R for Beginners - R for Finance Code File-1

This R code book written by Rohit Dhankar . GitHub - https://github.com/RohitDhankar

Code and Data > https://github.com/RohitDhankar/R-Beginners-Online-Virtual-Learning-Session

Good practice to keep track of current Working Directory , list all Objects in R ENVIRONMENT - specially so when committing changes to Git or any other version control Remote directory.

R for Finance

```
library("forecast");
library("ggplot2");
library("ggfortify")
```

```
##
## Attaching package: 'ggfortify'

## The following object is masked from 'package:forecast':
##
##     gglagplot
```

```
library("tseries")
```

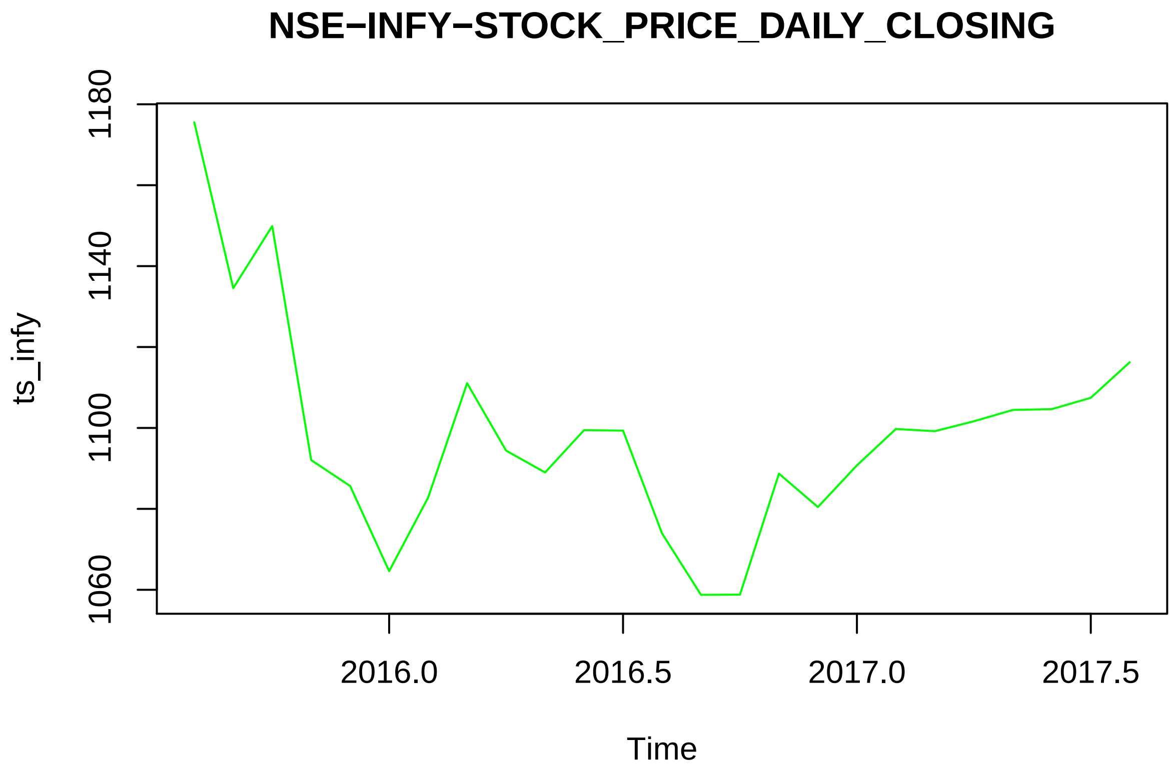
```
# Set Seed -- ensure reproducible results

set.seed(123)

infy_df <- read.csv("~/Desktop/R_Own/R_Finance/DATA_Files/INFY.csv")
str(infy_df)
```

```
## 'data.frame':    494 obs. of  1 variable:
##  $ Close.Price: num  1176 1135 1150 1092 1086 ...
```

```
summary(infy_df)
```

```
##   Close.Price
##  Min.   : 911.1
##  1st Qu.: 982.0
##  Median :1049.1
##  Mean   :1060.4
##  3rd Qu.:1134.1
##  Max.   :1267.6
```

```
start_date <- infy_df$Date[1] ## [1] 19-Aug-2015
len_df<-length(infy_df$Date)
end_date <-infy_df$Date[len_df] ## [1] 17-Aug-2017

# Convert DF to TS

ts_infy <-ts(infy_df, start = c(2015,8), end =  c(2017,8),  frequency = 12) #
plot.ts(ts_infy,main="NSE-INFY-STOCK_PRICE_DAILY_CLOSING",col="green")
```




```
#
#
```

```
#?ts() ## Uncomment to seek help
# frequency ---
# the number of observations per unit of time.
# deltat    ---
# the fraction of the sampling period between successive
# observations; e.g., 1/12 for monthly data. Only one of frequency
# or deltat should be provided.
#
ts_infy1 <-ts(infy_df, start = c(2015,8), end =  c(2017,8), frequency = 24,names = "NSE-INFY-STOCK_PRIC
#
str(ts_infy1);summary(ts_infy1)
```

```
##  Time-Series [1:49] from 2015 to 2017: 1176 1135 1150 1092 1086 ...
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    1059    1095    1107    1117    1141    1182
```

```
#
typeof(ts_infy1) ## [1] "double"
```

```
## [1] "double"
```

```
#
typeof(ts_infy) ## [1] "double"
```

```
## [1] "double"
```

```
#
class(ts_infy)
```

```
## [1] "ts"
```

