

Financial Modelling

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Introduction

In this case study various time series modelling methods are discussed along with R implementation for each of them. Main idea followed is to analyse the data, identify trend, separate stationary part of the data, build model on that residual data. In this case study we model closing price for all the stocks.

Data

In this case study 5 different pharmaceutical companies (on NSE India) were considered for analysis. Data obtained from yahoo finance starting from 6th November 2016 to 7th November 2018. Companies selected were:

- GlaxoSmithkline Pharmaceuticals Limited (GLAXO.NS)
- Glenmark Pharmaceuticals Limited (GLENMARK.NS)
- Aurobindo Pharma Limited (AUROPHARMA.NS)
- Sun Pharmaceutical Industries Limited (SUNPHARMA.NS)
- Alembic Pharmaceuticals Limited (APLLTD.NS)

Data Analysis

In this section pre-processing steps involved in data analysis are explored, few of them involve:

- Data Standardization: let Y be the time-series data standardization involves converting the data to zero mean and unit standard deviation data:

$$Y = \frac{Y - \mu_Y}{\sigma_Y}$$

- Variance Stationarity (remove hetroskedasticity):

$$Y = \begin{cases} \ln(Y) & \text{if } \lambda = 0 \\ \frac{Y^\lambda - 1}{\lambda} & \text{otherwise} \end{cases}$$

The conditions for predictability of any time series is illustrated using auto correlation and partial auto correlation functions.

- Auto correlation:

$$Y[l] = \frac{E((Y[k] - \mu)(Y[k-l] - \mu))}{\sigma_Y^2}$$

```
loadCSVData <- function(path){
  data = read.csv(path, header = TRUE)
  print(summary(data$Close))
  return(data$Close)
}

standardize <- function(data){
  data = (data - mean(data)) / sd(data)
  print(summary(data))
  return(data)
}
```

```

boxcox <- function(y, lambda){
  if (lambda != 0){
    return((y^{lambda} - 1.0)/lambda)
  }
  else{
    return(log(y))
  }
}

```

Analysis of Alembic Pharmaceuticals Limited (APLLTD.NS)

```

aplltd = NULL
aplltd$raw_daily = loadCSVData('../Data/APLLTD/APLLTD.NS_daily.csv')

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   418.1   515.7   546.0   553.7   597.5   661.9

aplltd$raw_weekly = loadCSVData('../Data/APLLTD/APLLTD.NS_weekly.csv')

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   420.0   516.4   547.7   554.4   595.0   654.2

aplltd$raw_monthly = loadCSVData('../Data/APLLTD/APLLTD.NS_monthly.csv')

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   427.5   519.3   552.8   553.0   590.5   629.0

aplltd$sd_daily = standardize(aplltd$raw_daily)

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  -2.7140 -0.7624 -0.1560  0.0000  0.8758  2.1650

aplltd$sd_weekly = standardize(aplltd$raw_weekly)

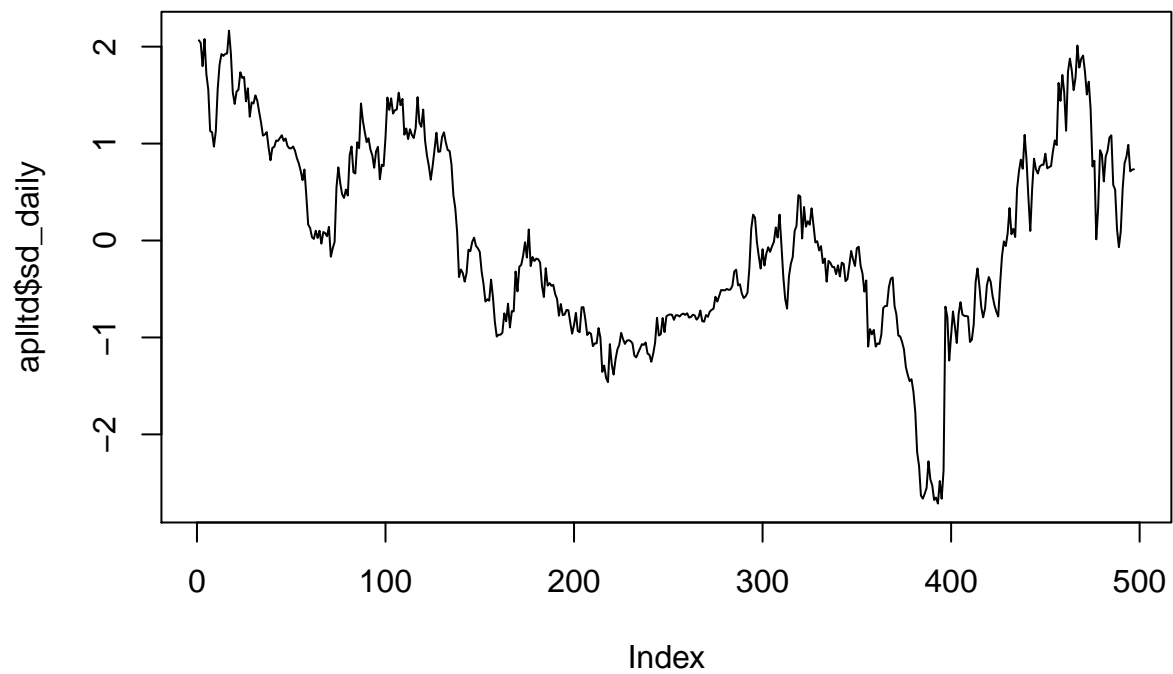
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  -2.6640 -0.7536 -0.1326  0.0000  0.8057  1.9800

aplltd$sd_monthly = standardize(aplltd$raw_monthly)

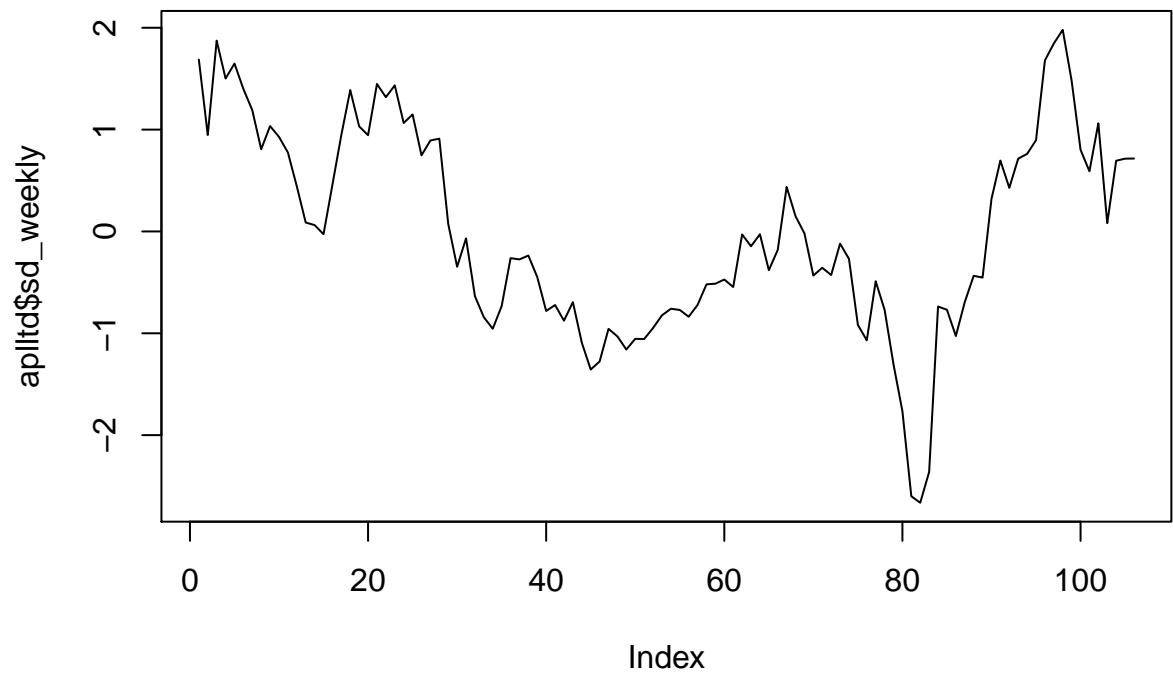
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -2.657000 -0.713800 -0.005926  0.000000  0.793000  1.608000

# plot all the data
plot(aplltd$sd_daily, type='l')

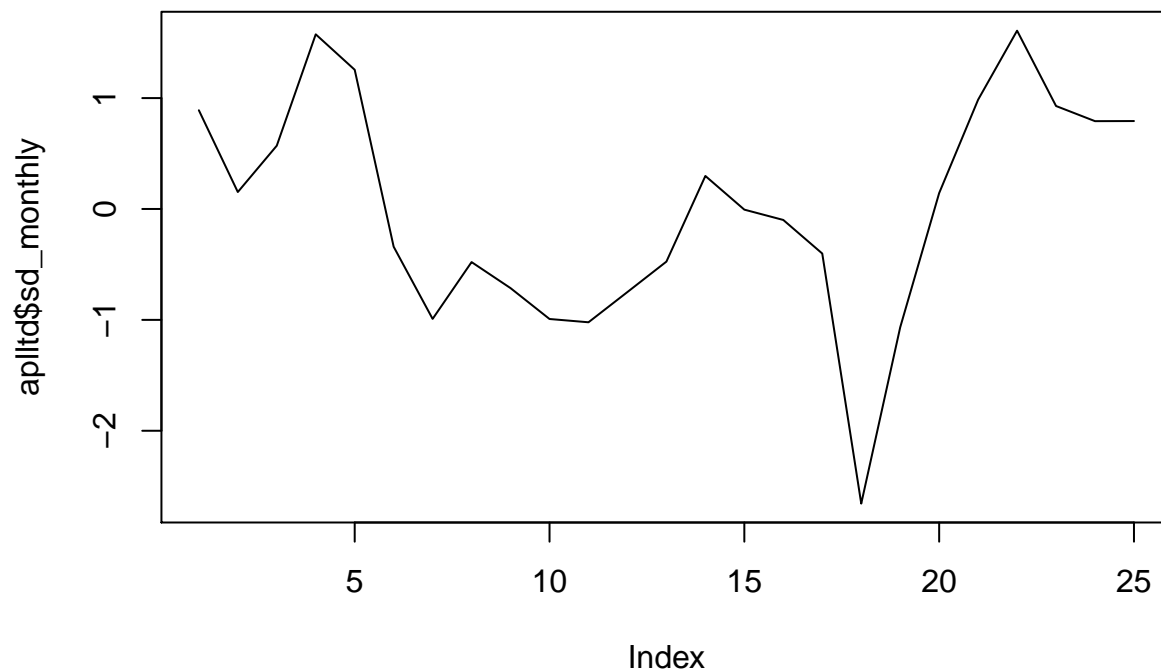
```



```
plot(apl1td$sd_weekly, type='l')
```



