Comparison of Deferent Machine Learning Approaches for Forecasting Apple's and Nvidia's Stock Market

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Background

The stock market is a complex and dynamic system, where prices are influenced by a myriad of factors including economic indicators, company performance, market sentiment, and geopolitical events. Accurate forecasting of stock prices is a crucial task for investors, financial analysts, and policy makers, as it helps in making informed decisions, optimizing portfolios, and mitigating risks. Time series analysis, which deals with sequential data, has become an essential tool for analyzing historical stock price data and predicting future movements.

Objective

The primary objective of this project is to analyze and forecast the stock prices of Apple and Nvidia Inc. using a variety of time series analysis and forecasting techniques. This involves:

1. Collecting and preprocessing stock price data.
2. Conducting exploratory data analysis to understand the underlying patterns and structures.
3. Implementing different time series models, including both traditional statistical methods and modern machine learning approaches.
4. Evaluating the performance of these models using appropriate metrics.
5. Providing insights and actionable forecasts for short-term and long-term horizons.

Scope

The scope of this project encompasses the following:

- **Data Collection:** Acquiring daily stock price data for Apple and Nvidia Inc. over a period of eleven years from a reliable financial database.
- **Data Preprocessing:** Cleaning and transforming the data to ensure it is suitable for analysis.
- **Modeling:** Applying various time series forecasting models, such as ARIMA, GARCH, LSTM networks and Facebook Prophet.
- **Evaluation:** Assessing model accuracy and performance using metrics like Mean Squared Error (MSE) and Root Mean Squared Error (RMSE).

Scope

In our stock forecasting study, we utilize various models to analyze market behavior. While most focus on predicting stock prices, we specifically use the GARCH model for forecasting volatility. This model effectively captures changing variances and covariances of stock returns, enhancing our ability to manage risk and anticipate market volatility.
This report is structured to provide a comprehensive overview of the methodologies employed, the analysis conducted, and the results obtained. By comparing traditional and modern forecasting techniques, this study aims to highlight the strengths and limitations of each approach and offer recommendations for future researchand practical applications.

Oveview of Time Series Analysis

Time series analysis involves statistical techniques for analyzing temporal data points collected or recorded at specific time intervals. In finance, it is widely used for analyzing stock prices, economic indicators, and other financial metrics. Time series analysis helps in understanding the underlying patterns, trends, and seasonal effects in the data, which can be crucial for making forecasts.

Time Series Decomposition

Time series decomposition is a crucial step in understanding the underlying components of the stock price data. By decomposing the time series, we can separate it into its constituent components: trend, seasonality, and residuals. This helps in identifying the patterns in the data and aids in more accurate forecasting. In this section, we perform time series decomposition on Apple's and Nvidia's stock price data.

Trend

The trend component represents the long-term progression of the series. It shows the general direction in which the stock prices are moving over time. In financial time series, trends can be influenced by various factors such as company performance, market conditions, and economic events.

Seasonality

The seasonal component captures the repeating patterns or cycles within the data at fixed intervals, such as daily ,monthly, or yearly.

Seasonal patterns are particularly relevant in stock prices due to recurring events like earnings reports, product launches, and market cycles.

Residuals

The residual component (or noise) is what remains after removing the trend and seasonal components from the original time series. It represents the irregular, random fluctuations that cannot be explained by the trend or seasonality.

Methodology

Decomposition Method

Decomposition in time series analysis is a technique used to break down a time series into several distinct components, typically to better understand the underlying patterns and structures.

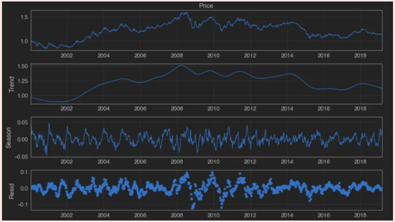


Figure: An example of Time Series Decompositin.

There are two main types of decomposition:

1. **Additive Decomposition:** Assumes that the components add together to form the observed time series. It's used when the variations around the trend do not vary with the level of the time series
2. **Multiplicative Decomposition:** Multiplicative Decomposition: Assumes that the components multiply together to form the observed time series. It's used when the variations around the trend are proportional to the level of the time series.