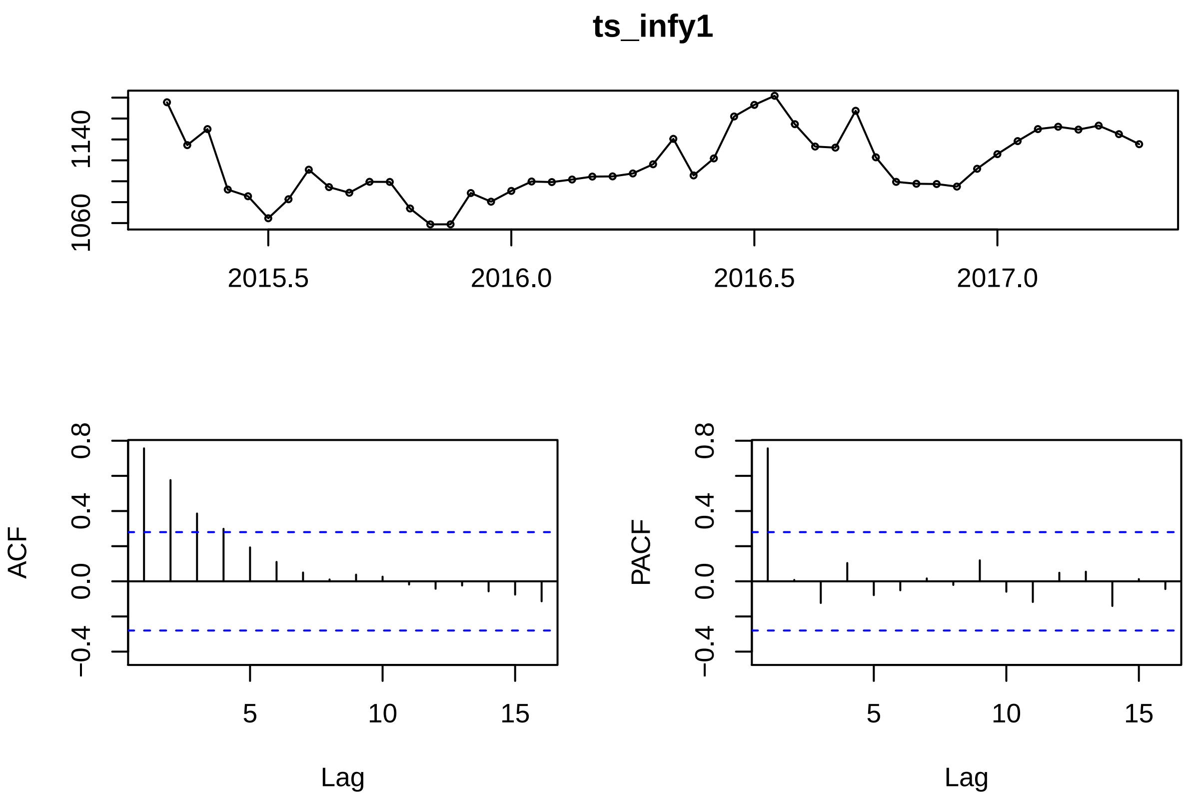
```r
#
head(ts_infy1);head(time(ts_infy1));tail(time(ts_infy1))
```

```
## Time Series:
## Start = c(2015, 8)
## End = c(2015, 13)
## Frequency = 24
## [1] 1175.55 1134.55 1149.90 1092.05 1085.65 1064.60

## Time Series:
## Start = c(2015, 8)
## End = c(2015, 13)
## Frequency = 24
## [1] 2015.292 2015.333 2015.375 2015.417 2015.458 2015.500

## Time Series:
## Start = c(2017, 3)
## End = c(2017, 8)
## Frequency = 24
## [1] 2017.083 2017.125 2017.167 2017.208 2017.250 2017.292
```