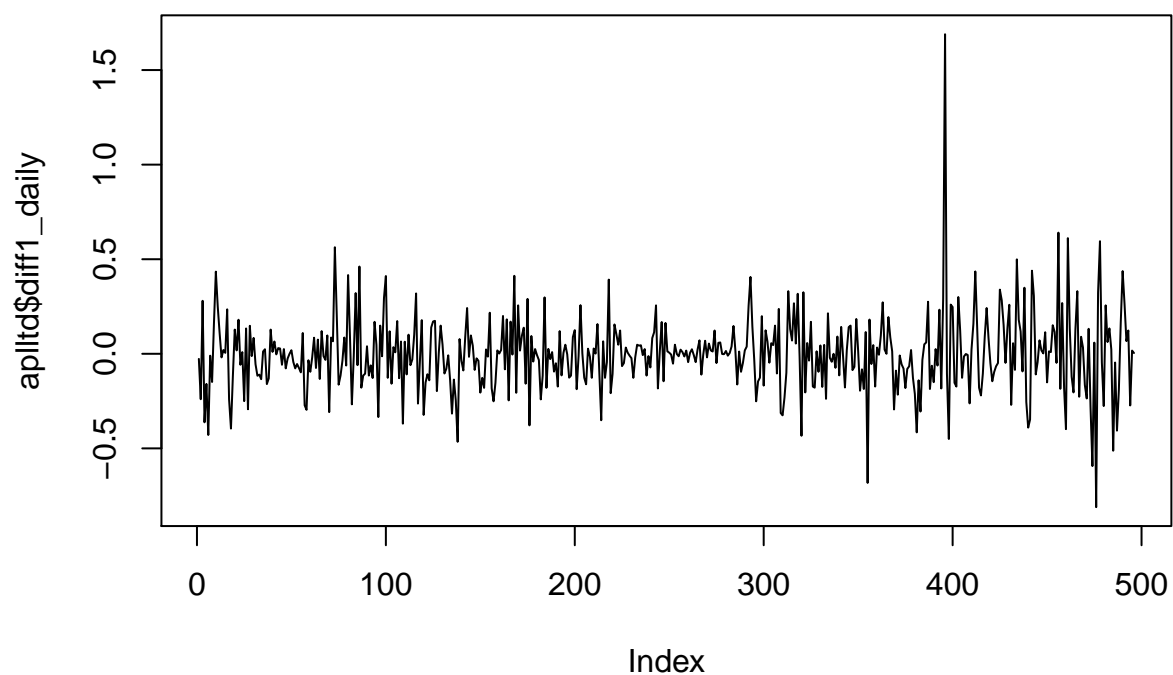
```
plot(apl1td$sd_monthly, type='l')
```



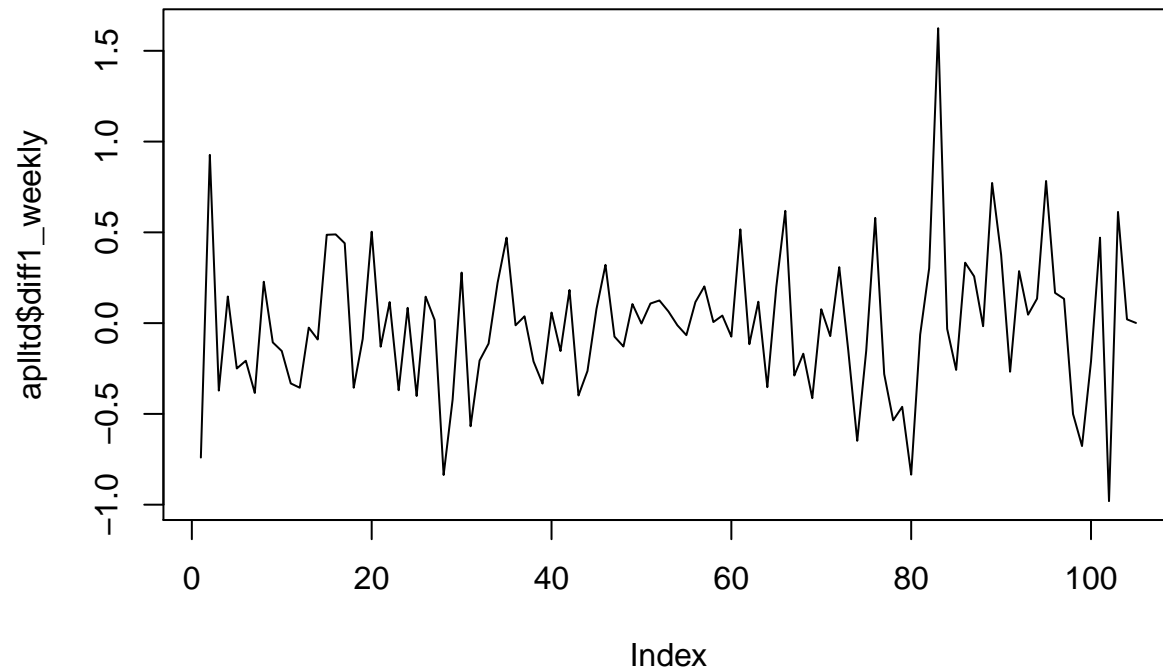
*# Based on plots we can clearly see that given data is
 # non stationary (data has some integrating effect, which should estimated)
 # which can be converted to stationary by taking difference of order = n*

```
aplltd$diff1_daily = diff(aplltd$sd_daily)
aplltd$diff1_weekly = diff(aplltd$sd_weekly)
aplltd$diff1_monthly = diff(aplltd$sd_monthly)
```

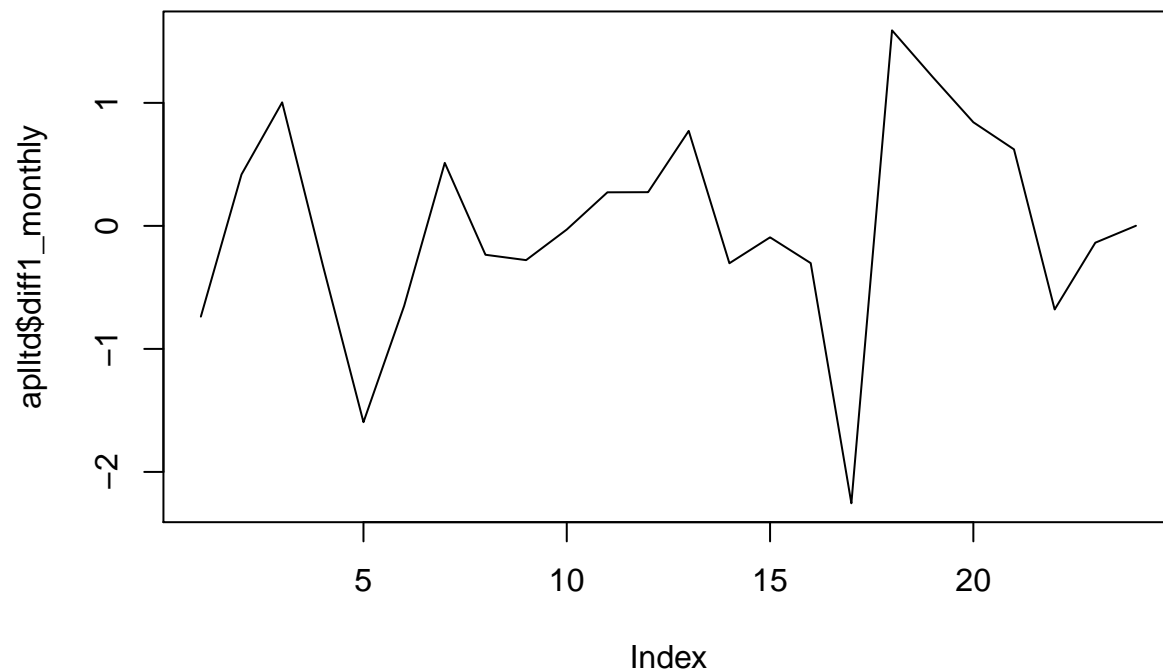
Plotting differenced data
`plot(aplltd$diff1_daily, type='l')`



```
plot(aplltd$diff1_weekly, type='l')
```



```
plot(aplltd$diff1_monthly, type='l')
```



