Data Aquisition From Yahoo Finance

In [100…

```
import pandas as pd
import numpy as np
import pandas_datareader.data as web
import datetime
import matplotlib.pyplot as plt
import yfinance as yf
%matplotlib inline

# Define the stock symbol and the date range
stock_symbol = 'AAPL'
start_date = '2014-01-01'
end_date = '2023-12-31'

# Download the stock data
df_aapl = yf.download(stock_symbol, start=start_date, end=end_date)

# Display the first few rows of the DataFrame
print("Apple stock data from 2014 to 2023:")
print(df_aapl.head())

# Save the DataFrame to a CSV file
df_aapl.to_csv('C:\\Users\\nelso\\OneDrive\\Documents\\Nelson\\Data Training\\TMU\\Cap
```

```
[*********************100%%**********************]  1 of 1 completed
Apple stock data from 2014 to 2023:
                 Open       High        Low      Close  Adj Close     Volume
Date
2014-01-02  19.845715  19.893929  19.715000  19.754642  17.273224  234684800
2014-01-03  19.745001  19.775000  19.301071  19.320715  16.893805  392467600
2014-01-06  19.194643  19.528570  19.057142  19.426071  16.985929  412610800
2014-01-07  19.440001  19.498571  19.211430  19.287144  16.864449  317209200
2014-01-08  19.243214  19.484285  19.238930  19.409286  16.971256  258529600
```

Load saved data into a dataframe

In [101…

```
import pandas as pd

# Load the CSV file
df_aapl = pd.read_csv("C:\\Users\\nelso\\OneDrive\\Documents\\Nelson\\Data Training\\T

# Print the tail of the DataFrame to confirm successful loading
print("Original DataFrame:")
print(df_aapl.tail())
```

```
Original DataFrame:
                  Open        High         Low       Close   Adj Close  \
Date
2023-12-22  195.179993  195.410004  192.970001  193.600006  193.091385
2023-12-26  193.610001  193.889999  192.830002  193.050003  192.542831
2023-12-27  192.490005  193.500000  191.089996  193.149994  192.642548
2023-12-28  194.139999  194.660004  193.169998  193.580002  193.071426
2023-12-29  193.899994  194.399994  191.729996  192.529999  192.024185

              Volume
Date
2023-12-22  37122800
2023-12-26  28919300
2023-12-27  48087700
2023-12-28  34049900
2023-12-29  42628800
```

Exploratory Data Analysis and Data Processing

In [102…

```
# 1. Rename Adj Close to price
df_aapl.rename(columns={'Adj Close': 'price'}, inplace=True)
df_aapl.head()
```

Out[102]:

Date	Open	High	Low	Close	price	Volume
2014-01-02	19.845715	19.893929	19.715000	19.754642	17.273224	234684800
2014-01-03	19.745001	19.775000	19.301071	19.320715	16.893805	392467600
2014-01-06	19.194643	19.528570	19.057142	19.426071	16.985929	412610800
2014-01-07	19.440001	19.498571	19.211430	19.287144	16.864449	317209200
2014-01-08	19.243214	19.484285	19.238930	19.409286	16.971256	258529600

In [103…

```
df_aapl['price'].plot( figsize=(12, 8))
plt.grid(True)
plt.ylabel('Price');
```

In [104…

```
# 2. Check for missing values

df_aapl.isnull().sum()
```

Out[104]:

```
Open      0
High      0
Low       0
Close     0
price     0
Volume    0
dtype: int64
```

In [105…

```
# 3. Check data type of the columns

df_aapl.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 2516 entries, 2014-01-02 to 2023-12-29
Data columns (total 6 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   Open    2516 non-null   float64
 1   High    2516 non-null   float64
 2   Low     2516 non-null   float64
 3   Close   2516 non-null   float64
 4   price   2516 non-null   float64
 5   Volume  2516 non-null   int64  
dtypes: float64(5), int64(1)
memory usage: 137.6 KB
```

In [106…

```
# 4. Subset Dataframe

df_aapl_price = df_aapl[['price']]
```

In [107…

```
df_aapl_price.head()
```

Out[107]:

Date	price
2014-01-02	17.273224
2014-01-03	16.893805
2014-01-06	16.985929
2014-01-07	16.864449
2014-01-08	16.971256

In [108…

```
# 5. Get Summary statistics for the stock price

df_aapl_price.describe()
```

Out[108]:

	price
count	2516.000000
mean	75.785417
std	56.582072
min	15.607208
25%	27.160179
50%	45.970673
75%	132.304100
max	197.589523

In [109…

```
#6. Confirm data is a time series data suitalbe for various time series modelling appr

df_aapl_price.index
```

