UNIVERSITAT DE BARCELONA

Facultat de Matemàtiques i Informàtica

Fundamental Principles of Data Science

Time Series Final Project

Analysis of Apple Stock Price

Dafni Tziakouri, Madison E. Chester

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Contents

1 Introduction

In this project, we utilize the Apple Stock Price (in USD) dataset spanning from 2014 to 2023 to conduct a comprehensive time series analysis and perform limited forecasting. The primary objective of this analysis is to address the following questions using the data and various time series methodologies learned throughout the course.

The specific questions we aim to answer are:

- What is the change in price of the stock over time?
- What is apple stock's moving average?
- How can we predict the closing price of APPLE Inc.?
- Over the next 30 days (January 2024), what are the closing prices and what will the volatility look like?

We will begin by detailing the contents of the dataset [1]. It contains 6 columns named:

Open: This is the price at which the stock first starts trading at during a trading session. It represents the initial valuation of the stock on that day.

Close: This is the price at which the stock finishes trading at wehn the trading session ends. It's considered the most crucial price point as it reflects the final sentiment towards the stock for that day.

High: This is the highest price the stock reaches during the trading session. It shows the peak demand for the stock throughout the day.

Low: This is the lowest price the stock reaches during the trading session. It highlights the weakest point of demand and potential selling pressure.

Volume: This represents the total number of shares of the stock that are traded during the session. It indicates the level of buying and selling activity for the stock.

Adj Close (Adjusted Close): This is the closing price adjusted for any corporate actions (e.g. stock splits or dividends). It allows for accurate comparison of prices over time by removing the distorting effects of such events.

Let's proceed with the analysis to find answers to the previously stated questions.

2 What is the change in price of the stock over time?

To check how the price of Apple stock changes over time, we examine the plot of the stock price trend and the daily trading volume.

2.1 Apple Stock Trend

First, we explore the historical trend of the stock prices as shown in Figure1.

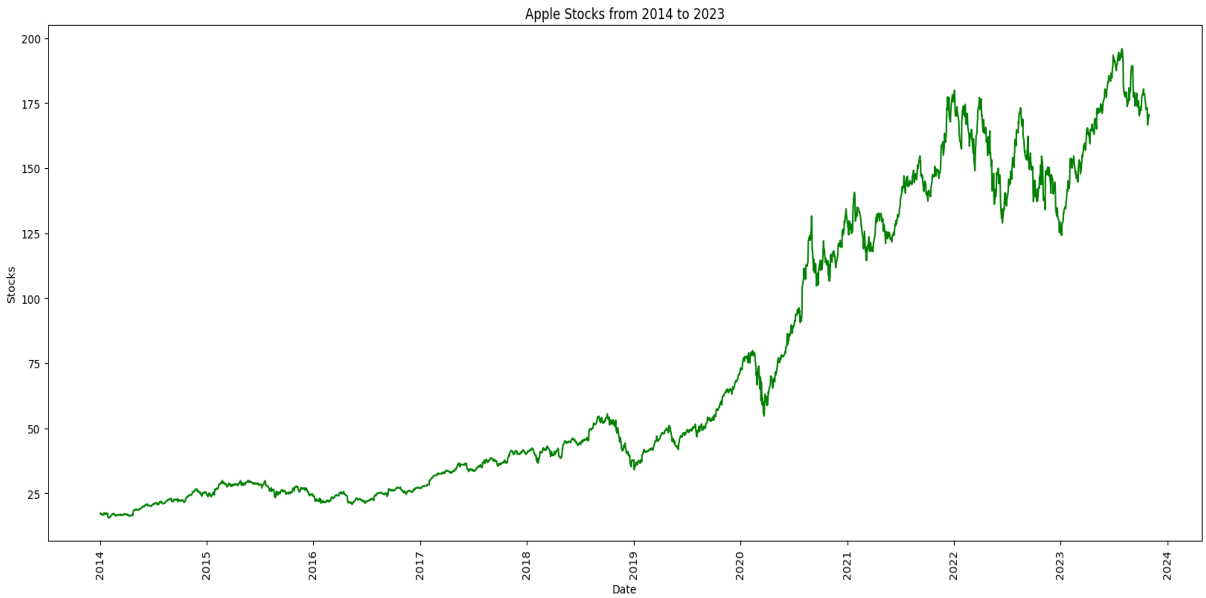

Figure 1: *Historical Trend of Apple Stock Price from 2014-2023*

Apple stock adjusted closing prices (in USD) from 2014 to 2023 show a generally upward trajectory with notable fluctuations. However, it must be noted that stock prices are not solely a direct reflection of a company's financial health and performance. Stock prices are historically very hard to model and forecast as there are many variables to consider. Although the financial well-being of a company plays a big role, closing price values can be heavily affected by public brand perception and the economy as a whole.