Differenced plots seems to be stationary this can also be verified by summary of the data

```
print(summary(aplltd$diff1_daily))
```

```
##      Min.   1st Qu.   Median     Mean   3rd Qu.    Max.
## -0.810600 -0.115100 -0.003003 -0.002683  0.091820  1.689000
```

```
print(summary(aplltd$diff1_weekly))
```

```
##      Min.   1st Qu.     Median       Mean   3rd Qu.      Max.
## -0.980200 -0.257700 -0.011890 -0.009251  0.182400  1.624000
```

```
print(summary(apllttd$diff1_monthly))
```

```
##      Min.   1st Qu.     Median       Mean   3rd Qu.      Max.
## -2.255000 -0.307700 -0.061370 -0.004056  0.539700  1.589000
```

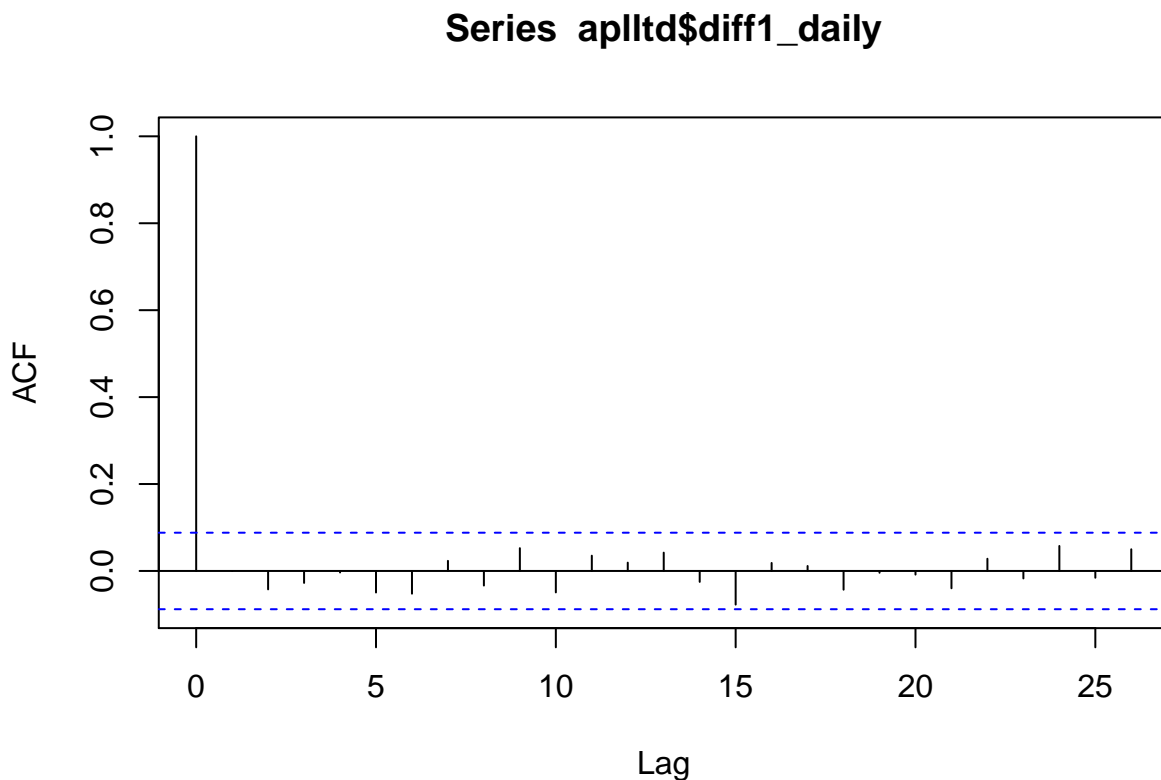
- Actual Raw data is non stationary
- By analysing the data it's clear that some integrating effect exists, which can be removed by taking first order difference of the signal
- Stationary component of the data is estimated using first order difference of the time series
- Resulting plot after removing integrating effect are stationary

Trend Estimation

In this section we'll try to separate predictable part of the series from random white noise. This is achieved using ACF PACF analysis.

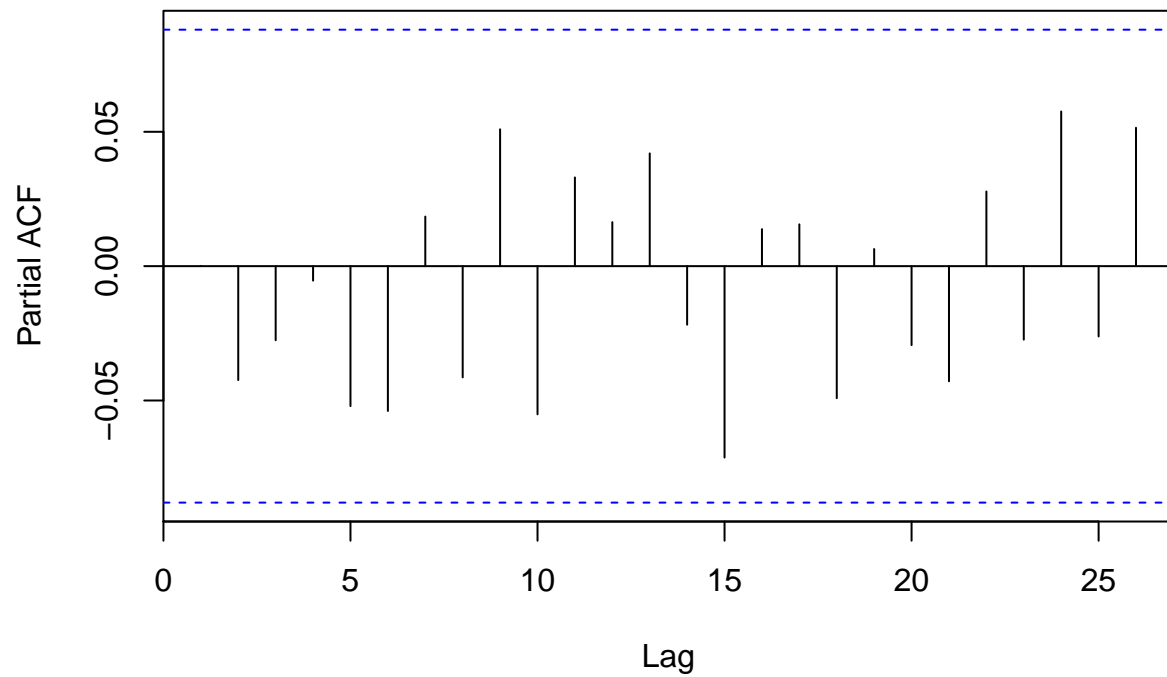
Daily Series

```
acf(apllttd$diff1_daily)
```



```
pacf(apllttd$diff1_daily)
```

Series aplltd\$diff1_daily



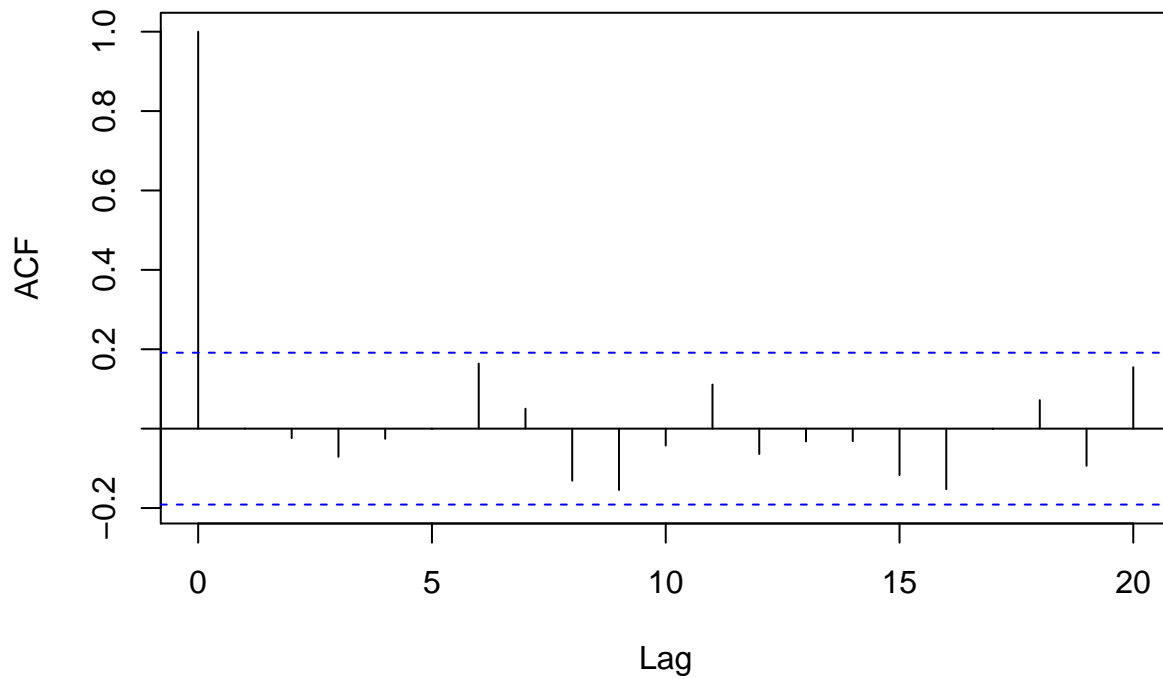
*# As ACF and PACF are inbetween significant bands, this shows that signal
is random (i.e there exists no trend to model) and stationary*

- As it can be seen that acf at any lag is bounded by significant limits, which means that the stationary series obtained after taking first order difference is white noise.