Out[109]:

```
DatetimeIndex(['2014-01-02', '2014-01-03', '2014-01-06', '2014-01-07',
               '2014-01-08', '2014-01-09', '2014-01-10', '2014-01-13',
               '2014-01-14', '2014-01-15',
               ...
               '2023-12-15', '2023-12-18', '2023-12-19', '2023-12-20',
               '2023-12-21', '2023-12-22', '2023-12-26', '2023-12-27',
               '2023-12-28', '2023-12-29'],
              dtype='datetime64[ns]', name='Date', length=2516, freq=None)
```

In [110…

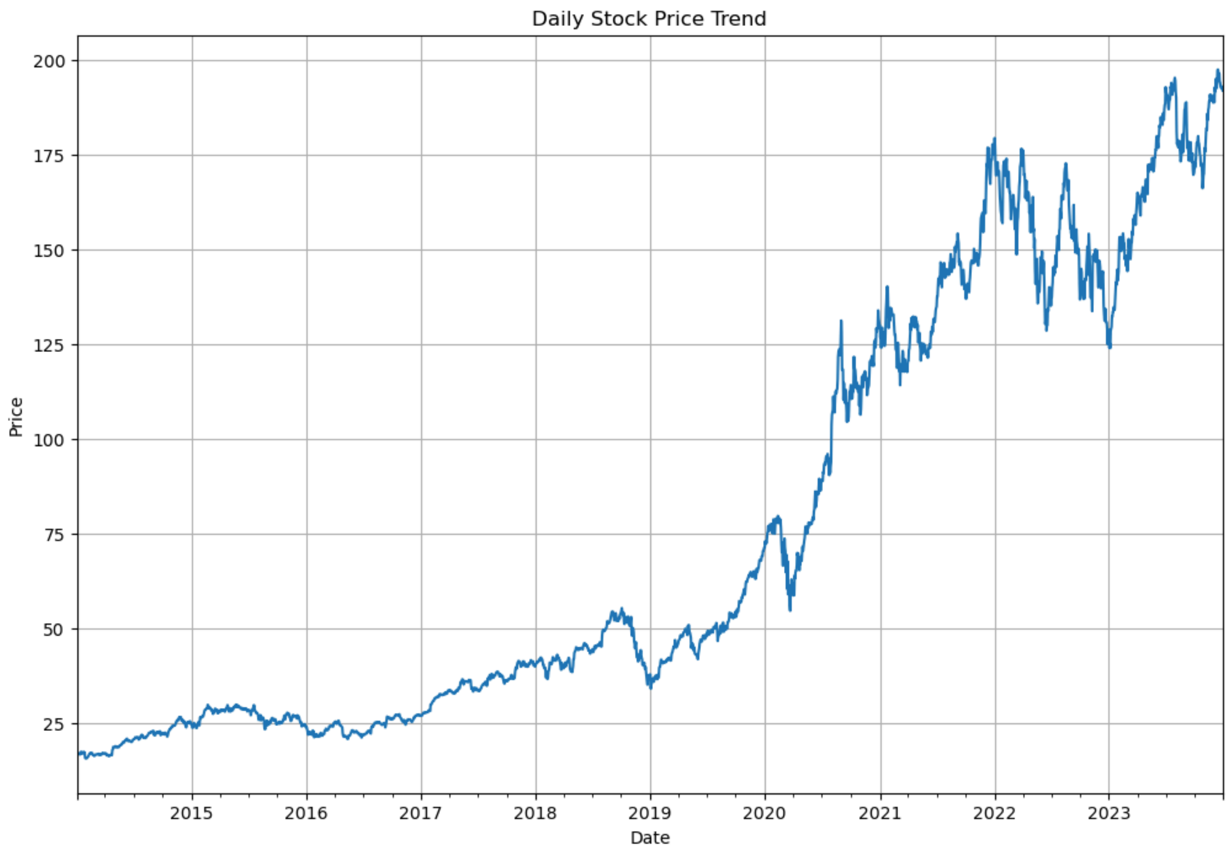
```
# 7.Account for weekends and holidays by setting the frequencey to business days and f

start_date = df_aapl_price.index.min()
end_date = df_aapl_price.index.max()
date_range = pd.date_range(start=start_date, end=end_date, freq='B')  # 'B' frequency

# Reindex the dataframe to the new date range
df_aapl_price_daily = df_aapl_price.reindex(date_range)

# lastly, forward-fill missing values to handle weekends and holidays
df_aapl_price_daily.ffill(inplace=True)
```

```
print(df_aapl_price_daily.head())
```

```
                price
2014-01-02  17.273224
2014-01-03  16.893805
2014-01-06  16.985929
2014-01-07  16.864449
2014-01-08  16.971256
```

In [111…

```
#. Plot price for the re-indexed data
import matplotlib.pyplot as plt

df_aapl_price_daily['price'].plot(title='Daily Stock Price Trend', figsize=(12, 8))
plt.xlabel('Date')
plt.ylabel('Price')
plt.grid(True)
plt.show();
```



In [112…

```
df_aapl_price_daily.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 2607 entries, 2014-01-02 to 2023-12-29
Freq: B
Data columns (total 1 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   price   2607 non-null   float64
dtypes: float64(1)
memory usage: 40.7 KB
```