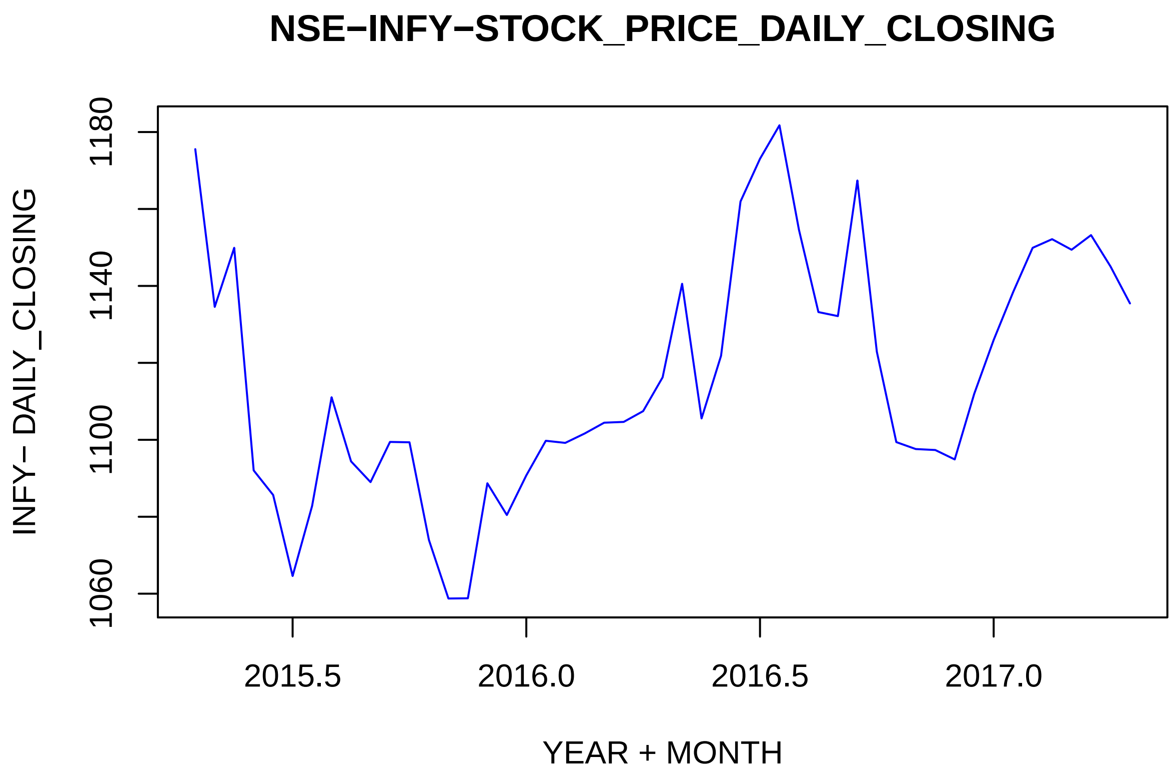
```r
# Head of TS # view Head - sampled times # view Tail of sampled times
dim(ts_infy1);
```

```
## NULL
```

```r
#
tsdisplay(ts_infy1)
```



```
#
plot.ts(ts_infy1,main="NSE-INFY-STOCK_PRICE_DAILY_CLOSING",col="blue",xlab="YEAR + MONTH",ylab="INFY- DA
```



Decomposition of TIME SERIES :-

" to construct, from an observed time series, a number of
component series (that could be used to reconstruct the original by additions
or multiplications) where each of these has a certain characteristic or type of behaviour.

SOURCE – WIKI – https://en.wikipedia.org/wiki/Decomposition_of_time_series

There are many lively discussions with regards which functions from the STATS
package to be used for decomposition i am refering a few below here - i shall
experiment with a couple of methods and see what works best for us.

```
#
```

Various Sources —

STACK_EXCHANGE – https://stats.stackexchange.com/questions/9506/stl-trend-of-time-series-using-r?rq=1

STACK_EXCHANGE – https://stats.stackexchange.com/questions/85987/which-is-better-stl-or-decompose

ESTIMATING and ELIMINATING THE TREND

We need to identify , then estimate and eliminate the trend component if present
in the Time Series Model .We also endevaour to eliminate the other TWO
Deterministic Features of the TS MODEL

We are dealing with DISCRETE data of Stock Price Closing Values as
taken from the NSE on 18 AUG 17

SOURCE — http://userwww.sfsu.edu/efc/classes/biol710/timeseries/TimeSeriesAnalysis.html