Weekly Series

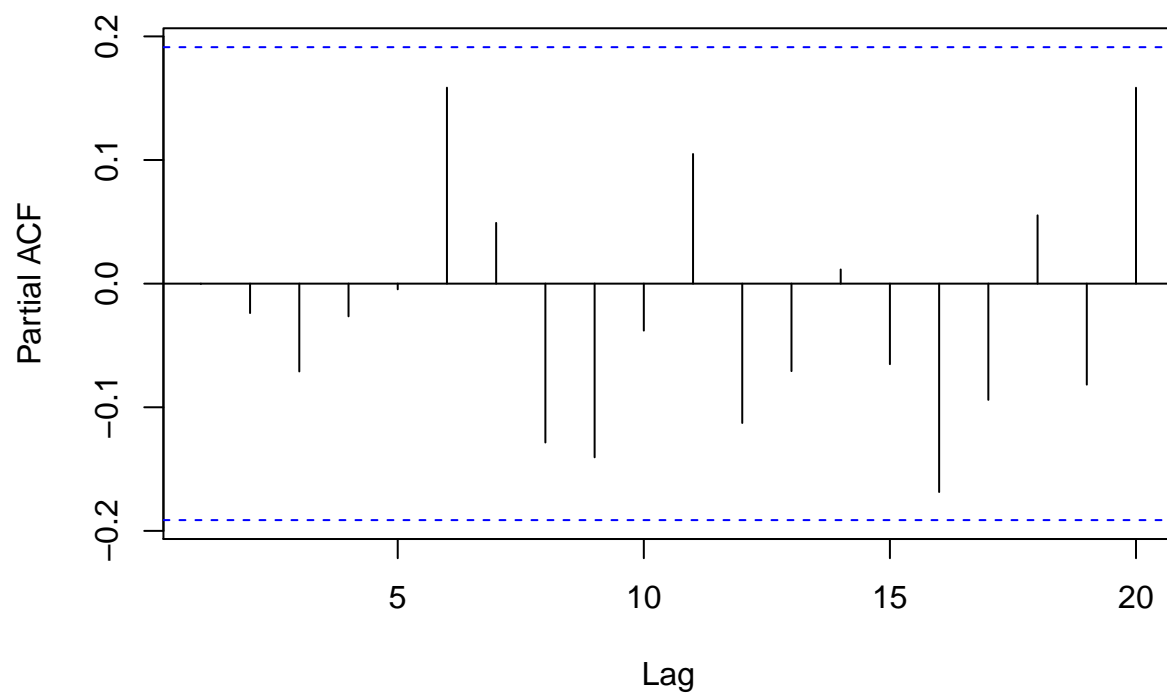
```
acf(aplltd$diff1_weekly)
```


Series aplltd\$diff1_weekly



```
pacf(aplltd$diff1_weekly)
```

Series aplltd\$diff1_weekly

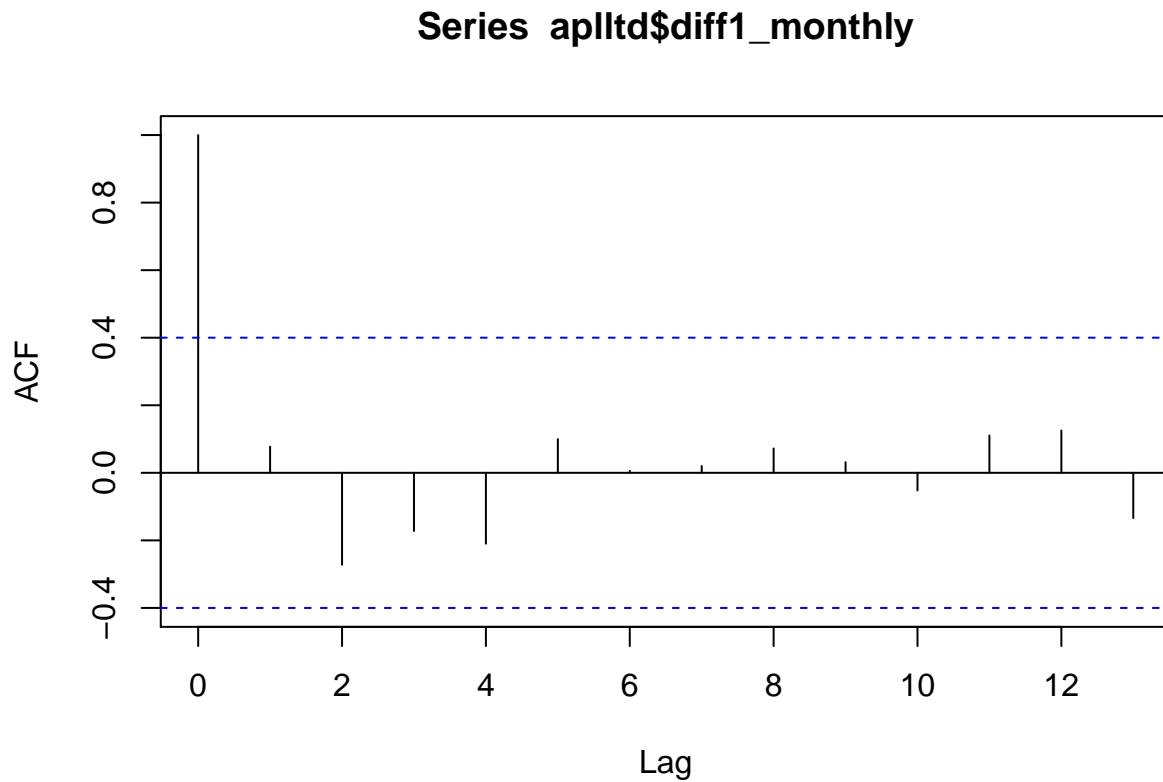


```
# As ACF and PACF are inbetween significant bands, this shows that signal  
# is random (i.e there exists no trend to model) and stationary
```

- As it can be seen that acf at any lag is bounded by significant limits, which means that the stationary series obtained after taking first order difference is white noise.

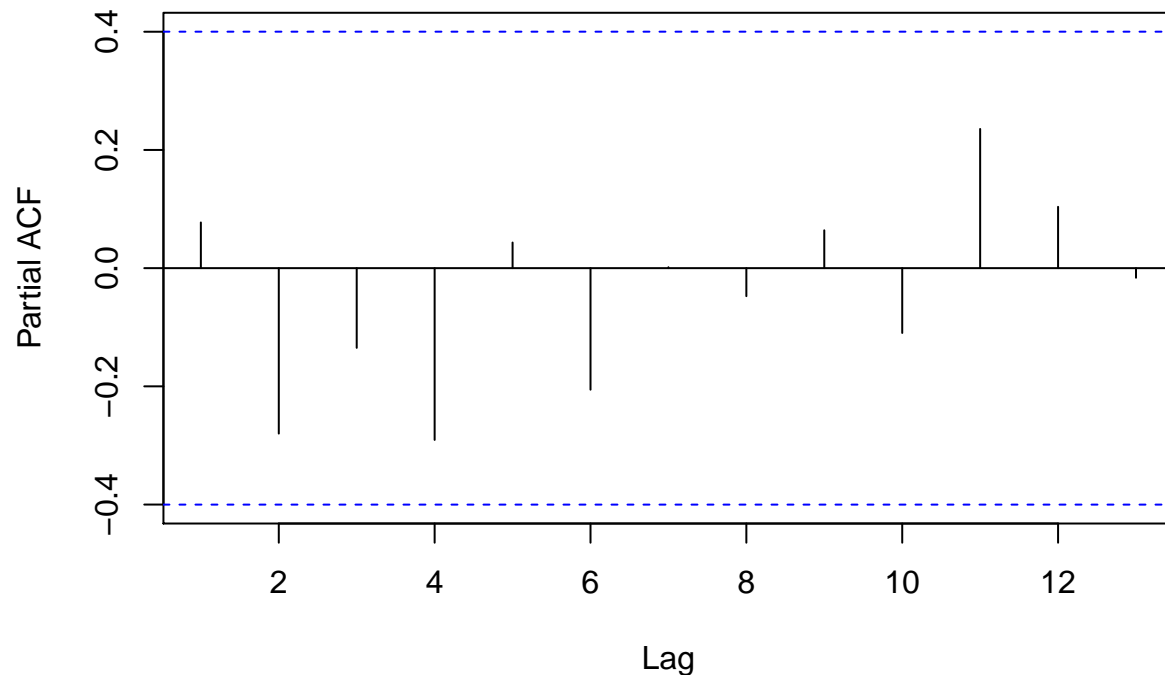
Monthly Series

```
acf(aplltd$diff1_monthly)
```



```
pacf(aplltd$diff1_monthly)
```

Series aplltd\$diff1_monthly



*# As ACF and PACF are inbetween significant bands, this shows that signal
is random (i.e there exists no trend to model) and stationary*

- As it can be seen that acf at any lag is bounded by significant limits, which means that the stationary series obtained after taking first order difference is white noise.

