session_23_90_days_AAPL_index.R

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Problem Statement
1. Perform the below given activities:
a. Take Apple Stock Prices from Yahoo Finance for last 90 days
b. Predict the Stock closing prices for next 15 days.
c. Submit your accuracy

d. After 15 days again collect the data and compare with your forecast

```
setwd("C:/Users/Seshan/Desktop/sv R related/acadgild/assignments/session 23/N
ew folder")
library(readr)
AAPLMay10toAug102018 <- read.csv("AAPLMay10toAug102018.csv")
View(AAPLMay10toAug102018)
df<-AAPLMay10toAug102018
head(df)
```

```
##         Date   Open   High    Low  Close Adj.Close   Volume
## 1 2018-05-10 187.74 190.37 187.65 190.04  188.6484 27989300
## 2 2018-05-11 189.49 190.06 187.45 188.59  187.9309 26212200
## 3 2018-05-14 189.01 189.53 187.86 188.15  187.4924 20778800
## 4 2018-05-15 186.78 187.07 185.10 186.44  185.7884 23695200
## 5 2018-05-16 186.07 188.46 186.00 188.18  187.5223 19183100
## 6 2018-05-17 188.00 188.91 186.36 186.99  186.3365 17294000
```

```
str(df)
```

```
## 'data.frame':    65 obs. of  7 variables:
##  $ Date     : Factor w/ 65 levels "2018-05-10","2018-05-11",..: 1 2 3 4 5
6 7 8 9 10 ...
##  $ Open     : num  188 189 189 187 186 ...
##  $ High     : num  190 190 190 187 188 ...
##  $ Low      : num  188 187 188 185 186 ...
##  $ Close    : num  190 189 188 186 188 ...
##  $ Adj.Close: num  189 188 187 186 188 ...
##  $ Volume   : int  27989300 26212200 20778800 23695200 19183100 17294000 1
8297700 18400800 15240700 19467900 ...
```

```
new_date <- as.Date(df$Date)
new_date
```

```
##  [1] "2018-05-10" "2018-05-11" "2018-05-14" "2018-05-15" "2018-05-16"
##  [6] "2018-05-17" "2018-05-18" "2018-05-21" "2018-05-22" "2018-05-23"
## [11] "2018-05-24" "2018-05-25" "2018-05-29" "2018-05-30" "2018-05-31"
## [16] "2018-06-01" "2018-06-04" "2018-06-05" "2018-06-06" "2018-06-07"
## [21] "2018-06-08" "2018-06-11" "2018-06-12" "2018-06-13" "2018-06-14"
## [26] "2018-06-15" "2018-06-18" "2018-06-19" "2018-06-20" "2018-06-21"
## [31] "2018-06-22" "2018-06-25" "2018-06-26" "2018-06-27" "2018-06-28"
## [36] "2018-06-29" "2018-07-02" "2018-07-03" "2018-07-05" "2018-07-06"
## [41] "2018-07-09" "2018-07-10" "2018-07-11" "2018-07-12" "2018-07-13"
## [46] "2018-07-16" "2018-07-17" "2018-07-18" "2018-07-19" "2018-07-20"
## [51] "2018-07-23" "2018-07-24" "2018-07-25" "2018-07-26" "2018-07-27"
## [56] "2018-07-30" "2018-07-31" "2018-08-01" "2018-08-02" "2018-08-03"
## [61] "2018-08-06" "2018-08-07" "2018-08-08" "2018-08-09" "2018-08-10"
```

```
str(df)
```