Learning pointers to be highlighted from the above cited source -

STATIONARY TIME SERIES DATA -

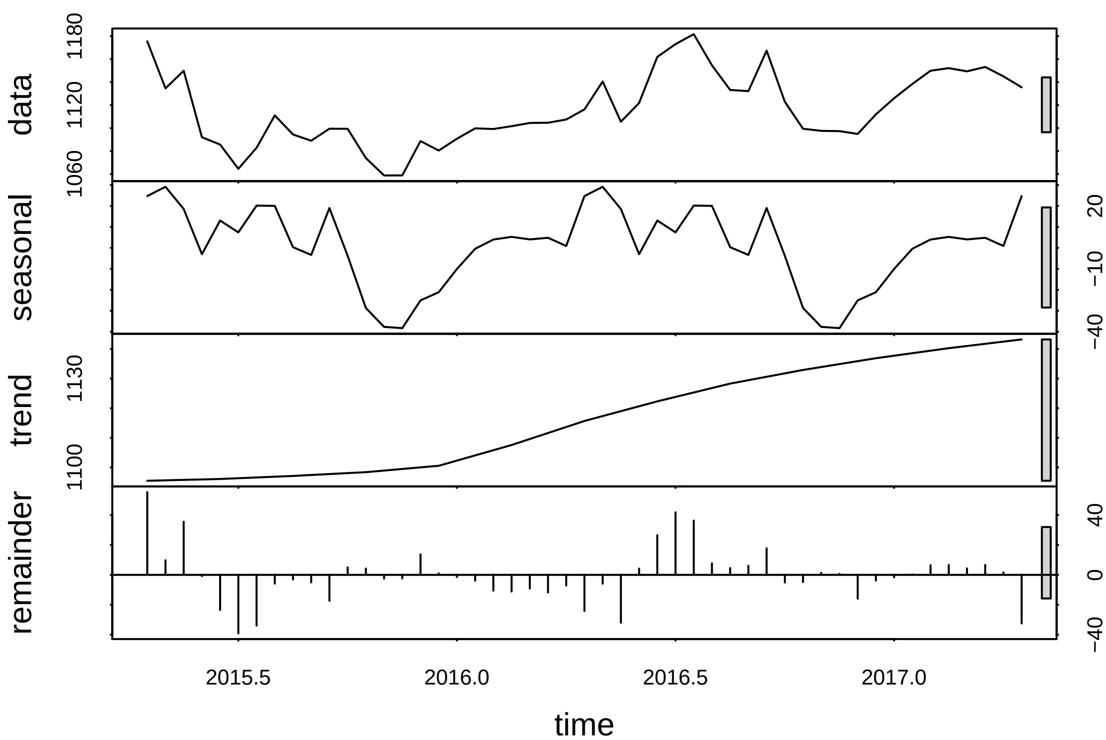
Definitions – TBD

NON STATIONARY TIME SERIES DATA -

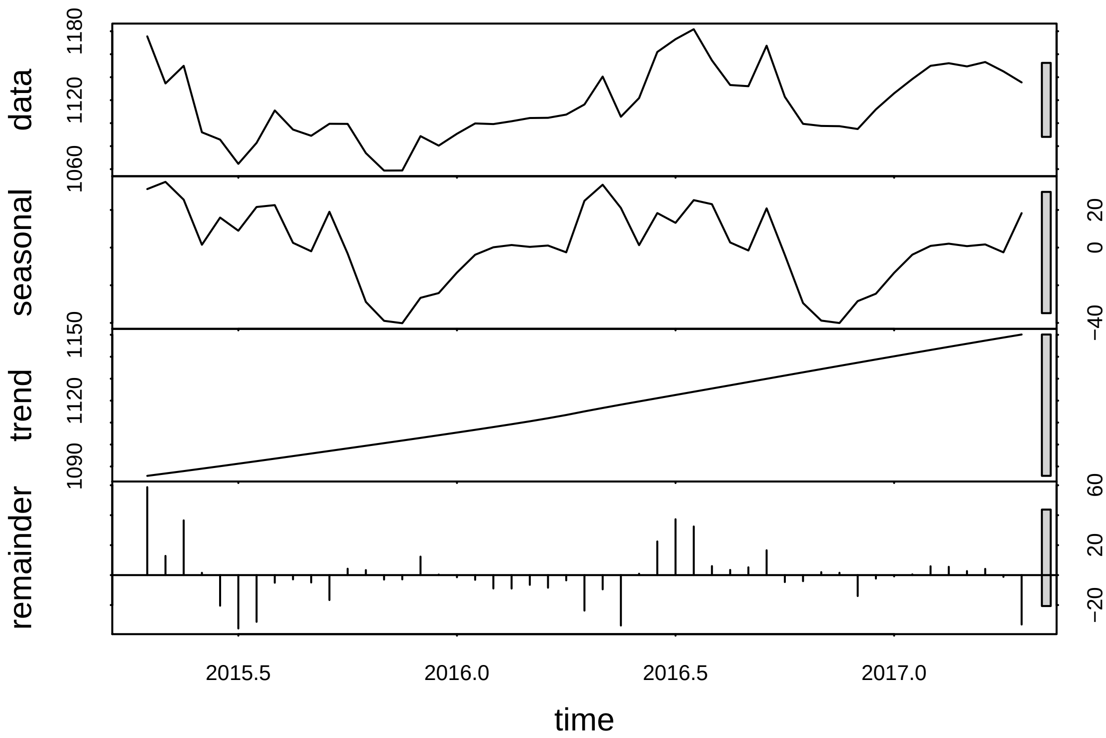
Quoting verbatim from the source mentioned above – "Box and Jenkins developed the AutoRegressive Integrative Moving Average (ARIMA) model
which combined the AutoRegresive (AR) and Moving Average (MA) models developed earlier
with a differencing factor that removes in trend in the data."

Further Reading – Multiple Sources :- WIKI —

```
#?stl() # stl {stats}
# Decompose a time series into seasonal, trend and irregular
# components using loess, acronym STL.

require(graphics)

plot(stl(ts_infy1, "per"))
```



```r
plot(stl(ts_infy1, s.window = 7, t.window = 50, t.jump = 1))
```




```r
#plot(stllc <- stl(log(co2), s.window = 21))
#summary(stllc)
```