Sun Pharmaceutical Industries Limited (SUNPHARMA.NS)

```
sunpharma = NULL
sunpharma$raw_daily = loadCSVData(' ../Data/SUNPHARMA/SUNPHARMA.NS_daily.csv')
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  443.8   523.8   567.7   577.4   637.3   721.5
```

```
sunpharma$raw_weekly = loadCSVData(' ../Data/SUNPHARMA/SUNPHARMA.NS_weekly.csv')
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  450.0   525.0   570.4   578.4   640.3   720.3
```

```
sunpharma$raw_monthly = loadCSVData(' ../Data/SUNPHARMA/SUNPHARMA.NS_monthly.csv')
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  480.4   531.7   568.5   571.1   623.2   688.2
```

```
sunpharma$sd_daily = standardize(sunpharma$raw_daily)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -2.0070 -0.8044 -0.1459  0.0000  0.9009  2.1650
```

```
sunpharma$sd_weekly = standardize(sunpharma$raw_weekly)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -1.8950 -0.7879 -0.1180  0.0000  0.9132  2.0950
```

```
sunpharma$sd_monthly = standardize(sunpharma$raw_monthly)
```

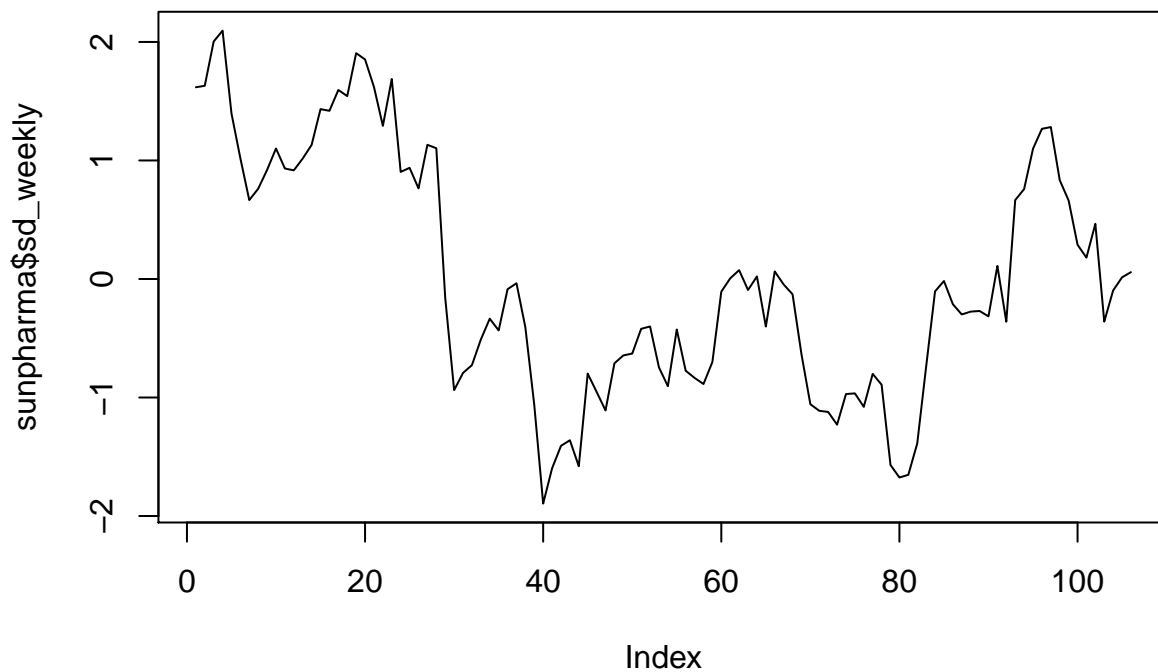
```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -1.52500 -0.66280 -0.04372  0.00000  0.87610  1.96600
```

```
# plot all the data
```

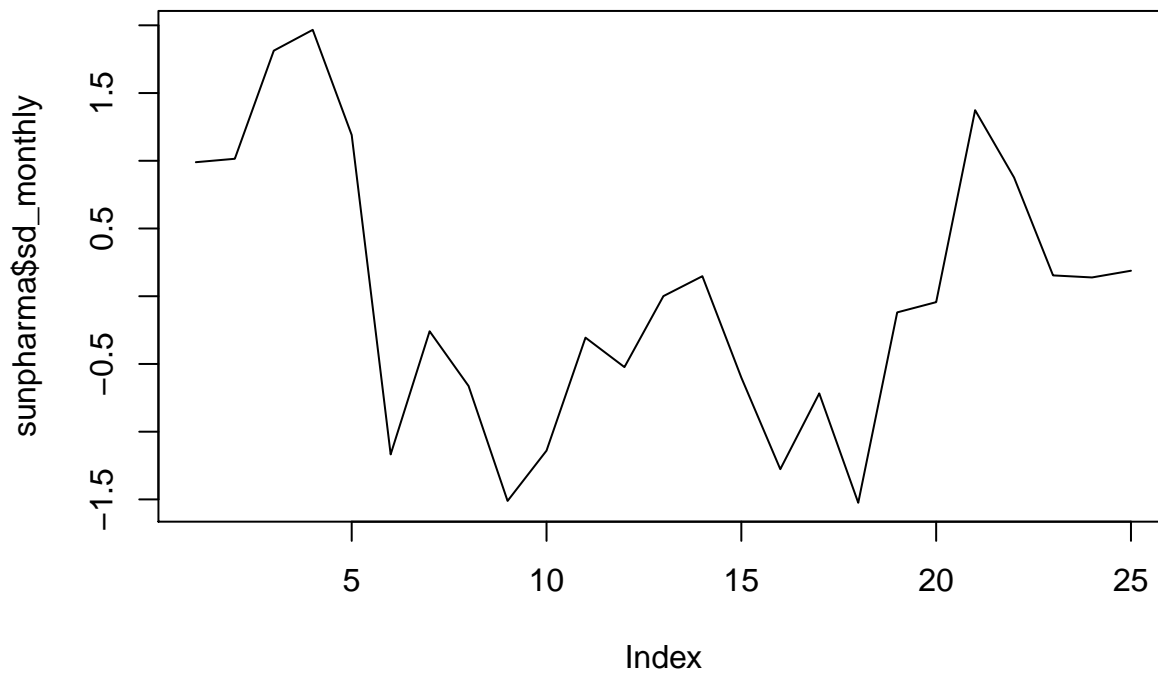
```
plot(sunpharma$sd_daily, type='l')
```



```
plot(sunpharma$sd_weekly, type='l')
```



```
plot(sunpharma$sd_monthly, type='l')
```

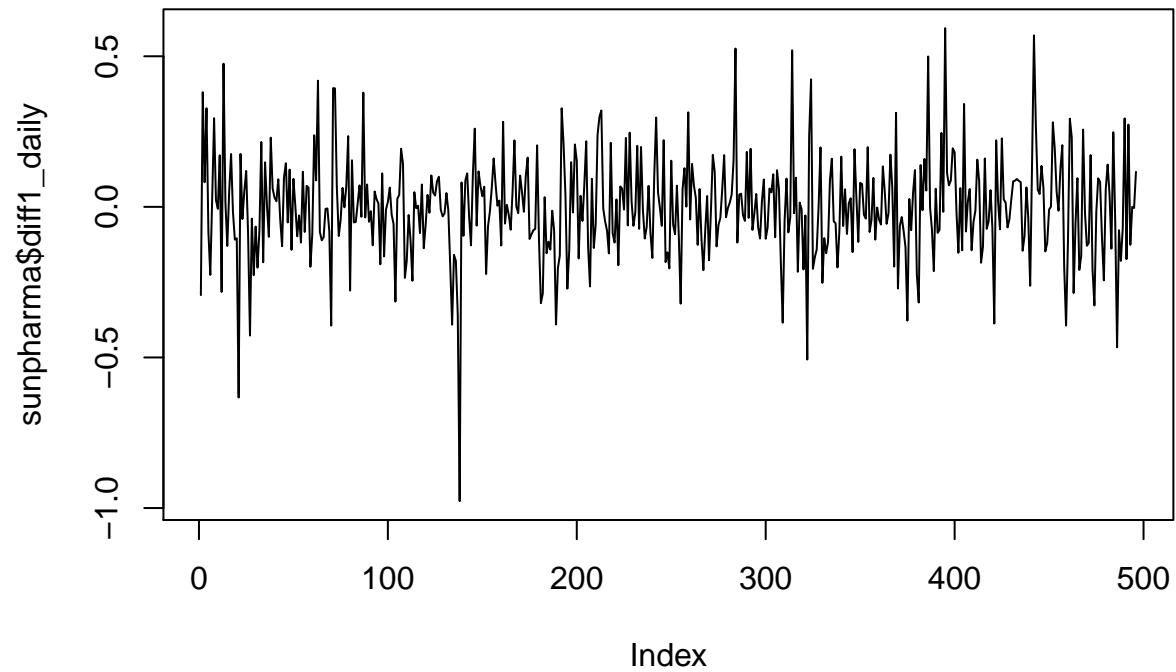


```
# Based on plots we can clearly see that given data is
# non stationary (data has some integrating effect, which should estimated)
# which can be converted to stationary by taking difference of order = n

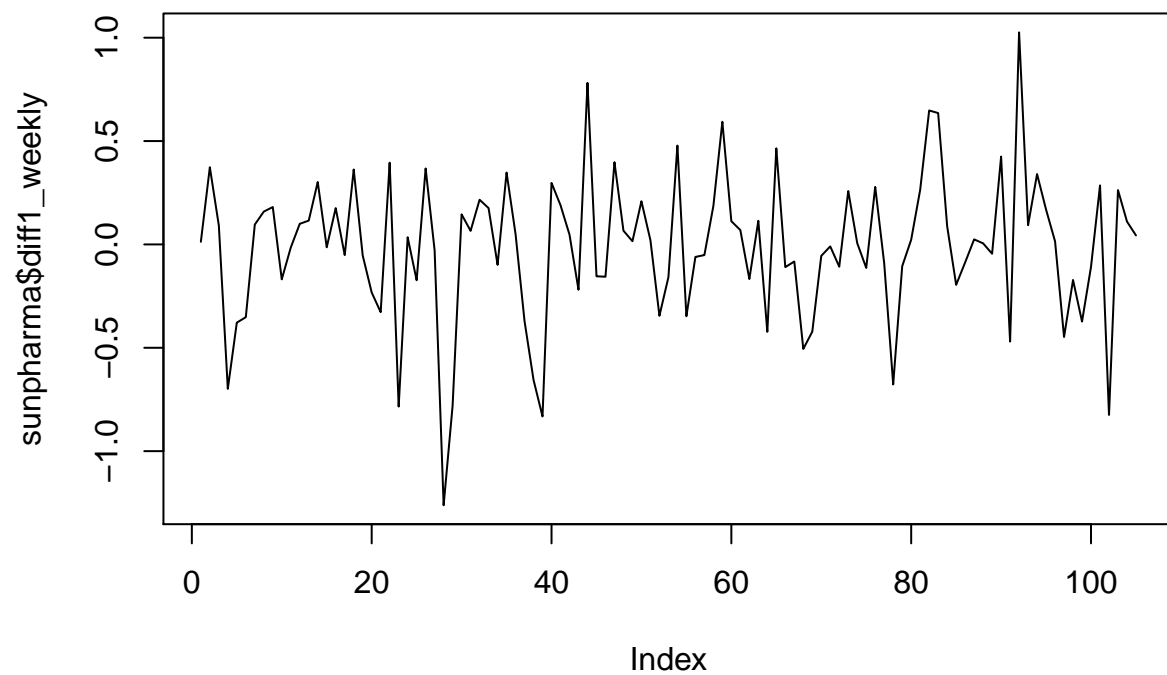
sunpharma$diff1_daily = diff(sunpharma$sd_daily)
sunpharma$diff1_weekly = diff(sunpharma$sd_weekly)
sunpharma$diff1_monthly = diff(sunpharma$sd_monthly)

# Plotting differenced data
```