2.2 Comparative Analysis

In this section, we examine how Apple Inc.'s stock has performed relative to the broader market, specifically comparing its performance to the S&P 500 index over the last decade.

2.2.1 Apple's Performance vs. S&P 500

Over the past ten years, Apple (AAPL) has significantly outperformed the S&P 500 index. From 2014 to 2024, Apple achieved an annualized return of approximately 26.28%, while the S&P 500 had an annualized return of about 12.74% during the same period. This means that Apple has provided more than double the annual returns compared to the broader market index [4][2].

Moreover, Apple's exceptional performance over a longer horizon further underscores its strong market position. For example, since 2003, Apple has seen a return of over 59,000%, making it one of the top-performing stocks in the S&P 500 over the past two decades [2]. This outstanding performance is driven by Apple's innovation, robust product lines, and effective market strategies, which have continuously attracted investor confidence and significantly boosted its stock value.

2.2.2 Factors Contributing to Apple's Outperformance

Several key factors have contributed to Apple's substantial outperformance:

- **Innovation and Product Launches:** Apple's continuous innovation and the successful launch of new products, such as the iPhone series, Apple Watch, and various services like Apple TV+, Apple Arcade, and Apple News+, have significantly boosted its revenues and stock price.
- **Brand Loyalty and Ecosystem:** Apple's strong brand loyalty and the integrated ecosystem of its products and services have ensured a steady and growing customer base.
- **Financial Performance:** Strong financial performance, reflected in consistent revenue growth, profitability, and efficient cost management, has bolstered investor confidence.
- **Market Adaptation:** Apple's ability to adapt to market conditions and trends, such as the increased demand for technology products during the global pandemic, has further propelled its stock performance.

2.2.3 Implications for Investors

The implications of Apple's stock performance are significant for investors:

- **Higher Returns:** Investors who held Apple stock over the last decade have seen substantial returns compared to those who invested in the S&P 500 index.
- **Risk and Volatility:** While Apple has outperformed the market, it is also subject to higher volatility. Investors must consider the potential for significant price swings.
- **Strategic Positioning:** Apple's strong market position and continuous innovation suggest potential for continued growth, making it an attractive option for long-term investors.

Overall, Apple's stock has demonstrated remarkable performance, significantly outpacing the S&P 500 and offering substantial returns to its investors. This analysis highlights the importance of strategic investment in high-performing companies within the broader market context.

2.2.4 Event Analysis

Examining significant events that caused sharp fluctuations in Apple's stock price:

- **2019 Drop**: Due to escalating trade tensions between the United States and China and weaker-than-expected iPhone sales.
- **2020 Growth**: Driven by new product launches and increased demand for technology products due to the global pandemic.
- **2022 Drop**: Influenced by high global inflation rates and geopolitical tensions, notably the Russian-Ukraine war.

2.3 Daily Trading Volume

Now to analyze the daily trading volume of Apple stock from 2014-2024 as shown in Figure 2.