In the plot above –Vertical Grey Bars - seen on right of each plot.
These signify relative importance Component.
Longest Vertical bar is of - TREND
In general terms - if the GREY BAR is Larger
The impact of the Component in this case TREND is LEAST
###Source – https://stats.stackexchange.com/questions/7876/interpreting-range-bars-in-rs-plot-stl

```r
dcomp_infy_1 <-stl(ts_infy1,s.window = 12,t.window = 10) ;head(dcomp_infy_1$time.series) ;str(dcomp_inf
```

```
## Time Series:
## Start = c(2015, 8)
## End = c(2015, 13)
## Frequency = 24
##             seasonal    trend  remainder
## 2015.292  20.854384 1142.521  12.174863
## 2015.333  19.671386 1129.986 -15.107597
## 2015.375  10.343246 1118.022  21.534308
## 2015.417 -10.910514 1106.855  -3.894247
## 2015.458   6.329533 1096.497 -17.176779
## 2015.500   3.019051 1086.892 -25.311028
```

```
## List of 8
##  $ time.series: Time-Series [1:49, 1:3] from 2015 to 2017: 20.85 19.67 10.34 -10.91 6.33 ...
##   ..- attr(*, "dimnames")=List of 2
##   .. ..$ : NULL
##   .. ..$ : chr [1:3] "seasonal" "trend" "remainder"
##  $ weights    : num [1:49] 1 1 1 1 1 1 1 1 1 1 ...
```

```
##  $ call       : language stl(x = ts_infy1, s.window = 12, t.window = 10)
##  $ win        : Named num [1:3] 12 10 25
##   ..- attr(*, "names")= chr [1:3] "s" "t" "l"
##  $ deg        : Named int [1:3] 0 1 1
##   ..- attr(*, "names")= chr [1:3] "s" "t" "l"
##  $ jump       : Named num [1:3] 2 1 3
##   ..- attr(*, "names")= chr [1:3] "s" "t" "l"
##  $ inner      : int 2
##  $ outer      : int 0
##  - attr(*, "class")= chr "stl"
```

```
typeof(dcomp_infy_1) # LIST
```

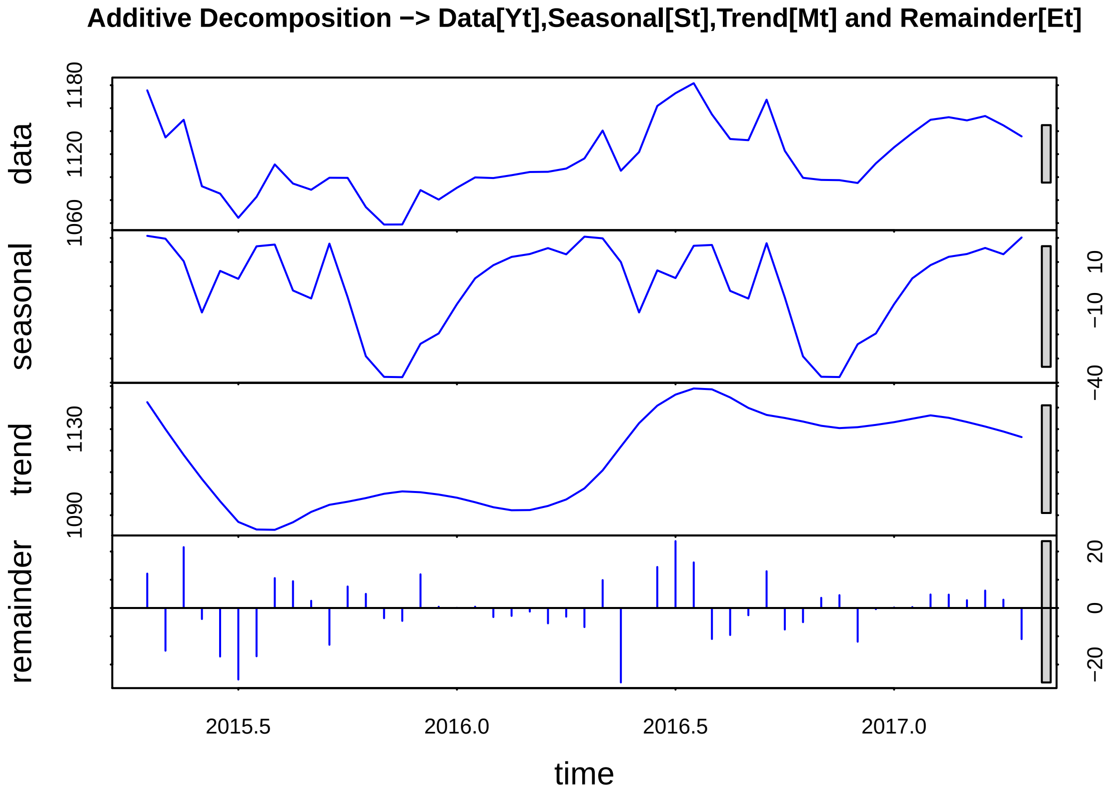
```
## [1] "list"
```

```
summary(dcomp_infy_1)
```