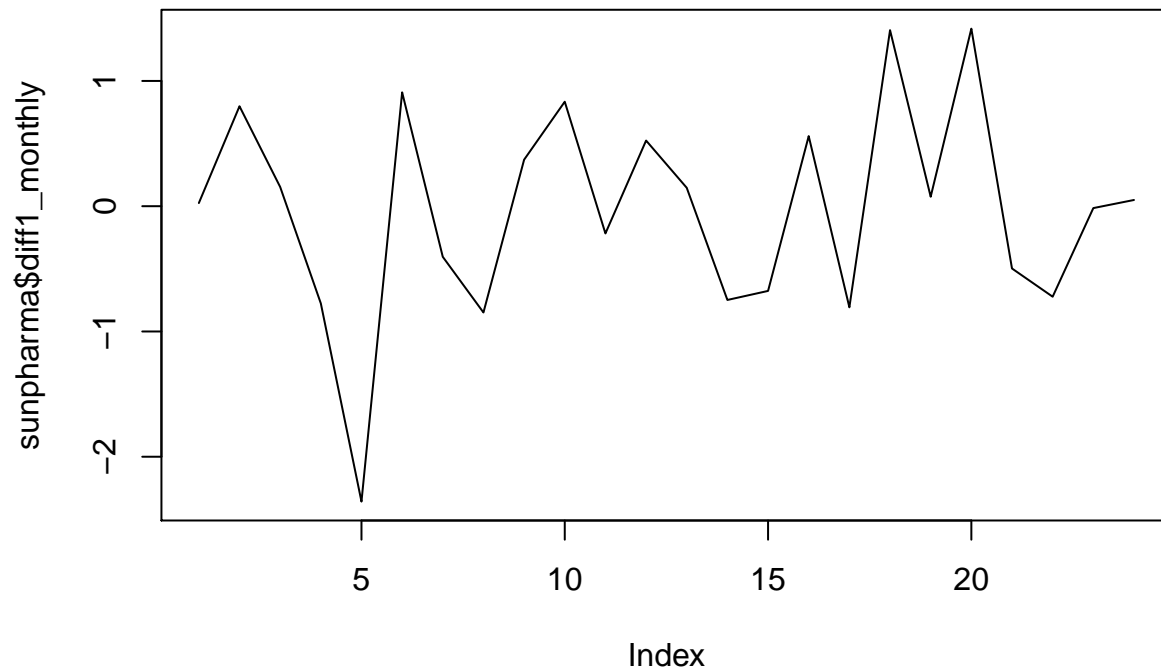
```
plot(sunpharma$diff1_daily, type='l')
```



```
plot(sunpharma$diff1_weekly, type='l')
```



```
plot(sunpharma$diff1_monthly, type='l')
```



Differenced plots seems to be stationary this can also be verified by summary of the data
`print(summary(sunpharma$diff1_daily))`

```
##      Min.   1st Qu.   Median     Mean   3rd Qu.     Max.
## -0.976900 -0.097060 -0.009011 -0.002288  0.087290  0.593200
```

`print(summary(sunpharma$diff1_weekly))`

```
##      Min.   1st Qu.   Median     Mean   3rd Qu.     Max.
## -1.26200 -0.16750  0.01476 -0.01486  0.18080  1.02600
```

`print(summary(sunpharma$diff1_monthly))`

```
##      Min.   1st Qu.   Median     Mean   3rd Qu.     Max.
## -2.35800 -0.68780  0.03738 -0.03339  0.53300  1.41700
```

- Actual Raw data is non stationary
- By analysing the data it's clear that some integrating effect exists, which can be removed by taking first order difference of the signal
- Stationary component of the data is estimated using first order difference of the time series
- Resulting plot after removing integrating effect are stationary

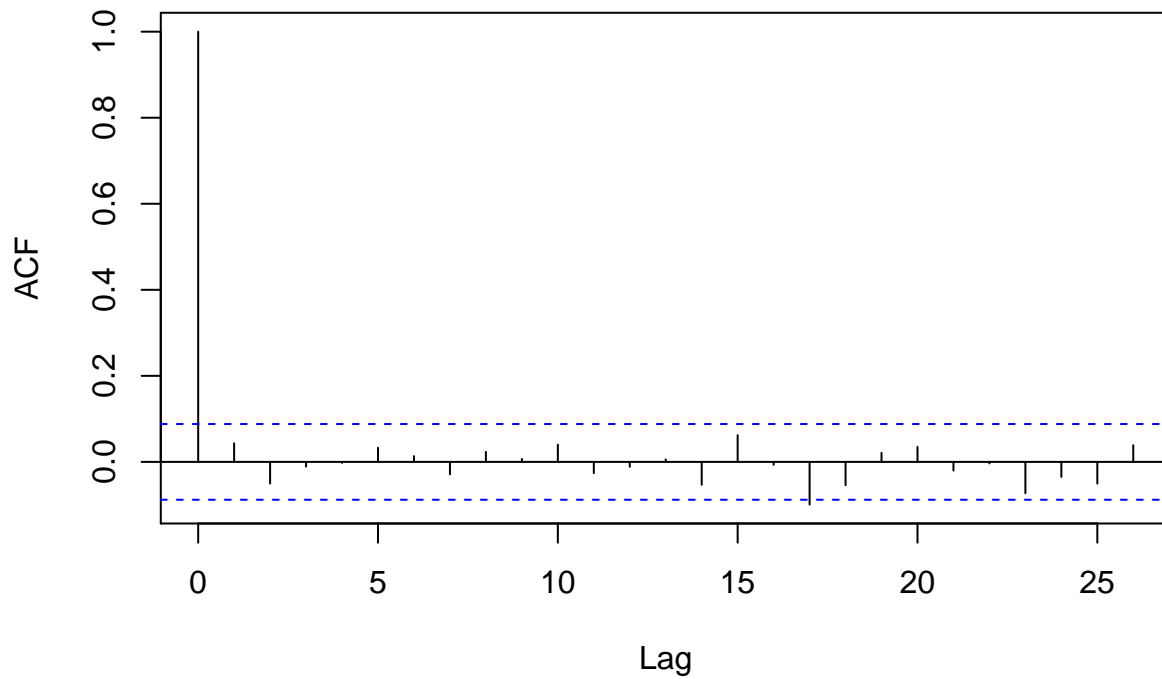
Trend Estimation

In this section we'll try to separate predictable part of the series from random white noise. This is achieved using ACF PACF analysis.

