Stock prices forecasting project

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Disclaimer: This project was conducted for educational purposes only. Do not attempt to use results of this analysis to make financial decisions. The views expressed in this document do not necessarily reflect the views of the U.S. Department of Justice.

Summary

This project compares the high stock prices for 5 stocks: Apple, Netflix, CBS/Viacom, Amazon, and Disney. It took prices from the Yahoo Finance website https://finance.yahoo.com/ for the dates from September 23, 2020 to November 17, 2020 when the New York Stock Exchange was open. For each stock, it used the high prices for the first 24 dates in the time period to predict the high prices for the next 16 dates. For Amazon, Apple, and Netflix high stock prices, the forecasted model performed better than the average one-step, naïve forecast computed in-sample. However, for CBS/Viacom and Disney high stock prices, the forecasted model performed worse than the average one-step, naive forecast computed in-sample.

```r
#attach libraries
library(ggplot2)
library(ggthemes)
library(tidyr)
library(quantmod)
```

```
## Loading required package: xts
```

```
## Loading required package: zoo
```

```
##
## Attaching package: 'zoo'
```

```
## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric
```

```
## Loading required package: TTR
```

```
## Registered S3 method overwritten by 'quantmod':
##   method            from
##   as.zoo.data.frame zoo
```

```r
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:xts':
##
##     first, last

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```r
library(forecast)
```

Loading Data

Creating data folder, downloading datasets from Yahoo Finance and loading data into R Studio.

```r
if(!dir.exists("./data")) {dir.create("./data")}
download.file("https://query1.finance.yahoo.com/v7/finance/download/AMZN?period1=1600819200&period2=1605

download.file("https://query1.finance.yahoo.com/v7/finance/download/AAPL?period1=1600819200&period2=1605

download.file("https://query1.finance.yahoo.com/v7/finance/download/VIAC?period1=1600819200&period2=1605

download.file("https://query1.finance.yahoo.com/v7/finance/download/DIS?period1=1600819200&period2=1605

download.file("https://query1.finance.yahoo.com/v7/finance/download/NFLX?period1=1600819200&period2=1605
amazon<-read.csv("./data/amazon.csv")
apple<-read.csv("./data/apple.csv")
disney<-read.csv("./data/disney.csv")
cbs<-read.csv("./data/cbs.csv")
netflix<-read.csv("./data/netflix.csv")
```

Data Wrangling

Merge into a single dataset and look at merged dataset.

```
## 'data.frame':    40 obs. of  7 variables:
##  $ Date     : chr  "2020-09-23" "2020-09-24" "2020-09-25" "2020-09-28" ...
##  $ Open     : num  3120 2978 3055 3149 3175 ...
##  $ High     : num  3127 3069 3102 3175 3188 ...
##  $ Low      : num  2992 2965 2999 3117 3133 ...
```

```
##  $ Close    : num  3000 3020 3095 3174 3145 ...
##  $ Adj.Close: num  3000 3020 3095 3174 3145 ...
##  $ Volume   : int  5652700 5529400 4615200 4224200 3495800 4896100 4971900 5613100 3775300 5086900 .

## 'data.frame':    40 obs. of  7 variables:
##  $ Date     : chr  "2020-09-23" "2020-09-24" "2020-09-25" "2020-09-28" ...
##  $ Open     : num  112 105 108 115 115 ...
##  $ High     : num  112 110 112 115 115 ...
##  $ Low      : num  107 105 108 113 114 ...
##  $ Close    : num  107 108 112 115 114 ...
##  $ Adj.Close: num  106 108 112 114 113 ...
##  $ Volume   : int  150718700 167743300 149981400 137672400 99382200 142675200 116120400 144712000 10

## 'data.frame':    40 obs. of  7 variables:
##  $ Date     : chr  "2020-09-23" "2020-09-24" "2020-09-25" "2020-09-28" ...
##  $ Open     : num  29.7 28.6 28.9 30 29.6 ...
##  $ High     : num  30 29.5 29.6 30.2 29.9 ...
##  $ Low      : num  28.6 28.1 28.8 29.6 28.9 ...
##  $ Close    : num  28.8 29.1 29.5 29.8 29 ...
##  $ Adj.Close: num  28.2 28.5 28.9 29.2 28.4 ...
##  $ Volume   : int  9744900 13542900 9418000 9323400 11466500 9358800 13944100 9109000 5874900 872440

## 'data.frame':    40 obs. of  7 variables:
##  $ Date     : chr  "2020-09-23" "2020-09-24" "2020-09-25" "2020-09-28" ...
##  $ Open     : num  127 122 121 126 126 ...
##  $ High     : num  127 124 124 127 126 ...
##  $ Low      : num  123 121 121 125 124 ...
##  $ Close    : num  123 122 124 126 125 ...
##  $ Adj.Close: num  123 122 124 126 125 ...
##  $ Volume   : int  8323600 8480000 6851800 6283700 7405800 13642500 8908300 6490200 5919200 9052000

## 'data.frame':    40 obs. of  7 variables:
##  $ Date     : chr  "2020-09-23" "2020-09-24" "2020-09-25" "2020-09-28" ...
##  $ Open     : num  491 471 474 489 490 ...
##  $ High     : num  491 477 485 492 496 ...
##  $ Low      : num  469 468 468 478 487 ...
##  $ Close    : num  471 473 483 491 493 ...
##  $ Adj.Close: num  471 473 483 491 493 ...
##  $ Volume   : int  3726400 3727200 3769400 4773500 3541500 4634100 8153700 6071200 4088100 4199000 .

##       Date              amazonOpen     amazonHigh     amazonLow
##  Min.   :2020-09-23   Min.   :2978   Min.   :3069   Min.   :2950
##  1st Qu.:2020-10-06   1st Qu.:3140   1st Qu.:3173   1st Qu.:3086
##  Median :2020-10-20   Median :3187   Median :3209   Median :3137
##  Mean   :2020-10-20   Mean   :3193   Mean   :3235   Mean   :3140
##  3rd Qu.:2020-11-03   3rd Qu.:3226   3rd Qu.:3289   3rd Qu.:3179
##  Max.   :2020-11-17   Max.   :3468   Max.   :3496   Max.   :3424
##   amazonClose   amazonAdj.Close  amazonVolume       appleOpen
##  Min.   :3000   Min.   :3000    Min.   :3174100   Min.   :105.2
##  1st Qu.:3128   1st Qu.:3128    1st Qu.:4304800   1st Qu.:114.0
##  Median :3181   Median :3181    Median :4939900   Median :116.0
##  Mean   :3185   Mean   :3185    Mean   :5189758   Mean   :115.9
##  3rd Qu.:3226   3rd Qu.:3226    3rd Qu.:5795150   3rd Qu.:118.8
```