Split Dataset into training and test sets

In [113…

```
# Determine the split index
split_index = int(len(df_aapl_price_daily) * 0.75)

# Split the data
train_data = df_aapl_price_daily[:split_index]
test_data = df_aapl_price_daily.iloc[split_index:]

# Print the sizes of the training and test sets
print(f"Training set size: {len(train_data)}")
print(f"Test set size: {len(test_data)}")
```

```
Training set size: 1955
Test set size: 652
```

In [114…

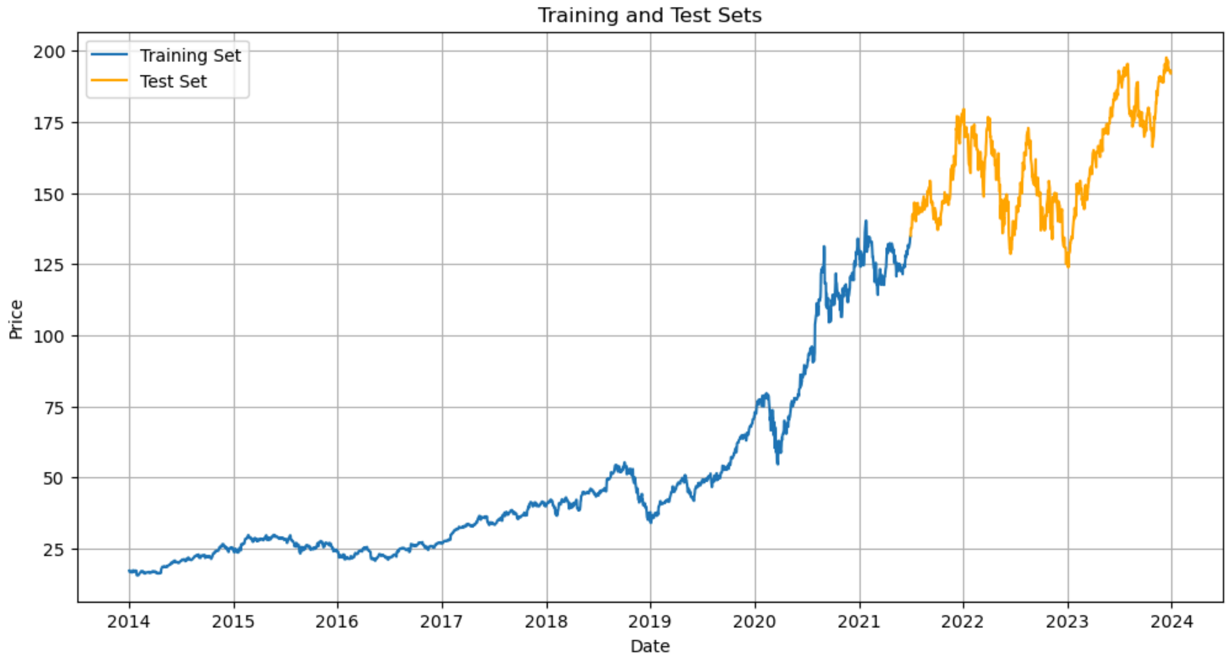
```
test_data.describe()
```

Out[114]:

	price
count	652.000000
mean	159.914230
std	17.486788
min	123.998459
25%	145.822430
50%	157.942818
75%	173.118259
max	197.589523

In [115…

```
import matplotlib.pyplot as plt

# Plot the training and test sets
plt.figure(figsize=(12, 6))
plt.plot(train_data[['price']], label='Training Set')
plt.plot(test_data[['price']], label='Test Set', color='orange')
plt.title('Training and Test Sets')
plt.xlabel('Date')
plt.ylabel('Price')
plt.legend()
plt.grid(True)
plt.show()
```



Functions for Statistical Evaluation of Models Not available in pyhton libraries

In [116…

```
def mape(y_true, y_pred):
    return np.mean(np.abs((y_true - y_pred) / y_true)) * 100


def directional_accuracy(y_true, y_pred):
    return np.mean((np.sign(np.diff(y_true)) == np.sign(np.diff(y_pred)))[1:]) * 100
```