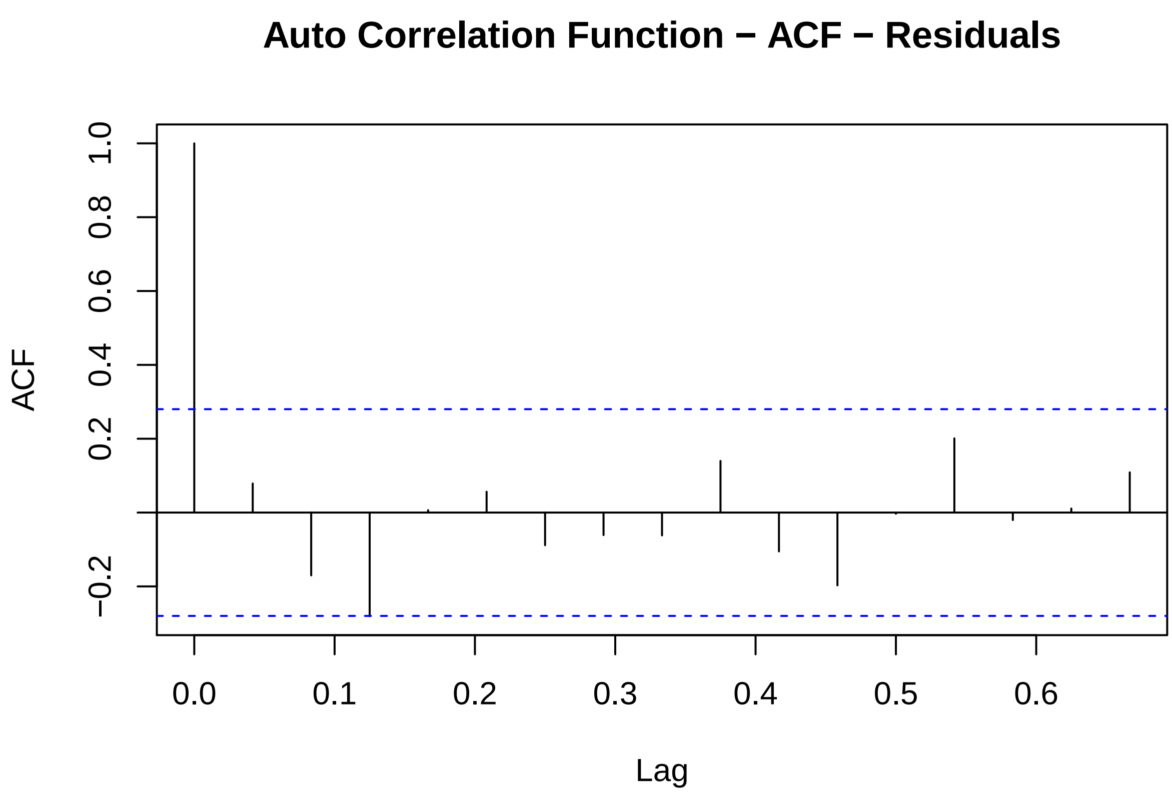
```
##  Call:
##  stl(x = ts_infy1, s.window = 12, t.window = 10)
##
##  Time.series components:
##     seasonal             trend            remainder
##  Min.   :-37.72765   Min.   :1083.233   Min.   :-26.341639
##  1st Qu.: -7.48136   1st Qu.:1096.497   1st Qu.: -5.424921
##  Median :  6.32953   Median :1121.906   Median :  0.074595
##  Mean   :  0.41636   Mean   :1116.466   Mean   : -0.376051
##  3rd Qu.: 15.76663   3rd Qu.:1133.521   3rd Qu.:  5.006186
##  Max.   : 20.85438   Max.   :1148.884   Max.   : 23.671716
##  IQR:
##      STL.seasonal STL.trend STL.remainder data
##      23.25        37.02     10.43         45.65
##    %  50.9         81.1      22.9         100.0
##
##  Weights: all == 1
##
##  Other components: List of 5
##  $ win  : Named num [1:3] 12 10 25
##  $ deg  : Named int [1:3] 0 1 1
##  $ jump : Named num [1:3] 2 1 3
##  $ inner: int 2
##  $ outer: int 0
```

```
# We focus on the IQR Values ---

# IQR:
#      STL.seasonal STL.trend STL.remainder data
#      23.25        37.02     10.43         45.65
#    %  50.9         81.1      22.9         100.0
```