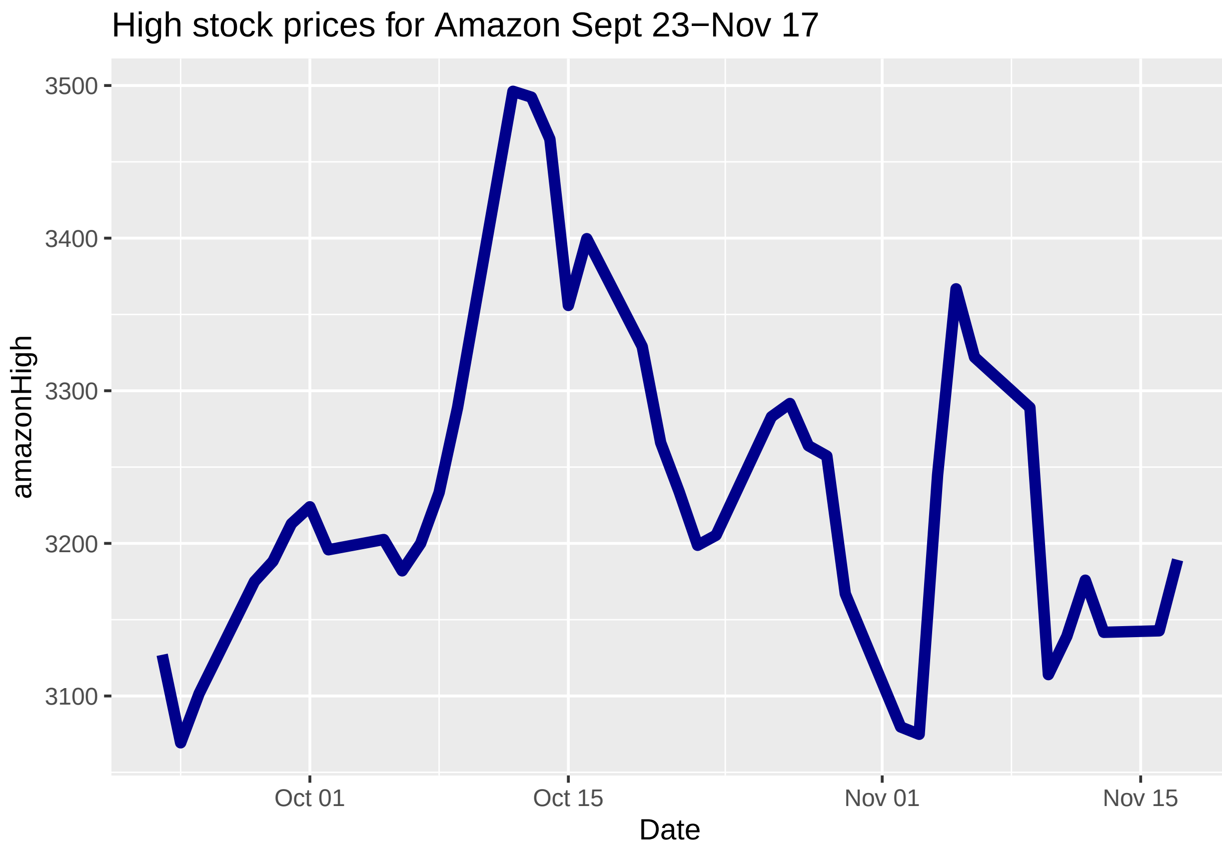
```
##  Max.   :3444   Max.   :3444    Max.   :8386400   Max.   :125.3
##    appleHigh       appleLow       appleClose    appleAdj.Close
##  Min.   :110.2   Min.   :105.0   Min.   :107.1   Min.   :106.4
##  1st Qu.:115.5   1st Qu.:112.3   1st Qu.:114.7   1st Qu.:114.0
##  Median :117.3   Median :114.6   Median :116.0   Median :115.3
##  Mean   :117.6   Mean   :114.2   Mean   :115.9   Mean   :115.2
##  3rd Qu.:119.9   3rd Qu.:116.6   3rd Qu.:119.0   3rd Qu.:118.3
##  Max.   :125.4   Max.   :119.7   Max.   :124.4   Max.   :123.6
##   appleVolume           cbsOpen         cbsHigh          cbsLow
##  Min.   : 74271000   Min.   :27.15   Min.   :27.77   Min.   :26.99
##  1st Qu.:101617725   1st Qu.:28.07   1st Qu.:28.52   1st Qu.:27.50
##  Median :118379850   Median :28.84   Median :29.50   Median :28.52
##  Mean   :127686085   Mean   :28.94   Mean   :29.49   Mean   :28.42
##  3rd Qu.:145066300   3rd Qu.:29.79   3rd Qu.:30.11   3rd Qu.:28.90
##  Max.   :262330500   Max.   :31.60   Max.   :32.89   Max.   :30.99
##     cbsClose      cbsAdj.Close     cbsVolume         disneyOpen
##  Min.   :27.13   Min.   :26.56   Min.   : 4870500   Min.   :118.2
##  1st Qu.:28.10   1st Qu.:27.51   1st Qu.: 7796575   1st Qu.:123.2
##  Median :28.89   Median :28.27   Median : 9282400   Median :125.0
##  Mean   :28.98   Mean   :28.37   Mean   :10299698   Mean   :127.3
##  3rd Qu.:29.60   3rd Qu.:28.98   3rd Qu.:11809500   3rd Qu.:127.9
##  Max.   :32.29   Max.   :31.61   Max.   :26843600   Max.   :144.4
##    disneyHigh      disneyLow      disneyClose    disneyAdj.Close
##  Min.   :121.5   Min.   :117.2   Min.   :118.5   Min.   :118.5
##  1st Qu.:124.2   1st Qu.:122.2   1st Qu.:123.3   1st Qu.:123.3
##  Median :126.9   Median :123.7   Median :125.0   Median :125.0
##  Mean   :128.8   Mean   :125.6   Mean   :127.3   Mean   :127.3
##  3rd Qu.:128.5   3rd Qu.:126.1   3rd Qu.:127.5   3rd Qu.:127.5
##  Max.   :147.7   Max.   :142.6   Max.   :144.7   Max.   :144.7
##   disneyVolume       netflixOpen     netflixHigh      netflixLow
##  Min.   : 5177700   Min.   :470.5   Min.   :477.0   Min.   :463.4
##  1st Qu.: 6758225   1st Qu.:486.7   1st Qu.:491.5   1st Qu.:478.2
##  Median : 8401800   Median :493.6   Median :505.3   Median :484.9
##  Mean   :10167048   Mean   :503.8   Mean   :511.8   Mean   :495.0
##  3rd Qu.:11094200   3rd Qu.:518.2   3rd Qu.:530.6   3rd Qu.:507.1
##  Max.   :35634700   Max.   :562.6   Max.   :572.5   Max.   :541.0
##   netflixClose   netflixyAdj.Close netflixVolume
##  Min.   :470.5   Min.   :470.5     Min.   : 3002700
##  1st Qu.:485.0   1st Qu.:485.0     1st Qu.: 4171275
##  Median :492.1   Median :492.1     Median : 5255050
##  Mean   :502.8   Mean   :502.8     Mean   : 6030592
##  3rd Qu.:525.9   3rd Qu.:525.9     3rd Qu.: 7140300
##  Max.   :554.1   Max.   :554.1     Max.   :17405700
```

```
## 'data.frame':    40 obs. of  31 variables:
##  $ Date             : Date, format: "2020-09-23" "2020-09-24" ...
##  $ amazonOpen       : num  3120 2978 3055 3149 3175 ...
##  $ amazonHigh       : num  3127 3069 3102 3175 3188 ...
##  $ amazonLow        : num  2992 2965 2999 3117 3133 ...
##  $ amazonClose      : num  3000 3020 3095 3174 3145 ...
##  $ amazonAdj.Close  : num  3000 3020 3095 3174 3145 ...
##  $ amazonVolume     : num  5652700 5529400 4615200 4224200 3495800 ...
##  $ appleOpen        : num  112 105 108 115 115 ...
##  $ appleHigh        : num  112 110 112 115 115 ...
```

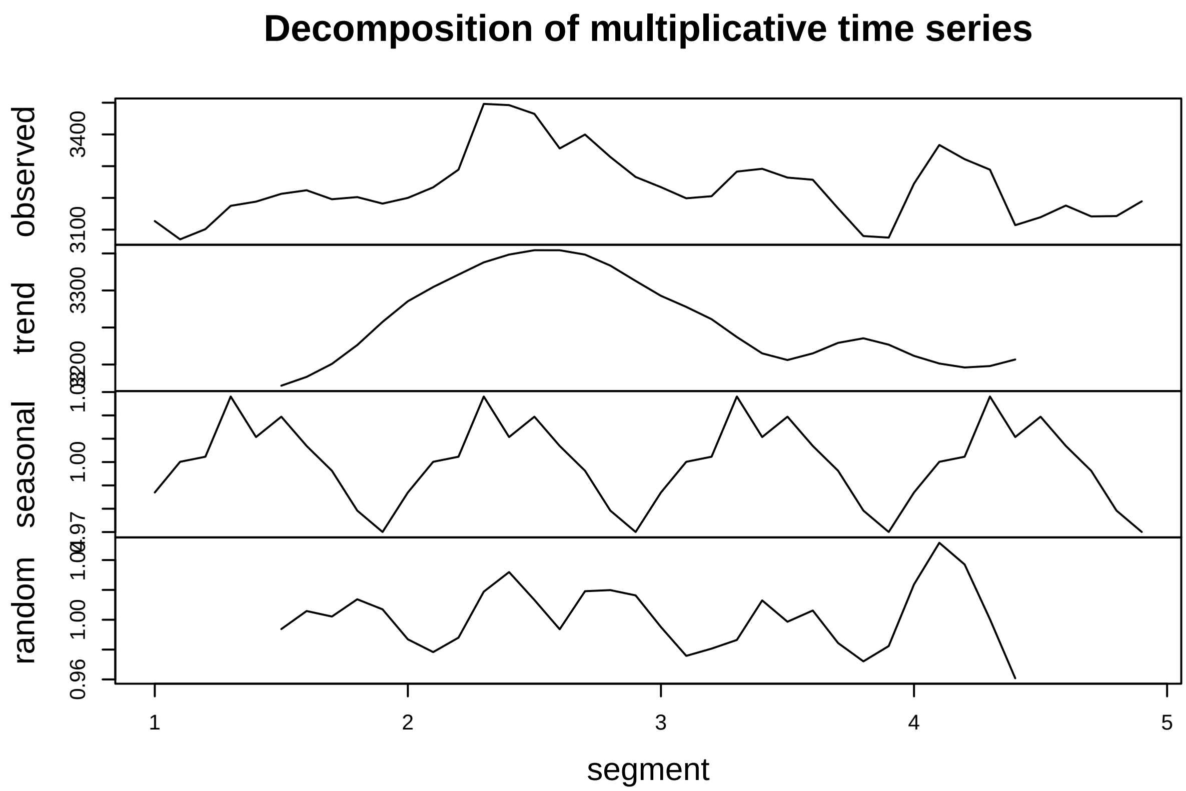
```
##  $ appleLow         : num  107 105 108 113 114 ...
##  $ appleClose       : num  107 108 112 115 114 ...
##  $ appleAdj.Close   : num  106 108 112 114 113 ...
##  $ appleVolume      : num  1.51e+08 1.68e+08 1.50e+08 1.38e+08 9.94e+07 ...
##  $ cbsOpen          : num  29.7 28.6 28.9 30 29.6 ...
##  $ cbsHigh          : num  30 29.5 29.6 30.2 29.9 ...
##  $ cbsLow           : num  28.6 28.1 28.8 29.6 28.9 ...
##  $ cbsClose         : num  28.8 29.1 29.5 29.8 29 ...
##  $ cbsAdj.Close     : num  28.2 28.5 28.9 29.2 28.4 ...
##  $ cbsVolume        : num  9744900 13542900 9418000 9323400 11466500 ...
##  $ disneyOpen       : num  127 122 121 126 126 ...
##  $ disneyHigh       : num  127 124 124 127 126 ...
##  $ disneyLow        : num  123 121 121 125 124 ...
##  $ disneyClose      : num  123 122 124 126 125 ...
##  $ disneyAdj.Close  : num  123 122 124 126 125 ...
##  $ disneyVolume     : num  8323600 8480000 6851800 6283700 7405800 ...
##  $ netflixOpen      : num  491 471 474 489 490 ...
##  $ netflixHigh      : num  491 477 485 492 496 ...
##  $ netflixLow       : num  469 468 468 478 487 ...
##  $ netflixClose     : num  471 473 483 491 493 ...
##  $ netflixyAdj.Close: num  471 473 483 491 493 ...
##  $ netflixVolume    : num  3726400 3727200 3769400 4773500 3541500 ...
```