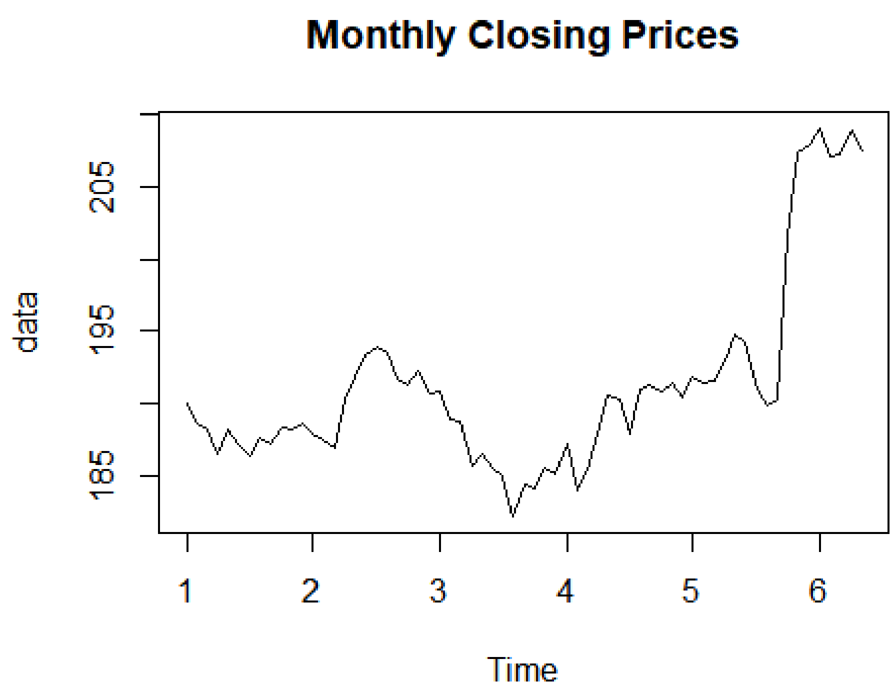
```
## 'data.frame':    65 obs. of  7 variables:
##  $ Date     : Factor w/ 65 levels "2018-05-10","2018-05-11",..: 1 2 3 4 5
6 7 8 9 10 ...
##  $ Open     : num  188 189 189 187 186 ...
##  $ High     : num  190 190 190 187 188 ...
##  $ Low      : num  188 187 188 185 186 ...
##  $ Close    : num  190 189 188 186 188 ...
##  $ Adj.Close: num  189 188 187 186 188 ...
##  $ Volume   : int  27989300 26212200 20778800 23695200 19183100 17294000 1
8297700 18400800 15240700 19467900 ...
```

```
format(new_date,format="%B %d %Y")
```

```
##  [1] "May 10 2018"    "May 11 2018"    "May 14 2018"    "May 15 2018"
##  [5] "May 16 2018"    "May 17 2018"    "May 18 2018"    "May 21 2018"
##  [9] "May 22 2018"    "May 23 2018"    "May 24 2018"    "May 25 2018"
## [13] "May 29 2018"    "May 30 2018"    "May 31 2018"    "June 01 2018"
## [17] "June 04 2018"   "June 05 2018"   "June 06 2018"   "June 07 2018"
## [21] "June 08 2018"   "June 11 2018"   "June 12 2018"   "June 13 2018"
## [25] "June 14 2018"   "June 15 2018"   "June 18 2018"   "June 19 2018"
## [29] "June 20 2018"   "June 21 2018"   "June 22 2018"   "June 25 2018"
## [33] "June 26 2018"   "June 27 2018"   "June 28 2018"   "June 29 2018"
## [37] "July 02 2018"   "July 03 2018"   "July 05 2018"   "July 06 2018"
## [41] "July 09 2018"   "July 10 2018"   "July 11 2018"   "July 12 2018"
## [45] "July 13 2018"   "July 16 2018"   "July 17 2018"   "July 18 2018"
## [49] "July 19 2018"   "July 20 2018"   "July 23 2018"   "July 24 2018"
## [53] "July 25 2018"   "July 26 2018"   "July 27 2018"   "July 30 2018"
## [57] "July 31 2018"   "August 01 2018" "August 02 2018" "August 03 2018"
## [61] "August 06 2018" "August 07 2018" "August 08 2018" "August 09 2018"
## [65] "August 10 2018"
```

```
# %d - day as number 1-31
# %a - weekday such as Mon
# %A- complete day name ex.Monday
# %m - month as a number
```

```r
# %b - short form of month Jan, Feb
# %B - full form of month, January
# %y - two digit year
# %Y- four digit year

data = ts(df$Close,frequency =12)

plot(data,main="Monthly Closing Prices")
```




```r
# Additive Time Series
# Trend + Seasonality+ Cyclicity+ error
# Multiplicative Time Series
## Trend * Seasonality * Cyclicity * error

# additive model is easy to explain, easy to forecast and interpret
# multiplicate models can be converted to additive models using log of the ti
me series
log(data)

##        Jan      Feb      Mar      Apr      May      Jun      Jul      Aug
## 1 5.247235 5.239575 5.237239 5.228109 5.237399 5.231055 5.227412 5.234472
## 2 5.235910 5.233779 5.230413 5.248286 5.256610 5.264295 5.267755 5.265071
## 3 5.251226 5.240900 5.240370 5.224079 5.228431 5.222839 5.219923 5.204940
## 4 5.232071 5.214501 5.222516 5.236282 5.250072 5.248865 5.235803 5.252430
## 5 5.256870 5.254574 5.255462 5.262690 5.272076 5.268940 5.252169 5.246550
## 6 5.342669 5.333250 5.333926 5.341760 5.335276
##        Sep      Oct      Nov      Dec
```

```
## 1 5.231964 5.238355 5.237239 5.239522
## 2 5.255932 5.253477 5.258953 5.250701
## 3 5.217270 5.215805 5.223055 5.220950
## 4 5.254000 5.251802 5.254627 5.249127
## 5 5.248549 5.305789 5.334601 5.337490
## 6

# assumption for time series forecst:
#1- the time series should be stationary

# Identify the stationarity of a time series
#1- mean value of the time series is constant over time, the trend should not
be present in the series
#2- the variance does not increase over time
#3- the seasonality impact is minimal, deseasonalization of the time series d
ata

decompose(data) # default method is additive

## $x
##      Jan    Feb    Mar    Apr    May    Jun    Jul    Aug    Sep    Oct
## 1 190.04 188.59 188.15 186.44 188.18 186.99 186.31 187.63 187.16 188.36
## 2 187.90 187.50 186.87 190.24 191.83 193.31 193.98 193.46 191.70 191.23
## 3 190.80 188.84 188.74 185.69 186.50 185.46 184.92 182.17 184.43 184.16
## 4 187.18 183.92 185.40 187.97 190.58 190.35 187.88 191.03 191.33 190.91
## 5 191.88 191.44 191.61 193.00 194.82 194.21 190.98 189.91 190.29 201.50
## 6 209.07 207.11 207.25 208.88 207.53
##      Nov    Dec
## 1 188.15 188.58
## 2 192.28 190.70
## 3 185.50 185.11
## 4 191.45 190.40
## 5 207.39 207.99
## 6
##
## $seasonal
##           Jan         Feb         Mar         Apr         May         Jun
## 1  0.58831620 -0.99907935 -0.82543364  0.07509057  1.44529961  0.94269711
## 2  0.58831620 -0.99907935 -0.82543364  0.07509057  1.44529961  0.94269711
## 3  0.58831620 -0.99907935 -0.82543364  0.07509057  1.44529961  0.94269711
## 4  0.58831620 -0.99907935 -0.82543364  0.07509057  1.44529961  0.94269711
## 5  0.58831620 -0.99907935 -0.82543364  0.07509057  1.44529961  0.94269711
## 6  0.58831620 -0.99907935 -0.82543364  0.07509057  1.44529961
##           Jul         Aug         Sep         Oct         Nov         Dec
## 1 -0.94316286 -1.23007568 -1.40158058  0.50225588  1.87600261 -0.03032988
## 2 -0.94316286 -1.23007568 -1.40158058  0.50225588  1.87600261 -0.03032988
## 3 -0.94316286 -1.23007568 -1.40158058  0.50225588  1.87600261 -0.03032988
## 4 -0.94316286 -1.23007568 -1.40158058  0.50225588  1.87600261 -0.03032988
## 5 -0.94316286 -1.23007568 -1.40158058  0.50225588  1.87600261 -0.03032988
## 6
```

```
##
## $trend
##         Jan      Feb      Mar      Apr      May      Jun      Jul      Aug
## 1        NA       NA       NA       NA       NA       NA 187.7925 187.6579
## 2 188.9729 189.5354 189.9675 190.2762 190.5679 190.8283 191.0375 191.2142
## 3 189.5708 188.7229 187.9496 187.3521 186.7750 186.2596 185.8758 185.5200
## 4 186.0975 186.5900 187.2467 187.8154 188.3446 188.8129 189.2292 189.7383
## 5 191.7925 191.8750 191.7850 192.1829 193.2883 194.6854 196.1346 197.5038
## 6        NA       NA       NA       NA       NA
##         Sep      Oct      Nov      Dec
## 1 187.5592 187.6642 187.9746 188.3900
## 2 191.3479 191.2362 190.8246 190.2754
## 3 185.1758 185.1317 185.3967 185.7704
## 4 190.3104 190.7788 191.1650 191.5025
## 5 198.8083 200.1217 201.3129       NA
## 6
##
## $random
##           Jan         Feb         Mar         Apr         May         Jun
## 1          NA          NA          NA          NA          NA          NA
## 2 -1.66123862 -1.03633707 -2.27207090 -0.11133461 -0.18321332  1.53896851
## 3  0.64085296  1.11615847  1.61585564 -1.73717174 -1.72029982 -1.74227386
## 4  0.49417750 -1.67092228 -1.02123907  0.07949335  0.79011876  0.59439235
## 5 -0.50081275  0.56407997  0.65043343  0.74199210  0.08637347 -1.41810790
## 6          NA          NA          NA          NA          NA
##           Jul         Aug         Sep         Oct         Nov         Dec
## 1 -0.53933810  1.20216485  1.00241853  0.19357891 -1.70059198  0.22033175
## 2  3.88565965  3.47591660  1.75366124 -0.50850984 -0.42058669  0.45491017
## 3 -0.01267264 -2.11992615  0.65574078 -1.47391751 -1.77266827 -0.63008483
## 4 -0.40599889  2.52174060  2.42116470 -0.37100334 -1.59100723 -1.07217800
## 5 -4.21142614 -6.36367202 -7.11676138  0.87607566  4.20107806          NA
## 6
##
## $figure
##  [1]  0.58831620 -0.99907935 -0.82543364  0.07509057  1.44529961
##  [6]  0.94269711 -0.94316286 -1.23007568 -1.40158058  0.50225588
## [11]  1.87600261 -0.03032988
##
## $type
## [1] "additive"
##
## attr(,"class")
## [1] "decomposed.ts"
```