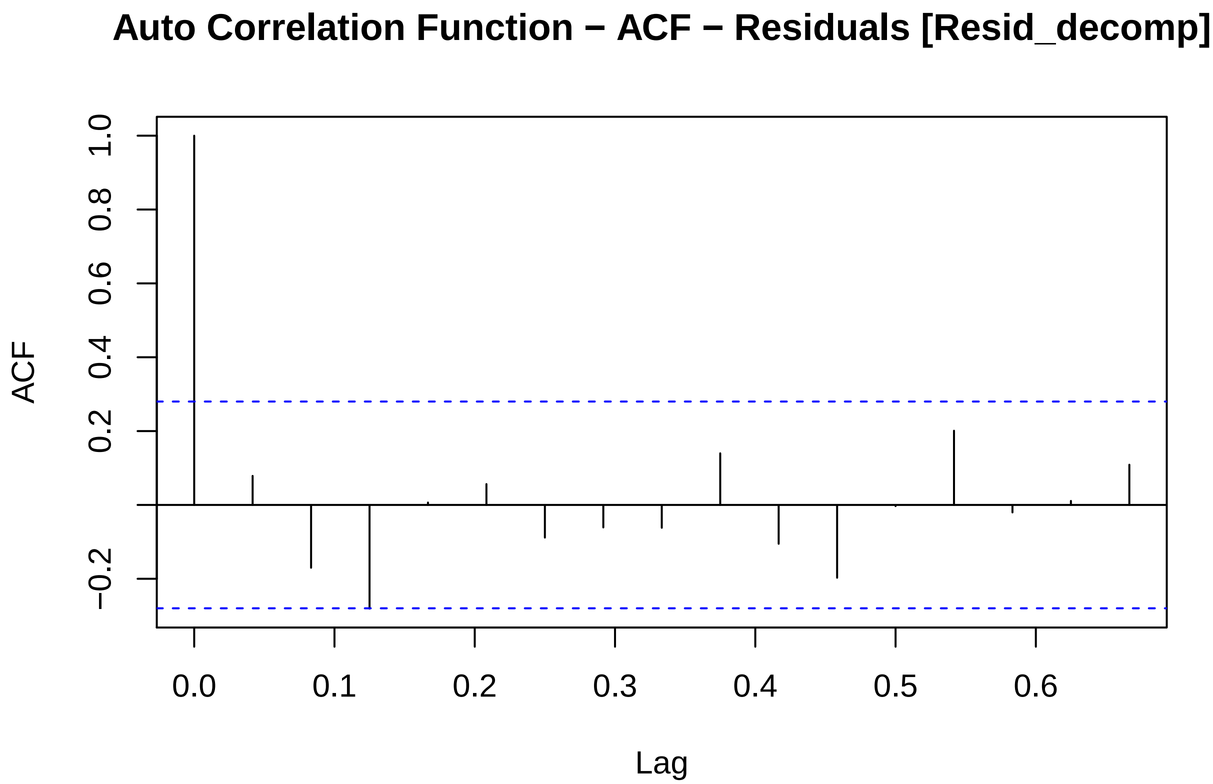
```
plot(dcomp_infy_1,main="Additive Decomposition -> Data[Yt],Seasonal[St],Trend[Mt] and Remainder[Et]",col
```



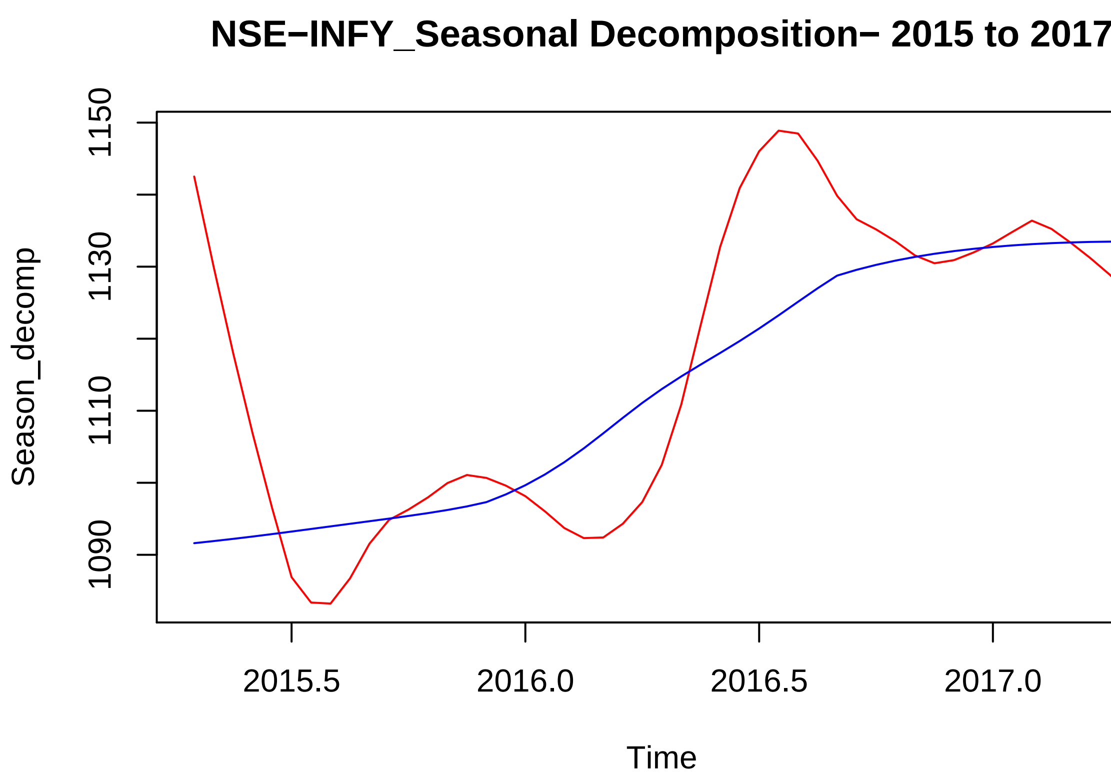

```
acf(dcomp_infy_1$time.series[,3],main="Auto Correlation Function - ACF - Residuals")
```




```
Resid_decomp<-dcomp_infy_1$time.series[,3] # Time Series of Residuals
acf(Resid_decomp,main="Auto Correlation Function - ACF - Residuals [Resid_decomp]")
```