Methodology

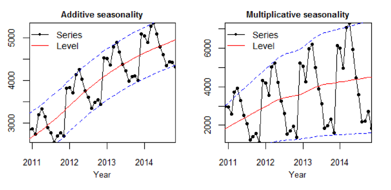


Figure: Additive and Multiplicative Decomposition.

The figure compares additive and multiplicative seasonality models, showing how the series (black) and level (red) lines capture the seasonal and trend components, with additive seasonality displaying constant seasonal variation and multiplicative seasonality showing variation proportional to the trend.

Methodology

Overview of Forecasting Methods

Several forecasting methods have been developed and applied to time series data, particularly in the context of stock prices. These methods can be broadly categorized into traditional statistical models and modern machine learning approaches.

Methodology (Statistical Models)

ARIMA (Auto-Regressive Integrated Moving Average):

The ARIMA model, introduced by Box and Jenkins(1970), is one of the most popular methods for time series forecasting.

It combines autoregression (AR), differencing (I), and moving average (MA) components to capture various patterns in the data.

ARIMA is effective for stationary time series data and can model a wide range of temporal structures by adjusting it sparameters (p, d, q).

Let's have a look at the equation of a simple ARIMA model, with all orders equal to 1. Suppose P is the price variable we're trying to model. Then, the simple ARIMA equation for P would look as follows:

$$\Delta P_t = c + \phi_1 \Delta P_{t-1} + \theta_1 \epsilon_{t-1} + \epsilon_t \tag{1}$$

Methodology (Statistical Models)

GARCH (Generalized Autoregressive Conditional Heteroskedasticity):

The GARCH model, developed by Bollerslev (1986), extends the ARCH model introduced by Engle (1982) to capture volatility clustering in financial time series data. GARCH models are particularly useful for modeling time series data with changing variances over time, suchas stock returns. A GARCH(p, q) sequence at, t = …, −1, 0, 1, … with parameters $\alpha_0 > 0, \alpha_1 \geq 0, 1 \leq i \leq p, \beta_j \geq 0, 1 \leq j \leq q$ is of the form:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i a_{t-i}^2 + \sum_{i=1}^{q} \beta_j \sigma_{t-j}^2 \tag{2}$$

LSTM (Long Short-Term Memory) Networks:

LSTM networks, a type of recurrent neural network (RNN), are designed to learn long-term dependencies in sequential data. They have been shown to be effective in capturing complex patterns in time series data.

Fischer and Krauss (2018) demonstrated that LSTM networks can outperform traditional models in stock price prediction by leveraging their ability to learn from historical data with varying lengths of memory. The structure of an LSTM architecture is illustrated here.

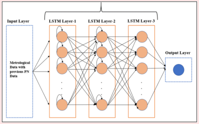


Figure: LSTM Neural Network

Methodology

Facebook Prophet

Facebook Prophet, developed by Taylor and Letham (2018), is an open-source tool designed for producing high-quality forecasts for time series data with strong seasonal effects and missing data. Prophet is robust to missing data and shifts in the trend, making it suitable for stock price forecasting where data irregularities are common. It also provides intuitive parameters for trend and seasonality adjustments, making it accessible for both experts and non-experts. The Prophet framework is represented as shown.

Methodological framework

$$y(t) = c(t) + s(t) + h(t) + x(t) + \epsilon$$

Where:

c(t)	Trend +
s(t)	Seasonality +
h(t)	Holiday effects +
x(t)	External regressors +
e	error

Figure: Facebook Prophet

Data Source

The stock price data for this project was obtained from Yahoo Finance, a reliable and widely used source for financial data. Yahoo Finance provides comprehensive historical stock price information, including open, high,low, close prices, and trading volume for various publicly traded companies.

