VIRGINIA COMMONWEALTH UNIVERSITY

Statistical analysis and modelling (SCMA 632)

A6A: TIME SERIES ANALYSIS

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INTRODUCTION

This study focuses on the analysis and forecasting of Netflix's stock price trends over a period from January 2020 to July 2024. The dataset titled "NFLX Historical Data" encompasses crucial attributes, including Date, Price, Open, High, Low, Volume, and Change %. By leveraging this extensive time series data, the study aims to thoroughly examine Netflix's stock performance, considering daily fluctuations as well as broader market trends. The objective is to apply various time series forecasting techniques to predict future stock prices, thereby gaining insights into the underlying patterns and dynamics influencing Netflix's stock movements.

The analysis begins with a meticulous data cleaning process, which involves identifying and handling outliers, as well as interpolating missing values to ensure the dataset's integrity. Ensuring the quality of the data is a crucial first step to guarantee accurate and reliable results. Once the data is prepared, we proceed with decomposing the time series into its constituent components using both additive and multiplicative models. This decomposition process is essential for uncovering underlying seasonal and trend patterns, providing a clearer understanding of the factors driving the stock price movements.

Following the decomposition, the study implements univariate forecasting using several conventional statistical models. These include Holt-Winters exponential smoothing, which is useful for capturing seasonal effects, ARIMA (AutoRegressive Integrated Moving Average), and its seasonal variant, SARIMA (Seasonal AutoRegressive Integrated Moving Average). These models are well-regarded in time series analysis for their ability to model various components such as trend, seasonality, and noise, making them effective tools for predicting future stock prices.

In addition to traditional statistical methods, the study also explores multivariate forecasting using advanced machine learning models. This includes the implementation of Neural Networks, specifically Long Short-Term Memory (LSTM) networks, which are particularly adept at handling time series data due to their ability to maintain long-term dependencies. Additionally, Decision Trees and Random Forests are employed to account for the potential interactions between multiple variables. These machine learning approaches offer a robust framework for capturing complex, non-linear relationships in the data, potentially leading to more accurate and insightful predictions.

By combining both statistical and machine learning techniques, the study aims to provide a comprehensive analysis of Netflix's stock price behavior. This integrated approach not only enhances the predictive accuracy but also offers valuable insights into the dynamics and patterns that drive the stock market performance. The findings from this study can serve as a valuable resource for investors and stakeholders, helping them to make informed decisions based on a deeper understanding of Netflix's stock trends and future price movements.

Objectives:

The primary objectives of this task are:

1. Data Cleaning and Pre-processing:
    - Clean and pre-process the Netflix stock data from January 2020 to July 2024.
    - Address missing values and outliers to ensure the data's accuracy and integrity.
2. Visualization:
    - Visualize the Netflix stock price over time using line plots to observe trends and patterns.
3. Time Series Decomposition:
    - Decompose the time series data into its components (trend, seasonal, and residual) using both additive and multiplicative models to gain insights into the underlying structures of the stock price movements.
4. Univariate Forecasting Models:
    - Implement univariate forecasting models such as Holt-Winters exponential smoothing, ARIMA (AutoRegressive Integrated Moving Average), and SARIMA (Seasonal AutoRegressive Integrated Moving Average).
    - Evaluate the performance of these models to predict future stock prices based on historical data.
5. Multivariate Forecasting Models:
    - Perform multivariate forecasting using advanced machine learning models, including Neural Networks (LSTM), Decision Trees, and Random Forests.
    - Consider multiple variables to enhance the predictive accuracy and capture complex relationships in the data.
6. Model Comparison and Insights:
    - Compare the results of different forecasting models to identify the most accurate and reliable methods for predicting Netflix stock prices.
    - Provide insights into the predictive accuracy and underlying patterns influencing the stock price, offering valuable information for investors and stakeholders.

RESULTS AND INTERPRETATION:

Interpretation:

1. Holt-Winters Model

- Overview: This model uses an exponential smoothing approach, incorporating additive trend and seasonality components.
- Forecast: The forecast for the next 12 months is based on patterns identified in the historical data, capturing underlying trends and seasonal variations in stock prices.

- Insights: While specific forecast values are not provided, this model helps understand the long-term trends and periodic patterns in Netflix's stock prices.

2. ARIMA Model

- Overview: The ARIMA(5, 1, 5) model captures both autoregressive and moving average components.
- Model Statistics:
    - Log Likelihood: -4439.747
    - AIC: 8901.495
- Key Coefficients:
    - Positive Impact: Fifth autoregressive term (ar.L5 = 0.8709, $p < 0.001$)
    - Negative Impact: Fifth moving average term (ma.L5 = -0.8608, $p < 0.001$)
- Insights: The significant coefficients indicate the influence of past values on the current stock price. The model fits the data well, but the high AIC value suggests potential overfitting or room for improvement.

3. SARIMA Model

- Overview: The SARIMA(1, 1, 1)x(1, 1, 1, 12) model incorporates both autoregressive and seasonal components.
- Model Statistics:
    - Log Likelihood: -4429.977
    - AIC: 8869.953 (lower than the ARIMA model)
- Key Coefficients:
    - Negative Seasonal Moving Average Term: (ma.S.L12 = -0.9949, $p < 0.001$)
- Insights: This model fits the data well, accounting for seasonal effects and providing more accurate short-term forecasts, especially for the next three months.