Amazon forecasting analysis

The time chart of the data of the high stock prices for Amazon shows a non-stationary time series. There was an increase in the high stock prices from September 23 to around October 14. From there, the trend generally decreased until around November 2 and increased sharply on November 3. This preceded a decrease in the high stock price until around November 8. After that decerease, the trend generally remained steady.



The data was turned into a time series object in R with 40 observations, one for each day that the stock market was open during the time period. A multiplicative decomposition of the time series was conducted. Plotting the trend-cycle and seasonal indices shows that the data has an upward trend during the 1st 2 segments with a downward trend in the 3rd segment followed by a stable trend in the 4th segment. It also has seasonal fluctuations, with the data increasing at the beginning of each segment, reaching a peak in the middle of the segment and decreasing by the end of the segment.The data also has fairly random residuals.

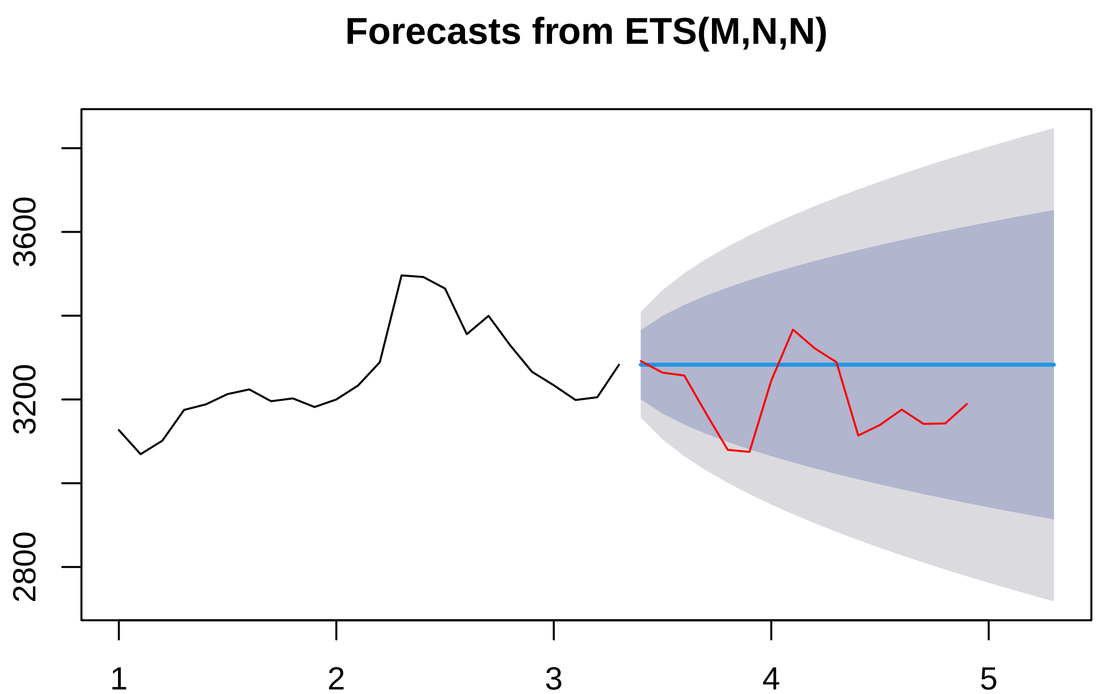


Training and test data sets were created from the time series object with the high stock prices for the first 24 days (60% of the data) being put into the training data while the data for the remaining 16 days (40% of the data) were put into the test data set.

The ets() function was applied to the training data to choose the best ets (error, trend, seasonality) model to fit to the data. It returned a model with simple exponential smoothing with multiplicative errors. This model had in a smoothing parameter of 0.9999 which means that in the model, more weight is given to the more recent high stock prices. This ets model was then used to forecast future values. The forecasted data was plotted along with the test data. The plot showed that the test data appears to fall within the 95% prediction intervals from the ets model.

```
## ETS(M,N,N)
##
## Call:
##  ets(y = ts1Train)
##
```

```
##   Smoothing parameters:
##     alpha = 0.9999
##
##   Initial states:
##     l = 3125.1279
##
##   sigma:  0.0196
##
##      AIC     AICc      BIC
## 279.5340 280.7340 283.0681
```

