Predicting Apple's Stock Performance using Time Series Analysis

Date: 05/25/2023

Author: Ha Doan, Ha Pham

I. Project Description:

In this project, our primary focus is to study how Apple's stock has changed. By analyzing these trends, we hope to develop forecasting models that predict Apple's stock's future direction and prices. The dataset includes the Adjusted Close prices of Apple stock from January 1, 1985, to April 1, 2023. As we only focus on studying the trend of Apple's stock, we do not need to have access to any additional data beyond the historical stock prices. Therefore, we will use time series analysis techniques to analyze the data and generate predictions for future prices.

We will specifically utilize two time series forecasting methods to achieve our goals: ARIMA(Autoregressive integrated moving average) and Holt-Winters. These techniques are widely used in financial forecasting due to their effectiveness in capturing patterns and trends in time series data. ARIMA can help us model the underlying patterns and forecast future stock prices based on historical data. Similarly, the Holt-Winters method is suitable for analyzing time series data with trends and seasonality. Holt-Winters considers three components of a time series: level, trend, and seasonality, and uses them to make forecasts for future periods.

In addition to the time series model, we will also include a traditional financial model called the Discounted Cash Flow (DCF) model, which will estimate the intrinsic value of a stock by analyzing its future cash flows and discounting them to their present value. By comparing with the DCF model, we hope to evaluate its performance on the time series forecasting model to see which model can predict Apple's stock price most accurately.

In conclusion, we hope to gain insights into Apple's performance by thoroughly analyzing its historical stock price. This analysis will allow us to understand the key factors that have influenced Apple's stock price movements in the past. Additionally, we hope to produce a reliable forecast for the performance of Apple's stock in the future. We hope our predictions can assist investors and researchers in making informed decisions and assessments for potential investment opportunities.

II. Project Data Exploration:

1. Holt-Winter's model

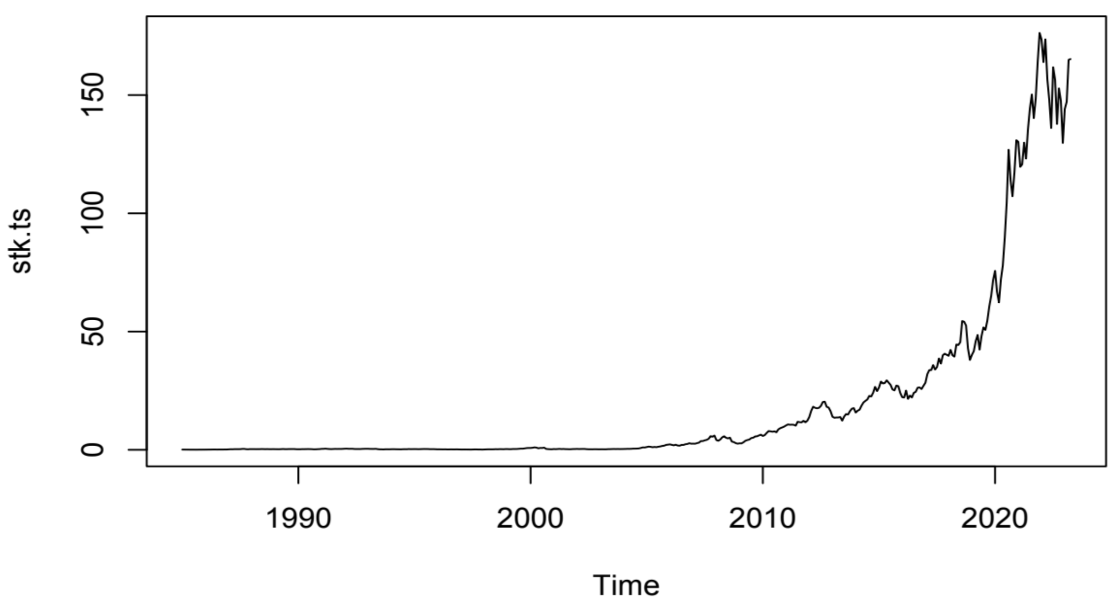
To start our analysis, we utilized the R programming language and gathered data on the Adj—close of Apple stock from January 1, 1985, to April 1, 2023. We used time series analysis to examine how Apple's stock has performed throughout this period and created a plot to visualize the data to understand it comprehensively. We then decomposed the plot to identify trends and residuals that may have affected the model and integrated necessary libraries such as library(zoo) and library(forecast) into our model. After that, we imported Apple's historical stock price data from a CSV file, assigning it the variable name "app.df." These are initial steps to build the foundation for our subsequent analysis and modeling of Apple's stock.

```
app.df <- read.csv("AAPL.csv")
app.vec <- app.df$Adj.Close
summary(app.vec)
```