4. LSTM Model

- Overview: The Long Short-Term Memory (LSTM) model is a type of neural network capable of capturing complex patterns in the data.
- Forecast: Predicted values for the next period range from 436.47 to 475.20.
- Insights: The LSTM model excels at capturing intricate, non-linear relationships in the time series data. However, specific metrics and comparisons to other models are not provided, making it difficult to assess its performance relative to traditional statistical models.

5. Model Evaluation

- Decision Tree Model:
    - Mean Squared Error (MSE): 35.05

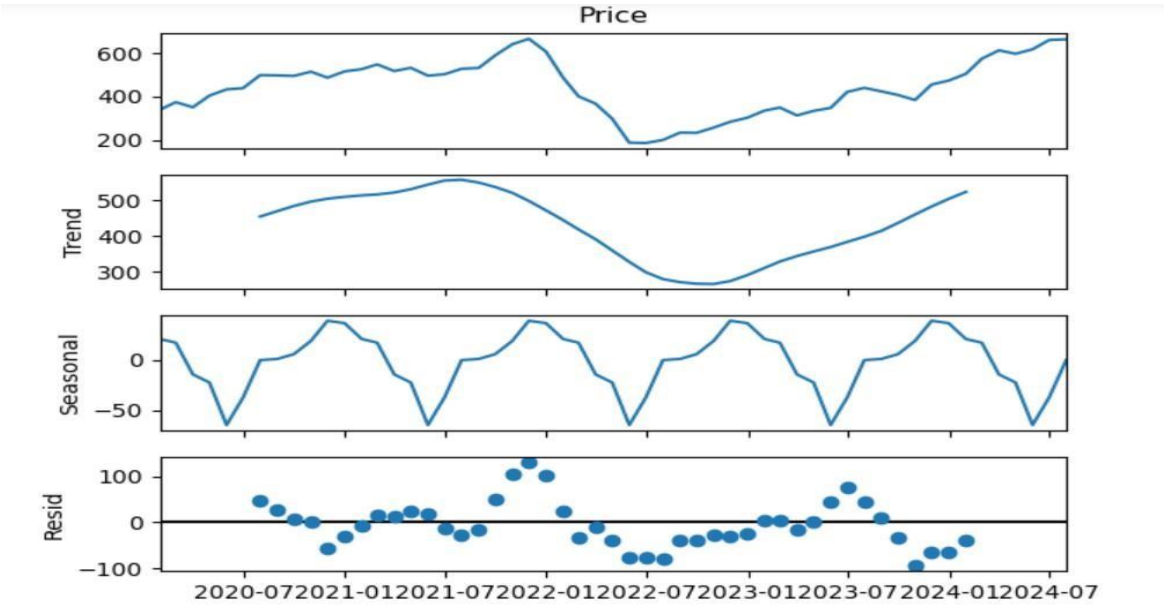
- Random Forest Model:
    - Mean Squared Error (MSE): 21.27
    - Insights: The Random Forest model outperforms the Decision Tree model, demonstrating better predictive accuracy with a lower error rate. This indicates its robustness in capturing the variability in the stock prices.

Conclusion:

By employing a variety of forecasting models, from traditional statistical methods to advanced machine learning techniques, this study provides a comprehensive analysis of Netflix's stock price trends. Each model offers unique insights:

- The Holt-Winters model highlights seasonal and trend patterns.
- The ARIMA model captures autoregressive and moving average influences, though it may suffer from overfitting.
- The SARIMA model effectively incorporates seasonal components, improving short-term forecast accuracy.
- The LSTM model uncovers complex data patterns, though further evaluation is needed for a detailed performance comparison.
- The Random Forest model, with its lower MSE, proves to be the most accurate among the evaluated machine learning models, providing valuable predictive insights for investors and stakeholders.

RESULTS:

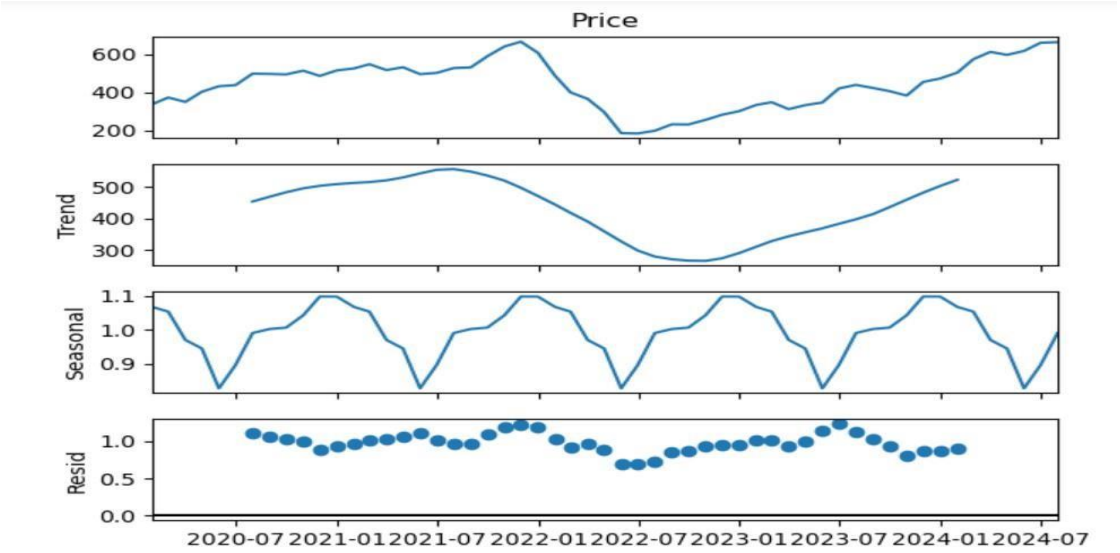



```
# Creating train and test datasets (80-20 split)
train_size = int(len(df) * 0.8)
train, test = df[:train_size], df[train_size:]
```