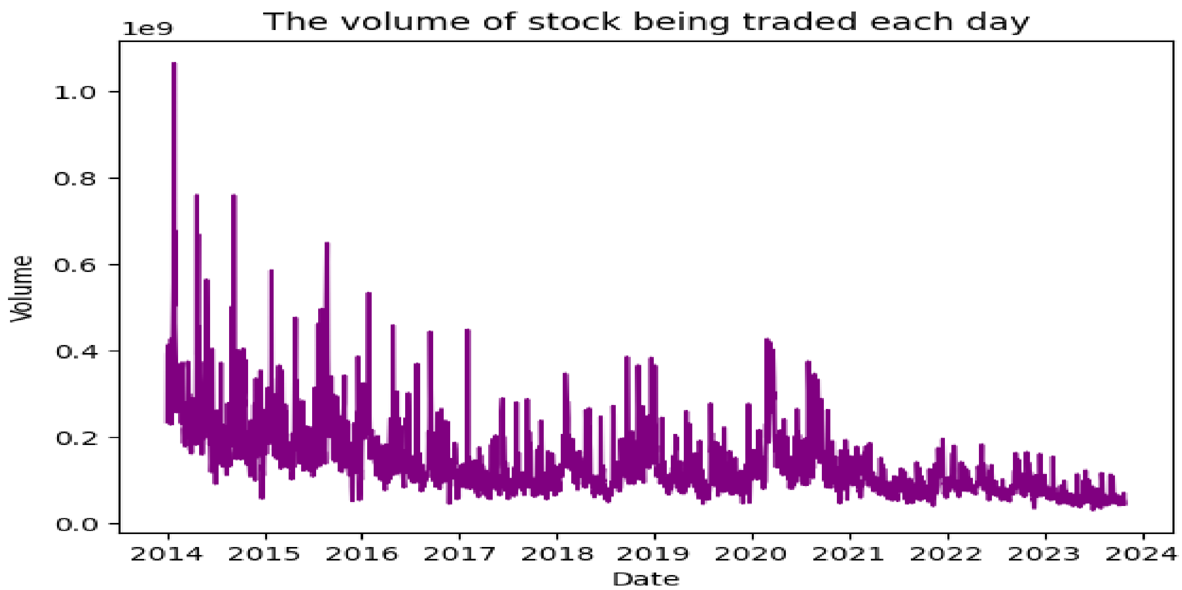

Figure 2: *Apple Stock Trading Volume from 2014-2023*

The graph shows a clear downward trend, meaning the stock has become less actively traded over time. In the early period from 2014 to 2016, trading volume was very high, with several peaks close to 1 billion shares traded on a single day. This high volume was likely due to significant excitement around new product launches such as the iPhone 6 and 6 Plus. However, after 2014, there was a noticeable decline in volume, although significant spikes still occurred, indicating occasional high trading activity. From 2017 to 2020, the trading volume continued to decline but at a more gradual pace compared to the earlier period. In the recent period from 2021 to 2024, the trading volume further decreased and stabilized at a relatively low level. This stabilization reflects a more mature market perception of Apple as a stable, long-term investment.

2.3.1 Factors Influencing Volume

Several factors could explain the overall decline in trading volume:

- **Market Maturity**: As Apple becomes a more mature company, its stock may be seen as a stable investment, reducing speculative trading.
- **Product Launches**: Early excitement around new product launches has waned.
- **Economic Conditions**: Market conditions such as economic downturns, industry shifts, or changes in investor sentiment.

2.3.2 Implications for Investors

The implications of lower trading volumes are significant:

- **Liquidity**: Reduced trading volumes can indicate lower liquidity, making it harder for investors to buy or sell the stock without affecting its price.
- **Volatility**: Lower trading volume can sometimes lead to higher price volatility, as fewer shares traded can result in larger price swings with each transaction.
- **Credit Rating Impact**: Lower liquidity could potentially impact the credit rating of Apple, influencing their brand perception and, consequently, their trading volume.

3 What is apple stock's moving average?

Moving averages are useful for identifying trends and potential reversal points in Apple's stock price. By selecting different periods for moving averages, investors and analysts can gain insights into price trends over various time-frames, each providing a unique perspective on the stock's behavior.