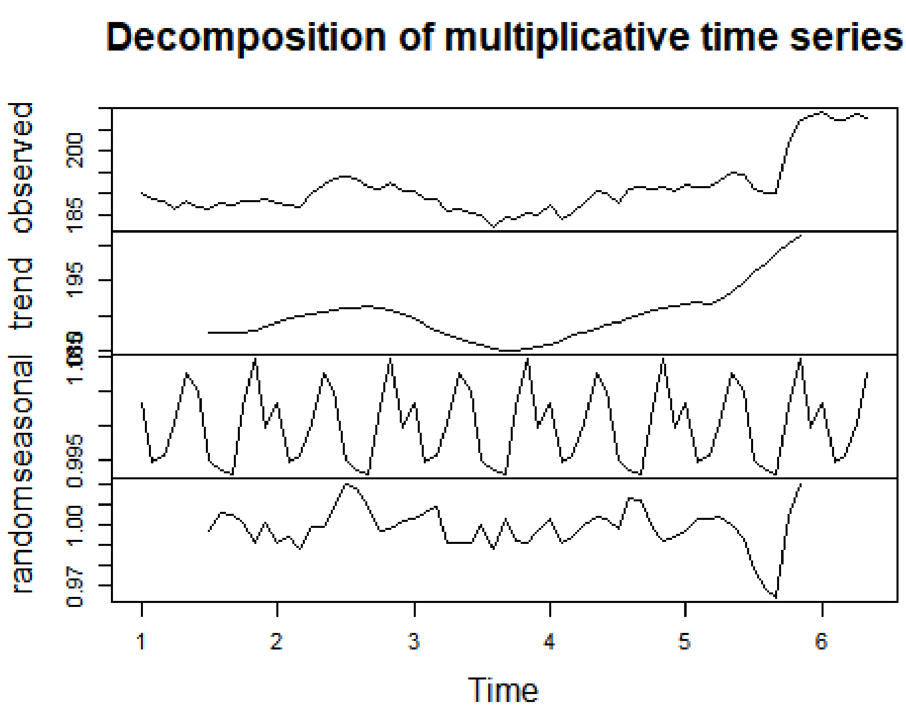
```
decompose(data, type='multi')
```

```
## $x
##      Jan    Feb    Mar    Apr    May    Jun    Jul    Aug    Sep    Oct
## 1 190.04 188.59 188.15 186.44 188.18 186.99 186.31 187.63 187.16 188.36
## 2 187.90 187.50 186.87 190.24 191.83 193.31 193.98 193.46 191.70 191.23
```

```
## 3 190.80 188.84 188.74 185.69 186.50 185.46 184.92 182.17 184.43 184.16
## 4 187.18 183.92 185.40 187.97 190.58 190.35 187.88 191.03 191.33 190.91
## 5 191.88 191.44 191.61 193.00 194.82 194.21 190.98 189.91 190.29 201.50
## 6 209.07 207.11 207.25 208.88 207.53
##      Nov    Dec
## 1 188.15 188.58
## 2 192.28 190.70
## 3 185.50 185.11
## 4 191.45 190.40
## 5 207.39 207.99
## 6
##
## $seasonal
##         Jan       Feb       Mar       Apr       May       Jun       Jul
## 1 1.0031182 0.9946632 0.9956196 1.0003478 1.0075902 1.0049535 0.9951287
## 2 1.0031182 0.9946632 0.9956196 1.0003478 1.0075902 1.0049535 0.9951287
## 3 1.0031182 0.9946632 0.9956196 1.0003478 1.0075902 1.0049535 0.9951287
## 4 1.0031182 0.9946632 0.9956196 1.0003478 1.0075902 1.0049535 0.9951287
## 5 1.0031182 0.9946632 0.9956196 1.0003478 1.0075902 1.0049535 0.9951287
## 6 1.0031182 0.9946632 0.9956196 1.0003478 1.0075902
##         Aug       Sep       Oct       Nov       Dec
## 1 0.9937153 0.9929736 1.0025480 1.0095161 0.9998259
## 2 0.9937153 0.9929736 1.0025480 1.0095161 0.9998259
## 3 0.9937153 0.9929736 1.0025480 1.0095161 0.9998259
## 4 0.9937153 0.9929736 1.0025480 1.0095161 0.9998259
## 5 0.9937153 0.9929736 1.0025480 1.0095161 0.9998259
## 6
##
## $trend
##        Jan      Feb      Mar      Apr      May      Jun      Jul      Aug
## 1       NA       NA       NA       NA       NA       NA 187.7925 187.6579
## 2 188.9729 189.5354 189.9675 190.2762 190.5679 190.8283 191.0375 191.2142
## 3 189.5708 188.7229 187.9496 187.3521 186.7750 186.2596 185.8758 185.5200
## 4 186.0975 186.5900 187.2467 187.8154 188.3446 188.8129 189.2292 189.7383
## 5 191.7925 191.8750 191.7850 192.1829 193.2883 194.6854 196.1346 197.5038
## 6       NA       NA       NA       NA       NA
##        Sep      Oct      Nov      Dec
## 1 187.5592 187.6642 187.9746 188.3900
## 2 191.3479 191.2362 190.8246 190.2754
## 3 185.1758 185.1317 185.3967 185.7704
## 4 190.3104 190.7788 191.1650 191.5025
## 5 198.8083 200.1217 201.3129       NA
## 6
##
## $random
##         Jan       Feb       Mar       Apr       May       Jun       Jul
## 1        NA        NA        NA        NA        NA        NA 0.9969622
## 2 0.9912315 0.9945689 0.9880225 0.9994619 0.9990398 1.0080115 1.0203733
## 3 1.0033553 1.0059892 1.0086237 0.9907840 0.9910057 0.9907993 0.9997277
## 4 1.0026902 0.9909792 0.9944940 1.0004751 1.0042463 1.0031716 0.9977305
```

```
## 5 0.9973463 1.0030862 1.0034832 1.0039024 1.0003316 0.9926410 0.9784856
## 6        NA        NA        NA        NA        NA
##         Aug       Sep       Oct       Nov       Dec
## 1 1.0061748 1.0049329 1.0011569 0.9914980 1.0011829
## 2 1.0181439 1.0089291 0.9974259 0.9981287 1.0024060
## 3 0.9881529 1.0030199 0.9922233 0.9911258 0.9966185
## 4 1.0131751 1.0124715 0.9981447 0.9920504 0.9944160
## 5 0.9676326 0.9639259 1.0043284 1.0204763        NA
## 6
##
## $figure
##  [1] 1.0031182 0.9946632 0.9956196 1.0003478 1.0075902 1.0049535 0.9951287
##  [8] 0.9937153 0.9929736 1.0025480 1.0095161 0.9998259
##
## $type
## [1] "multiplicative"
##
## attr(,"class")
## [1] "decomposed.ts"
```

```
par(mfrow=c(1,2))
plot(decompose(data, type='multi'))
library(forecast)
```

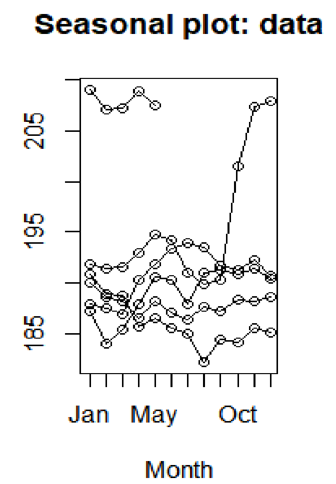


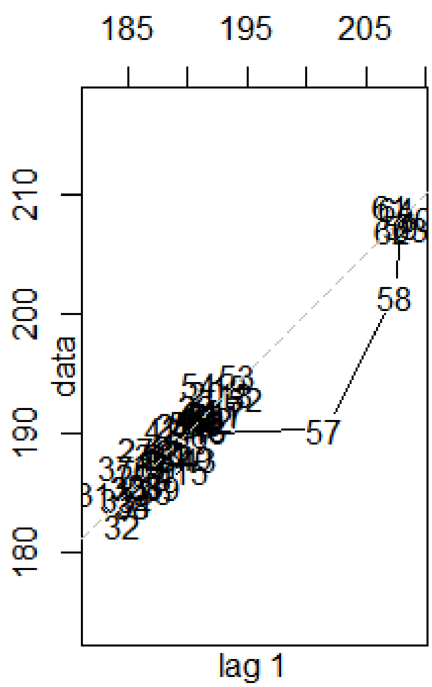

```
seasonplot(data)
```

```
lag(data,10)
```

```
##      Jan    Feb    Mar    Apr    May    Jun    Jul    Aug    Sep    Oct
## 0                 190.04 188.59 188.15 186.44 188.18 186.99 186.31 187.63
## 1 188.15 188.58 187.90 187.50 186.87 190.24 191.83 193.31 193.98 193.46
## 2 192.28 190.70 190.80 188.84 188.74 185.69 186.50 185.46 184.92 182.17
## 3 185.50 185.11 187.18 183.92 185.40 187.97 190.58 190.35 187.88 191.03
## 4 191.45 190.40 191.88 191.44 191.61 193.00 194.82 194.21 190.98 189.91
## 5 207.39 207.99 209.07 207.11 207.25 208.88 207.53
##      Nov    Dec
## 0 187.16 188.36
## 1 191.70 191.23
## 2 184.43 184.16
## 3 191.33 190.91
## 4 190.29 201.50
## 5
```

```r
lag.plot(data)
```