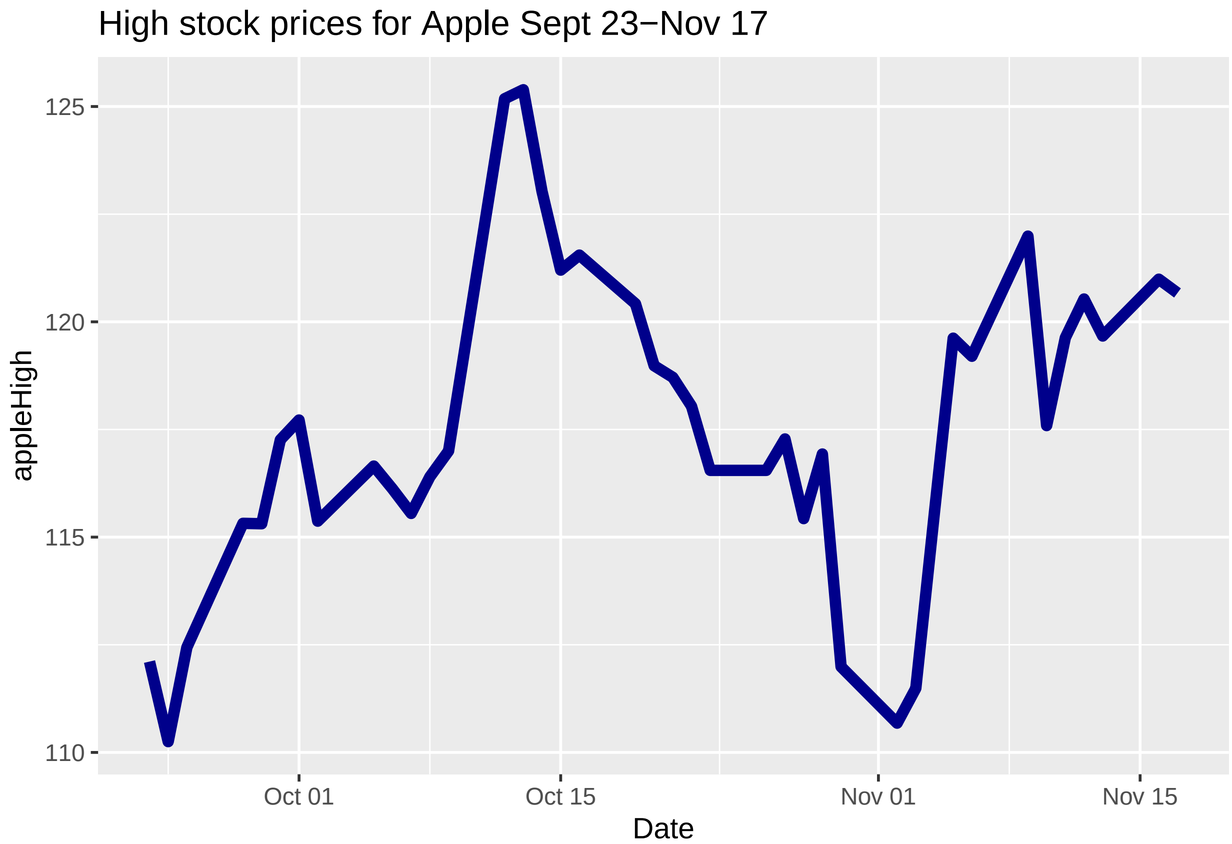


In terms of accuracy, the mean absolute scaled error (MASE) of the forecast was about 0.6 for the test data. With MASE<1, the forecast did better in predicting the later high stock prices than the average one-step, naïve forecast computed in-sample.

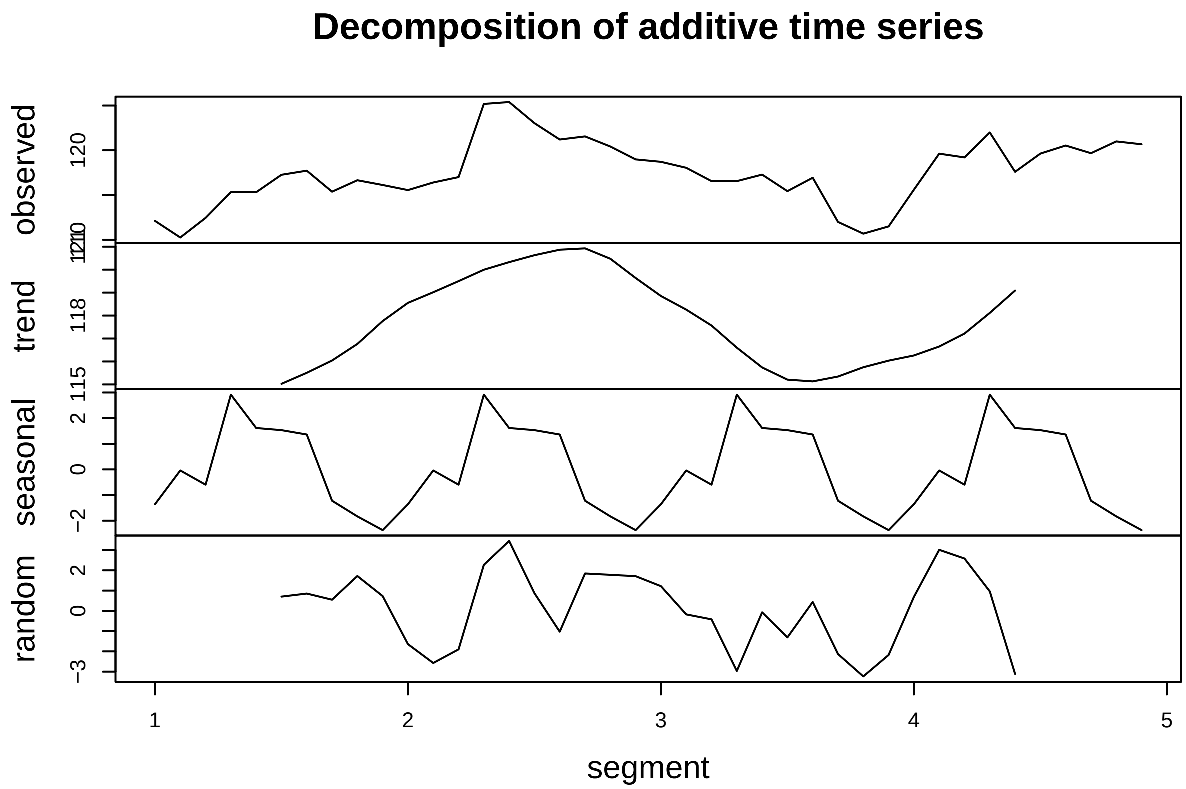
```
##                      ME      RMSE      MAE        MPE     MAPE      MASE
## Training set   6.577504  61.67829 43.88522  0.1883105 1.330191 0.2775902
## Test set     -79.229107 116.80991 96.42549 -2.5462514 3.060235 0.6099267
##                   ACF1 Theil's U
## Training set 0.1853532        NA
## Test set     0.5447402  1.498007
```

Apple forecasting analysis

The time chart of the data of the high stock prices for Apple shows a non-stationary time series. There was an increase in the high stock prices from September 23 to around October 14. From there, the trend generally decreased until around November 2 and increased sharply on November 3 until around November 7. This preceded a slight decrease in the high stock price until around November 8. After that decrease, the trend generally increased until the end of the time period.



The data was turned into a time series object in R with 40 observations, one for each day that the stock market was open during the time period. An additive decomposition of the time series was conducted. Plotting the trend-cycle and seasonal indices shows that the data have an upward trend during the 1st segment lasting throught the 1st half of the 2nd segment. The trend declined from the 2nd half of the 2nd segment until the middle of the 3rd segment. From there, it increased through the 4th segment. It also has seasonal fluctuations, with the data increasing at the beginning of each segment, reaching a peak in the middle of the segment and decreasing by the end of the segment.The data also has fairly random residuals.

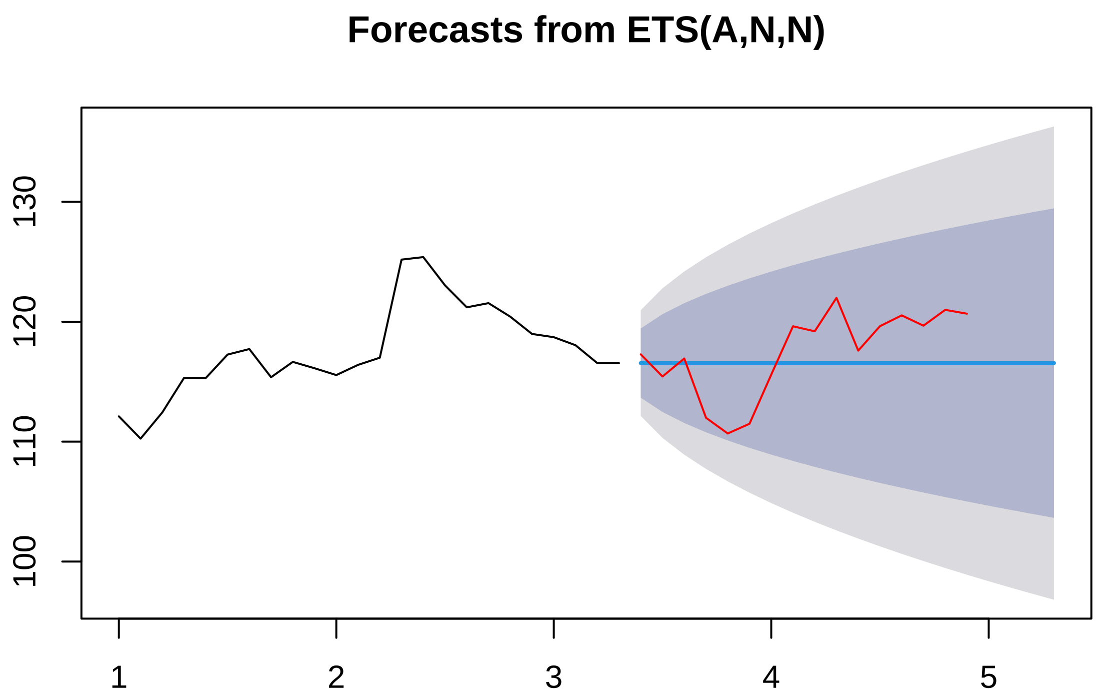


Training and test data sets were created from the time series object with the high stock prices for the first 24 days (60% of the data) being put into the training data while the data for the remaining 16 days (40% of the data) were put into the test data set.