Daily Series

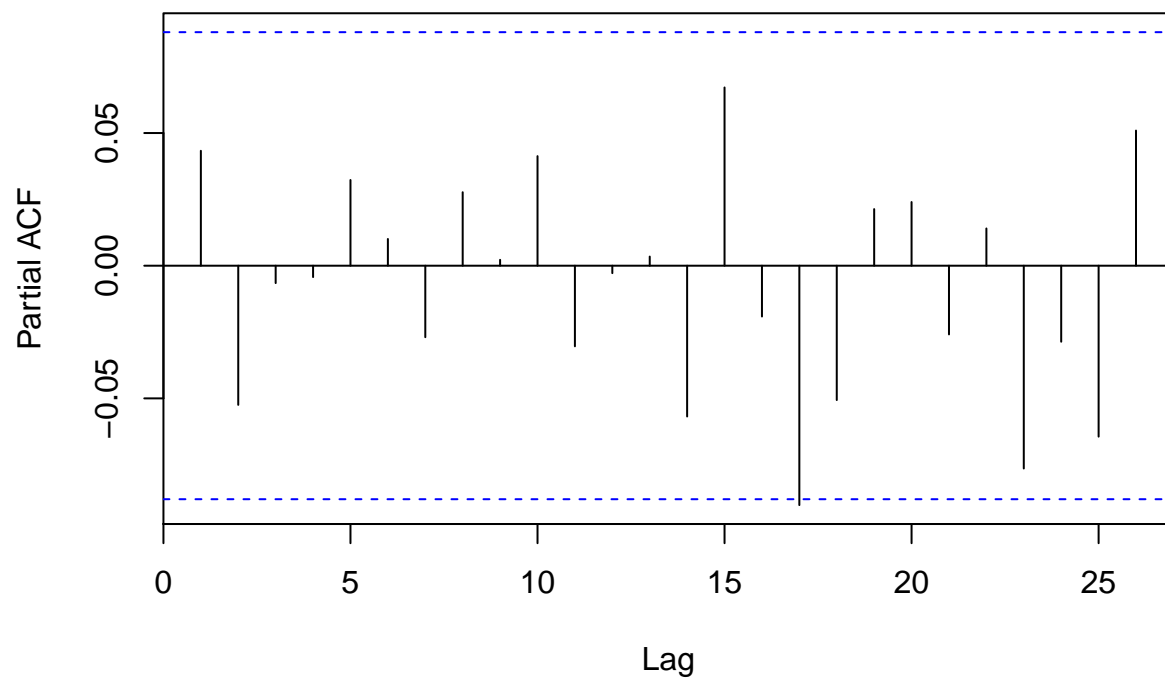
`acf(sunpharma$diff1_daily)`

Series sunpharma\$diff1_daily



```
pacf(sunpharma$diff1_daily)
```

Series sunpharma\$diff1_daily



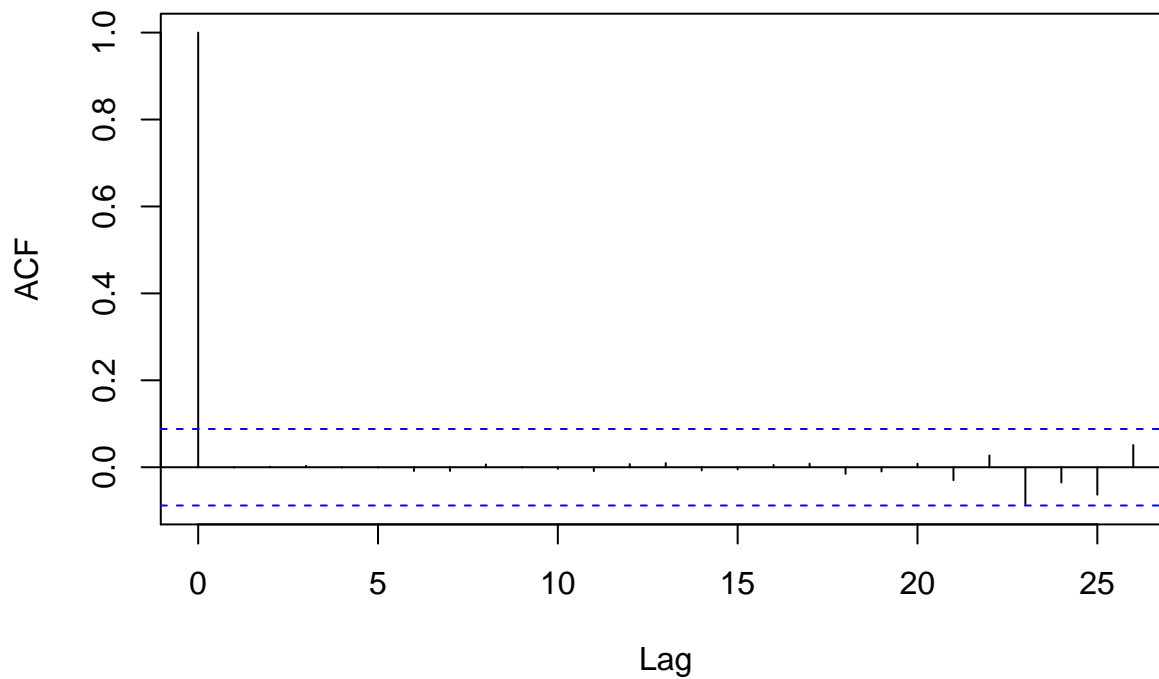
```
# As ACF and PACF are inbetween significant bands, this shows that signal  
# is random (i.e there exists no trend to model) and stationary
```


- As it can be seen that pacf at lag = 20 exceeds significant bounds, which means Autoregressive model AR(20) can fit the data

```
sunpharma$ar20_daily = arima(sunpharma$diff1_daily, order=c(20,0,0))

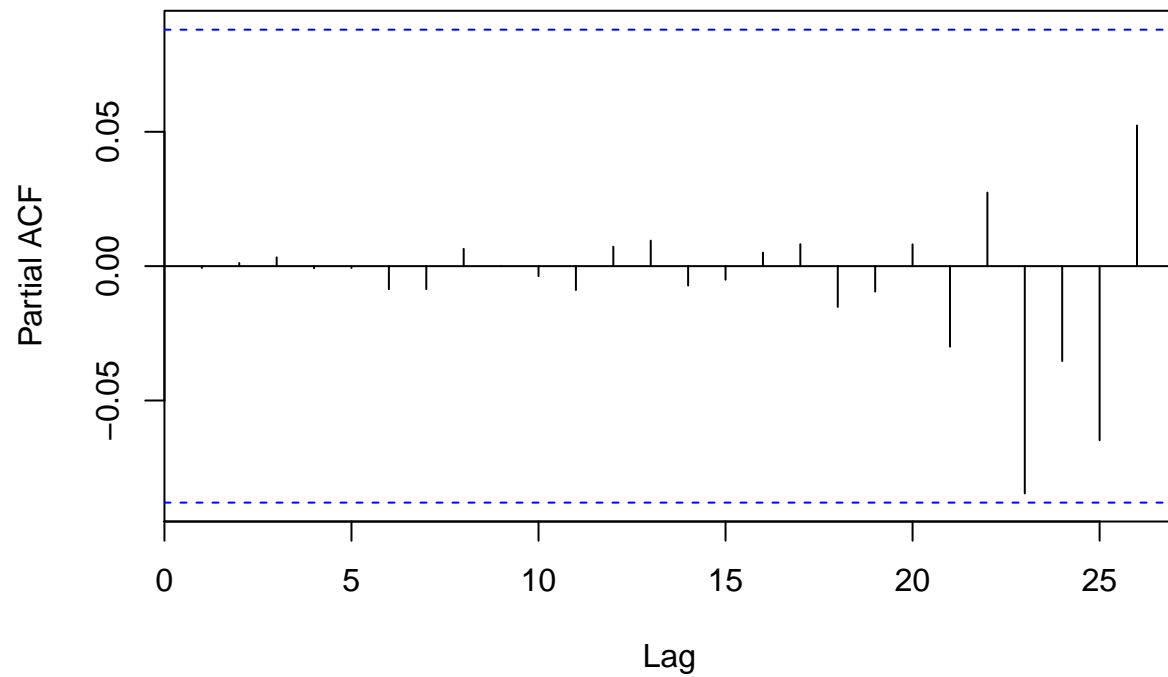
# ACF of residuals should be white if model captures entire information
acf(sunpharma$ar20_daily$residuals)
```

Series sunpharma\$ar20_daily\$residuals



```
pacf(sunpharma$ar20_daily$residuals)
```

Series sunpharma\$ar20_daily\$residuals

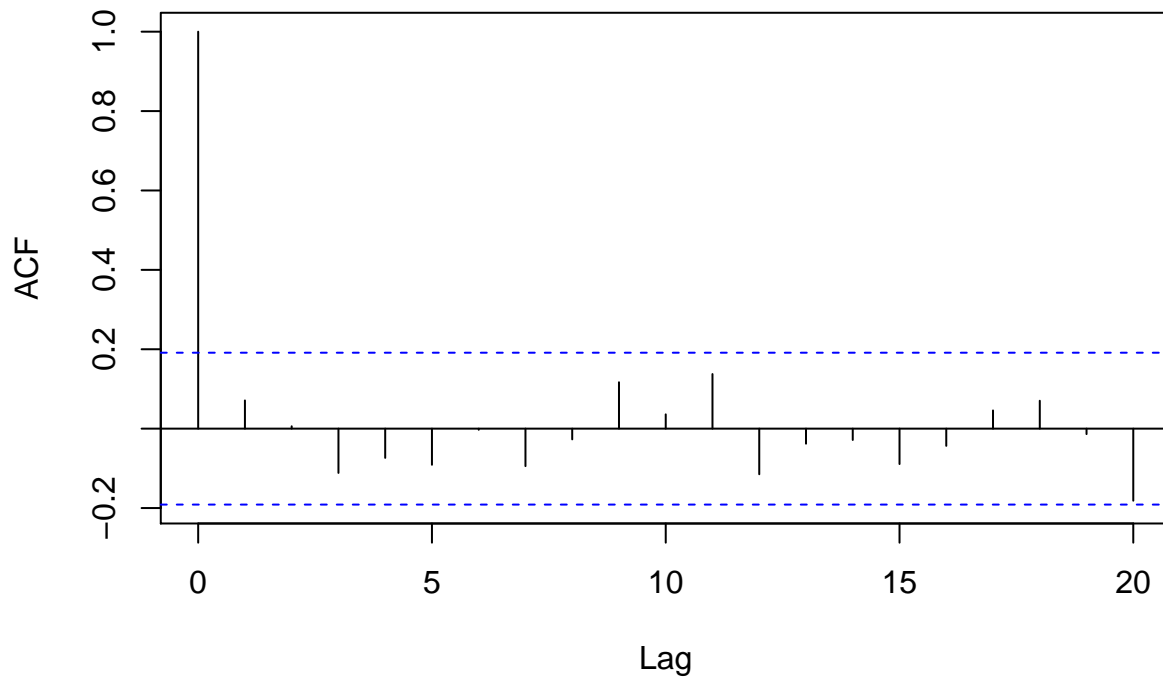


- By fitting AR(20) model predictable component of the data is exploited, residuals obtained forms white noise
- Auto regressive trend is followed in case of Daily data, Data can be made stationary after considering first order difference