Price	Close	High	Low	Open	Volume
Ticker	AAPL	AAPL	AAPL	AAPL	AAPL
Date					
2013-10-01	15.115498	15.152050	14.818738	14.820907	353883600
2013-10-02	15.165052	15.234441	14.985078	15.043314	289184000
2013-10-03	14.974551	15.251485	14.891844	15.194487	322753200
2013-10-04	14.962782	15.011415	14.825554	14.988492	258868400
2013-10-07	15.108988	15.260774	15.034643	15.072126	312292400
...	...	...	...	...	...
2024-09-23	226.221115	229.197836	225.561837	227.090154	54146000
2024-09-24	227.120117	229.097952	225.481920	228.398709	43556100
2024-09-25	226.121216	227.040203	223.773808	224.682796	42308700
2024-09-26	227.269958	228.248877	225.162277	227.050199	36636700
2024-09-27	227.539658	229.267767	227.050206	228.208935	34026000

Figure: Data Summary(AAPL)

Data Analysis and Results (Dataset Overview)

Dataset Description

The dataset used in this project consists of daily stock prices for Apple Inc. (AAPL) over a period of 11 years, from October 1, 2013, to September 30, 2024. This dataset includes the following columns:

- **Date:** The specific trading day.
- **Open:** The price at which the stock opened on the trading day.
- **High:** The highest price reached during the trading day.
- **Low:** The lowest price reached during the trading day.
- **Close:** The price at which the stock closed on the trading day.
- **Volume:** The number of shares traded during the trading day.

Data Analysis and Results (Dataset Overview)

Latest Valuation Measures of Apple Inc:

	Current	9/30/2024	6/30/2024	3/31/2024	12/31/2023	9/30/2023
Market Cap	3.35T	3.52T	3.23T	2.65T	2.99T	2.68T
Enterprise Value	3.39T	3.56T	3.27T	2.68T	3.06T	2.72T
Trailing P/E	36.64	35.46	32.76	26.67	31.41	28.73
Forward P/E	29.85	30.67	28.65	26.32	29.15	25.77
PEG Ratio (5yr expected)	2.03	2.24	2.23	2.11	2.31	2.18
Price/Sales	8.78	9.38	8.62	6.99	7.94	7.10
Price/Book	58.83	52.80	43.21	35.49	47.90	44.17
Enterprise Value/Revenue	8.67	9.24	8.56	6.96	7.98	7.09
Enterprise Value/EBITDA	25.19	26.35	24.57	20.10	23.66	21.46

Data Analysis and Results (Dataset Overview)

Latest Valuation Measures of Nvidia Inc:

	Current	10/31/2024	7/31/2024	4/30/2024	1/31/2024	10/31/2023
Market Cap	3.49T	3.26T	2.87T	2.13T	1.52T	1.01T
Enterprise Value	3.46T	3.23T	2.85T	2.11T	1.51T	1.00T
Trailing P/E	56.30	62.24	68.47	72.42	81.17	98.50
Forward P/E	33.33	33.90	44.64	35.71	30.40	24.51
PEG Ratio (5yr expected)	1.02	1.03	1.33	1.16	0.60	0.82
Price/Sales	31.31	34.33	36.58	35.37	34.14	31.09
Price/Book	53.00	56.00	58.49	49.45	45.57	36.57
Enterprise Value/Revenue	30.59	33.56	35.78	34.64	33.63	30.62
Enterprise Value/EBITDA	46.27	51.32	56.32	59.31	66.16	77.37

Exploratory Data Analysis (EDA):

Exploratory Data Analysis (EDA) is a crucial step in understanding the characteristics of the dataset, identifying patterns, trends, and anomalies, and preparing the data for further modeling. In this section, we perform various analyses and visualizations to gain insights into Apple's and Nvidia's stock price data over the period from October 1, 2013, to September 30, 2024.