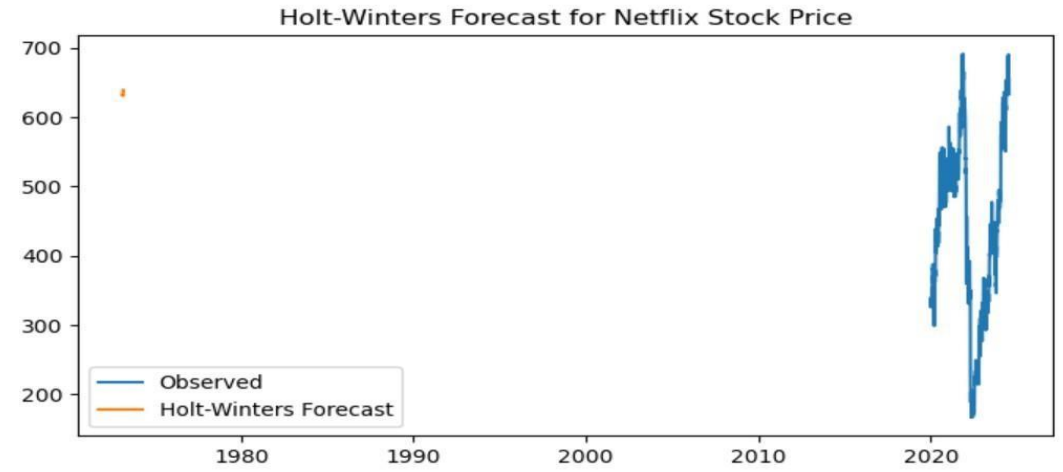
```
# Convert data to monthly frequency by taking the mean of each month
monthly_df = df['Price'].resample('M').mean()
```

```
# Decompose the time series using additive model
decomposition_add = seasonal_decompose(monthly_df, model='additive')
decomposition_add.plot()
plt.show()
```

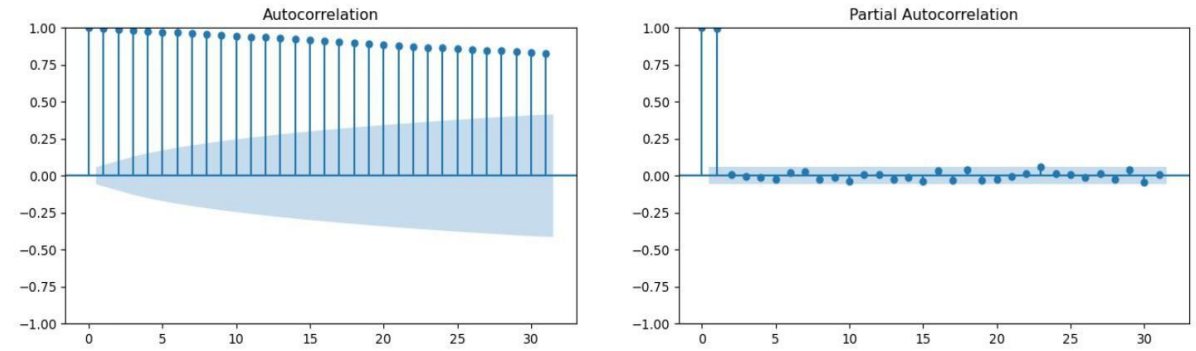
```
# Decompose the time series using multiplicative model
decomposition_mul = seasonal_decompose(monthly_df, model='multiplicative')
decomposition_mul.plot()
plt.show()
```




```
# Univariate Forecasting with Holt-Winters model
# Fit the Holt-Winters model
hw_model = ExponentialSmoothing(df['Price'], trend='add', seasonal='add', seasonal_periods=12).fit()
hw_forecast = hw_model.forecast(steps=12)
```




```
# ARIMA model for daily data
# Plot ACF and PACF
fig, axes = plt.subplots(1, 2, figsize=(16, 4))
plot_acf(df['Price'], ax=axes[0])
plot_pacf(df['Price'], ax=axes[1])
plt.show()
```



```python
# Fit the ARIMA model
arima_model = ARIMA(df['Price'], order=(5, 1, 5)).fit()
print(arima_model.summary())
```