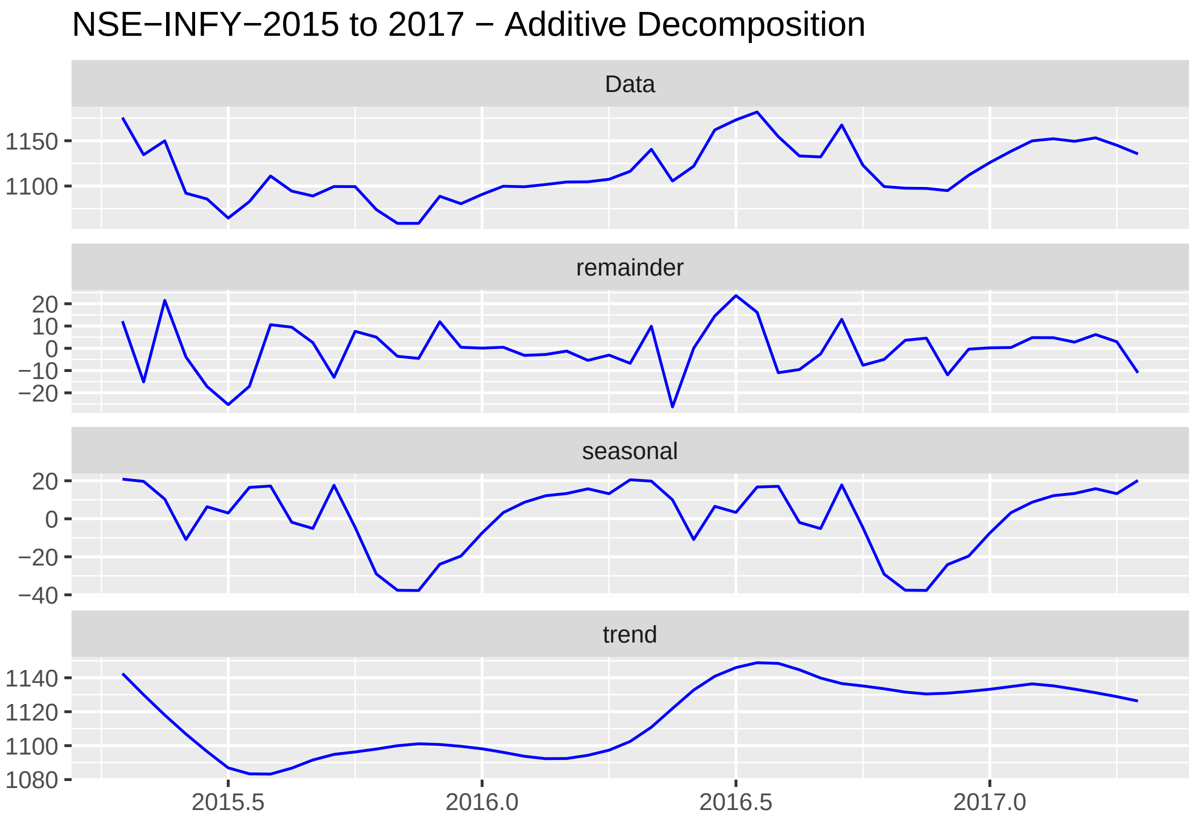



```r
Season_decomp<-dcomp_infy_1$time.series[,2] # Time Series of Seasonal Components
plot(Season_decomp,col="red", cex = 5,main="NSE-INFY_Seasonal Decomposition- 2015 to 2017")
lines(stats::lowess(Season_decomp),col="blue")
```



```
#lines(stats::lowess(Season_decomp),col="blue")
```

```
# The stl() function presumes an ADDITIVE Decomposition
# We now take a Natural Log [ Log-transform] the response to give a MULTIPLICATIVE Decomposition

require(ggplot2)
require(ggfortify)
autoplot(stl(ts_infy1, s.window = 12, t.window = 10), ts.colour = 'blue',main="NSE-INFY-2015 to 2017 - A
```




```
#
```

```
# Start the clock!
# ptm <- proc.time()
#
# vec_gross_sale <- p_sale_count_rnd*p_sale_cost_rnd
#
# summary(vec_gross_sale)
#
# proc.time() - ptm
#
#
# As seen below in our case
# ELAPSED time - 1st 0.011 , 2nd - 0.012
# Thus the WALL CLOCK or REAL / ELAPSED
# timings are almost same .
#
# The USER TIME and SYSTEM TIME's in our case
# add upto -
# 1st - 0.008
```

```r
# 2nd - 0.012

# Thus it would seem we are better off
# with Vector Multiplication

# But we also need to consider
# once we have the "vec_gross_sale"
# we will need to add it to out "mdf"

# Kindly also note the Timings will
# differ for each system - also for each run
# of the chunk of code on same sys

# Definition of user Time --- The 'user time' is the CPU time
# charged for execution of user instructions of the calling process.
#
# REFER- https://stat.ethz.ch/R-manual/R-devel/library/base/html/proc.time.html
```

```r
# Now to multiply TWO Columns of the DF
# Also called COLUMNAR VECTORS

# Again start the clock!
# ptm <- proc.time()
#
# mdf$gross_sale<- mdf$p_sale_count_rnd*mdf$p_sale_cost_rnd
#
# proc.time() - ptm
# #
# str(mdf)
# #
# summary(mdf)
# #
# write.csv(mdf,file="Mkt_DATA_Files/mdf.csv")
# ## Writes to Sub Directory - DATA_Files
# #
```