Data Analysis and Results (Dataset Overview)

Descriptive Statistics:

Price	Close	High	Low	Open	Volume
Ticker	**AAPL**	**AAPL**	**AAPL**	**AAPL**	**AAPL**
count	2767.000000	2767.000000	2767.000000	2767.000000	2.767000e+03
mean	82.434357	83.251119	81.541408	82.369538	1.357115e+08
std	62.897338	63.520916	62.213100	62.845643	8.844991e+07
min	14.898041	15.011415	14.815642	14.820907	2.404830e+07
25%	27.086346	27.268820	26.950116	27.077041	7.646280e+07
50%	48.966965	49.276117	48.522552	48.942914	1.092963e+08
75%	143.556641	145.115812	141.865106	143.370136	1.676280e+08
max	234.290756	236.695312	232.564644	235.947003	1.065523e+09

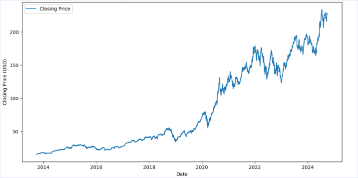
Key statistics to note:

- **Mean:** The average value of each feature.
- **Standard Deviation:** A measure of the amount of variation or dispersion.
- **Minimum and Maximum:** The range of values.
- **25th, 50th (Median), and 75th Percentiles:** Quartiles that provide insights into the distribution of the data.

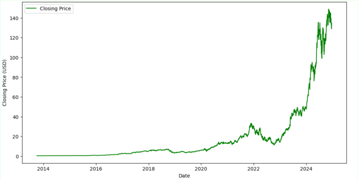
Visualizations help in understanding the temporal dynamicsof the stock prices and identifying trends, seasonality, andoutliers.

1. Line Plot of Closing Prices

(a)-APPLE (Closing Price)



(b)-NVIDIA (Closing Price)

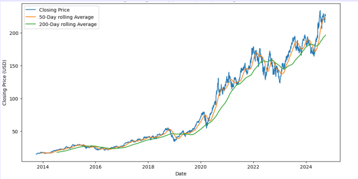


The line plot of the closing prices provides a visual representation of the stock price movements over time.

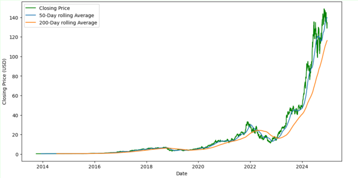
Data Analysis and Results (Visualization)

2. Moving Averages

(a)-APPLE (Closing Price)



(b)-NVIDIA (Closing Price)



Moving averages smooth out short-term fluctuations and highlight longer-term trends or cycles.

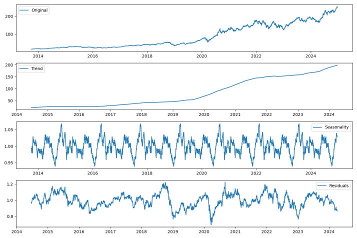
3. Seasonal Decomposition

For the decomposition of Apple's and Nvidia's stock price data, we use the additive decomposition method, which assumes that the components add together to form the original series. This method is favored when the components of the time seriescan be reasonably separated and added together to reconstruct the original series.

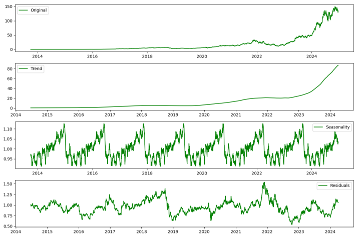
Data Analysis and Results (Visualization)

Time Series Decomposition

(a)-APPLE (Closing Price)

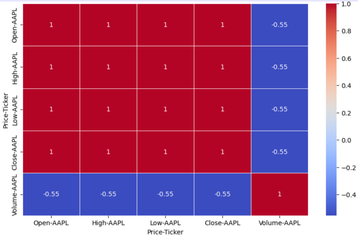


(b)-NVIDIA (Closing Price)

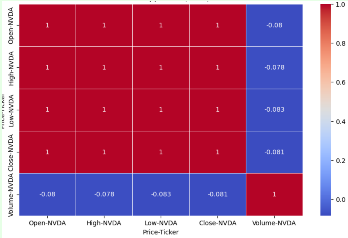


4. Correlational Analysis

(a)-APPLE (Closing Price)



(b)-NVIDIA (Closing Price)



Correlation analysis helps in understanding the relationship between different features in the dataset. A correlation matrix can be used to visualize these relationships.