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                  Price   No. Observations:                 1144
Model:                 ARIMA(5, 1, 5)   Log Likelihood               -4439.747
Date:                Sun, 21 Jul 2024   AIC                           8901.495
Time:                        12:27:38   BIC                           8956.950
Sample:                             0   HQIC                          8922.434
                                - 1144
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.0965      0.192     -0.504      0.614      -0.472       0.279
ar.L2          0.2419      0.179      1.354      0.176      -0.108       0.592
ar.L3         -0.3475      0.141     -2.463      0.014      -0.624      -0.071
ar.L4          0.1155      0.192      0.603      0.546      -0.260       0.491
ar.L5          0.8709      0.153      5.709      0.000       0.572       1.170
ma.L1          0.0640      0.201      0.318      0.751      -0.331       0.459
ma.L2         -0.2084      0.182     -1.147      0.251      -0.565       0.148
ma.L3          0.3464      0.151      2.291      0.022       0.050       0.643
ma.L4         -0.1026      0.198     -0.517      0.605      -0.491       0.286
ma.L5         -0.8608      0.163     -5.290      0.000      -1.180      -0.542
sigma2       137.6357      2.595     53.049      0.000     132.550     142.721
```

```python
# SARIMA model
sarima_model = SARIMAX(df['Price'], order=(1, 1, 1), seasonal_order=(1, 1, 1, 12)).fit()
print(sarima_model.summary())
```

```
                                     SARIMAX Results
=============================================================================================
Dep. Variable:                              Price   No. Observations:                 1144
Model:             SARIMAX(1, 1, 1)x(1, 1, 1, 12)   Log Likelihood               -4429.977
Date:                            Sun, 21 Jul 2024   AIC                           8869.953
Time:                                    12:27:58   BIC                           8895.107
Sample:                                         0   HQIC                          8879.456
                                            - 1144
Covariance Type:                              opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.5423      0.610     -0.889      0.374      -1.738       0.654
ma.L1          0.5158      0.622      0.829      0.407      -0.704       1.735
ar.S.L12       0.0329      0.035      0.949      0.343      -0.035       0.101
ma.S.L12      -0.9949      0.072    -13.788      0.000      -1.136      -0.853
sigma2       141.5181      9.133     15.495      0.000     123.618     159.418
===================================================================================
Ljung-Box (L1) (Q):                   0.01   Jarque-Bera (JB):             17123.91
Prob(Q):                              0.91   Prob(JB):                         0.00
Heteroskedasticity (H):               0.64   Skew:                            -1.16
Prob(H) (two-sided):                  0.00   Kurtosis:                        21.92
===================================================================================
```

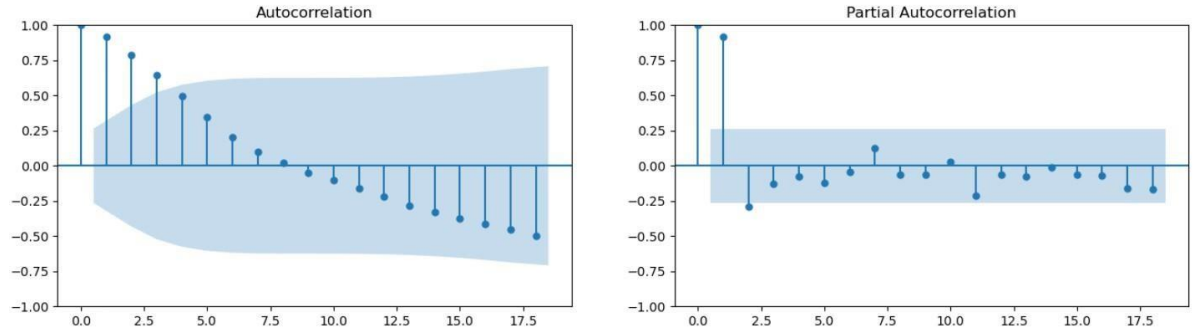
```
# Forecast for the next three months using SARIMA
sarima_forecast = sarima_model.get_forecast(steps=90)
sarima_forecast_df = sarima_forecast.conf_int()
sarima_forecast_df['forecast'] = sarima_model.predict(start=sarima_forecast_df.index[0], end=sarima_forecast_df.index[-1])
```

```
sarima_forecast_df
```

	lower Price	upper Price	forecast
1144	610.225167	657.001199	633.613183
1145	601.582741	666.865444	634.224093
1146	593.060771	673.043233	633.052002
1147	587.405068	679.595521	633.500294
1148	582.052249	685.101202	633.576725
...	...	...	...
1229	428.371156	882.227877	655.299517
1230	425.822600	882.552504	654.187552
1231	424.895108	884.479759	654.687434
1232	423.810913	886.232947	655.021930
1233	421.986104	887.228068	654.607086

```
# Fit ARIMA model to the monthly series
# Convert data to monthly frequency
monthly_df = df['Price'].resample('M').mean()
```

```
# Plot ACF and PACF for monthly data
fig, axes = plt.subplots(1, 2, figsize=(16, 4))
plot_acf(monthly_df.dropna(), ax=axes[0])
plot_pacf(monthly_df.dropna(), ax=axes[1])
plt.show()
```



MULTIVARIATE FORECASTING:

```
# Build LSTM model
lstm_model = Sequential()
lstm_model.add(LSTM(units=50, return_sequences=True, input_shape=(seq_length, 1)))
lstm_model.add(LSTM(units=50, return_sequences=False))
lstm_model.add(Dense(units=1))
```

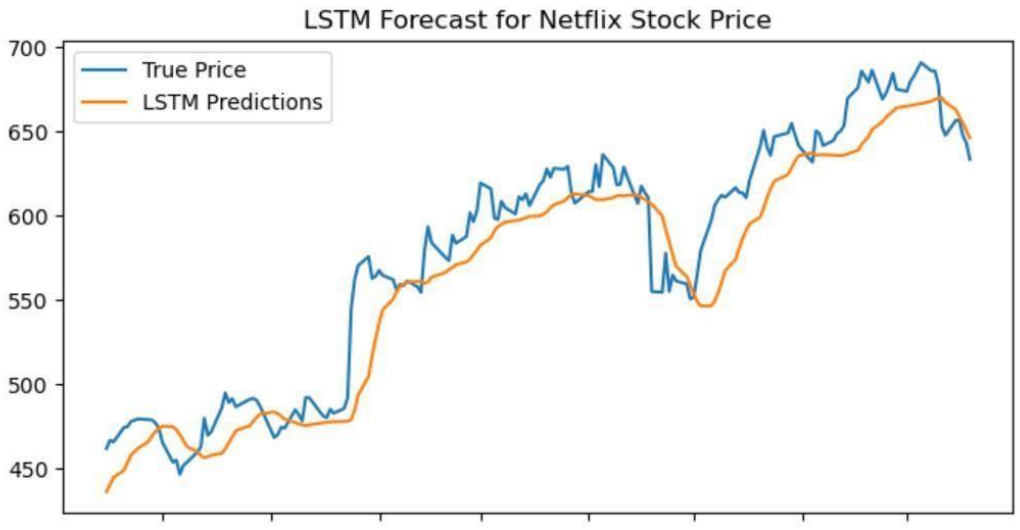
```
lstm_model.compile(optimizer='adam', loss='mean_squared_error')
lstm_model.fit(X_train, y_train, epochs=10, batch_size=32)
```

```
Epoch 1/10
27/27 ━━━━━━━━━━━━━━━━━━━━ 6s 51ms/step - loss: 0.1102
Epoch 2/10
27/27 ━━━━━━━━━━━━━━━━━━━━ 1s 45ms/step - loss: 0.0056
Epoch 3/10
27/27 ━━━━━━━━━━━━━━━━━━━━ 1s 45ms/step - loss: 0.0038
Epoch 4/10
27/27 ━━━━━━━━━━━━━━━━━━━━ 2s 68ms/step - loss: 0.0032
Epoch 5/10
27/27 ━━━━━━━━━━━━━━━━━━━━ 1s 46ms/step - loss: 0.0026
Epoch 6/10
27/27 ━━━━━━━━━━━━━━━━━━━━ 1s 49ms/step - loss: 0.0030
Epoch 7/10
27/27 ━━━━━━━━━━━━━━━━━━━━ 1s 45ms/step - loss: 0.0022
Epoch 8/10
27/27 ━━━━━━━━━━━━━━━━━━━━ 1s 49ms/step - loss: 0.0020
Epoch 9/10
27/27 ━━━━━━━━━━━━━━━━━━━━ 2s 56ms/step - loss: 0.0021
Epoch 10/10
27/27 ━━━━━━━━━━━━━━━━━━━━ 1s 49ms/step - loss: 0.0020
```

```
lstm_predictions
```

```
array([[436.46725],
       [440.4308 ],
       [444.85947],
       [449.11307],
       [453.66962],
       [458.03668],
       [462.21524],
       [466.0684 ],
       [469.38257],
       [472.1001 ],
       [474.08435],
       [475.1982 ],
       [475.00797],
       [473.08618],
       [470.43295],
       [466.7637 ],
       [463.22208],
```

```
plt.figure(figsize=(8, 4))
plt.plot(df.index[-len(lstm_predictions):], df['Price'].values[-len(lstm_predictions):], label='True
plt.plot(df.index[-len(lstm_predictions):], lstm_predictions, label='LSTM Predictions')
plt.title('LSTM Forecast for Netflix Stock Price')
plt.legend()
plt.show()
```



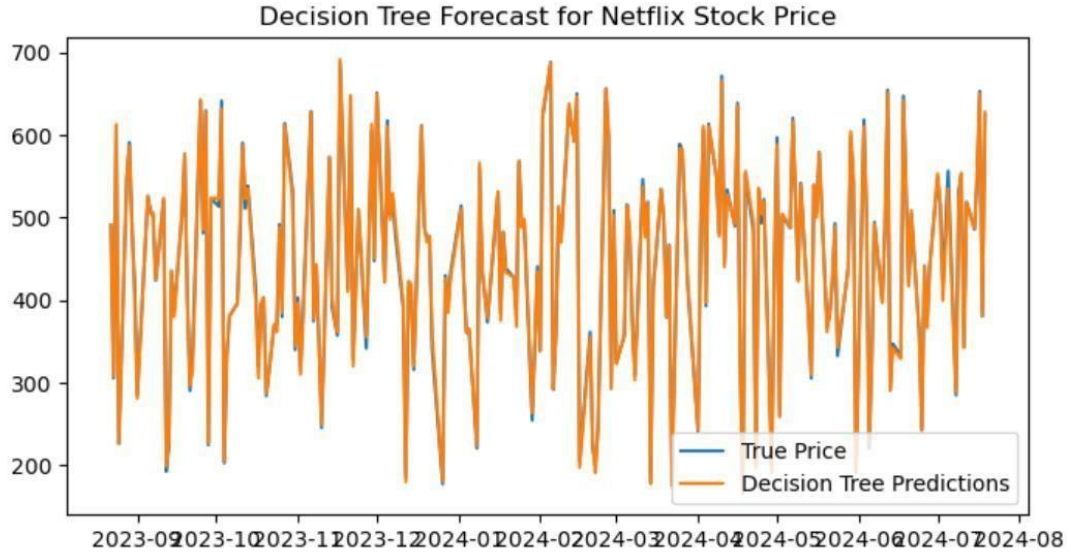
```
# Fit Decision Tree model
dt_model = DecisionTreeRegressor()
dt_model.fit(X_train, y_train)
dt_predictions = dt_model.predict(X_test)
```