The ets() function was applied to the training data to choose the best ets (error, trend, seasonality) model to fit to the data. It returned a model with simple exponential smoothing with multiplicative errors. This model had in a smoothing parameter of 0.9999 which means that in the model, more weight is given to the more recent stock prices. This ets model was then used to forecast future values. The forecasted data was plotted along with the test data. The plot showed that the test data appears to fall within the 80% prediction intervals from the ets model.

```
## ETS(A,N,N)
##
## Call:
##  ets(y = ts1Train)
```

```
##
##   Smoothing parameters:
##     alpha = 0.9999
##
##   Initial states:
##     l = 112.1082
##
##   sigma:  2.2513
##
##      AIC     AICc      BIC
## 119.1378 120.3378 122.6720
```

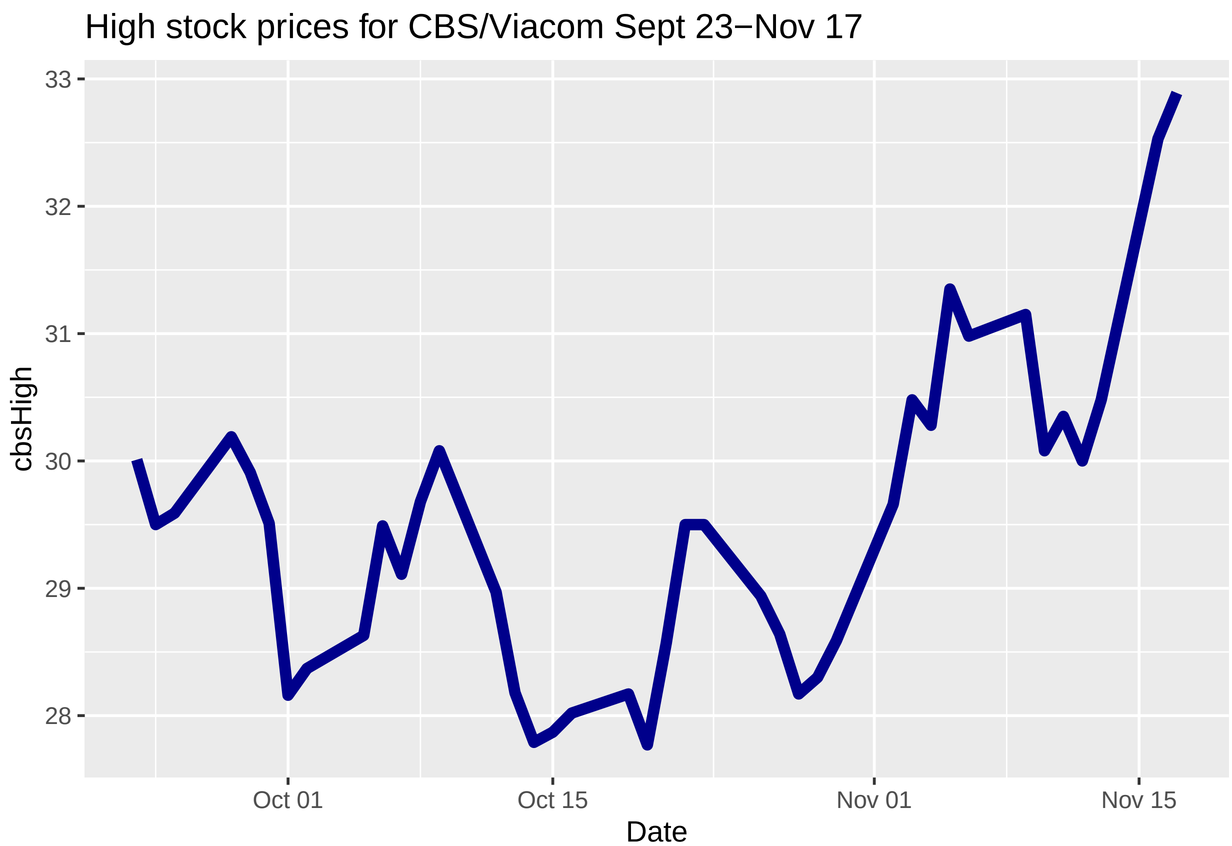


In terms of accuracy, the mean absolute scaled error (MASE) of the forecast was about 0.6 for the test data. With MASE<1, the forecast did better in predicting the later high stock prices than the average one-step, naïve forecast computed in-sample.

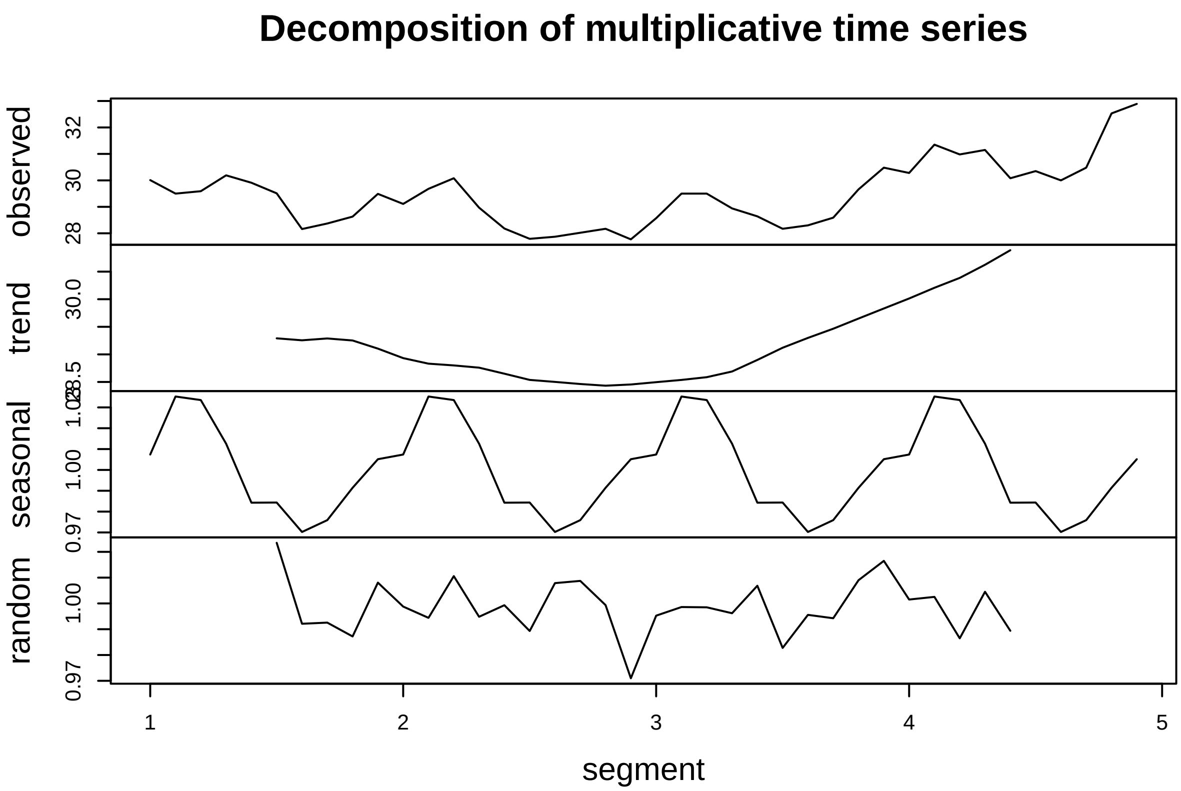
```
##                     ME     RMSE      MAE       MPE     MAPE      MASE
## Training set 0.1850931 2.155474 1.394282 0.1457702 1.173510 0.2787370
## Test set     0.9050000 3.558258 3.101250 0.6833750 2.647713 0.6199843
##                    ACF1 Theil's U
## Training set 0.09397187        NA
## Test set     0.70776444  1.422214
```

CBS/Viacom forecasting analysis

The plot of time series of the high stock prices for CBS/Viacom shows a more stationary time series than the plots of the Apple and Amazon time series. However, the CBS/Viacom time series is still nonstationary, with the high stock prices increasing from around October 28 until around November 4 and another sharp increase from November 9 to the end of the time series.



The data was turned into a time series object in R with 40 observations, one for each day that the stock market was open during the time period. A multiplicative decomposition of the time series was conducted. Plotting the trend-cycle and seasonal indices shows that the data have a downward trend during the 1st 2 segments with an upward trend in the 3rd and 4th segments. It also has seasonal fluctuations, with the data increasing in the middle of each segment, reaching a peak in the middle of the segment and and peak at the beginning of each segment.The time series also has fairly random residuals.