Summary:

The Exploratory Data Analysis (EDA) revealed several key insights about Apple's and Nvidia's stock price data:

- The line plot and moving averages highlight the general upward trend in Apple's and Nvidia's stock prices over the last decade.
- Seasonal decomposition indicates the presence of seasonal patterns and a long-term trend.
- The correlation matrix shows strong correlations between different price features (Open, High, Low, Close), while the Volume feature has a weaker correlation with the price features.

These insights provide a solid foundation for building and validating time series forecasting models in the subsequent sections of this report.

Model Selection and Implementation

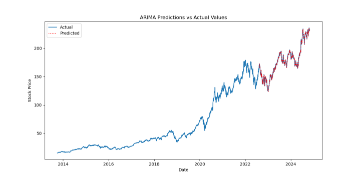
In this section, we detail the selection and implementation of various time series forecasting models to predict Apple's and Nvidia's stock prices. We employ both traditional statistical models and modern machine learning approaches to provide a comprehensive analysis. The models selected include **ARIMA**, **GARCH**, **LSTM**, and **Facebook Prophet**.

Please note that the GARCH model will be employed for volatility forecasting rather than for predicting stock prices.

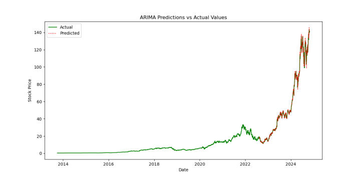
Model Selection and Implementation (ARIMA Model)

One-Step Forward Prediction

(a)-APPLE (MSE: 7.490 and RMSE: 2.736)



(b)-NVIDIA (MSE: 6.242 and RMSE: 2.498)

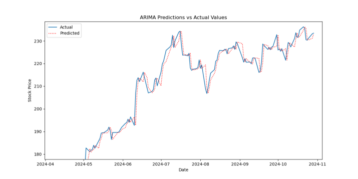


The graph compares the ARIMA model's predicted stock prices (red line) with the actual stock prices (blue and green line) of Apple and Nvidia Inc. from 2022 to 2024 (testing dataset).

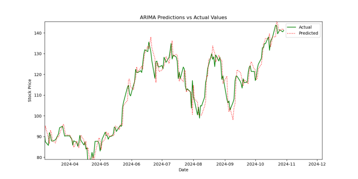
Model Selection and Implementation (ARIMA Model)

One-Step Forward Prediction (Close Up)

(a)-APPLE (Closing Price)



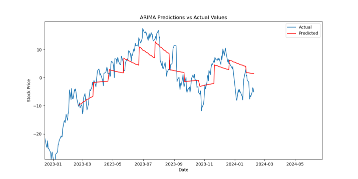
(b)-NVIDIA (Closing Price)



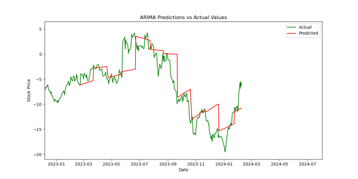
Model Selection and Implementation (ARIMA Model)

Twenty-Step Forward Prediction (Residuals)

(a)-APPLE (MSE: 23.549 and RMSE: 4.852)



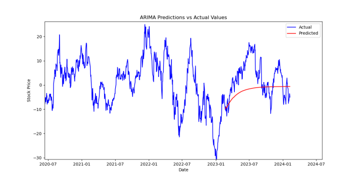
(b)-NVIDIA (MSE: 9.593 and RMSE: 3.097)



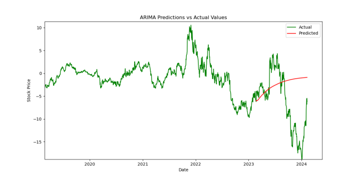
Model Selection and Implementation (ARIMA Model)

Prediction based on predictions (Residuals)

(a)-APPLE (MSE: 67.3159 and RMSE: 8.2046)

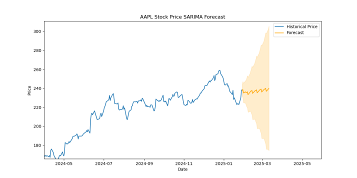


(b)-NVIDIA (MSE: 64.7632 and RMSE: 8.0475)

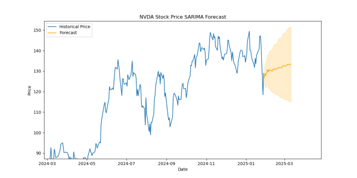


Prediction based on predictions (Future!)