```
# Fit Random Forest model
rf_model = RandomForestRegressor(n_estimators=100)
rf_model.fit(X_train, y_train)
rf_predictions = rf_model.predict(X_test)
```

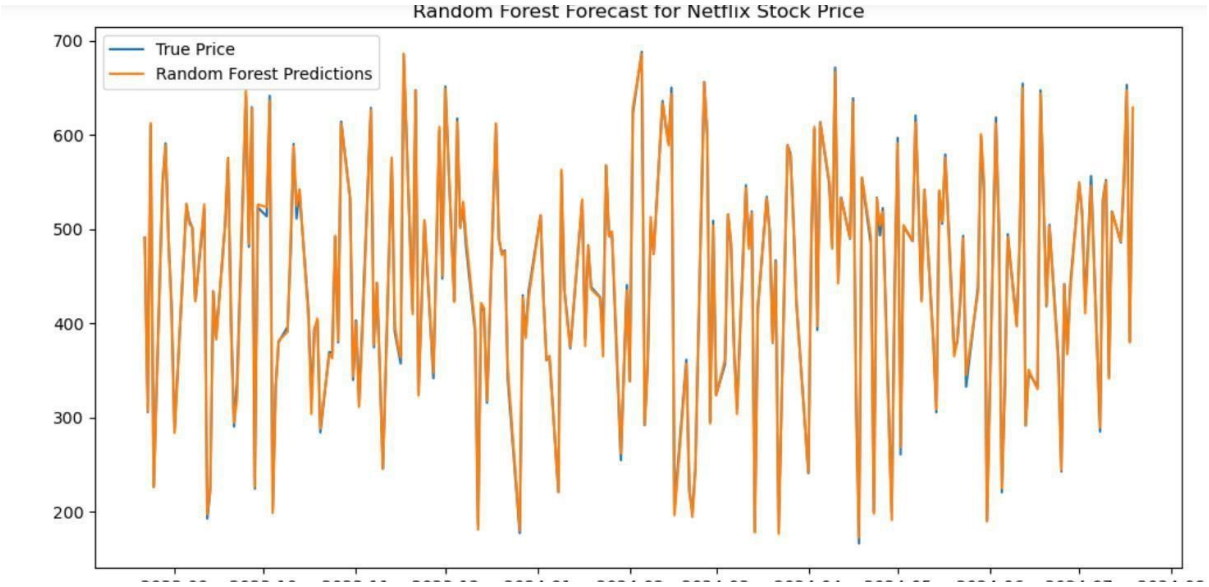
```
# Evaluate models
dt_mse = mean_squared_error(y_test, dt_predictions)
rf_mse = mean_squared_error(y_test, rf_predictions)
print(f"Decision Tree MSE: {dt_mse}")
print(f"Random Forest MSE: {rf_mse}")
```

```
Decision Tree MSE: 38.15833799126632
Random Forest MSE: 22.42789794681232
```