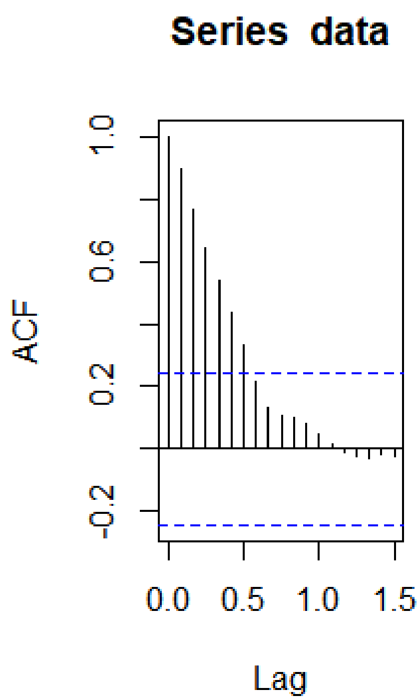

```
# Calculation of Autocorrelation and Partial Autocorrelation
data

##       Jan    Feb    Mar    Apr    May    Jun    Jul    Aug    Sep    Oct
## 1 190.04 188.59 188.15 186.44 188.18 186.99 186.31 187.63 187.16 188.36
## 2 187.90 187.50 186.87 190.24 191.83 193.31 193.98 193.46 191.70 191.23
## 3 190.80 188.84 188.74 185.69 186.50 185.46 184.92 182.17 184.43 184.16
## 4 187.18 183.92 185.40 187.97 190.58 190.35 187.88 191.03 191.33 190.91
## 5 191.88 191.44 191.61 193.00 194.82 194.21 190.98 189.91 190.29 201.50
## 6 209.07 207.11 207.25 208.88 207.53
##       Nov    Dec
```

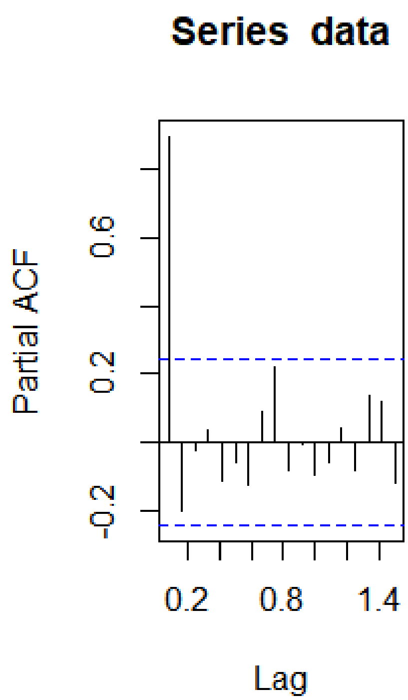
```
## 1 188.15 188.58
## 2 192.28 190.70
## 3 185.50 185.11
## 4 191.45 190.40
## 5 207.39 207.99
## 6
```

```r
ac<-acf(data)

ac$acf
```

```
## , , 1
##
##                [,1]
##  [1,]  1.000000000
##  [2,]  0.897834549
##  [3,]  0.766959609
##  [4,]  0.642380728
##  [5,]  0.540362058
##  [6,]  0.435258811
##  [7,]  0.329717557
##  [8,]  0.213959913
##  [9,]  0.130089131
## [10,]  0.108939188
## [11,]  0.096442343
## [12,]  0.081448406
## [13,]  0.048226570
## [14,]  0.012083704
## [15,] -0.008036572
## [16,] -0.024501683
## [17,] -0.027889568
## [18,] -0.018651269
## [19,] -0.020409708
```

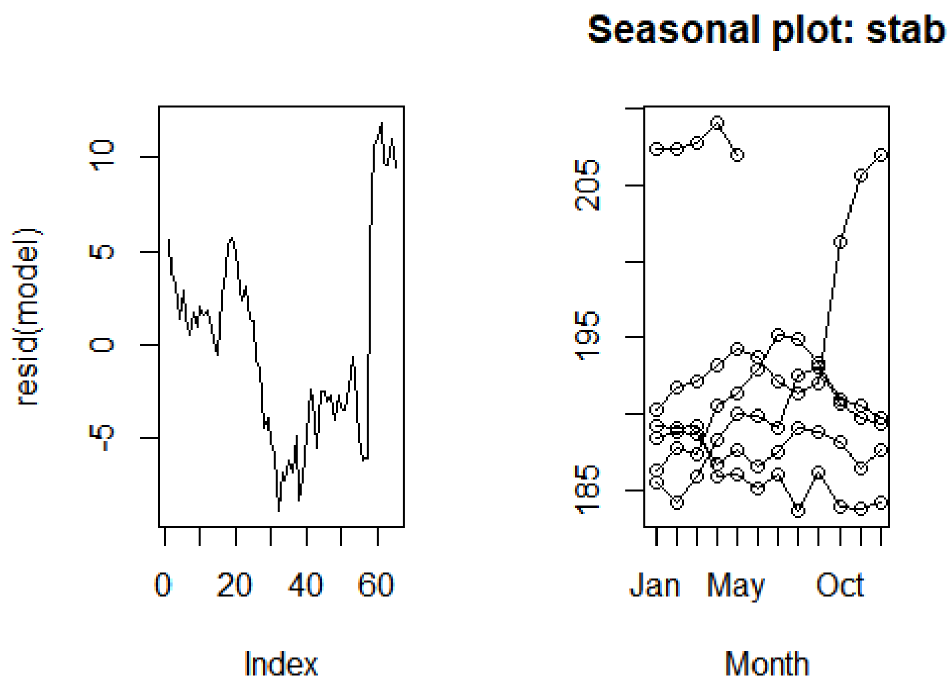
```r
# data time series may not have stationarity

pac<-pacf(data)
```