(a)-APPLE

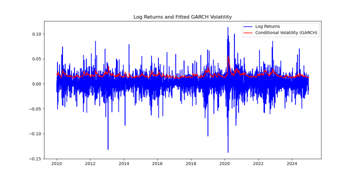


(b)-NVIDIA

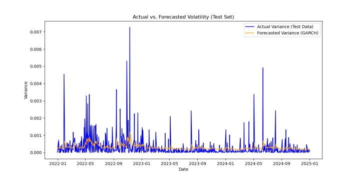


GARCH Model (Apple Inc)

(a)- GARCH(1,1) Model Fiting



(b)- GARCH(1,1) Model Predicting

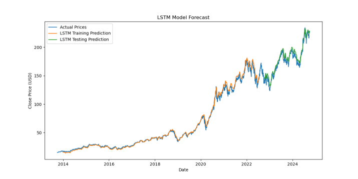


The graph shows the daily returns of Apple Inc. shares (AAPL) over time. The blue line represents the actual daily returns of AAPL, while the orange line represents the GARCH forecast.

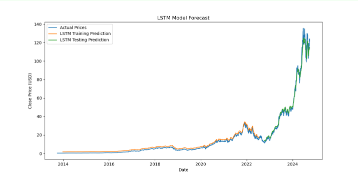
Model Selection and Implementation (LSTM Model)

LSTM Prediction

(a)-APPLE (MSE: 44.084 and RMSE: 6.639)



(b)-NVIDIA (MSE: 19.923 and RMSE: 4.4635)

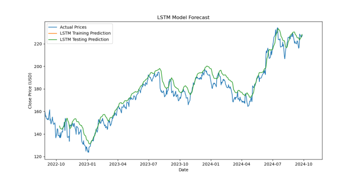


The graph compares the actual closing price of Apple and Nvidia Inc.(blue line) with the forecasted price from the LSTM model(orange/green line).

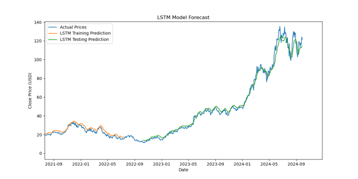
Model Selection and Implementation (LSTM Model)

LSTM Prediction (Close Up)

(a)-APPLE (Closing Price)



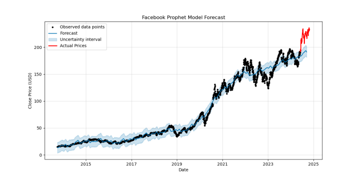
(b)-NVIDIA (Closing Price)



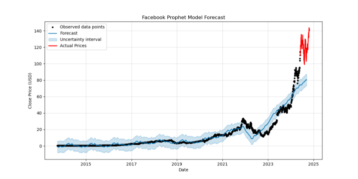
Model Selection and Implementation (Facebook Prophet Model)

Facebook Prophet Prediction

(a)-APPLE (MSE: 103.158 and RMSE: 10.183)



(b)-NVIDIA (MSE: 110.9105 and RMSE: 10.531)

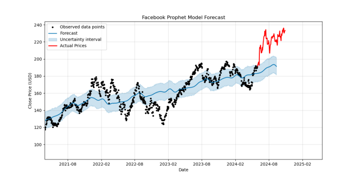


The graph shows the Facebook Prophet model forecast over time. It contains black dots and a red line representing the actual closing price data points, a blue line representing model forecast and a shaded area around the forecast line, representing the uncertainty interval of the forecast.

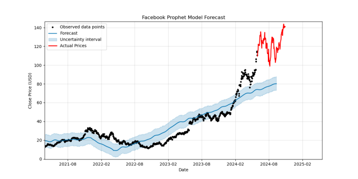
Model Selection and Implementation (Facebook Prophet Model)

Facebook Prophet Prediction (Close Up)

(a)-APPLE (Closing Price)



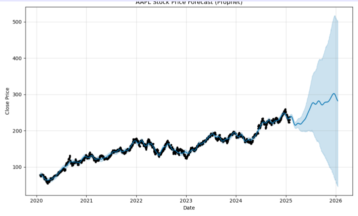
(b)-NVIDIA (Closing Price)



Model Selection and Implementation (Facebook Prophet Model)

Facebook Prophet Prediction (Future!)