After importing the historical stock price data into the app. df data frame, we created a time series vector called app.ts. To accomplish this, we used the ts function, which is designed specifically for time series analysis in R. We then passed the data and passed the data argument as the column of the data frame that contains the stock price data and set the timeline parameter to match the time intervals of the data.

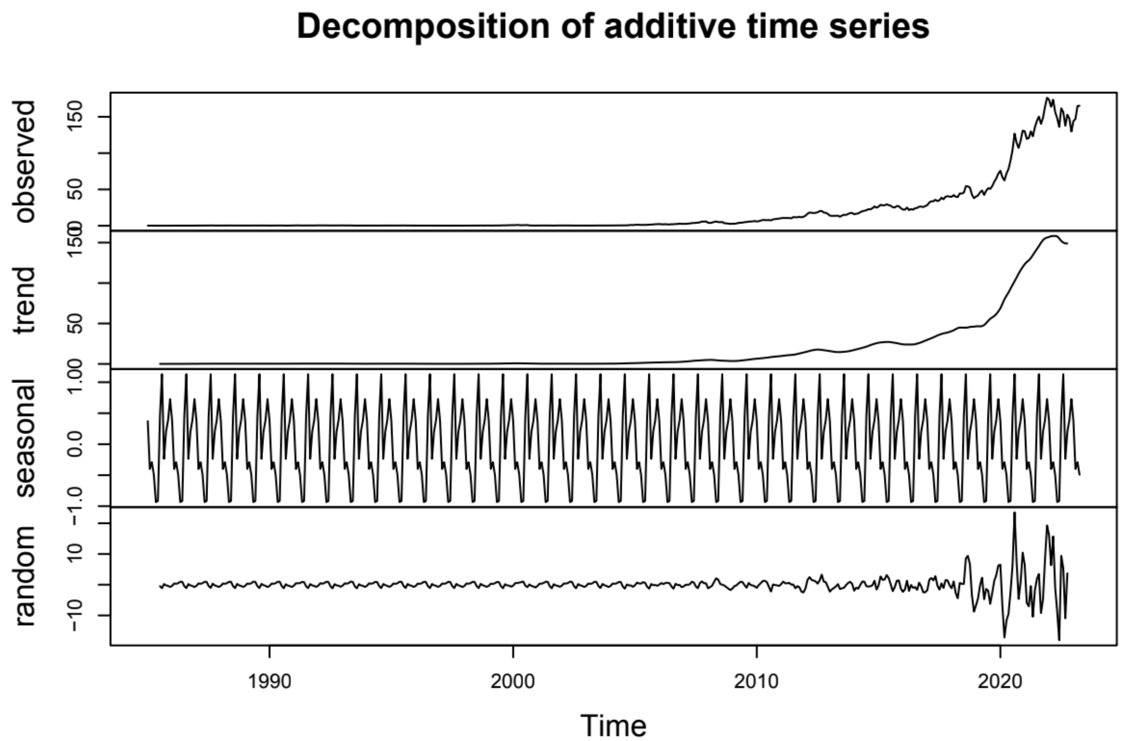
```
app.ts <- ts(data = app.vec, start = c(1985,01), frequency = 12)
```

We then plot the time series to enhance the visual representation and better understand the stock price trends.