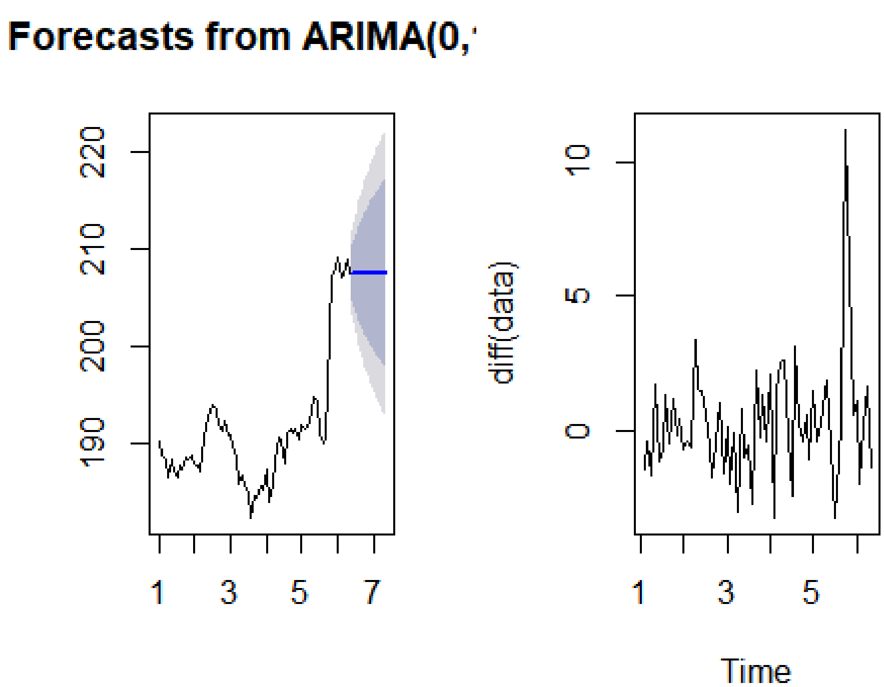

```
pac$acf

## , , 1
##
##              [,1]
##  [1,]  0.897834549
##  [2,] -0.201901271
##  [3,] -0.021388111
##  [4,]  0.033830089
##  [5,] -0.113123217
##  [6,] -0.061245804
##  [7,] -0.127001529
##  [8,]  0.089593010
##  [9,]  0.222548229
## [10,] -0.084860931
## [11,] -0.006016842
## [12,] -0.096866419
## [13,] -0.060046996
## [14,]  0.039563483
## [15,] -0.084282971
## [16,]  0.133672152
## [17,]  0.117993466
## [18,] -0.118439370

# looking at the ACF and PACF graph we can conclude that the time series is n
ot stationary
```

```r
model <- lm(data~c(1:length(data)))

summary(model)

##
## Call:
## lm(formula = data ~ c(1:length(data)))
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -8.8666 -4.0286 -0.5626  2.9954 11.8853
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)       184.25256    1.33272 138.253  < 2e-16 ***
## c(1:length(data))   0.21200    0.03511   6.039 9.13e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.31 on 63 degrees of freedom
## Multiple R-squared:  0.3666, Adjusted R-squared:  0.3566
## F-statistic: 36.46 on 1 and 63 DF,  p-value: 9.126e-08

plot(resid(model),type='l')

# the series is not stationary

# deseasonalize the time series


tbl <- stl(data,'periodic')

stab<-seasadj(tbl)

seasonplot(stab,12)
```



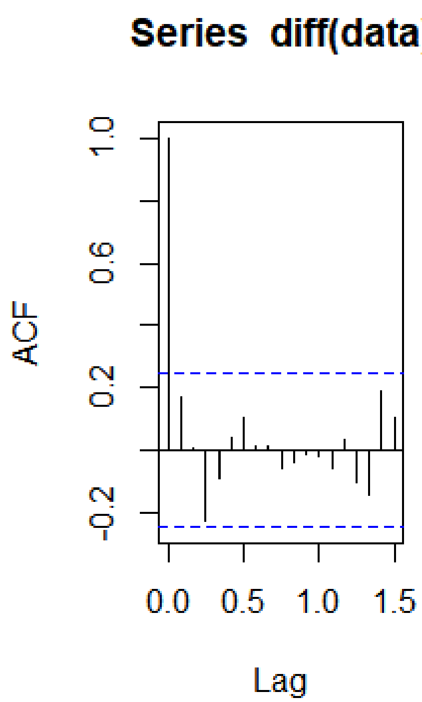

```
# statistically we need to test out if the series is stationary or not
# Augmented Dickey Fuller Test

library(tseries)

adf.test(data)

##
##  Augmented Dickey-Fuller Test
##
## data:  data
## Dickey-Fuller = -0.86015, Lag order = 3, p-value = 0.9516
## alternative hypothesis: stationary

# if the p-value is less than 0.05, then the time series is stationary, else
not

# Time Series Forecasting Models

# Simple Exponential Smoothing
# Double Expo. Smoothing
# Tripple Expo. Smoothing
# AR-I-MA model

#PACF- p
#diff - d
#ACF- q
```