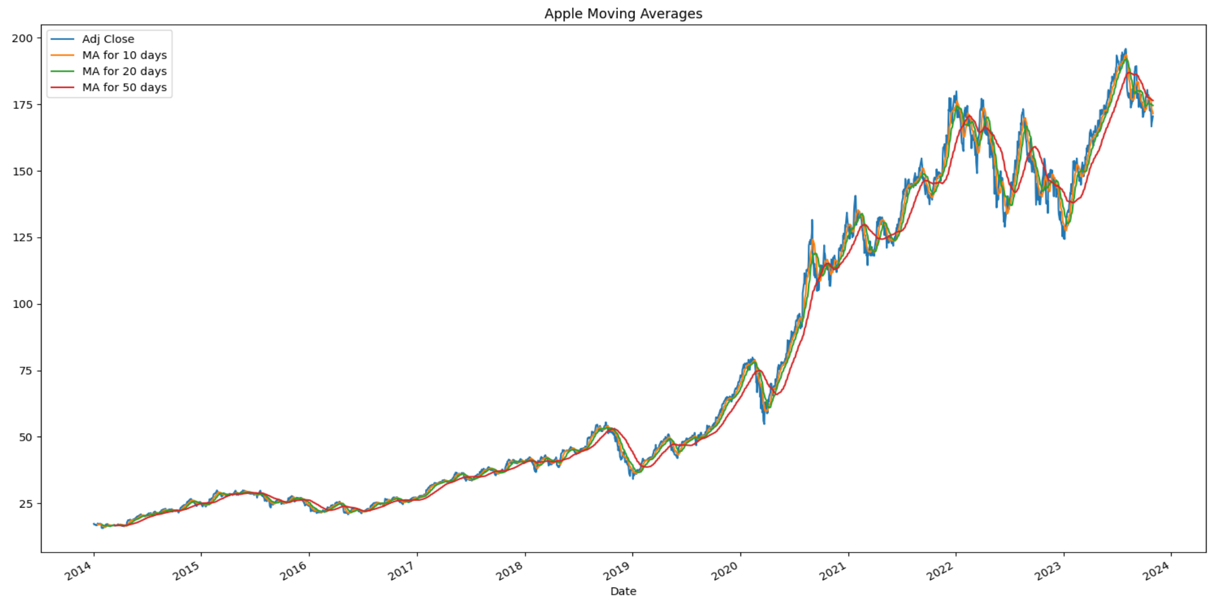

Figure 3: *Apple Moving Average from 2014-2024*

Apple stock has shown significant upward growth over the 10 year period (refer to Figure 3), especially since 2020, despite some volatility. The moving averages smooth out short-term fluctuations and highlight long-term trends. The 10-day MA is very responsive to recent price changes, the 20-day MA offers a balanced view, and the 50-day MA shows the long-term trend more clearly.

Crossovers between the stock price and moving averages can signal potential buy or sell opportunities. For example, when the stock price crosses above a moving average, it might indicate a bullish signal, while crossing below might suggest a bearish signal. That being said, crossovers between different moving averages are an indication of trend changes.

The moving averages analysis reveals distinct patterns coinciding with significant events in Apple's history. For instance, the strong performance observed around early 2020 aligns with the surge in demand for technology stocks during the COVID-19 pandemic. This period saw a convergence of moving averages, indicating robust trend strength amidst global economic uncertainties.

Looking ahead, the current positioning of moving averages suggests continued bullish sentiment, supported by ongoing innovation and market leadership. However, investors should remain cautious of potential market volatility and external factors influencing stock prices. Monitoring the convergence and divergence of moving averages will be crucial in identifying future trend shifts and investment opportunities.

While moving averages are valuable for trend identification, investors should remain mindful of their limitations during periods of heightened volatility or unexpected market events. Relying solely on moving averages without considering broader economic indicators or company-specific developments could lead to sub-optimal investment decisions.

4 How can we predict the closing price of APPLE Inc.?

4.1 Explanation of LSTM Model

Apple's closing stock prices are forecasted using a Long Short-Term Memory (LSTM) model [3], an advanced form of recurrent neural networks (RNN) designed by Hochreiter and Schmidhuber. LSTM excels in capturing long-term dependencies and is well-suited for sequence prediction tasks. Its applications span various domains, including time series forecasting, machine translation, and speech recognition.

Traditional RNNs struggle with learning long-term dependencies due to a single hidden state passed through time. LSTM addresses this by introducing a memory cell, capable of retaining information over extended periods. Controlled by input, forget, and output gates, the memory cell selectively stores or discards information, crucial for learning sequential data dependencies.

This model was chosen due to the non-stationary nature of the data, where statistical properties change over time due to trends and seasonality. Unlike stationary models like ARIMA, SARIMA, or AFRIMA, which require data pre-processing to enforce stationarity, LSTM models handle non-stationary data effectively.

4.2 Implementation of LSTM

The data were initially split into training (80%) and testing (20%) sets and scaled to a range of 0 to 1. This scaling enhances model convergence by stabilizing optimization gradients and ensures all input features contribute equally.

The LSTM model architecture comprises two layers, each with 50 units. The first layer captures lower-level temporal features, while the second layer extracts higher-level patterns, balancing complexity and efficiency in training. A dense layer with 25 neurons transforms temporal features into predictions, culminating in a single neuron output for the closing price.

Following training on the training set, predictions on the test data were re-scaled to the original scale. Evaluation metrics, Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE), reflect model performance. An RMSE of 5.74 indicates predictions deviate by $5.74 from actual closing prices on average, while a MAPE of 2.87% signifies a similar percentage deviation.