From examining this plot, it is evident that this is a non-stationary graph, indicating a significant exponential increase from 2010. From our time series plot, we can see that Apple's stock has seen many ups and downs, but overall, it has been on a steady upward trend. Studying the plot, we can see that there have been some significant peaks in the stock's growth. For example, there was a peak in 2018 when Apple became the first trillion-dollar company in the world. In addition, in September 2021, the stock reached a value of $157.26 per share, mainly due to the launch of the iPhone 13 and strong quarterly financial results.

To further analyze the components of the time series, we employed the decompose function to decompose the time series into trend, seasonality, and residual components. By analyzing the noise component, we can have valuable insights into abnormal fluctuations and random variations in the series. Therefore, we can identify any unusual patterns or outliers that may affect the overall results of the model.



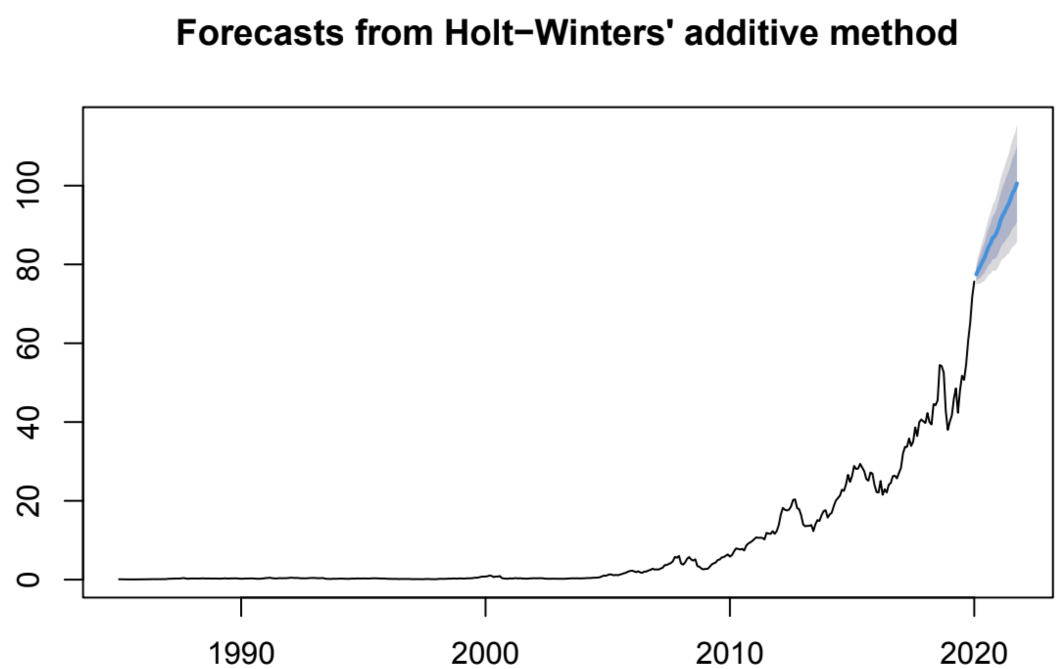
Based on the noise component, we can see that the more the stock has grown over time, the more noises are recorded in the model. This suggests that the increase in volatility of the company's stock shows as the stock is traded above its intrinsic value in the general market. Additionally, the observed trend in the stock indicates that, despite the volatility, there is an increased trend in the stock price over time. However, it is important to notice that there are other factors that can affect the stock price in the future besides its historical trend and data.

To further explain, we created a training and testing dataset by splitting the data into 80-20% proportions. Our training data set will start on 01/1985 and end on 01/2020, and our test data set will start on 02/2020 and end on 02/2023. From this data set, we hope to get an estimate of how Apple's stock will perform in the coming months.

```
train.data <- ts(data = stk.vec, start = c(1985,01), end = c(2020,01), frequency = 12)
test.data  <- ts(data = stk.vec, start = c(2020,02), end = c(2023,02), frequency = 12)
```

After that, we fit a Holt-Winters triple exponential model to the training data, using the "hw" function and passing it through the train—data frame. We set "h" to an accurate number of months, which is 21. We set "h" to 12 because we are predicting the stock's growth over the next 12 months based on the historical data in the training set. We then plot it to visualize the stock in the future better.