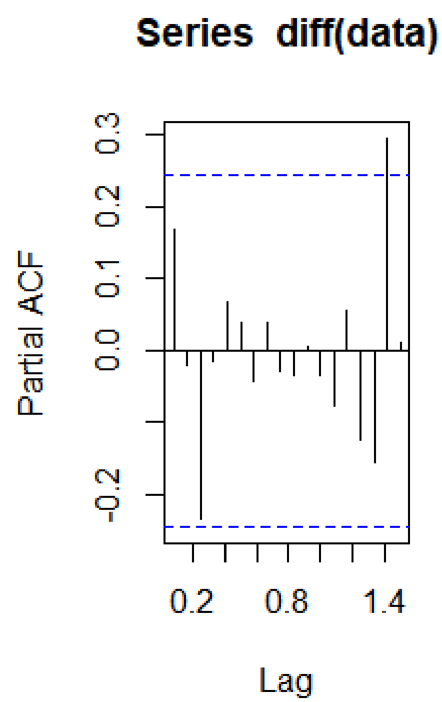
```
model2<-auto.arima(data)
accuracy(model2)

##                     ME     RMSE      MAE       MPE      MAPE      MASE
## Training set 0.2720007 2.171997 1.452924 0.1307485 0.7549219 0.2304089
##                   ACF1
## Training set 0.1700406

plot(forecast(model2,h=12))

adf.test(diff(data))

## Warning in adf.test(diff(data)): p-value smaller than printed p-value

##
##  Augmented Dickey-Fuller Test
##
## data:  diff(data)
## Dickey-Fuller = -4.5932, Lag order = 3, p-value = 0.01
## alternative hypothesis: stationary

plot(diff(data))
```




```
diff(data,differences = 3)
```

```
##           Jan       Feb       Mar       Apr       May       Jun
## 1                               -2.279985  4.719973 -6.379962
## 2 -1.750031  1.390030 -0.510025  4.230026 -5.780028  1.670012
## 3  4.310013 -3.740021  3.920029 -4.810028  6.810013 -5.709992
## 4  4.189986 -7.789978 10.069978 -3.649980 -1.050017 -2.879991
## 5  4.120010 -4.450028  2.530016  0.609998 -0.789992 -2.860015
## 6  5.769989 -3.520004  5.140013 -0.609999 -4.470017
##           Jul       Aug       Sep       Oct       Nov       Dec
## 1  3.439960  1.490033 -3.790022  3.460006 -3.080002  2.050019
## 2 -0.699997 -0.379989 -0.050034  2.530030  0.229995 -4.150009
## 3  2.349975 -2.709975  7.219986 -7.539979  4.139969 -3.339980
## 4  0.599992  7.860000 -8.469986  2.129990  1.679992 -2.549987
## 5 -0.190004  4.780030 -0.710038  9.380037 -16.150026  0.030015
## 6

#running a model on diff data
model3<-auto.arima(diff(data))

accuracy(model3)

##                     ME     RMSE      MAE MPE MAPE      MASE      ACF1
## Training set 0.2732813 2.188771 1.472657 100  100 0.7590256 0.1695623

acf(diff(data))

pacf(diff(data))
```





```r
#taking random order
model4 <- Arima(diff(data),order=c(4,0,5))
model4
```

```
## Series: diff(data)
## ARIMA(4,0,5) with non-zero mean
##
## Coefficients:
```

```
## Warning in sqrt(diag(x$var.coef)): NaNs produced
```

```
##           ar1      ar2      ar3      ar4     ma1     ma2     ma3     ma4
##       -0.2803  -1.4150  -0.0641  -0.4746  0.4821  1.7941  0.1249  0.6766
## s.e.      NaN   0.1265      NaN   0.1483     NaN     NaN     NaN     NaN
##           ma5    mean
##       -0.2638  0.2614
## s.e.   0.1724  0.2747
##
## sigma^2 estimated as 4.095:  log likelihood=-133.78
## AIC=289.56   AICc=294.64   BIC=313.31
```

```r
accuracy(model4)
```

```
##                        ME     RMSE      MAE      MPE     MAPE      MASE
## Training set 0.0006347165 1.858786 1.406267 92.29461 131.9952 0.7248077
##                    ACF1
## Training set 0.01349565
```

```r
model5 <- Arima(diff(data),order=c(4,0,4))
model5
```

```
## Series: diff(data)
## ARIMA(4,0,4) with non-zero mean
##
## Coefficients:
##          ar1     ar2      ar3     ar4      ma1      ma2      ma3      ma4
##       0.4456  0.0444  -0.1777  0.5375  -0.3143  -0.0540  -0.0711  -0.5606
## s.e.  0.6682  0.5270   0.4503  0.4737   0.6114   0.5523   0.3712   0.6958
##         mean
##       0.2479
## s.e.  0.1483
##
## sigma^2 estimated as 4.847:  log likelihood=-137.17
## AIC=294.34   AICc=298.49   BIC=315.93
```

```r
accuracy(model5)
```

```
##                      ME     RMSE      MAE      MPE     MAPE      MASE
## Training set -0.1080514 2.040884 1.479593 108.6686 139.0467 0.7626008
##                    ACF1
## Training set 0.01210928
```

```
model6<-Arima(data,order=c(3,0,5))
model6

## Series: data
## ARIMA(3,0,5) with non-zero mean
##
## Coefficients:
##          ar1      ar2     ar3     ma1     ma2     ma3     ma4      ma5
##       0.7731  -0.7050  0.8166  0.3971  1.1226  0.1251  0.0658  -0.1386
## s.e.  0.2638   0.1838  0.1065  0.2880  0.2760  0.2585  0.2129   0.1412
##           mean
##       193.6317
## s.e.    4.8020
##
## sigma^2 estimated as 4.67:  log likelihood=-140.1
## AIC=300.2   AICc=304.27   BIC=321.94

accuracy(model6)

##                      ME     RMSE      MAE        MPE     MAPE      MASE
## Training set 0.0750624 2.005746 1.468935 0.02667925 0.763838 0.2329479
##                     ACF1
## Training set 0.02072704

model7<-Arima(diff(data),order=c(4,0,4))
model7

## Series: diff(data)
## ARIMA(4,0,4) with non-zero mean
##
## Coefficients:
##          ar1     ar2      ar3     ar4      ma1      ma2      ma3      ma4
##       0.4456  0.0444  -0.1777  0.5375  -0.3143  -0.0540  -0.0711  -0.5606
## s.e.  0.6682  0.5270   0.4503  0.4737   0.6114   0.5523   0.3712   0.6958
##         mean
##       0.2479
## s.e.  0.1483
##
## sigma^2 estimated as 4.847:  log likelihood=-137.17
## AIC=294.34   AICc=298.49   BIC=315.93

accuracy(model7)

##                       ME     RMSE      MAE      MPE     MAPE      MASE
## Training set -0.1080514 2.040884 1.479593 108.6686 139.0467 0.7626008
##                     ACF1
## Training set 0.01210928

model8<-Arima(diff(data),order=c(0,0,1))
model8
```

```
## Series: diff(data)
## ARIMA(0,0,1) with non-zero mean
##
## Coefficients:
##          ma1    mean
##       0.1565  0.2648
## s.e.  0.1127  0.3090
##
## sigma^2 estimated as 4.734:  log likelihood=-139.56
## AIC=285.12   AICc=285.52   BIC=291.59
```

```
accuracy(model8)
```

```
##                       ME     RMSE      MAE      MPE     MAPE      MASE
## Training set 0.00374748 2.141417 1.506563 111.3245 117.7739 0.7765016
##                     ACF1
## Training set 0.01275007
```

```
model9<-Arima(diff(data),order=c(1,0,0))
model9
```

```
## Series: diff(data)
## ARIMA(1,0,0) with non-zero mean
##
## Coefficients:
##          ar1    mean
##       0.1702  0.2626
## s.e.  0.1233  0.3214
##
## sigma^2 estimated as 4.726:  log likelihood=-139.51
## AIC=285.01   AICc=285.41   BIC=291.49
```

```
accuracy(model9)
```

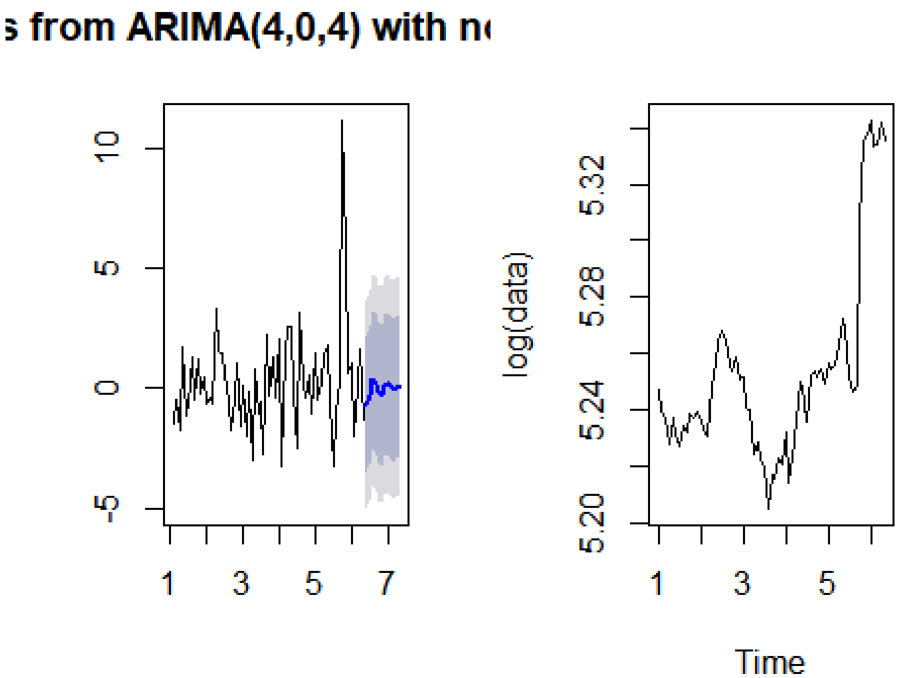
```
##                        ME     RMSE      MAE      MPE     MAPE      MASE
## Training set 0.004944389 2.139586 1.507873 110.3545 118.8004 0.7771767
##                      ACF1
## Training set 0.004464458
```

```
model10<-Arima(diff(data),order=c(1,0,1))
model10
```

```
## Series: diff(data)
## ARIMA(1,0,1) with non-zero mean
##
## Coefficients:
##          ar1     ma1    mean
##       0.1386  0.0329  0.2629
## s.e.  0.3916  0.3809  0.3199
##
## sigma^2 estimated as 4.802:  log likelihood=-139.5
## AIC=287   AICc=287.68   BIC=295.64
```

```
accuracy(model10)

##                        ME     RMSE      MAE      MPE     MAPE      MASE
## Training set 0.004743348 2.139462 1.508693 110.7547 119.1916 0.7775994
##                      ACF1
## Training set 0.001901816

model11<-Arima(diff(data),order=c(1,0,2))
model11

## Series: diff(data)
## ARIMA(1,0,2) with non-zero mean
##
## Coefficients:
##           ar1     ma1     ma2    mean
##       -0.4792  0.6771  0.2237  0.2612
## s.e.   0.6182  0.5892  0.1329  0.3388
##
## sigma^2 estimated as 4.782:  log likelihood=-138.87
## AIC=287.74   AICc=288.77   BIC=298.53

accuracy(model11)

##                        ME     RMSE      MAE      MPE     MAPE      MASE
## Training set 0.003565339 2.117405 1.510722 105.7682 123.4363 0.7786448
##                       ACF1
## Training set -0.009002027

model12<-Arima(diff(data),order=c(1,1,3))
model12

## Series: diff(data)
## ARIMA(1,1,3)
##
## Coefficients:
##           ar1      ma1      ma2      ma3
##       -0.4163  -0.3667  -0.3947  -0.2341
## s.e.   0.5693   0.7264   0.5525   0.1834
##
## sigma^2 estimated as 4.876:  log likelihood=-139.02
## AIC=288.04   AICc=289.09   BIC=298.75

accuracy(model12)

##                      ME     RMSE      MAE      MPE     MAPE     MASE
## Training set 0.2818303 2.120099 1.452976 88.80578 112.3296 0.748882
##                      ACF1
## Training set -0.03927055

#  MAPE = mean absolute percentage error (should be < 10%) for a good model
par(mfrow=c(1,2))
plot(forecast(model5,h=12))
```

```r
plot(log(data))
```




```r
# Holt Winters Exponential Smoothing Model

# if series is stationary then use simple exponential smoothing model
model4<-HoltWinters(data,beta = F, gamma = F)
summary(model4)

##              Length Class  Mode
## fitted       128    mts    numeric
## x             65    ts     numeric
## alpha          1    -none- numeric
## beta           1    -none- logical
## gamma          1    -none- logical
## coefficients   1    -none- numeric
## seasonal       1    -none- character
## SSE            1    -none- numeric
## call           4    -none- call

model4

## Holt-Winters exponential smoothing without trend and without seasonal comp
onent.
##
## Call:
## HoltWinters(x = data, beta = F, gamma = F)
```

```
##
## Smoothing parameters:
##  alpha: 0.9999498
##  beta : FALSE
##  gamma: FALSE
##
## Coefficients:
##       [,1]
## a 207.5301
```