Model 1 - Holt Winter Model

In [117…

```
#HoltWinters Model for price prediction. Justify why 'mul' as against 'add'

from statsmodels.tsa.holtwinters import ExponentialSmoothing

import warnings
warnings.filterwarnings("ignore")

# Fit the Exponential Smoothing model on the training set
fitted_model = ExponentialSmoothing(train_data['price'],
                                    trend='mul',
                                    seasonal='mul',
                                    seasonal_periods=365).fit()

# Forecast on the test set
model1_predictions = fitted_model.forecast(len(test_data))

# Plot the forecasted values against the test set
plt.figure(figsize=(12, 6))
plt.plot(train_data['price'], label='Training Set')
plt.plot(test_data['price'], label='Test Set', color='orange')
plt.plot(model1_predictions, label='Model1 Prediction', color='green')
```

```
plt.title('Training, Test, and Forecast')
plt.xlabel('Date')
plt.ylabel('Price')
plt.legend()
plt.grid(True)
plt.show()

# Print the predicted price values
print("\nForecasted values:")
print(forecast)
```


```
Forecasted values:
2021-07-01    136.250821
2021-07-02    134.568552
2021-07-05    134.015461
2021-07-06    133.369249
2021-07-07    134.846792
                 ...
2023-12-25    225.595248
2023-12-26    231.432172
2023-12-27    230.234629
2023-12-28    233.040237
2023-12-29    232.144428
Freq: B, Length: 652, dtype: float64
```

Statiscal Quantitative Evaluation of Model 1

In [127…

```
#Evaluation of Holtwinters prediction. Since this is a regressional model, possible ev

from sklearn.metrics import mean_squared_error,mean_absolute_error, mean_absolute_perc

y_true = test_data['price'].values
y_pred = model1_predictions[-len(y_true):]


# Calculate mean squared error (MSE)
mse = mean_squared_error(y_true, y_pred)
```

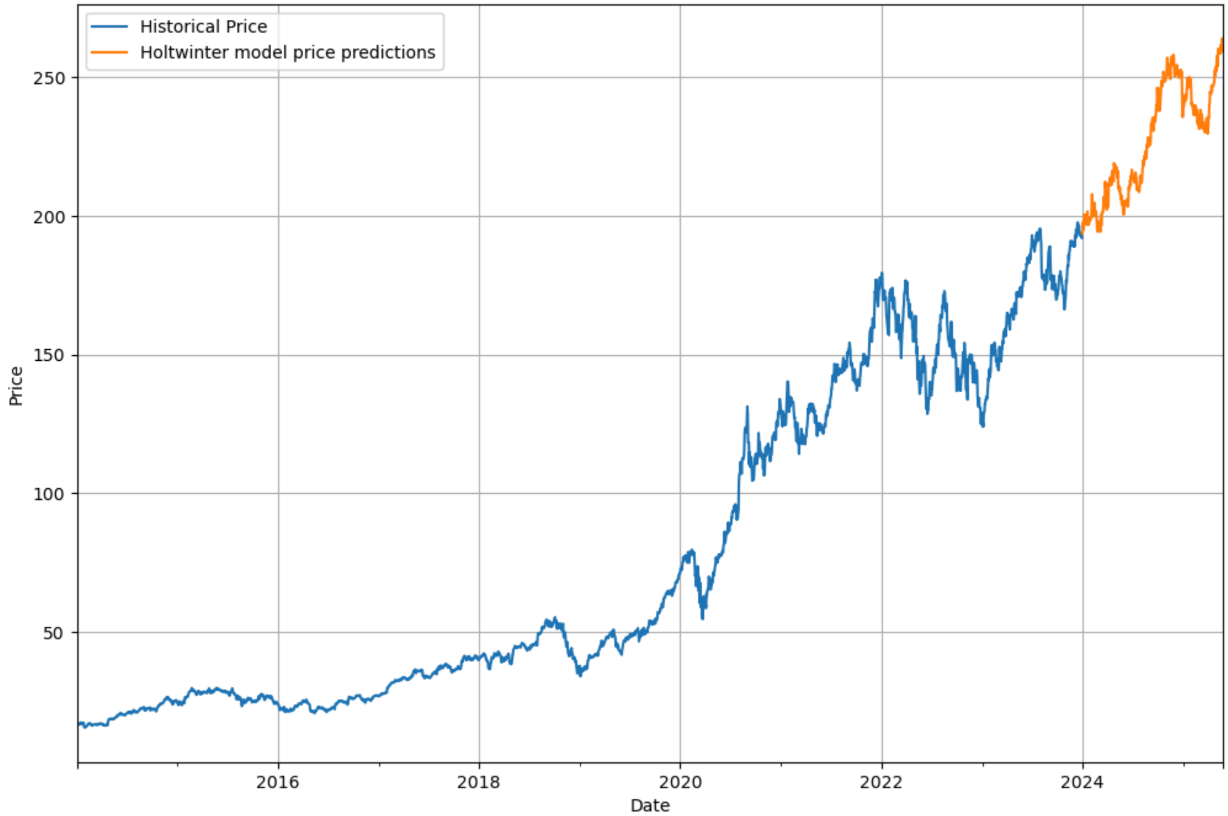
```python
# Calculate root mean squared error (RMSE)
rmse = np.sqrt(mean_squared_error(y_true, y_pred))

# Print the RMSE
print(f"RMSE (Model1 - Holt Winter): {rmse}")


# Calculate mean absolute error (MAE)
mae = mean_absolute_error(y_true, y_pred)

# Print the MAE
print(f"MAE (Model1 - Holt Winter): {mae}")



# Calculate mean absolute error percentage (MAPE)

mape_value = mape(y_true, y_pred)
print(f"MAPE: {mape_value:.2f}%")

# Directional Accuracy

directional_acc = directional_accuracy(y_true, y_pred)
print(f"Directional Accuracy: {directional_acc:.2f}%")

# Print the mean of test data prices
print(f"Mean of Test Data Prices: {test_data['price'].mean()}")

# Print the mean of predictions
print(f"Mean of model1 Predictions: {model1_predictions.mean()}")
```

```
RMSE (Model1 - Holt Winter): 31.50248958250686
MAE (Model1 - Holt Winter): 28.303819831764347
MAPE: 17.77%
Directional Accuracy: 48.00%
Mean of Test Data Prices: 159.9142299371263
Mean of model1 Predictions: 172.7274482286411
```