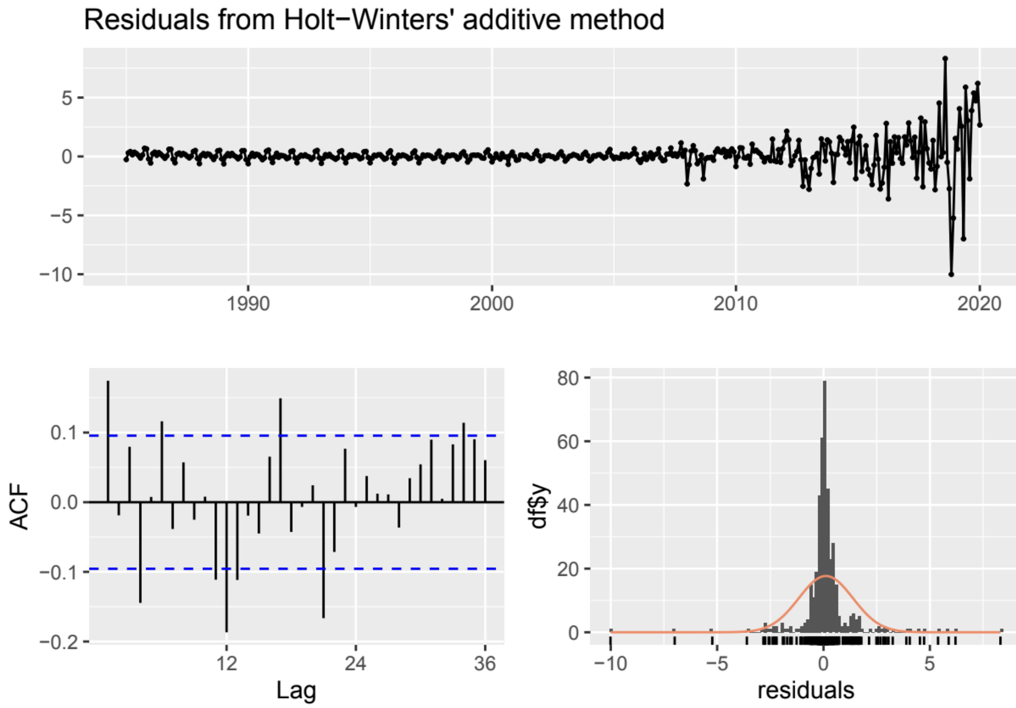
```
hw.fit <- hw(train.data, h= 12)
plot(hw.fit)
```



Based on this forecast, we predict that Apple's stock will continue to grow after 2020, expected to exceed $100 in the next 12 months. Comparing this forecast with the actual data, we observe that on January 4, 2021, the adjusted closing price of Apple's stock was indeed $127.5. This alignment between the prediction and the real value suggests that our anticipation is moving in the correct direction.

We use the check residuals function in R and passing apple to check the Holt-Winters model residuals.hw through the checkresiduals function to ensure that the model accurately captured the patterns in the data. The residuals represent the differences between the actual and predicted values, so a small residual means that the model accurately predicted the stock's behavior.

```
hw.check <- checkresiduals(hw.fit)
```




```
##
##  Ljung-Box test
##
## data:  Residuals from Holt-Winters' additive method
## Q* = 89.886, df = 24, p-value = 1.506e-09
##
## Model df: 0.   Total lags used: 24
```