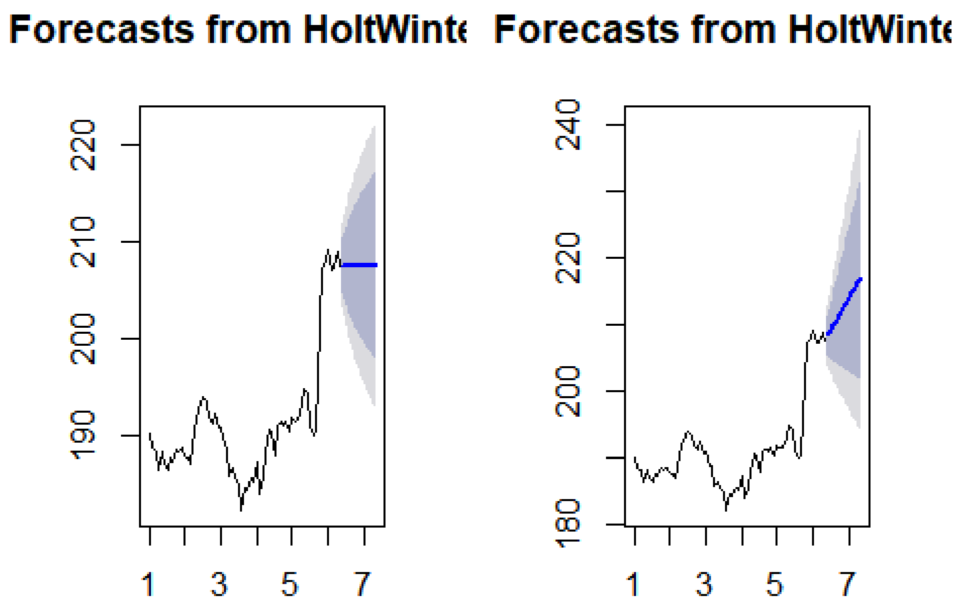
```
library(forecast)
plot(forecast(model4,12))

# Holt Winters Exponential Smoothing Model

# if series is not stationary and only trend component is present, then use d
ouble exponential smoothing model
model5<-HoltWinters(data,gamma = F)
summary(model5)
```

```
##              Length Class  Mode
## fitted       189    mts    numeric
## x             65    ts     numeric
## alpha          1    -none- numeric
## beta           1    -none- numeric
## gamma          1    -none- logical
## coefficients   2    -none- numeric
## seasonal       1    -none- character
## SSE            1    -none- numeric
## call           3    -none- call
```

```
model5
```

```
## Holt-Winters exponential smoothing with trend and without seasonal compone
nt.
##
## Call:
## HoltWinters(x = data, gamma = F)
##
## Smoothing parameters:
##  alpha: 1
##  beta : 0.08842156
##  gamma: FALSE
##
## Coefficients:
##          [,1]
## a 207.5299990
## b   0.7924614
```

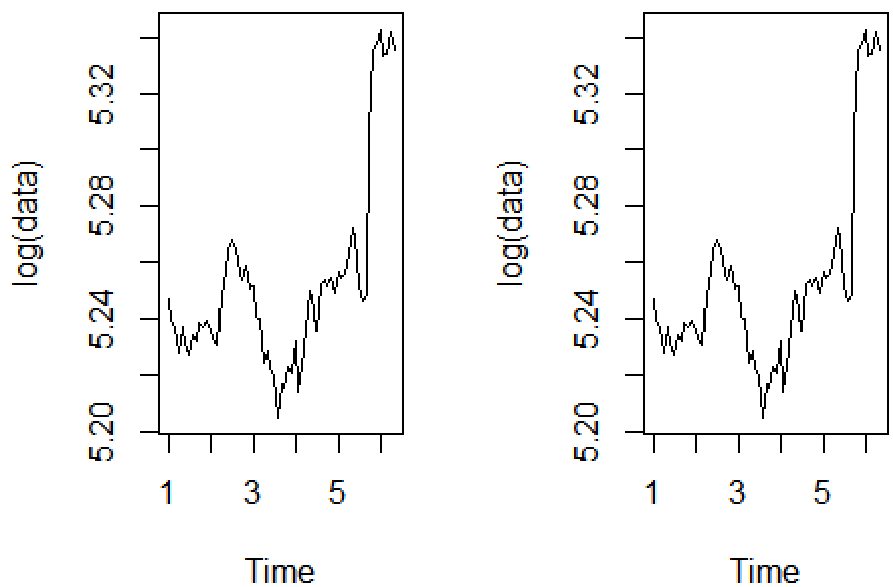
```
plot(forecast(model5,12))
```




```
plot(log(data))

# Holt Winters Exponential Smoothing Model
# if series is not stationary and trend, seasonality component is present, th
en use tripple exponential smoothing model
model6<-HoltWinters(data)
summary(model6)

##              Length Class  Mode
## fitted       212    mts    numeric
## x             65    ts     numeric
## alpha          1    -none- numeric
## beta           1    -none- numeric
## gamma          1    -none- numeric
## coefficients  14    -none- numeric
## seasonal       1    -none- character
## SSE            1    -none- numeric
## call           2    -none- call

model6

## Holt-Winters exponential smoothing with trend and additive seasonal compon
ent.
##
## Call:
## HoltWinters(x = data)
##
```

```
## Smoothing parameters:
##  alpha: 0.9039743
##  beta : 0
##  gamma: 1
##
## Coefficients:
##              [,1]
## a   206.47238517
## b     0.33351689
## s1    2.15703648
## s2   -0.63318618
## s3   -0.23391222
## s4   -0.11991297
## s5    1.47358988
## s6    1.27297528
## s7    0.29666706
## s8   -0.05308394
## s9   -1.96662951
## s10  -2.49227872
## s11  -0.54306702
## s12   1.05761383
```

```
plot(log(data))
```




```
plot(forecast(model6,12))

# MAPE
```

