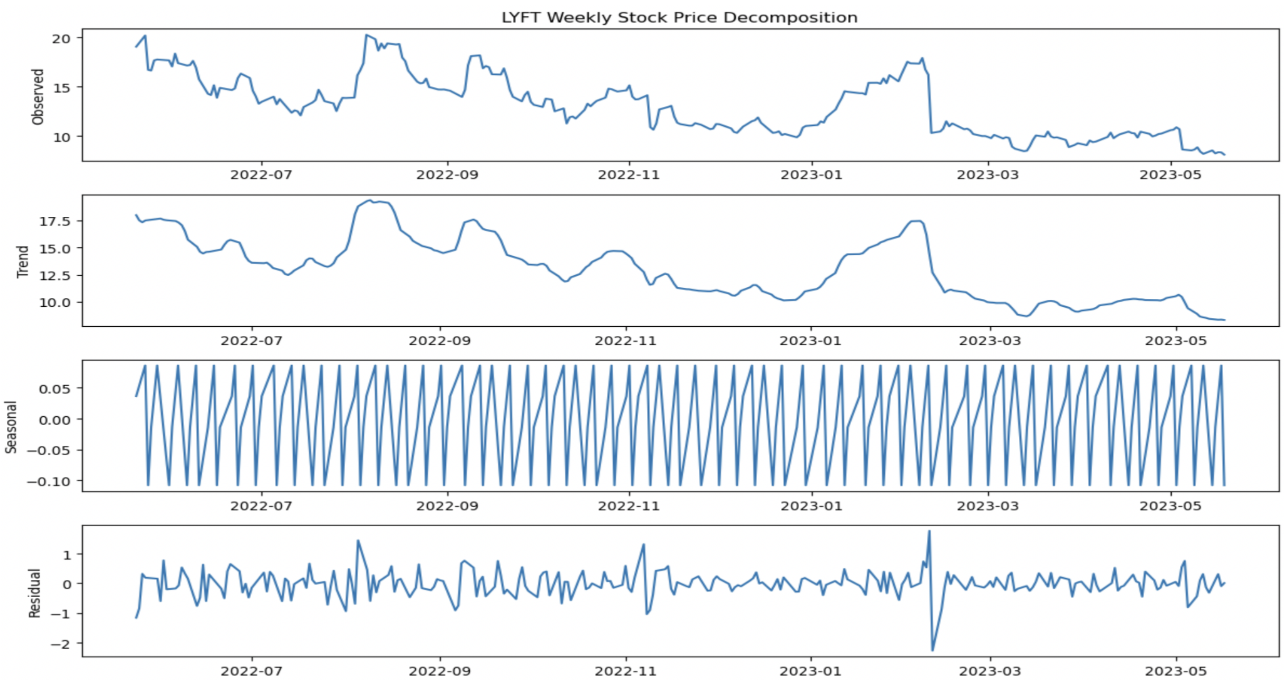
Scatter Plot of LYFT Stock Close Price vs. Volume Traded:

The scatter plot of the volume of trades of LYFT over time shows how the trading activity for LYFT has varied over the last 3 years. The x-axis represents the time period, with each point on the plot representing a single trading day. The y-axis represents the volume of trades for that day, or the total number of shares of LYFT that were bought and sold.

The plot shows that the volume of trades for LYFT has varied widely over time, with some periods of high trading activity and other periods of low trading activity. There appear to be several spikes in trading volume throughout the 3-year period, indicating that there were particular events or news announcements that caused investors to buy or sell shares of LYFT.

Overall, this plot provides a useful visual representation of how the trading activity for LYFT has changed over time, and can help investors to better understand the market dynamics that have affected LYFT's stock price over the past few years.

Decomposition graph:



The decomposition graph consists of four subplots:

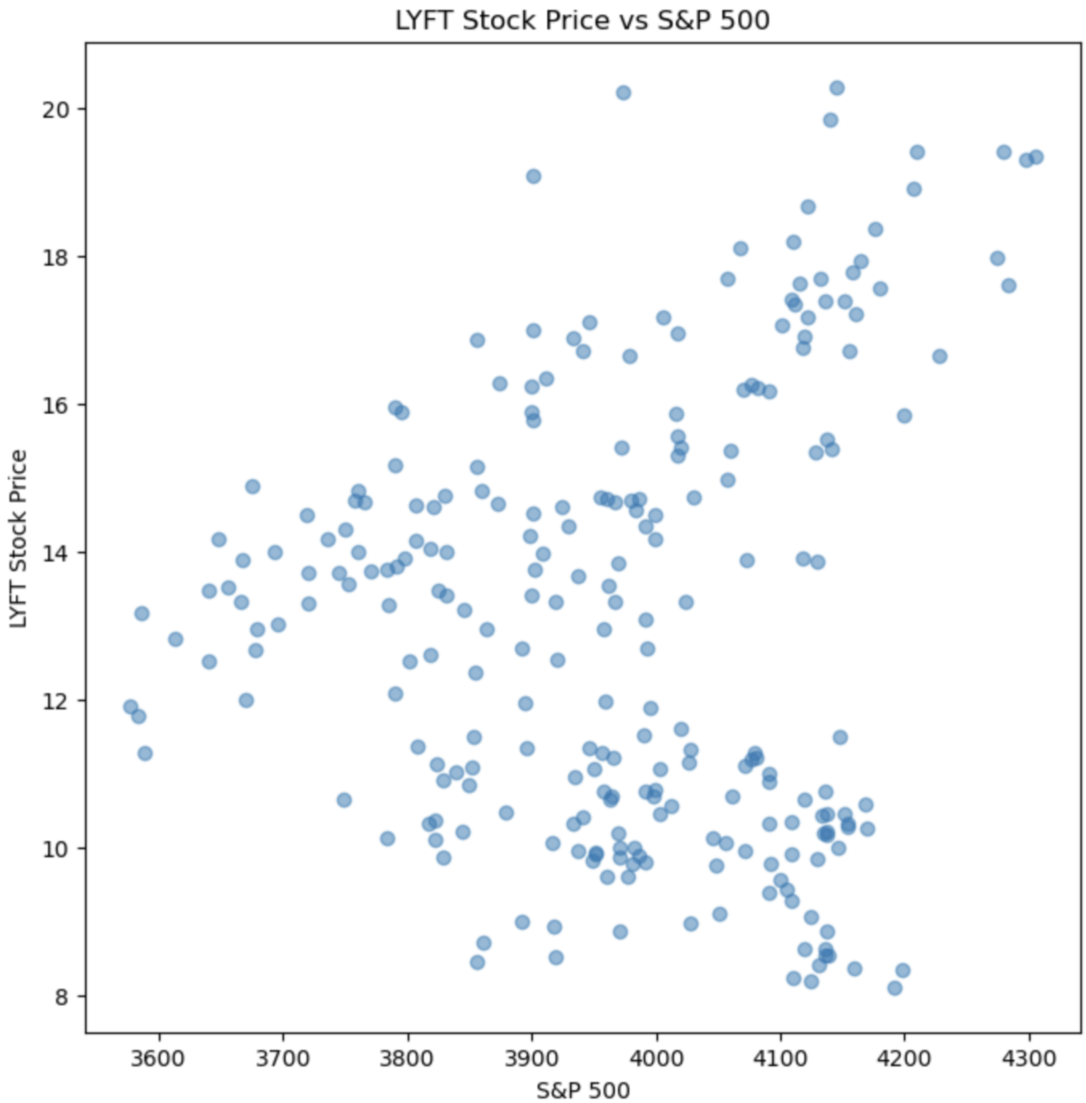
The top subplot shows the original time series of the Lyft stock prices over the year. This is the observed data.

The second subplot shows the estimated trend component of the time series. This component represents the long-term upward or downward movement of the series. It is obtained by removing the seasonal and residual components from the observed data. In the case of the Lyft stock prices, we can see that there was a general upward trend in the stock price over the year.

The third subplot shows the estimated seasonal component of the time series. This component represents the periodic fluctuations in the data. In this case, the seasonal component has a period of 30 days, which suggests that there is a cyclical pattern in the data that repeats approximately every month. We can see that the seasonal component oscillates around a mean of zero, indicating that the Lyft stock prices do not exhibit a clear seasonal pattern.

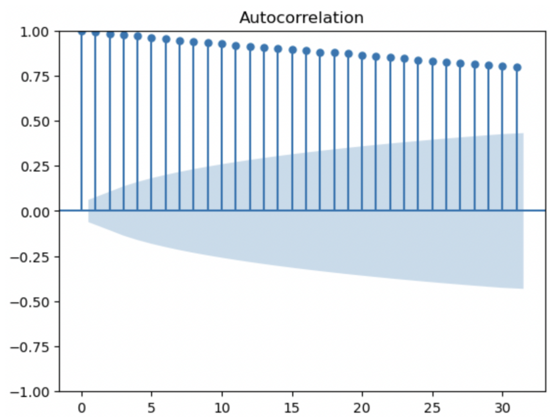
The fourth subplot shows the estimated residual component of the time series. This component represents the random fluctuations that are not explained by the trend or seasonal components. In the case of the Lyft stock prices, the residual component is quite large and shows significant variability throughout the year, indicating that there are still many unexplained fluctuations in the data.