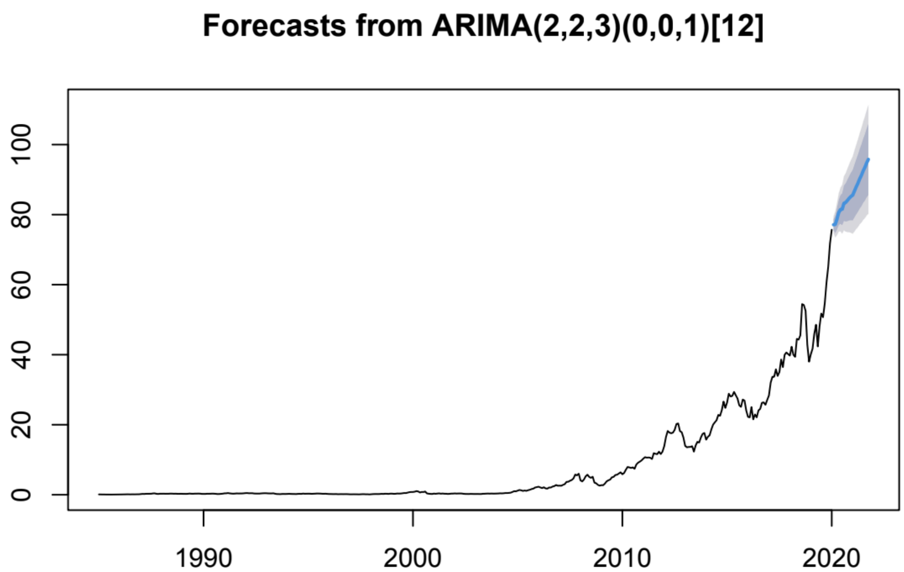
We observed that the residuals were mostly around 0 and normally distributed, demonstrating that Apple is a stable stock with little residual noise. According to the Ljung-Box test, a statistical test that can assess the autocorrelation of residuals, the p-value is very small. Therefore, we can reject the null hypothesis of the stock remaining the same over time. Therefore, there should be significant changes and trends present in the data. This finding supports the previous observations of an upward trend in Apple's stock price and reinforces our idea for future growth in the model.

2. Using Auto-regressive or ARIMA model

An alternative approach to predicting the trend of Apple's stock price is through the use of the ARIMA (Autoregressive Integrated Moving Average) model. We employed this popular time series forecasting method to understand the moving average components of the data. We fitted the ARIMA model using the arima function in R by the train—data set. Subsequently, we used the forecast function to generate predictions for the next 12 months. This utilization of the ARIMA model allowed us to leverage its capabilities in time series analysis and gain valuable insights into the potential direction of Apple's stock.

```
arima.fit <- auto.arima(train.data)
```

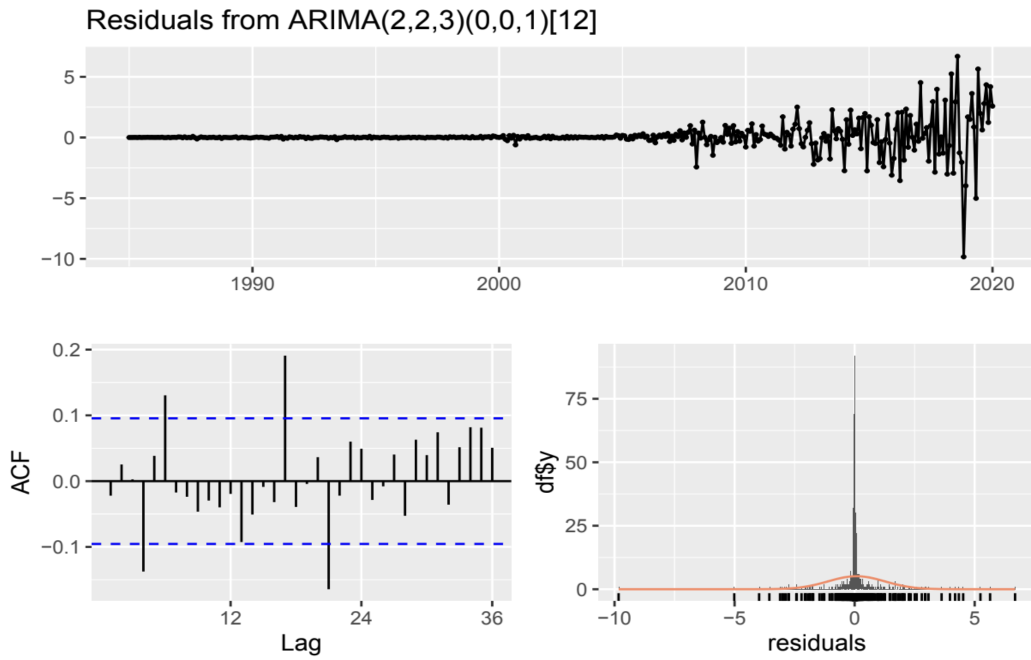
```
arima.pred <- forecast(arima.fit, h=12)
plot(arima.pred)
```



From the forecast, we can see that using the ARIMA model, Apple's stock will continue to grow after 2020 and is expected to exceed $100 in the next 12 months. From the forecasts generated using both the ARIMA and Holt-Winters models, these consistent forecasts indicate a positive outlook for Apple's stock and suggest that the company's performance will remain strong in the future.