Retrain the model on the entire historical price data and predict future prices with the final model

In [119…

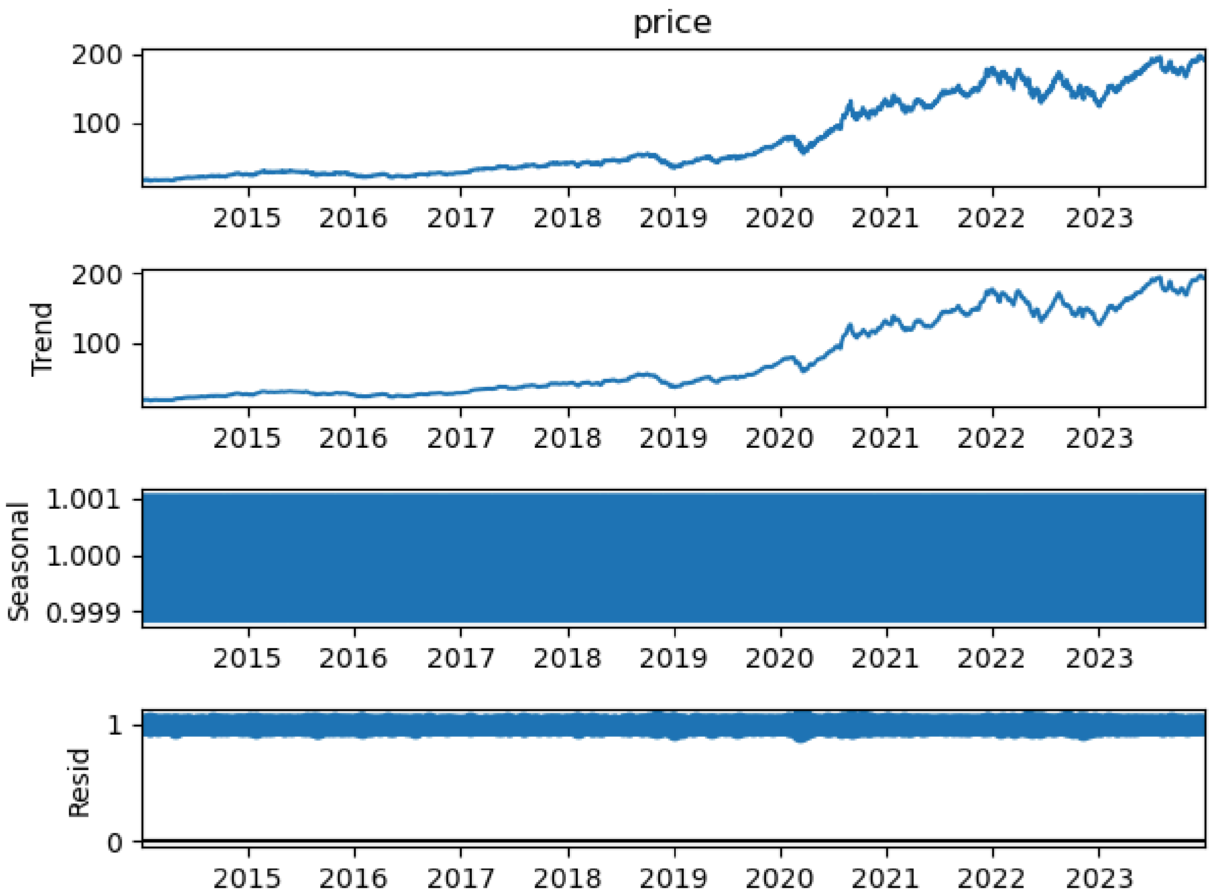
```python
final_model = ExponentialSmoothing(df_aapl_price_daily['price'],
                                   trend='mul',
                                   seasonal='mul',
                                   seasonal_periods=365).fit()

forecast_predictions = final_model.forecast(365)

df_aapl_price_daily['price'].plot(legend=True,label='Historical Price',figsize=(12,8))

forecast_predictions.plot(legend=True,label='Holtwinter model price predictions')

plt.xlabel('Date')
plt.ylabel('Price')
plt.grid(True);
```