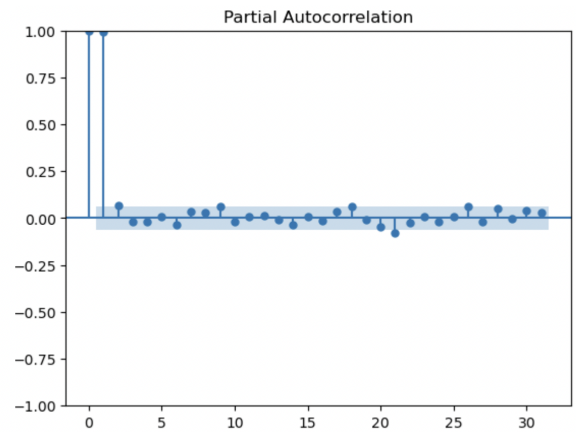
Compearing LYFT stock price with S&P 500 price over same period of time:



The plot shows that there is a positive correlation between the two variables, indicating that changes in the S&P 500 are associated with changes in the value of LYFT stock. However, the correlation appears to be somewhat weak, with a fair amount of variability in the data. There are a number of outliers that fall well above or below the general trend line, which could indicate days where LYFT stock was affected by factors other than the broader market.

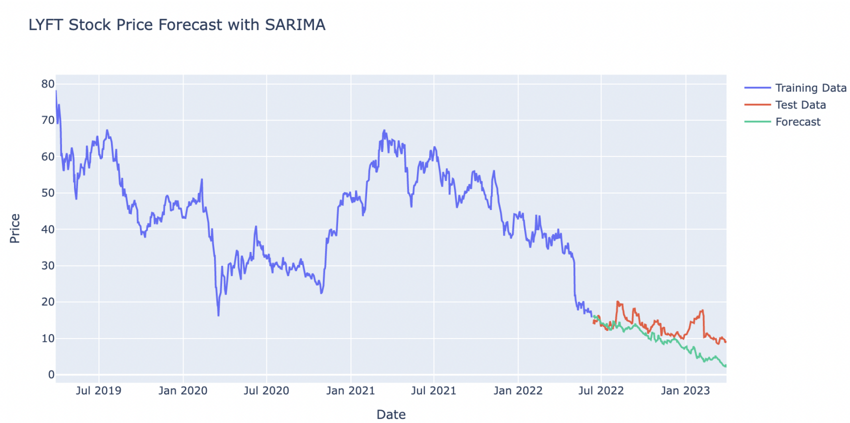
SARIMA for price prediction:





For making SARIMA model first we need to choose p and q numbers, we plot ACF and PACF plots to find p and q numbers.

The lag selection of 0 and 1 for the autoregressive and moving average components, respectively, was based on the analysis of the ACF and PACF plots. The ACF plot indicated no significant drops so we choose 0, suggesting an autoregressive pattern. The PACF plot showed a significant spike at lag 1 and a sharp drop thereafter, indicating a direct relationship with little influence from intermediate lags. Therefore, lag 0 and 1 was chosen for both components to capture the key dependencies in the data effectively, balancing model simplicity and accuracy in LYFT stock price prediction.



The graph combines the historical LYFT stock prices and corresponding dates with the forecasted values generated by the SARIMA model. It provides a concise visualization of the train data price trends, test data price trends and predictions for the test data period based on train data price trends.