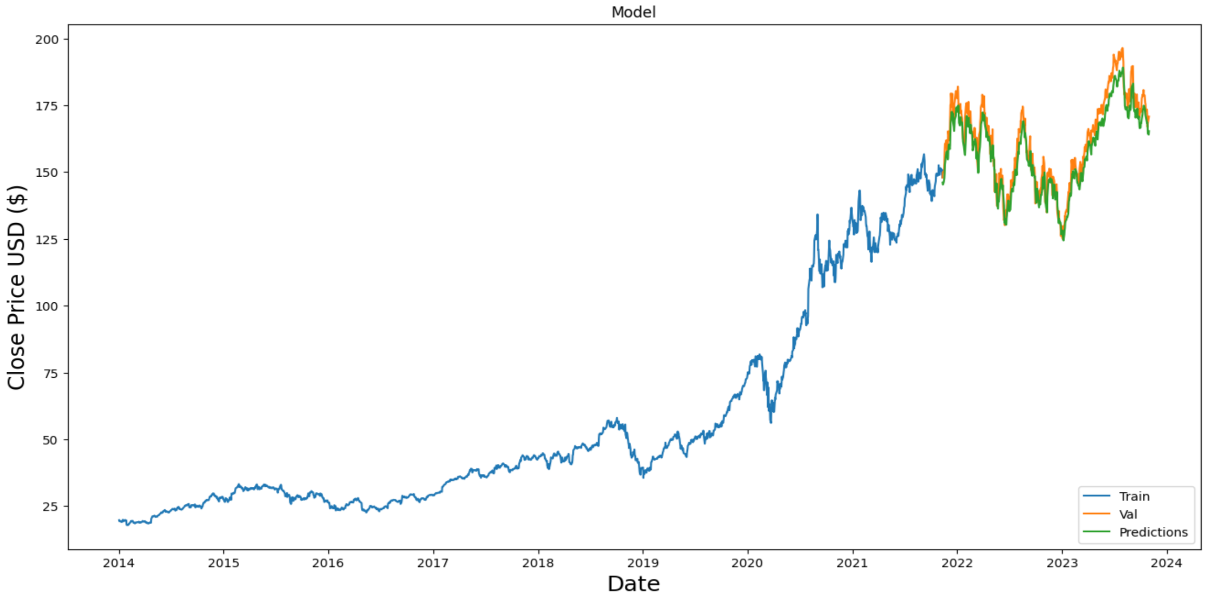

Figure 4: *Forecasting with LSTM model*

Figure4 depicts the LSTM model's effectiveness in forecasting Apple's closing prices. The blue line represents the training data from 2014 to early 2022, the orange line illustrates actual closing prices during the validation period from early 2022 to 2024, and the green line showcases predicted values for the validation period.

Overall, the LSTM model offers reliable forecasts with low prediction errors, making it a robust tool for predicting Apple's stock prices.

5 Over the next 30 days (January 2024), what are the closing prices and what will the volatility look like?

5.1 Explanation of ARIMA Model

The AutoRegressive Integrated Moving Average (ARIMA) model is a popular statistical method used for time series forecasting. It combines three components: autoregression (AR), differencing (I) to make the time series stationary, and moving average (MA). The model is denoted as ARIMA(p, d, q), where: - p is the number of lag observations included in the model (autoregressive part). - d is the number of times that the raw observations are differenced (integrated part). - q is the size of the moving average window (moving average part).

ARIMA models are powerful for understanding and predicting future points in the series, especially when the data show patterns over time. They are particularly effective for datasets where the relationship between the points can be assumed to be linear.

5.2 Explanation of GARCH Model

Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) [5] is a statistical model used for analyzing time-series data where the variance of the error term is believed to be serially autocorrelated. GARCH models assume that this variance follows an autoregressive moving average process.

While GARCH models can analyze various types of financial data, such as macroeconomic indicators, financial institutions typically use them to estimate the volatility[1] of returns for stocks, bonds, and market indices. This information aids in pricing, forecasting returns, asset allocation, hedging, risk management, and portfolio optimization.

GARCH models are particularly useful when the variance of the error term is not constant—i.e., when the error term is heteroskedastic. Heteroskedasticity refers to the irregular variation pattern of an error term or variable in a statistical model.

In essence, heteroskedasticity indicates that observations do not follow a linear pattern but instead tend to cluster. Consequently, using statistical models that assume constant variance on such data will yield unreliable conclusions and predictive values.

In GARCH models, the variance of the error term is assumed to vary systematically, conditional on the average size of the error terms in previous periods. This conditional heteroskedasticity arises because the error term follows an autoregressive moving average pattern, meaning it depends on an average of its own past values.

Moreover, GARCH models have extensions like EGARCH (Exponential GARCH) and GJR-GARCH (Generalized Jump Regression GARCH), which can capture asymmetries and leverage effects often observed in financial markets.