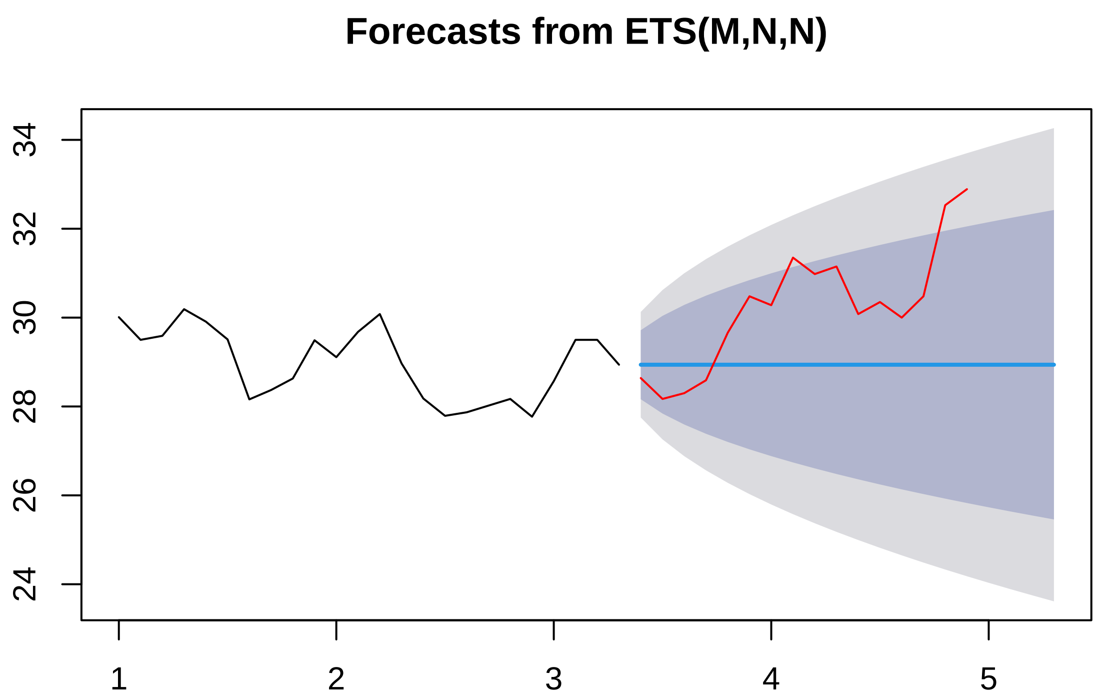


Training and test data sets were created from the time series object with the high stock prices for the first 24 days (60% of the data) being put into the training data while the data for the remaining 16 days (40% of the data) were put into the test data set.

The ets() function was applied to the training data to choose the best ets (error, trend, seasonality) model to fit to the data. It returned a model with simple exponential smoothing with multiplicative errors. This model had in a smoothing parameter of 0.9999 which means that in the model, more weight is given to the more recent stock prices. This ets model was then used to forecast future values. The forecasted data was plotted along with the test data. The plot showed that the test data appears to fall within the 95% prediction intervals from the ets model.

```
## ETS(M,N,N)
##
## Call:
##  ets(y = ts1Train)
##
```

```
##   Smoothing parameters:
##     alpha = 0.9999
##
##   Initial states:
##     l = 29.9983
##
##   sigma:  0.0209
##
##      AIC     AICc      BIC
## 56.28348 57.48348 59.81764
```

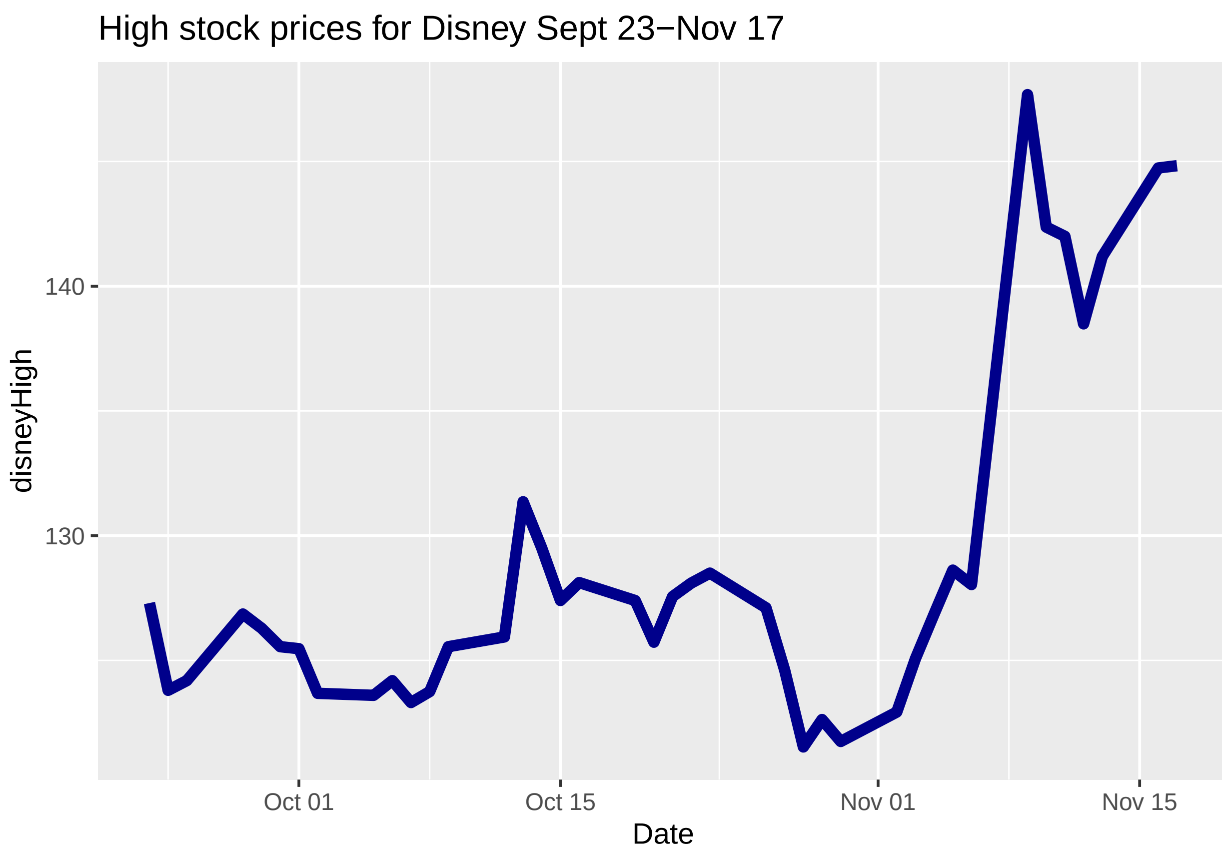


In terms of accuracy, the mean absolute scaled error (MASE) of the forecast was about 2.1 for the test data. With MASE>1, the forecast did worse in predicting the later high stock prices than the average one-step, naïve forecast computed in-sample.

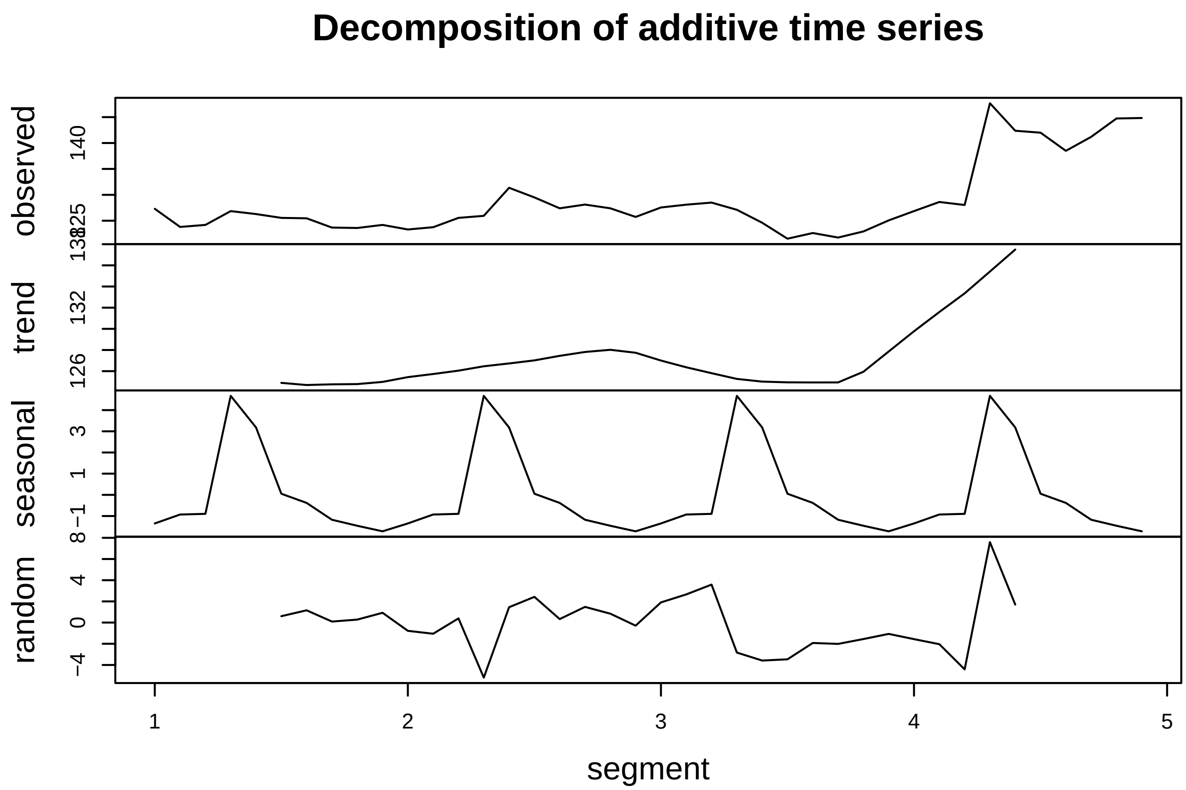
```
##                       ME     RMSE       MAE        MPE     MAPE     MASE
## Training set -0.04409949 0.584818 0.4700718 -0.1700425 1.624446 0.633398
## Test set      1.30556897 1.871256 1.5630970  4.1293770 5.037798 2.106194
##                   ACF1 Theil's U
## Training set 0.1531483        NA
## Test set     0.6702398  2.377506
```