Similarly, with the Holt-Winters models, we also need to check for residuals in the ARIMA model. Checking the residuals will allow us to examine the model's assumptions and ensure its reliability in predicting Apple's stock price trend.

```
arima.check <- checkresiduals(arima.fit)
```




```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(2,2,3)(0,0,1)[12]
## Q* = 56.643, df = 18, p-value = 7.051e-06
##
## Model df: 6.   Total lags used: 24
```

The tables above show that the residuals are normally distributed, which suggests that the model fits the data well. Additionally, the results of the Ljung-Box test are statistically significant, as demonstrated by the small p-value. Therefore, we reject the null hypothesis that the stock will be the same in the future.

We use the accuracy function from the forecast package to evaluate the accuracy of the ARIMA and Holt-Winters models in R. This function helps us to calculate many accuracy measures for each model, including ME (Mean Error), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Percentage Error (MPE), Mean Absolute Percentage Error (MAPE), and others. By comparing these values, we can evaluate our models' predictive performance and the accuracy of our model.

```
accuracy(hw.fit, test.data)
```

```
##                      ME      RMSE        MAE           MPE         MAPE
## Training set   0.1111146  1.274894  0.6173999      14.06786     59.89439
## Test set     -88.6989729 88.971546 88.6989729 -110262.12966 110262.12966
##                    MASE      ACF1 Theil's U
## Training set  0.283729 0.1743498        NA
## Test set     40.762033 0.8549245  9862.139
```

```
accuracy(arima.pred, test.data)
```

```
##                       ME      RMSE        MAE           MPE         MAPE
## Training set   0.07709958  1.178751  0.5098059  3.504126e-01     10.73428
## Test set     -85.83974164 86.012734 85.8397416 -1.070084e+05 107008.42775
##                     MASE        ACF1 Theil's U
## Training set  0.2342837 -0.02207559        NA
## Test set     39.4480593  0.84224757  9562.903
```

Overall, the two models effectively predict the direction of Apple's stock. However, the accuracy of predictions can vary depending on the dataset and time period that is being analyzed. Using the data from the 1980s to 2020 as the training data set may give us a relatively high value in overall errors. However, it is encouraging to see that both models have successfully captured the underlying trends and patterns, allowing for reliable predictions in the near future.

III. Using DCF as the model for valuation

To use the Discounted Cash Flow (DCF) Model for Valuation, we extracted data from Apple's 10-K report, focusing on its revenue breakdown across various categories. Subsequently, we projected the company's revenue linearly on a monthly basis for the next five years. To determine the proportion of Cost of Goods Sold (COGS) with revenue, we divided COGS by Revenue. By multiplying this ratio with each month's revenue, we calculated the COGS for each specific period. We did the same for Operating Expenses and Taxes.

In addition, we estimated Depreciation and Amortization (D&A) by calculating the average D&A based on the linearly increasing values of Plants, Properties, and Equipment (PP&E). To obtain Earnings Before Interest, Taxes, and Amortization (EBIAT), we subtracted COGS, Operating Expenses, Tax, and D&A from Revenue. From EBIAT, we added back D&A and subtracted changes in working capital and capital expenditures (CapEx) to determine Apple's Unlevered Free Cash Flow (UFCF).