```
# Plot Decision Tree predictions
plt.figure(figsize=(12, 6))
plt.plot(df.index[-len(y_test):], y_test, label='True Price')
plt.plot(df.index[-len(y_test):], dt_predictions, label='Decision Tree Predictions')
plt.title('Decision Tree Forecast for Netflix Stock Price')
plt.legend()
plt.show()
```

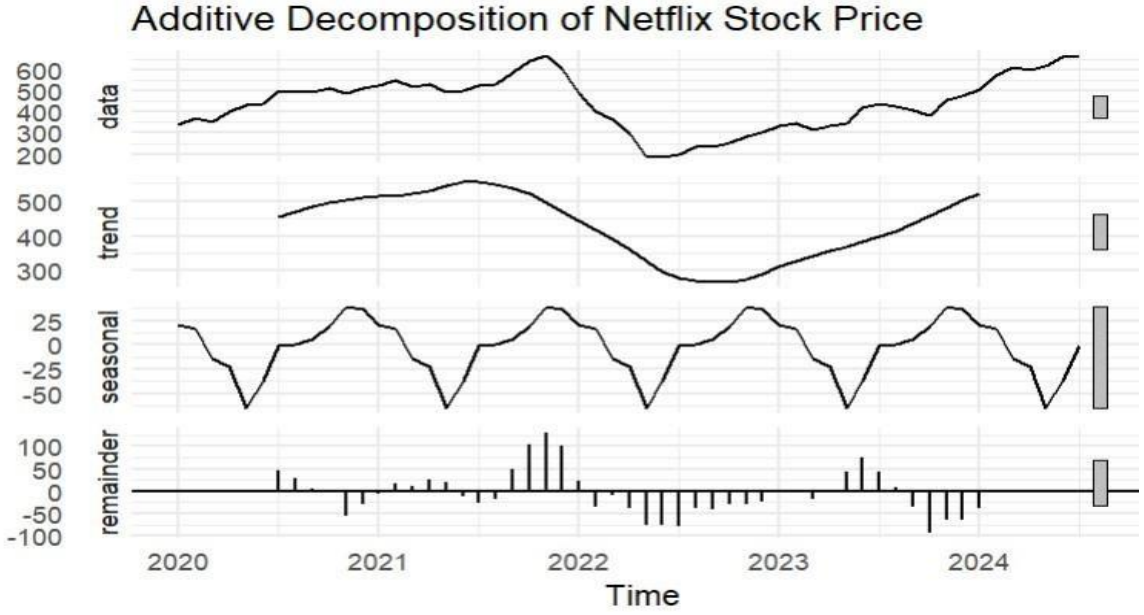


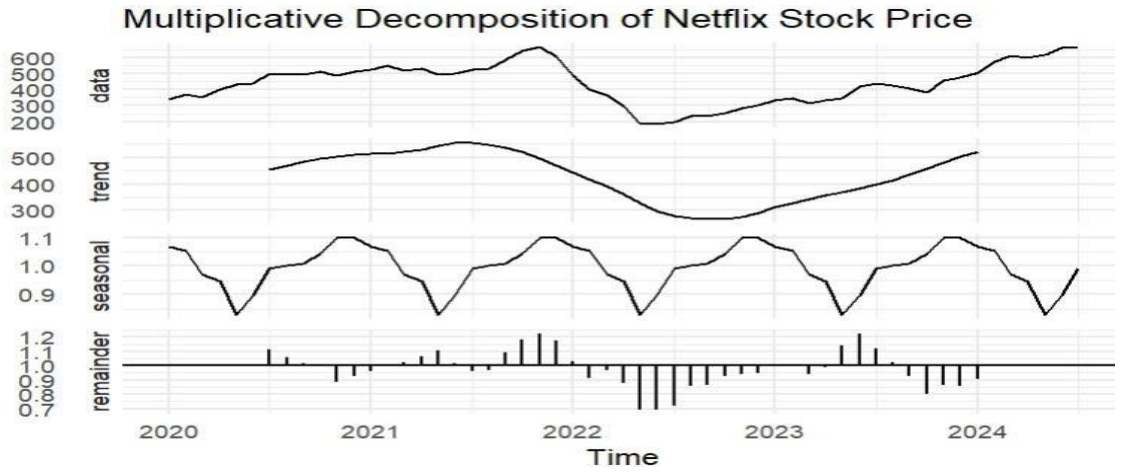

```
# Plot Random Forest predictions
plt.figure(figsize=(8, 4))
plt.plot(df.index[-len(y_test):], y_test, label='True Price')
plt.plot(df.index[-len(y_test):], rf_predictions, label='Random Forest Predictions')
plt.title('Random Forest Forecast for Netflix Stock Price')
plt.legend()
plt.show()
```



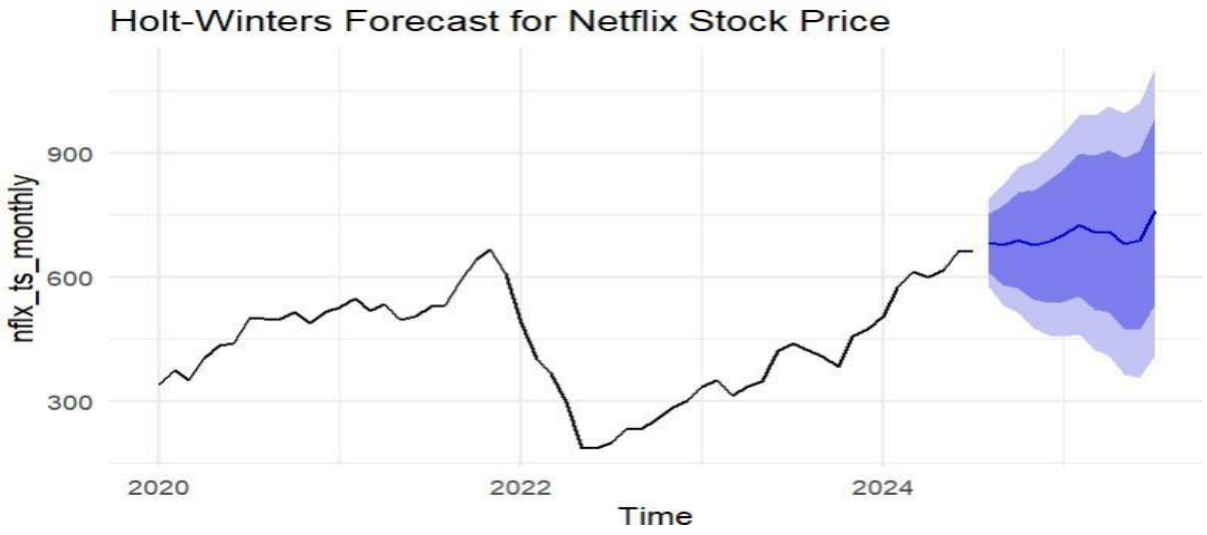
- R