5.3 Implementation of ARIMA and GARCH Models

To implement this, we first calculate the log returns of the stock prices, which measure the percentage change in the value of the asset over time. This is done to stabilize the variance and make the series stationary.

After calculating the log returns, we fit an ARIMA model to the log returns to capture any underlying trends or seasonality in the data. The ARIMA model helps us identify the mean and volatility components of the time series.

Once the ARIMA model is fitted, we obtain the residuals (Figure 5), which represent the portion of the data that the model was unable to explain. These residuals are assumed to contain information about the volatility of the time series.

We then fit a GARCH model on the ARIMA residuals to model the conditional variance of the time series. The parameters of the GARCH model are chosen based on minimizing the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Grid search is often used to explore different combinations of model parameters to find the best-fitted model.

For our practical implementation, we used a GARCH(1, 2) model, which means it has one

[1] The degree of variation of a trading price series over time, usually measured by the standard deviation of logarithmic returns.

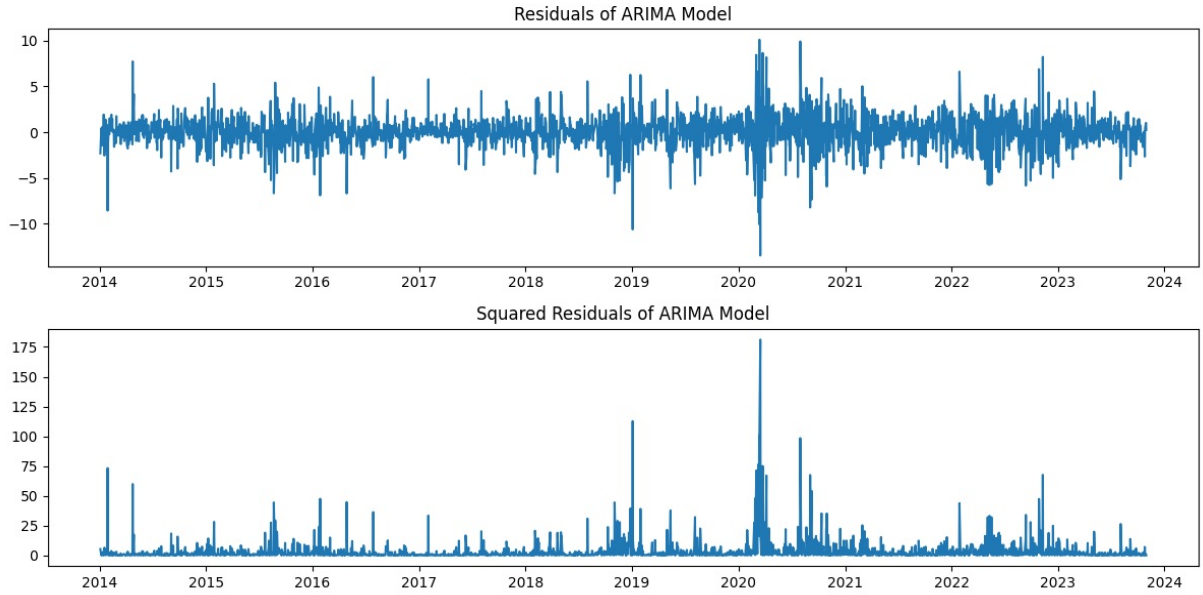

Figure 5: *Residuals & Squared Residuals*

lag for the variance and two lags for the squared residuals. These parameters were selected based on their ability to minimize AIC and BIC while adequately capturing the volatility patterns in the data.

We then forecasted the volatility for the next month (January 2024) (Figure 6) using the fitted GARCH model. This forecasted volatility provides insights into the expected fluctuation in the stock price over the forecast period, aiding in risk management and financial decision-making.