(a)-APPLE (Closing Price)



(b)-NVIDIA (Closing Price)

Evaluation

Model Performance:

- **ARIMA:** Provided a baseline forecast with moderate accuracy.
- **GARCH:** Modeled the volatility highly effectively but had limitations in capturing trends.
- **LSTM:** Showed improved accuracy by capturing complex patterns and dependencies.
- **Facebook Prophet:** Offered a user-friendly approach with Acceptable accuracy and handling of seasonality.

Different forecasting models excel in various areas.
The best choice depends entirely on what you need to predict. Some models shine at accuracy, while others handle uncertainty well.
Understanding each model's strengths is key to effective forecasting.

Model Evaluation

The model evaluation section is critical for understanding the performance of each forecasting model. In this section, we will evaluate the **ARIMA**, **GARCH**, **LSTM**, and **Facebook Prophet** models using the Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) metrics. These metrics provide insight into how well the model's predictions align with the actual observed values.

Evaluation

Evaluation Metrics

- **Mean Squared Error (MSE):** This metric measures the average of the squares of the errors that is, the average squared difference between the actual and predicted values.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \tag{3}$$

- **Root Mean Squared Error (RMSE):** This metric is the square root of the MSE and provides a measure of the average magnitude of the error.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2} \tag{4}$$

Comparative Analysis

After calculating the MSE and RMSE for each model, we can compare their performance to determine which model provides the most accurate forecasts. Here is a summary of the evaluation metrics for each model:

Model	MSE	RMSE
ARIMA	23.549	4.852
LSTM	44.084	6.639
Facebook Prophet	103.158	10.183

Table I. The model with the lowest RMSE value is considered the best performing model in terms of prediction accuracy.

Conclusion

Theoretical Implications (ARIMA):

- **Strengths:** ARIMA's strength lies in its simplicity and interpretability. The parameters (p,d,q) provide clear insights into the lagged values, differencing required, and error terms considered.
- **Weaknesses:** ARIMA assumes linear relationships and may not capture more complex patterns in the data. It also requires the time series to be stationary, necessitating transformations for non-stationary data.

Conclusion

Theoretical Implications (LSTM):

- **Strengths:** LSTM networks handle long-term dependencies and are effective in capturing non-linear patterns. Their ability to retain information over longer sequences makes them ideal for time series forecasting.
- **Weaknesses:** LSTMs require substantial computational resources and longer training times. They also require careful tuning of hyper parameters and are less interpretable compared to traditional models.

Conclusion

Theoretical Implications (Facebook Prophet):

- **Strengths:** Prophet is user-friendly and requires minimal tuning. It is robust to missing data and outliers, making it versatile for different time series forecasting scenarios.
- **Weaknesses:** While Prophet handles seasonality well, it may not capture complex, non-linear relationships as effectively as LSTM.

Evaluation

Comparative Analysis

The comparative analysis of these models provides insights into their relative strengths and weaknesses, guiding the choice of model based on specific forecasting requirements.

- **Accuracy:** ARIMA and GARCH models generally show superior accuracy in terms of lower MSE and RMSE values compared to LSTM and Prophet.
- **Interpretability:** ARIMA and Prophet offer better interpretability of results, with clear insights into the model parameters and seasonal components.
- **Complexity:** LSTM models, while powerful, are complex and computationally intensive, requiring careful tuning and longer training times.

Conclusion

Conclusion

The results demonstrate that each model has unique strengths and weaknesses. The **ARIMA** and **GARCH** models generally offer superior accuracy for forecasting, with the **GARCH** model providing a robust, interpretable baseline, and the **GARCH** model excelling in volatility modeling. The choice of model should be driven by the specific requirements of the forecasting task, includingthe importance of accuracy, interpretability, and computational efficiency.