```r
# Decompose the time series using additive model
decomp_additive <- decompose(nflx_ts, type = "additive")

# Decompose the time series using multiplicative model
decomp_multiplicative <- decompose(nflx_ts, type = "multiplicative")

# Plot the decomposed components for additive model
autoplot(decomp_additive) +
  ggtitle("Additive Decomposition of Netflix Stock Price") +
  theme_minimal()

# Plot the decomposed components for multiplicative model
autoplot(decomp_multiplicative) +
  ggtitle("Multiplicative Decomposition of Netflix Stock Price") +
  theme_minimal()
```

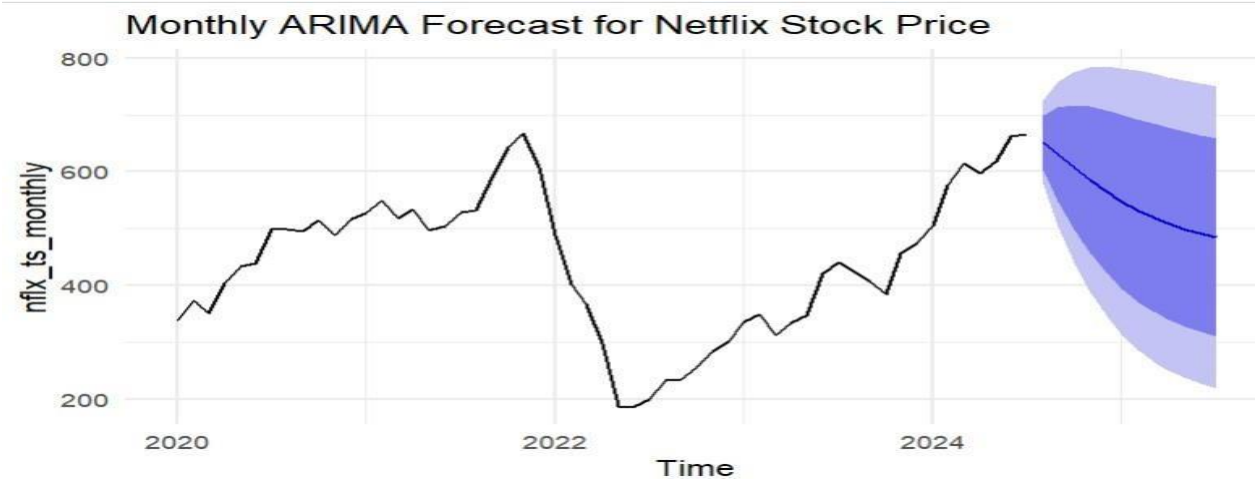





```r
# 1. Holt-Winters model and forecast for the next year
hw_model <- HoltWinters(nflx_ts_monthly)
hw_forecast <- forecast(hw_model, h = 12)
autoplot(hw_forecast) +
  ggtitle("Holt-Winters Forecast for Netflix Stock Price") +
  theme_minimal()

# 2. Fit ARIMA model to the daily data
arima_model_daily <- auto.arima(nflx_ts_daily)
summary(arima_model_daily)
```




```
Series: nflx_ts_daily
ARIMA(0,1,0)

sigma^2 = 140.4:  log likelihood = -4447.47
AIC=8896.94   AICc=8896.95   BIC=8901.98

Training set error measures:
                     ME     RMSE      MAE         MPE     MAPE       MASE
Training set -0.2647698 11.84228 7.861646 -0.1022131 1.935608 0.03416115
                    ACF1
Training set -0.02855902
```




```
> # Fit SARIMA model to the daily data
> sarima_model_daily <- auto.arima(nflx_ts_daily, seasonal = TRUE)
> summary(sarima_model_daily)
Series: nflx_ts_daily
ARIMA(0,1,0)

sigma^2 = 140.4:  log likelihood = -4447.47
AIC=8896.94   AICc=8896.95   BIC=8901.98

Training set error measures:
                     ME     RMSE      MAE         MPE     MAPE       MASE
Training set -0.2647698 11.84228 7.861646 -0.1022131 1.935608 0.03416115
                    ACF1
Training set -0.02855902
```

```
> # Compare ARIMA and SARIMA models
> arima_aic <- AIC(arima_model_daily)
> sarima_aic <- AIC(sarima_model_daily)
> print(paste("ARIMA AIC:", arima_aic))
[1] "ARIMA AIC: 8896.94154738081"
> print(paste("SARIMA AIC:", sarima_aic))
[1] "SARIMA AIC: 8896.94154738081"
```