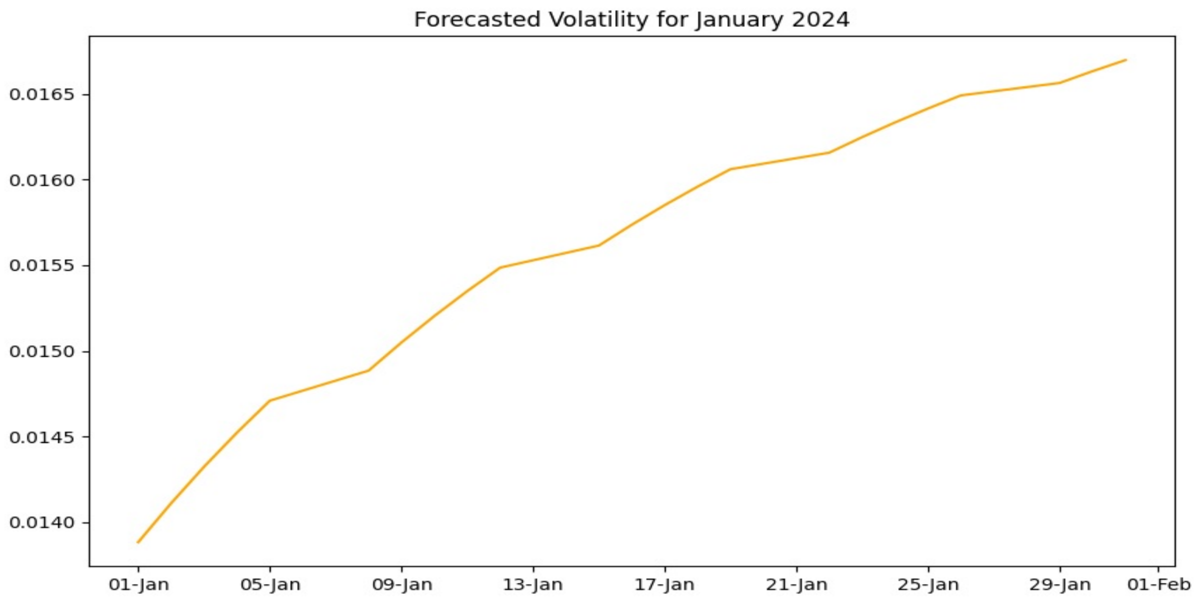

Figure 6: *Forecast Volatility of January 2024*

Finally, leveraging the forecasted log returns from the ARIMA model and the last known closing price, we computed the forecasted closing prices of Apple's stock for January 2024 (Figure 7). These forecasts play a pivotal role in strategic decision-making for investors and financial analysts, enabling them to anticipate potential returns and adjust their investment strategies accordingly.

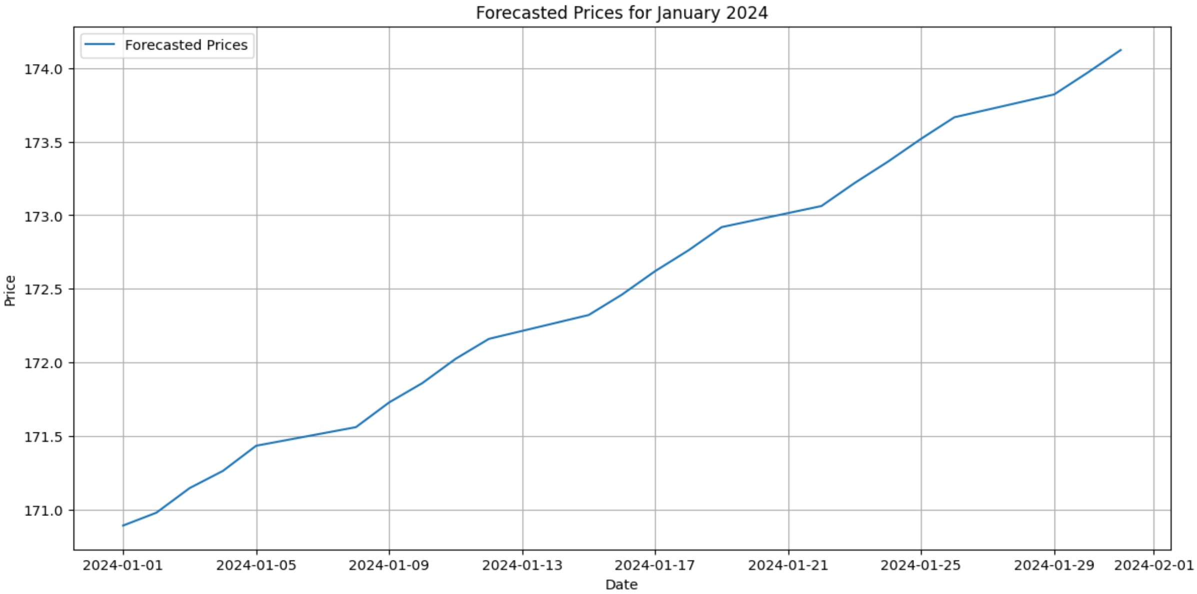

Figure 7: *Forecast Closing Prices of January 2024*

In conclusion, the combined use of ARIMA and GARCH models provides a robust framework for analyzing and forecasting Apple's stock prices. These models not only help in understanding the underlying trends and volatility patterns but also empower stakeholders with valuable insights for making informed financial decisions. By integrating these methodologies, we enhance our ability to navigate the complexities of financial markets and optimize portfolio management strategies.