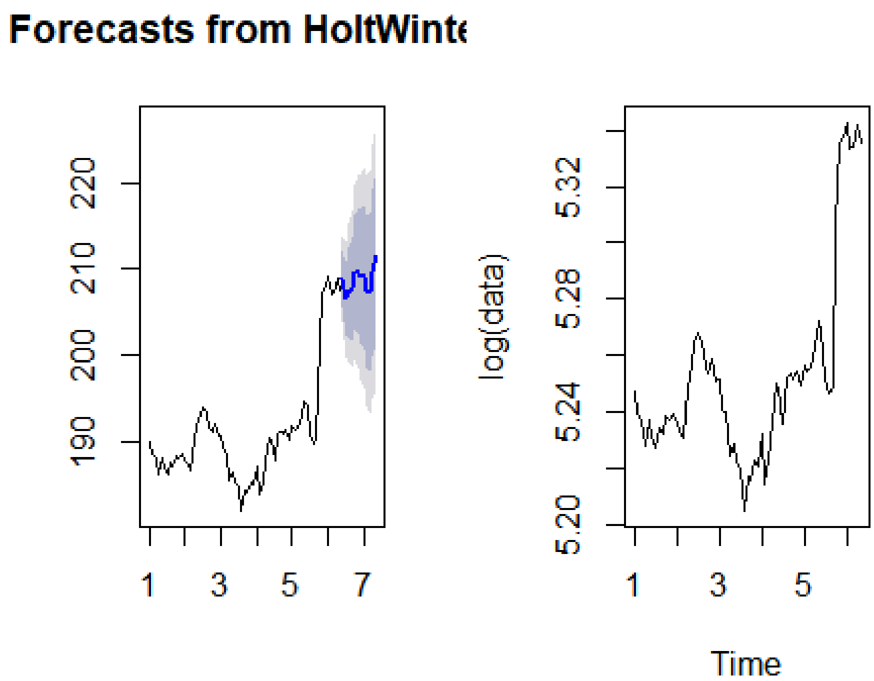
```r
# Automatic Exponential Smoothing Model
model7<-ets(data)
summary(model7)
```

```
## ETS(M,N,N)
##
## Call:
##  ets(y = data)
##
##   Smoothing parameters:
##     alpha = 0.9999
##
##   Initial states:
##     l = 190.0165
##
##   sigma:  0.0115
##
##      AIC     AICc      BIC
## 378.0199 378.4133 384.5431
##
## Training set error measures:
##                     ME     RMSE      MAE       MPE      MAPE     MASE
## Training set 0.2694668 2.171911 1.450364 0.1294136 0.7535737 0.230003
##                   ACF1
## Training set 0.1710693
```

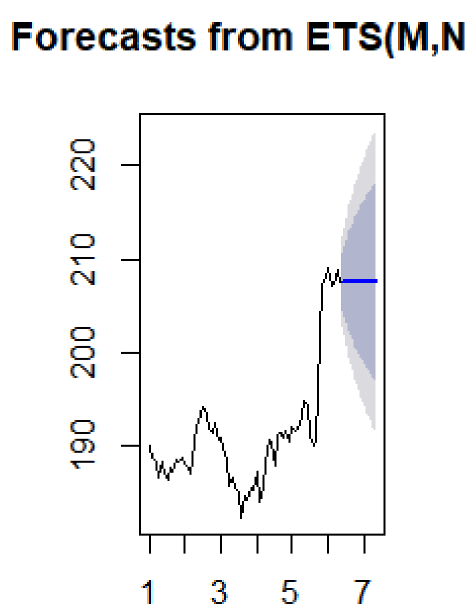
```r
accuracy(model7)
```

```
##                     ME     RMSE      MAE       MPE      MAPE     MASE
## Training set 0.2694668 2.171911 1.450364 0.1294136 0.7535737 0.230003
##                   ACF1
## Training set 0.1710693
```

```r
plot(log(data))
```




```
plot(forecast(model7,12))
```



d. After 15 days again collect the data and compare with your forecast

```
library(readr)
AAPLAug10toAug25 <- read.csv("AAPLAug10toAug25.csv")
View(AAPLAug10toAug25)
df<-AAPLAug10toAug25
head(df)
```

	Date	Open	High	Low	Close	Adj.Close	Volume
1	2018-08-10	207.36	209.10	206.67	207.53	207.53	24611200
2	2018-08-13	207.70	210.95	207.70	208.87	208.87	25869100
3	2018-08-14	210.16	210.56	208.26	209.75	209.75	20748000
4	2018-08-15	209.22	210.74	208.33	210.24	210.24	28807600
5	2018-08-16	211.75	213.81	211.47	213.32	213.32	28500400
6	2018-08-17	213.44	217.95	213.16	217.58	217.58	35427000

```
 str(df)
'data.frame':	11 obs. of  7 variables:
 $ Date     : Factor w/ 11 levels "2018-08-10","2018-08-13",..: 1 2 3 4 5 6 7 8 9 10 ...
 $ Open     : num  207 208 210 209 212 ...
 $ High     : num  209 211 211 211 214 ...
 $ Low      : num  207 208 208 208 211 ...
 $ Close    : num  208 209 210 210 213 ...
 $ Adj.Close: num  208 209 210 210 213 ...
 $ Volume   : int  24611200 25869100 20748000 28807600 28500400 35427000 30287700 261598
00 19018100 18883200 ...
 new_date <- as.Date(df$Date)
new_date
 [1] "2018-08-10" "2018-08-13" "2018-08-14" "2018-08-15" "2018-08-16" "2018-08-17" "2018
-08-20"
 [8] "2018-08-21" "2018-08-22" "2018-08-23" "2018-08-24"
 str(df)
'data.frame':	11 obs. of  7 variables:
 $ Date     : Factor w/ 11 levels "2018-08-10","2018-08-13",..: 1 2 3 4 5 6 7 8 9 10 ...
 $ Open     : num  207 208 210 209 212 ...
 $ High     : num  209 211 211 211 214 ...
 $ Low      : num  207 208 208 208 211 ...
 $ Close    : num  208 209 210 210 213 ...
 $ Adj.Close: num  208 209 210 210 213 ...
 $ Volume   : int  24611200 25869100 20748000 28807600 28500400 35427000 30287700 261598
00 19018100 18883200 ...
format(new_date,format="%B %d %Y")
 [1] "August 10 2018" "August 13 2018" "August 14 2018" "August 15 2018" "August 16 2018
"
 [6] "August 17 2018" "August 20 2018" "August 21 2018" "August 22 2018" "August 23 2018
"
[11] "August 24 2018"
>
> # %d - day as number 1-31
> # %a - weekday such as Mon
> # %A- complete day name ex.Monday
> # %m - month as a number
> # %b - short form of month Jan, Feb
> # %B - full form of month, January
> # %y - two digit year
> # %Y- four digit year
>
> data = ts(df$Close,frequency =12)
>
> plot(data,main="Monthly Closing Prices")
> # Additive Time Series
> # Trend + Seasonality+ Cyclicity+ error
> # Multiplicative Time Series
> ## Trend * Seasonality * Cyclicity * error
```

```
>
> # additive model is easy to explain, easy to forecast and interpret
# multiplicate models can be converted to additive models using log of the time series
log(data)
       Jan      Feb      Mar      Apr      May      Jun      Jul      Aug      Sep
Oct
1 5.335276 5.341712 5.345916 5.348250 5.362793 5.382567 5.372775 5.370824 5.370871 5.372
915
       Nov
1 5.376019
```