ARIMA Models

In [120…

```
# Seasonal Decompose - To see the effect of trend and seasonality on the data and deci

from statsmodels.tsa.seasonal import seasonal_decompose

result = seasonal_decompose(df_aapl_price_daily['price'], model='mul')
result.plot();

# The seasonal component ranges from 0.999 to 1.001, which indicates very small variat
```



Use Auto_Arima to perform grid search to determine the best form of ARIMA Model

In [121…

```
from statsmodels.tsa.arima.model import ARIMA

from statsmodels.tsa.statespace.sarimax import SARIMAX

from pmdarima import auto_arima

# Determine the ARIMA Orders using pmdarima.auto_arima

auto_arima(df_aapl_price_daily['price'],seasonal=False).summary()
```

Out[121]:

SARIMAX Results

Dep. Variable:	y	**No. Observations:**	2607
Model:	SARIMAX(0, 1, 2)	**Log Likelihood**	-5035.470
Date:	Thu, 04 Jul 2024	**AIC**	10078.941
Time:	22:30:55	**BIC**	10102.403
Sample:	01-02-2014	**HQIC**	10087.441
	- 12-29-2023		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
intercept	0.0671	0.031	2.185	0.029	0.007	0.127
ma.L1	-0.0443	0.011	-4.023	0.000	-0.066	-0.023
ma.L2	-0.0270	0.012	-2.190	0.029	-0.051	-0.003
sigma2	2.7917	0.036	77.875	0.000	2.721	2.862

Ljung-Box (L1) (Q):	0.00	**Jarque-Bera (JB):**	6260.79
Prob(Q):	0.99	**Prob(JB):**	0.00
Heteroskedasticity (H):	55.43	**Skew:**	-0.06
Prob(H) (two-sided):	0.00	**Kurtosis:**	10.59

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

Model 2 - SARIMAX of Order(0,1,2)

In [122…

```
model2 = SARIMAX(train_data['price'], order=(0, 1, 2), seasonal_order=(0, 0, 0, 0), tr

# Fit the model
results_model2 = model2.fit()

# Print the summary of the model
print(results_model2.summary())
```

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                  price   No. Observations:                 1955
Model:               SARIMAX(0, 1, 2)   Log Likelihood               -3066.110
Date:                Thu, 04 Jul 2024   AIC                           6140.221
Time:                        22:30:55   BIC                           6162.531
Sample:                    01-02-2014   HQIC                          6148.423
                         - 06-30-2021
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
intercept      0.0601      0.024      2.554      0.011       0.014       0.106
ma.L1         -0.1196      0.010    -11.404      0.000      -0.140      -0.099
ma.L2          0.0112      0.010      1.143      0.253      -0.008       0.030
sigma2         1.3504      0.015     91.895      0.000       1.322       1.379
===================================================================================
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):             19404.97
Prob(Q):                              1.00   Prob(JB):                         0.00
Heteroskedasticity (H):              25.78   Skew:                            -0.15
Prob(H) (two-sided):                  0.00   Kurtosis:                        18.44
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```

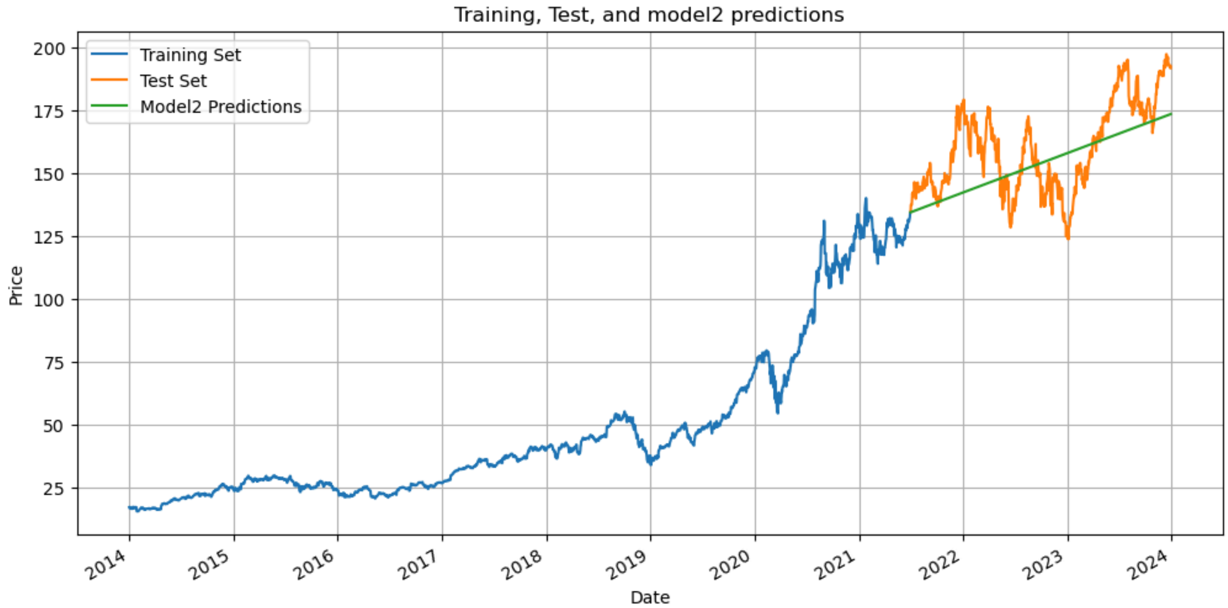
In [123…

```
# Obtain predicted values

start=len(train_data)
end=len(train_data)+len(test_data)-1
model2_predictions = results_model2.predict(start=start, end=end,type='levels').rename
print(model2_predictions)
```

```
2021-07-01    134.648511
2021-07-02    134.716835
2021-07-05    134.776904
2021-07-06    134.836973
2021-07-07    134.897042
                 ...
2023-12-25    173.521529
2023-12-26    173.581599
2023-12-27    173.641668
2023-12-28    173.701737
2023-12-29    173.761806
Freq: B, Name: Model 2 SARIMAX Predictions, Length: 652, dtype: float64
```