6 Conclusions

In this study, we conducted a comprehensive time series analysis of Apple Inc.'s stock prices spanning from 2014 to 2024, employing various statistical models to forecast future trends and volatility. Our analysis aimed to address several key research questions, utilizing theories such as ARIMA, GARCH, and LSTM models to interpret and predict stock price movements.

6.1 Overview of Research Questions Answered

We began by exploring the historical trend of Apple's stock prices, identifying significant events that influenced its performance over the years. Through visual analysis and statistical techniques, we observed both the long-term growth trajectory and short-term fluctuations, highlighting Apple's resilience and market adaptability.

Moving forward, we addressed the question of predicting Apple's stock closing prices using an LSTM model. LSTM, a type of recurrent neural network, proved effective in capturing complex patterns and long-term dependencies in the time series data. The model's ability to handle non-stationary data without explicit pre-processing made it particularly suitable for our dataset.

Next, we delved into forecasting future closing prices and volatility using ARIMA and GARCH models. ARIMA helped in modeling the underlying trend and seasonality of the stock prices, while GARCH provided insights into the conditional variance or volatility, crucial for risk management and financial decision-making.

Finally, we evaluated our forecasting models against actual data for January 2024. While the models performed well overall, there were discrepancies between our forecasted closing prices and the actual adjusted closing prices of Apple stock. This discrepancy prompts further exploration into possible factors contributing to forecasting errors.

6.2 Theories Used

The theories underpinning our analysis include:

- **Time Series Analysis:** Leveraging historical data to understand patterns, trends, and seasonality in Apple's stock prices.
- **LSTM Model:** Applying deep learning techniques to capture intricate relationships and long-term dependencies in the stock price data.
- **ARIMA Model:** Utilizing autoregressive, integrated, and moving average components to model and forecast time series data.
- **GARCH Model:** Exploring volatility clustering and conditional heteroskedasticity in financial time series to predict future volatility.

These theories provided a robust framework for interpreting the dynamics of Apple's stock prices and making informed predictions about future movements.

6.3 Implementation Details

The implementation involved rigorous data preprocessing, model selection, and evaluation. We carefully preprocessed the dataset, handling missing values, scaling data for neural network models, and transforming data for stationary model requirements. Model selection was based on empirical validation and comparison of different architectures and parameter settings. Evaluations included metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) to assess the accuracy of our forecasts.

6.4 Analysis of Forecast Accuracy

Despite the promising performance of our models, our forecasted closing prices for January 2024 exhibited slight deviations from the actual adjusted closing prices. Possible explanations for these discrepancies include:

- **Unexpected Market Events:** Unforeseen events, such as regulatory changes, geopolitical tensions, or macroeconomic shifts, may have impacted Apple's stock prices differently than predicted.

- **Model Assumptions:** Simplifying assumptions within the models, such as linear relationships or stationary conditions, may not fully capture the complexity and non-linearity of real-world stock price movements.

- **Data Limitations:** Inherent noise or irregularities in historical data, including data quality issues or outlier events, could have influenced model performance.

- **Parameter Sensitivity:** Sensitivity of model parameters to changes in training data or model specifications may have contributed to forecasting errors.

Addressing these factors could enhance the robustness and accuracy of future forecasts, ensuring more reliable predictions in dynamic financial markets.

In conclusion, our study underscores the importance of integrating advanced statistical techniques and deep learning models in financial analysis. By leveraging theories such as LSTM, ARIMA, and GARCH, we gained valuable insights into Apple's stock price dynamics and provided actionable forecasts for investors and financial analysts. Continued refinement and validation of these models will be essential for improving forecasting accuracy and adapting to evolving market conditions.

In the previously discussed project, the general concept of analyzing Apple stock prices was collaboratively developed by Daphne and Madison. Information and insights related to trends and trading volume, as well as the explanation of models used for forecasting closing prices and volatility, were primarily focused on by Daphne. Meanwhile, the structuring of the code and all necessary data pre-processing for the forecast were primarily handled by Madison. Additionally, the structure and implementation of the presentation were handled by Madison. In general, the entire process of the analysis, as well as the double-checking of the results and conclusions, was collaboratively contributed to by both Daphne and Madison.

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