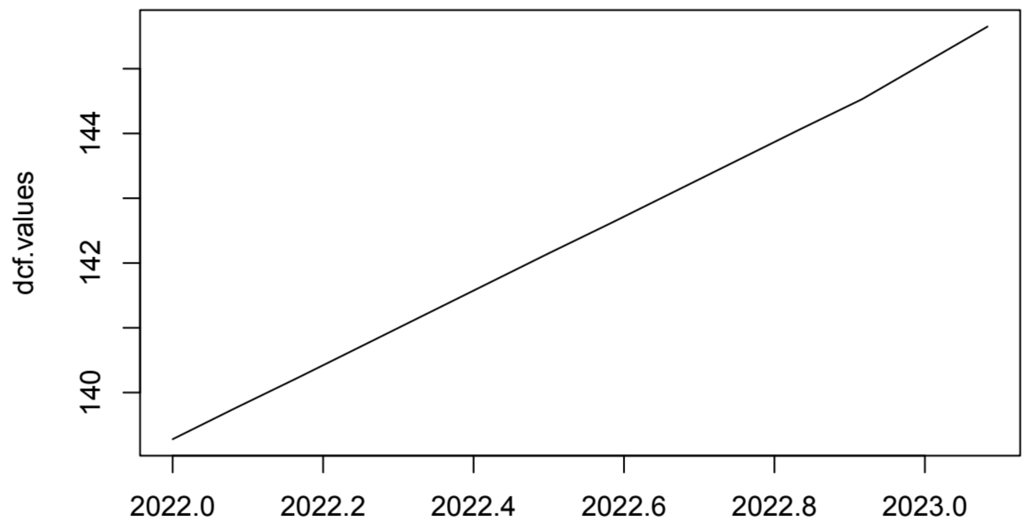
Moving on, we computed the perpetuity-free cash flow using the Gordon Growth Model. The growth rate is calculated by dividing dividends by the expected rate minus the growth rate. With this growth rate (g), the cash flow to perpetuity is calculated using the formula UFCF6 / (WACC - g), assuming it will continue to grow indefinitely.

By calculating the Weighted Average Cost of Capital (WACC), we discounted the Unlevered Free Cash Flows (UFCF) to their present value. These discounted cash flows were then summed together to determine Apple's total Free Cash Flows during the specified period. To obtain the stock's price, we divided the total Free Cash Flows by the total outstanding shares of Apple stock in the market. This valuation result can be found in the dcf.vec column in the provided code.

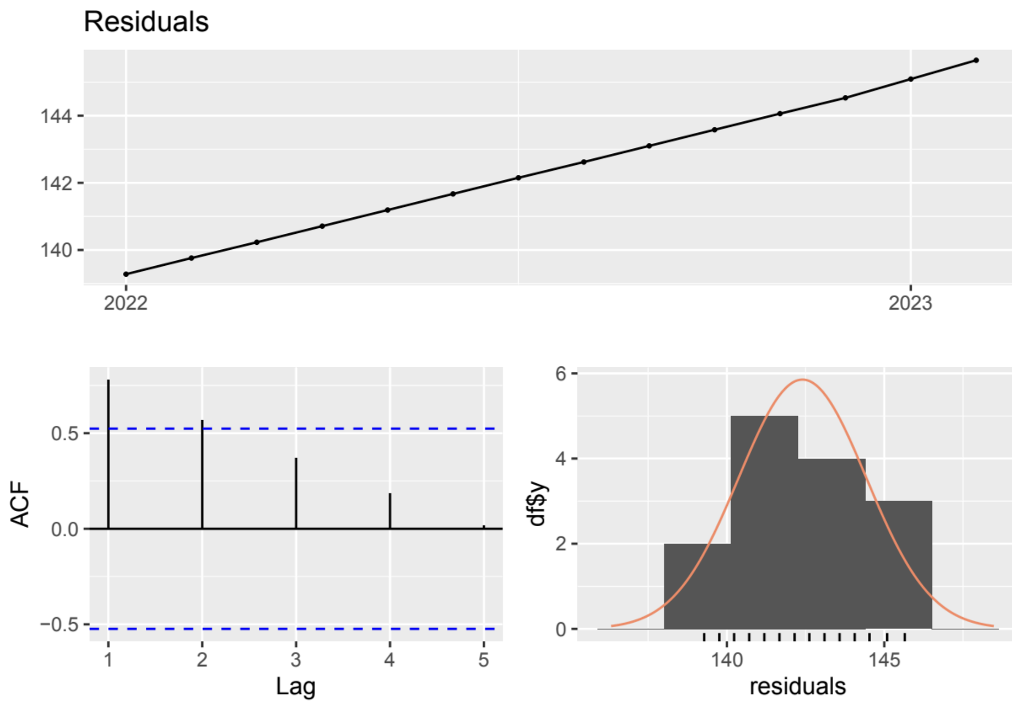
````
```{r}
dcf.vec <- c(139.28, 139.76, 140.23, 140.71, 141.19, 141.67, 142.15, 142.62, 143.10, 143.58, 144.06, 144.53,
145.09, 145.65)