Disney forecasting analysis

The time chart of the data of the high stock prices for Disney shows a non-stationary time series. This is primarily due to the trend at the end of the time period where the high stock prices increase sharply from around November 6 to November 8.



The data was turned into a time series object in R with 40 observations, one for each day that the stock market was open during the time period. An additive decomposition of the time series was conducted. Plotting the trend-cycle and seasonal indices shows that the trend was basically stable until a sharp increase starting at the end of the 3rd segment. It also has seasonal fluctuations, with the data increasing at the beginning of each segment, reaching a peak in the middle of the segment and decreasing by the end of the segment.The data also had random residuals.

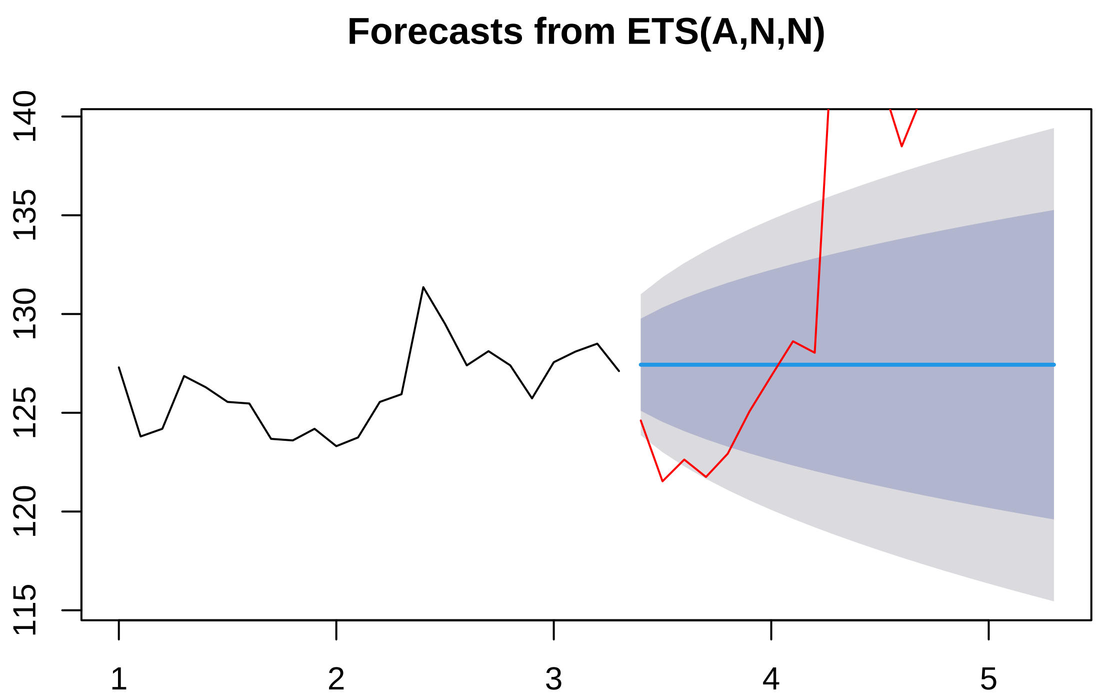


Training and test data sets were created from the time series object with the high stock prices for the first 24 days (60% of the data) being put into the training data while the data for the remaining 16 days (40% of the data) were put into the test data set.

The ets() function was applied to the training data to choose the best ets (error, trend, seasonality) model to fit to the data. It returned a model with simple exponential smoothing with additive errors. This model had in a smoothing parameter of 0.7352 which means that in the model, more weight is given to the more recent stock prices. This ets model was then used to forecast future values. The forecasted data was plotted along with the test data. The plot showed that a good portion of the test data to fell outside the 80% and 95% prediction intervals from the ets model.

```
## ETS(A,N,N)
##
## Call:
##  ets(y = ts1Train)
##
```

```
##   Smoothing parameters:
##     alpha = 0.7352
##
##   Initial states:
##     l = 126.447
##
##   sigma:  1.8208
##
##      AIC     AICc      BIC
## 108.9505 110.1505 112.4846
```

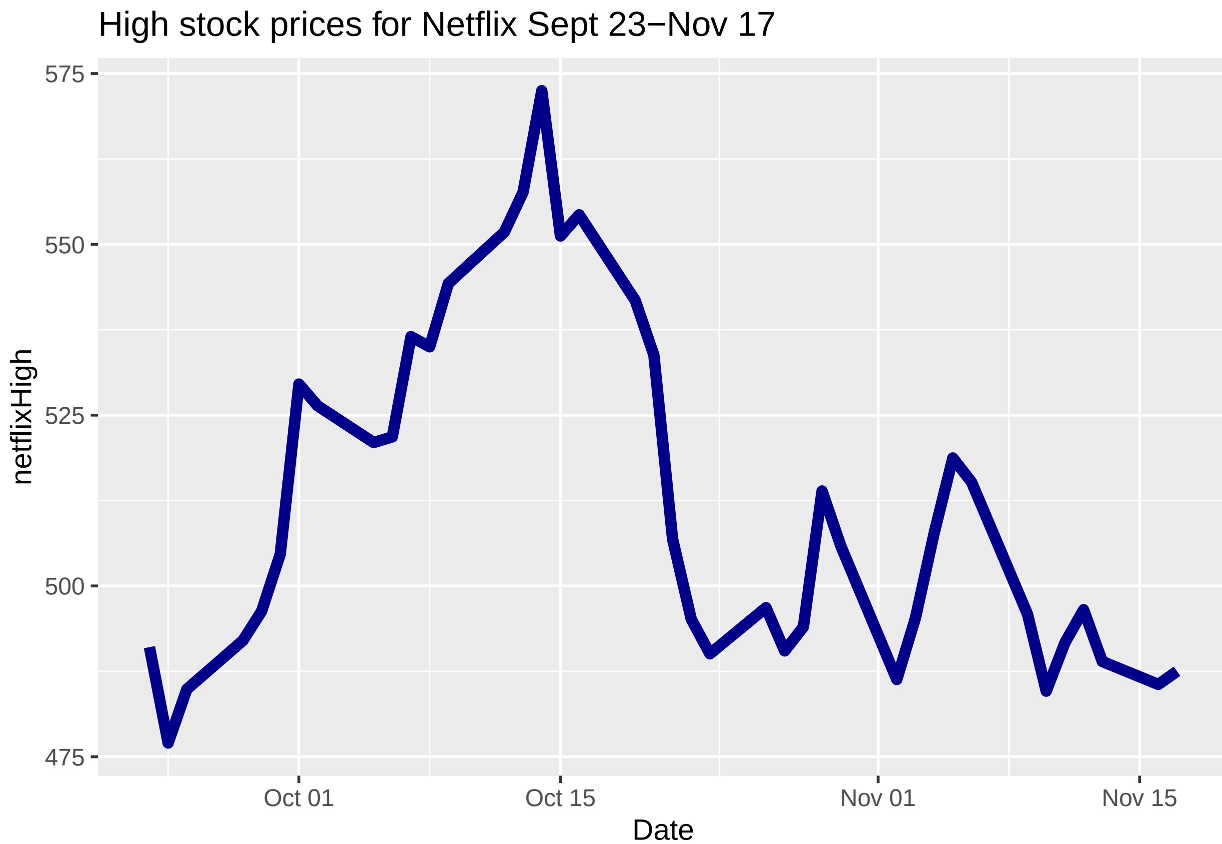


In terms of accuracy, the mean absolute scaled error (MASE) of the forecast was about 3.0 for the test data. With MASE>1, the forecast did worse in predicting the later high stock prices than the average one-step, naïve forecast computed in-sample.