In [124…

```
# Plot predictions against known price from historical data

plt.figure(figsize=(12, 6))
plt.plot(train_data['price'], label='Training Set')
plt.plot(test_data['price'], label='Test Set')

model2_predictions.plot(legend=True, label='Model2 Predictions')

plt.title('Training, Test, and model2 predictions')
plt.xlabel('Date')
plt.ylabel('Price')
plt.legend()
plt.grid(True)
plt.show();
```



Statiscal Quantitative Evaluation of Model 2

In [126…

```
from statsmodels.tools.eval_measures import rmse, meanabs

y_true = test_data['price'].values
y_pred = model2_predictions

# Calculate RMSE
errors_model2_sarimax = rmse(y_true, y_pred)

# Print the RMSE
print(f"RMSE (Model2): {errors_model2_sarimax}")

# Calculate MAE
mae_value = meanabs(y_true, y_pred)
print(f"MAE (Model2): {mae_value}")

# Calculate mean absolute error percentage (MAPE)
mape_value = mape(y_true, y_pred)
print(f"MAPE (Model2): {mape_value:.2f}%")

# Directional Accuracy
directional_acc = directional_accuracy(y_true, y_pred)
print(f"Directional Accuracy (Model2): {directional_acc:.2f}%")


# Print the mean of test data prices
print(f"Mean of Test Data: {test_data['price'].mean()}")

# Print the mean of predictions
print(f"Mean of model2 Predictions: {model2_predictions.mean()}")
```

```
RMSE (Model2): 15.634697005271583
MAE (Model2): 13.041036836304746
MAPE (Model2): 8.12%
Directional Accuracy (Model2): 50.46%
Mean of Test Data: 159.9142299371263
Mean of model2 Predictions: 154.20927322780713
```

Model 3 - SARIMAX of Order(0,1,2) & Seasonal order(1,1,1,252)

In [28]:
```
model3 = SARIMAX(train_data['price'], order=(0, 1, 2), seasonal_order=(1, 1, 1, 252))

# Fit a SARIMAX model
results_model3 = model3.fit()

# Print the summary of the model3
print(results_model3.summary())
```