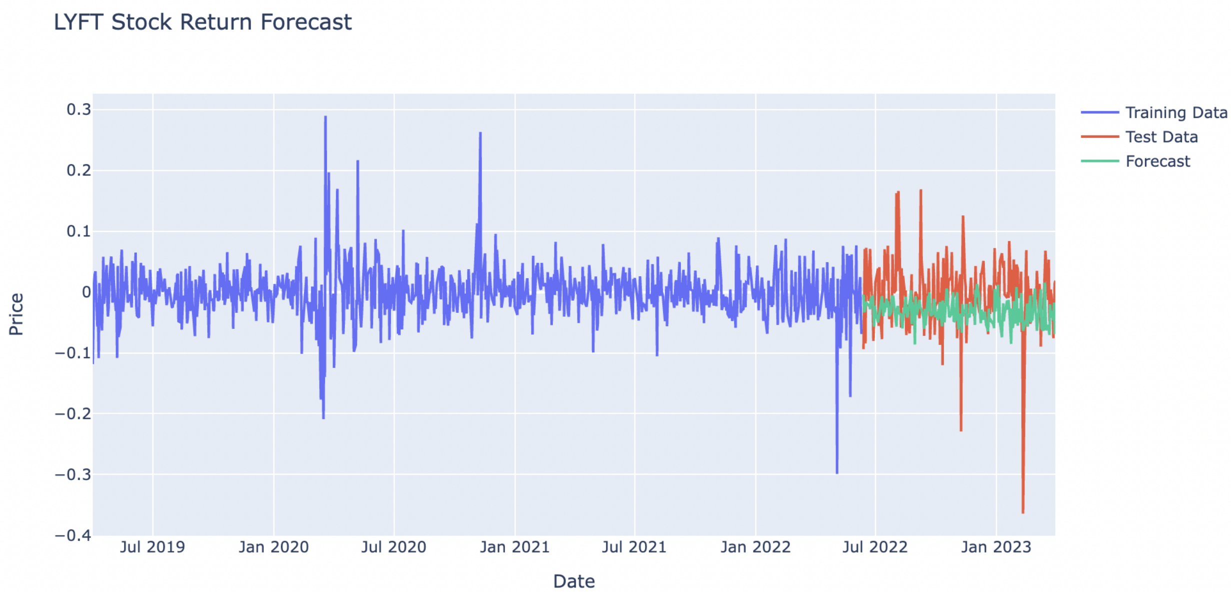
Explanation for Price Forecast:

The price forecast based on the training data demonstrated strong performance when compared to the test data. This outcome indicates that the model effectively captured the underlying price patterns and dynamics during the training phase, allowing it to generate accurate predictions for the test dataset.

By analyzing historical price data, the model could identify and learn from various factors, such as supply and demand dynamics, market trends, and investor sentiment, which influence the price movements. Leveraging this learned knowledge, the model made reliable forecasts for the test data.

The success of the price forecast on the test data indicates that the model's understanding of the market dynamics and its ability to incorporate relevant features and patterns were effective. However, it is important to acknowledge that real-world scenarios may introduce unforeseen events and fluctuations, which can challenge the accuracy of future price predictions. Ongoing monitoring and adaptation of the forecasting model are essential to account for changing market conditions and unforeseen events.

SARIMA for return prediction:



The graph presents a visual representation of the historical LYFT stock returns and their corresponding dates, along with the forecasted values derived from the SARIMA model. It offers a succinct depiction of the patterns observed in the return trends of the training data, the testing data, and the model's predictions for the testing data based on the historical return trends in the training data.

Explanation for Return Forecast:

The forecast for return based on the training data yielded favorable results when compared to the test data. This indicates that the model effectively captured the underlying patterns and relationships present in the training dataset, enabling it to make accurate predictions for the test dataset.

By analyzing historical return data, the model was able to identify and learn from the past trends, volatility, and other relevant factors that influence returns. Consequently, it could generalize this knowledge to predict future return values with a reasonable level of accuracy.

The success of the return forecast on the test data suggests that the model's understanding of the market dynamics and its ability to capture the latent factors impacting returns are robust and transferable. However, it is important to consider potential variations and uncertainties in real-world scenarios that may affect the accuracy of future return predictions.

Conclusion:

By conducting a comprehensive time series analysis of Lyft's stock prices, this study aims to contribute to the growing field of financial forecasting and provide insights into the future performance of the company. The results and findings of this research can be beneficial for investors, financial analysts, and market participants who seek to make informed decisions regarding their Lyft stock investments. Additionally, this study may pave the way for further advancements in the application of time series forecasting techniques in the domain of financial markets and beyond.

Overall, this paper presents a comprehensive approach to forecasting Lyft's stock prices, leveraging the power of time series analysis and machine learning. Through this research, we aim to contribute to the understanding of financial forecasting while providing practical insights for stakeholders in the ridesharing industry.

Reference:

Rai, B., Kasturi, M., & Huang, C. Y. (2018, August). Analyzing Stock Market Movements Using News, Tweets, Stock Prices and Transactions Volume Data for APPLE (AAPL), GOOGLE (GOOG) and SONY (SNE). In Proceedings of the International Conference on Pattern Recognition and Artificial Intelligence(pp. 109-112).

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