dcf.values <- ts(data = dcf.vec, start = c(2022,01), end = c(2023,02), frequency = 12)

plot(dcf.values)
dcf.check <- checkresiduals(dcf.values)
```
````




```
dcf.check <- checkresiduals(dcf.values)
```




```
##
##  Ljung-Box test
##
## data:  Residuals
## Q* = 19.361, df = 3, p-value = 0.0002303
##
## Model df: 0.   Total lags used: 3
```

Since the DCF model assumes a constant growth rate for the Unlevered Free Cash Flow, it implies a linear relationship between the cash flow and the resulting Apple stock price per share. This assumption indicates that the model is expected to resemble a linear regression, where the cash flow is the independent variable, and the price per share is the dependent variable. By applying this model, we can assess the potential linear relationship between the projected cash flows and the anticipated stock prices for Apple.

```
accuracy(hw1.fit, test1.data)
```

```
##                        ME       RMSE        MAE          MPE      MAPE
## Training set -0.000774971 0.04752094 0.03755228    0.8375468  17.27963
## Test set     -0.137097810 0.13870001 0.13709781 -199.1721581 199.17216
##                   MASE      ACF1 Theil's U
## Training set 0.4638453 0.5275548        NA
## Test set     1.6934303 0.3270370  19.37401
```

The accuracy test shows that Arima has the least Measured Square Error compared to the other 2 models. However, its capability to predict Apple stock price is still being determined since it fails to mimic the volatility of AAPL over time.

IV. Conclusion

It is very surprising that both time series models (Hotl Winter and Arima), in their unique way, are better than the traditional DCF modeling from finance.

Hotl Winter's model tried to grasp a certain pattern of the APPLE by using the given data's noises, which resulted in the lowest p-value with the Ljung-Box test and admirable predicting graph patterns. However, it still needs to be more accountable in actual values measured Errors. This model is particularly good at predicting a stock's momentum within the market.
The Arima model has no particular pattern recognition; however, it offers the least Measured Errors compared to the other two models. The Ljung-Box test also shows the highest residuals with a p-value = 0.03.

Finally, the DCF model substantially undervalues Apple's stock price. This happens because this model from the financial system took into consideration Apple's core values like revenue, cost, interest rate, and tax rate. The model also assumes that the company's Free Cash Flow from Operation constantly increases over time, resulting in linear linked regression resembling Apple's intrinsic values. Thus, this results in a much lower value predicted for AAPL, making the model the highest in measured Square Errors. This model showed the actual value of the stock instead of the inflated over-value current price of Apple.

In conclusion, each model has unique capabilities to offer when it comes to determining stock price. However, Holt Winter's and DCF models seem more incapable of projecting Apple's stock prices. In practical usage, Holt Winter's model can well formulate the momentum of Apple stock price while parallelly comparing with the intrinsic values from the DCF models. However, in reality, these models might only work particularly with Apple's stock, which does not apply to any scenarios.

V. References:

Data Source:
“Apple Inc. (AAPL).” Yahoo! Finance. Yahoo.com. Link: https://finance.yahoo.com/quote/AAPL/history?period1=345427200&period2=1683158400&interval=1mo&filter=history&frequency=1mo&includeAdjustedClose=true

Codes:
Roi Polanitzer. “Building a DCF Valuation in Python Step by Step.” medium. medium.com. https://medium.com/@polanitzer/building-a-dcf-valuation-in-python-step-by-step-9ba686e0b3a