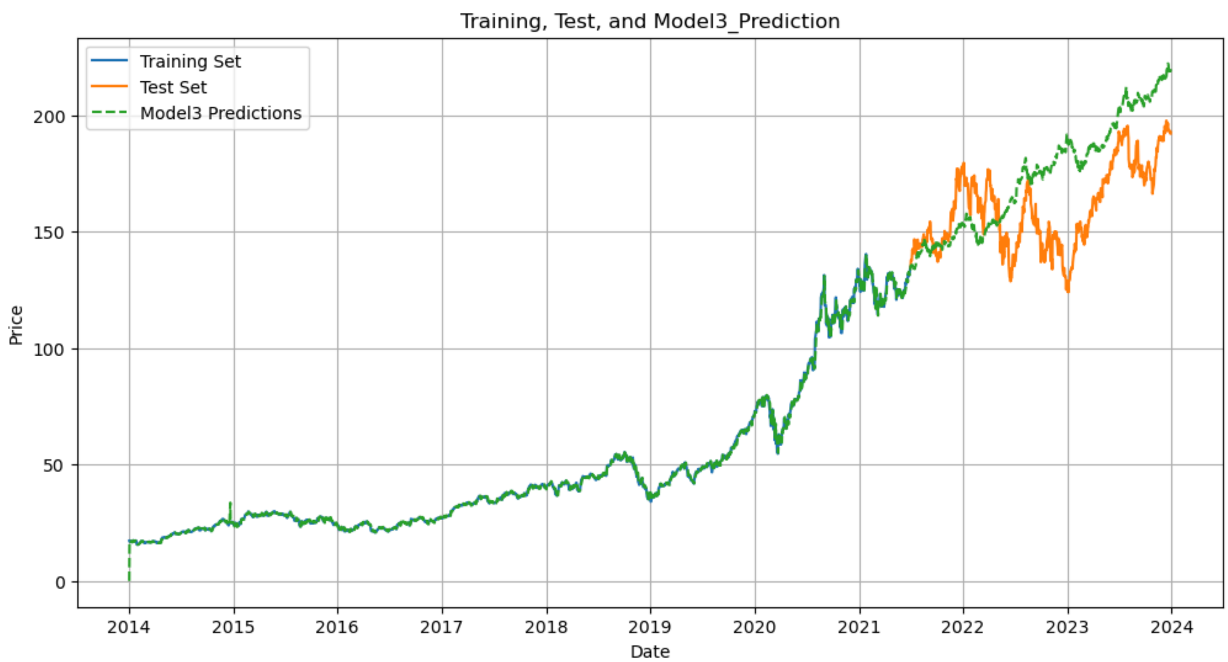
```
                                     SARIMAX Results
=====================================================================================
========
Dep. Variable:                                 price   No. Observations:
1955
Model:             SARIMAX(0, 1, 2)x(1, 1, [1], 252)   Log Likelihood               -
2906.400
Date:                               Thu, 04 Jul 2024   AIC
5822.799
Time:                                       20:13:27   BIC
5849.997
Sample:                                   01-02-2014   HQIC
5832.867
                                        - 06-30-2021
Covariance Type:                                 opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ma.L1         -0.1284      0.012    -10.634      0.000      -0.152      -0.105
ma.L2         -0.0119      0.012     -1.019      0.308      -0.035       0.011
ar.S.L252     -0.2077      0.065     -3.187      0.001      -0.335      -0.080
ma.S.L252     -0.5043      0.066     -7.654      0.000      -0.634      -0.375
sigma2         1.6453      0.022     73.704      0.000       1.602       1.689
===================================================================================
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):             12418.79
Prob(Q):                              0.96   Prob(JB):                         0.00
Heteroskedasticity (H):              26.69   Skew:                            -0.12
Prob(H) (two-sided):                  0.00   Kurtosis:                        16.23
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```

In [29]:
```
# Obtain predicted values
start=len(train_data)
end=len(train_data)+len(test_data)-1

# Make predictions
model3_predictions = results_model3.predict(start=start_date, end=end_date, typ='level


print(model3_predictions)
```

```
2014-01-02      0.000000
2014-01-03     17.273221
2014-01-06     16.893804
2014-01-07     16.985929
2014-01-08     16.864449
                  ...
2023-12-25    218.117059
2023-12-26    218.890372
2023-12-27    219.269520
2023-12-28    218.770065
2023-12-29    219.740258
Freq: B, Name: Model3 SARIMAX PREDICTIONS, Length: 2607, dtype: float64
```

In [30]:

```python
plt.figure(figsize=(12, 6))
plt.plot(train_data['price'], label='Training Set')
plt.plot(test_data['price'], label='Test Set')
plt.plot(model3_predictions, label='Model3 Predictions', linestyle='--')

plt.title('Training, Test, and Model3_Prediction')
plt.xlabel('Date')
plt.ylabel('Price')
plt.legend()
plt.grid(True)
plt.show()
```



Statiscal Quantitative Evaluation of Model 3

In [131…

```python
from statsmodels.tools.eval_measures import rmse, meanabs

y_true = test_data['price'].values
y_pred = model3_predictions

# Calculate RMSE
errors_model2_sarimax = rmse(y_true, y_pred)

# Print the RMSE
print(f"RMSE (Model3_SARIMAX): {errors_model2_sarimax}")
```

```python
# Calculate MAE
mae_value = meanabs(y_true, y_pred)
print(f"MAE (Model3_SARIMAX): {mae_value}")

# Calculate mean absolute error percentage (MAPE)
mape_value = mape(y_true, y_pred)
print(f"MAPE (Model3_SARIMAX): {mape_value:.2f}%")

# Directional Accuracy
directional_acc = directional_accuracy(y_true, y_pred)
print(f"Directional Accuracy (Model3_SARIMAX): {directional_acc:.2f}%")


# Print the mean of test data prices
print(f"Mean of Test Data Prices: {test_data['price'].mean()}")

# Print the mean of predictions
print(f"Mean of model3_Predictions: {model3_predictions.mean()}")
```

```
RMSE (Model3_SARIMAX): 24.692340934314192
MAE (Model3_SARIMAX): 20.90973741354183
MAPE (Model3_SARIMAX): 13.41%
Directional Accuracy (Model3_SARIMAX): 50.46%
Mean of Test Data Prices: 159.9142299371263
Mean of model3_Predictions: 174.25029874414236
```