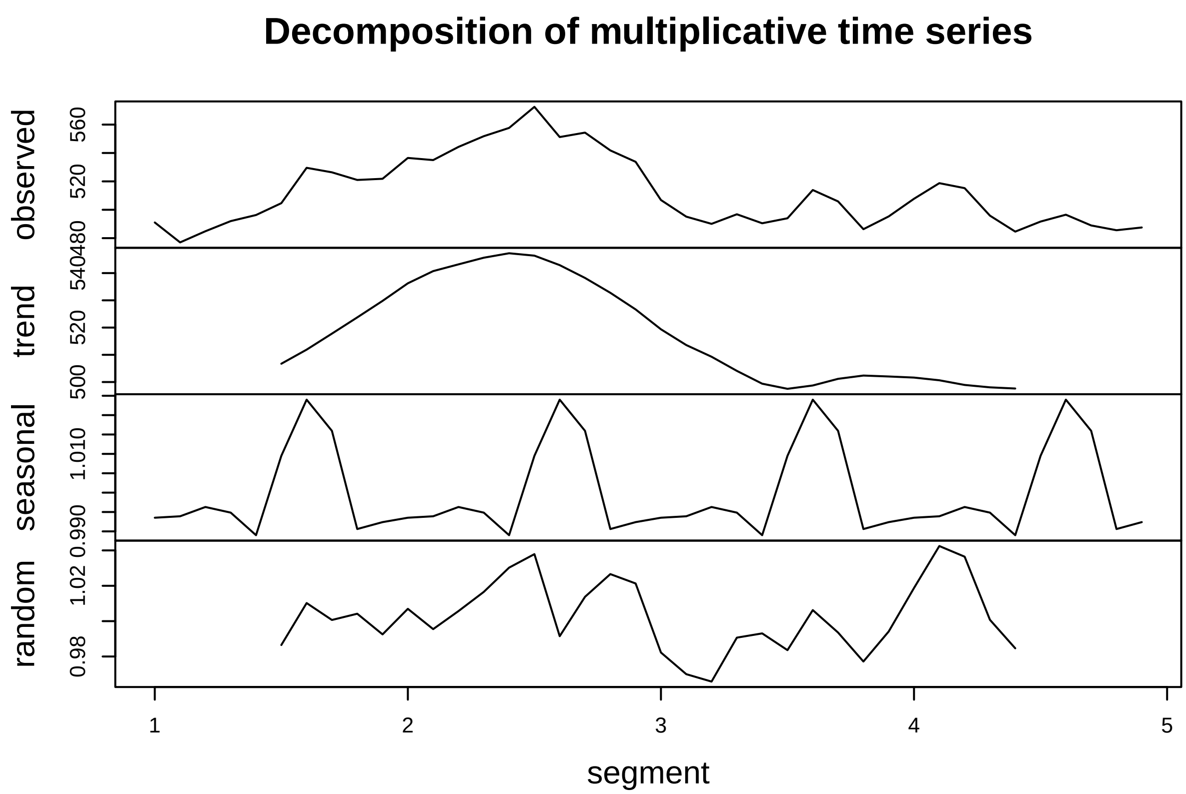
```
##                      ME      RMSE      MAE        MPE      MAPE      MASE
## Training set 0.05591236  1.743291 1.242970 0.03219821 0.9798233 0.4375556
## Test set     5.27529531 10.854211 8.607068 3.48983108 6.2040540 3.0298958
##                    ACF1 Theil's U
## Training set 0.05275571        NA
## Test set     0.76285026  1.879288
```

Netflix forecasting analysis

The time chart of the data of the high stock prices for Netflix shows a non-stationary time series. This is primarly due to the activity of the time series at the beginning of the time period. The data increases from the beginning of the time period to October 14. It then decreases until around October 22. Afterwards, it begins to become more stationary with a few fluctuations until around November 9.



The data was turned into a time series object in R with 40 observations, one for each day that the stock market was open during the time period. An multiplicative decomposition of the time series was conducted. Plotting the trend-cycle and seasonal indices shows that the data increased from the middle of the 1st segment until the middle of the 2nd segment. Afterwards, it decreased until the middle of the 3rd segement and remained flat until the end of the time period. It also has seasonal fluctuations, with the data increasing at the beginning of each segment, reaching a peak in the middle of the segment and decreasing by the end of the segment.The data also has fairly random residuals.

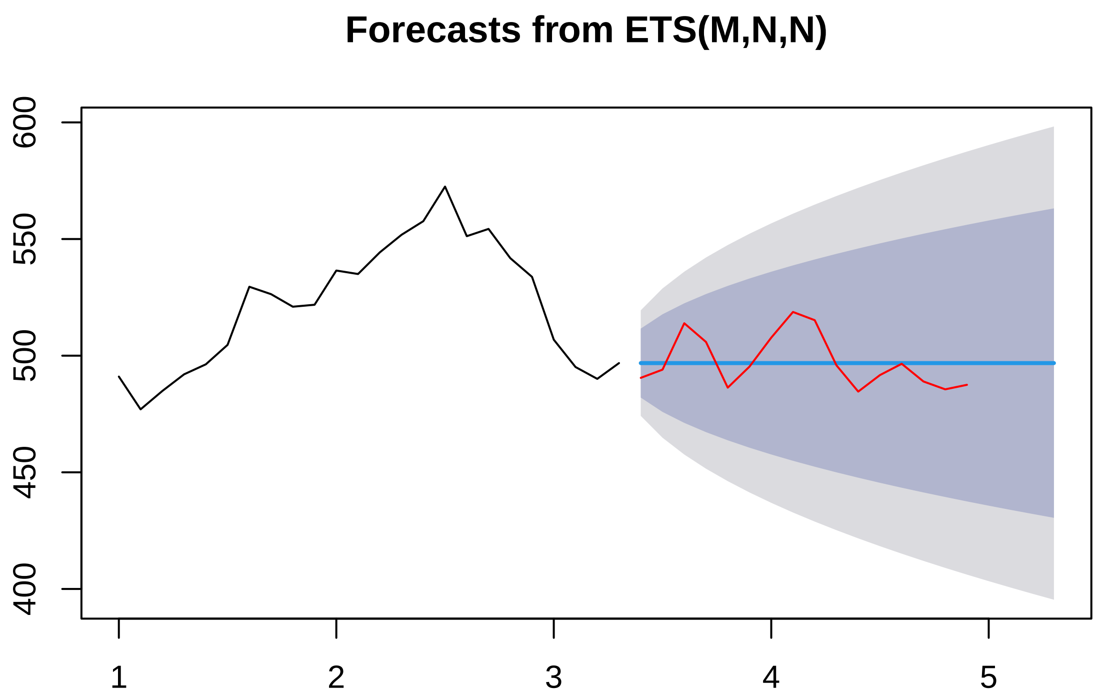


Training and test data sets were created from the time series object with the high stock prices for the first 24 days (60% of the data) being put into the training data while the data for the remaining 16 days (40% of the data) were put into the test data set.

The ets() function was applied to the training data to choose the best ets (error, trend, seasonality) model to fit to the data. It returned a model with simple exponential smoothing with multiplicative errors. This model had in a smoothing parameter of 0.9999 which means that in the model, more weight is given to the more recent stock prices. This ets model was then used to forecast future values. The forecasted data was plotted along with the test data. The plot showed that the test data appears to fall within the 80% prediction intervals from the ets model.

```
## ETS(M,N,N)
##
## Call:
##  ets(y = ts1Train)
```

```
##
##   Smoothing parameters:
##     alpha = 0.9999
##
##   Initial states:
##     l = 490.7364
##
##   sigma:  0.0232
##
##      AIC     AICc      BIC
## 199.8201 201.0201 203.3542
```



In terms of accuracy, the mean absolute scaled error (MASE) of the forecast was about 0.2 for the test data. With MASE<1, the forecast did better in predicting the later high stock prices than the average one-step, naïve forecast computed in-sample.

```
##                     ME     RMSE      MAE        MPE     MAPE      MASE
## Training set 0.2534795 11.70942 9.389351 0.02641231 1.797039 0.2144387
## Test set     0.5700515 10.96571 9.099121 0.06687166 1.815276 0.2078103
##                   ACF1 Theil's U
## Training set 0.1710957        NA
## Test set     0.4742796  1.001417
```