Weekly Series

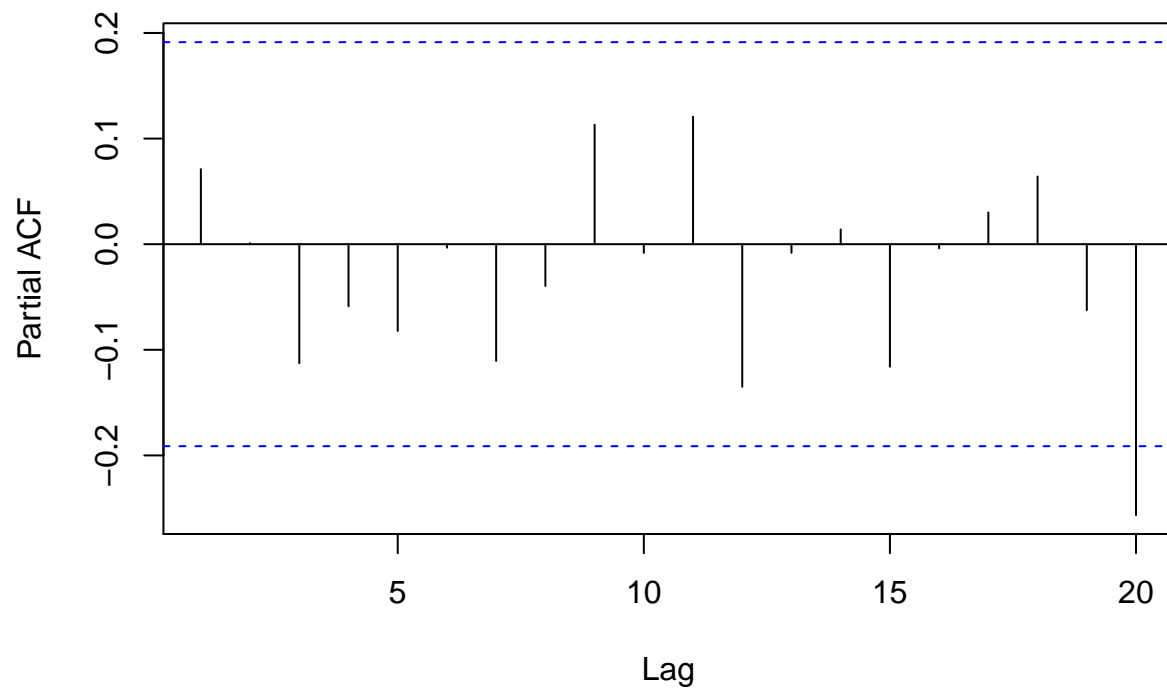
```
acf(sunpharma$diff1_weekly)
```

Series sunpharma\$diff1_weekly



```
pacf(sunpharma$diff1_weekly)
```

Series sunpharma\$diff1_weekly

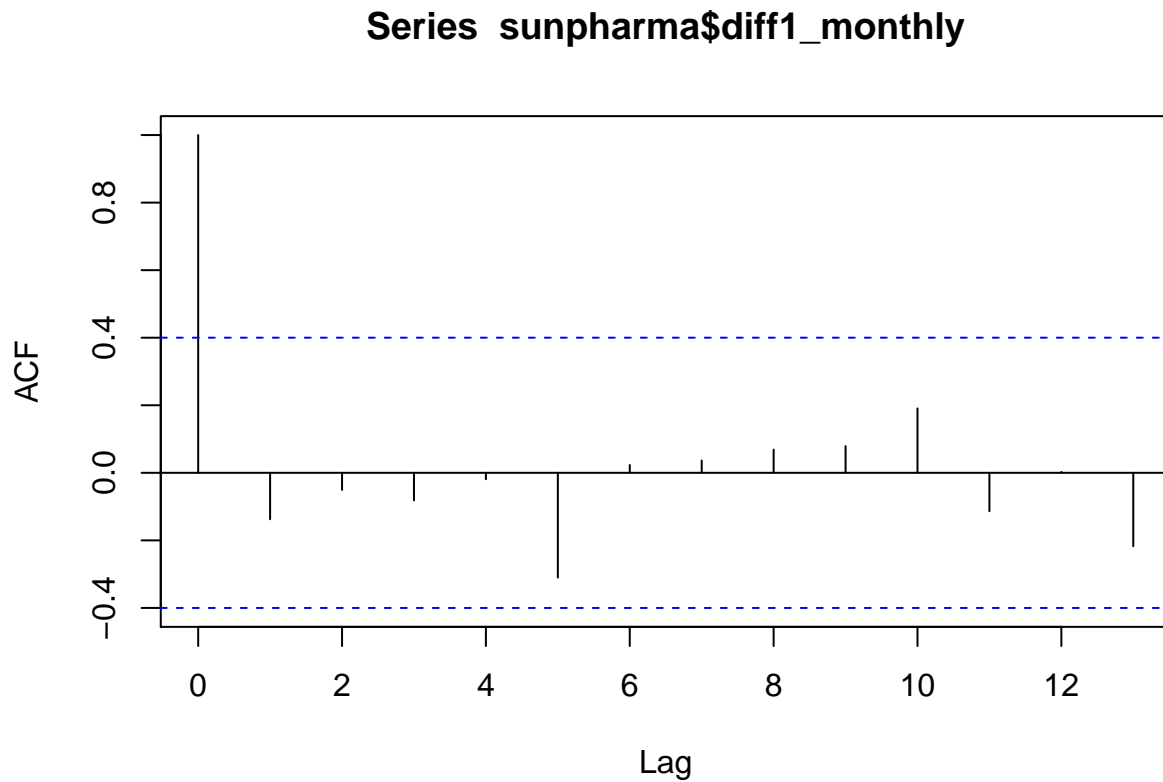


*# As ACF and PACF are inbetween significant bands, this shows that signal
is random (i.e there exists no trend to model) and stationary*

- As it can be seen that acf at any lag is bounded by significant limits, which means that the stationary series obtained after taking first order difference is white noise.

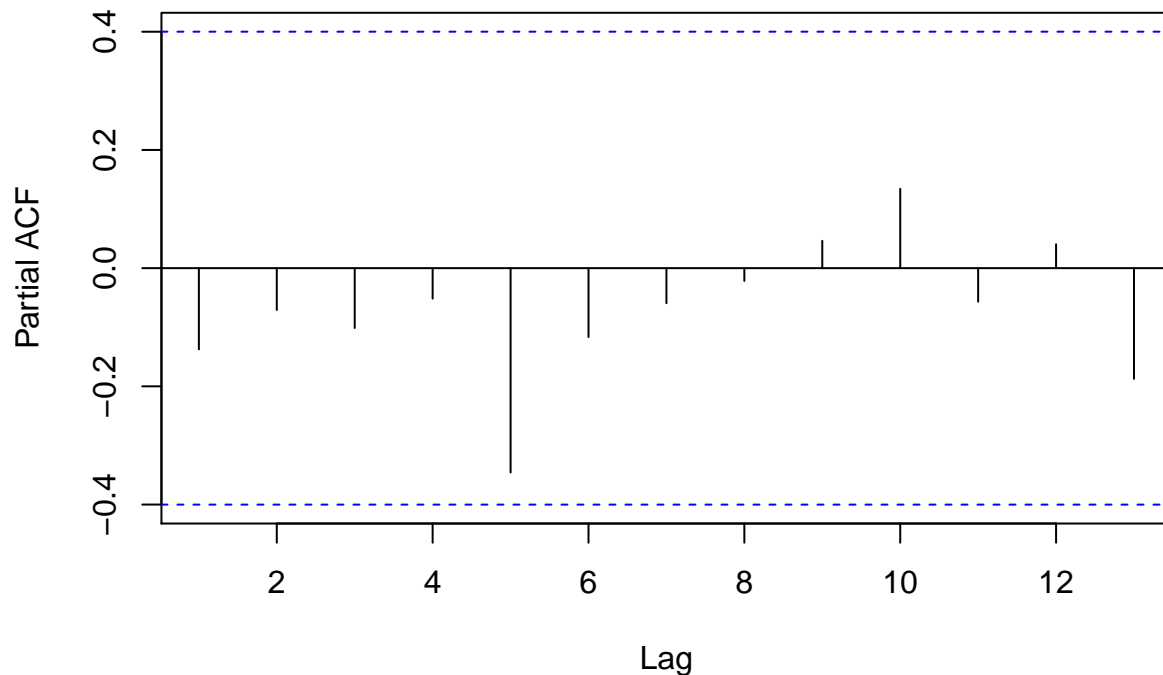
Monthly Series

```
acf(sunpharma$diff1_monthly)
```



```
pacf(sunpharma$diff1_monthly)
```

Series sunpharma\$diff1_monthly



*# As ACF and PACF are inbetween significant bands, this shows that signal
is random (i.e there exists no trend to model) and stationary*

- As it can be seen that acf at any lag is bounded by significant limits, which means that the stationary series obtained after taking first order difference is white noise.

Aurobindo Pharma Limited (AUROPHARMA.NS)

```

auropharma = NULL
auropharma$raw_daily = loadCSVData(' ../Data/AUROPHARMA/AUROPHARMA.NS_daily.csv')

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  512.4   613.8   672.4   669.5   719.8   800.8

auropharma$raw_weekly = loadCSVData(' ../Data/AUROPHARMA/AUROPHARMA.NS_weekly.csv')

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  532.5   614.8   673.7   672.8   723.9   800.8

auropharma$raw_monthly = loadCSVData(' ../Data/AUROPHARMA/AUROPHARMA.NS_monthly.csv')

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  556.3   613.9   681.8   674.9   718.6   794.2

auropharma$sd_daily = standardize(auropharma$raw_daily)

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -2.44700 -0.86660  0.04531  0.00000  0.78350  2.04600

```

```
auropharma$sd_weekly = standardize(auropharma$raw_weekly)
```

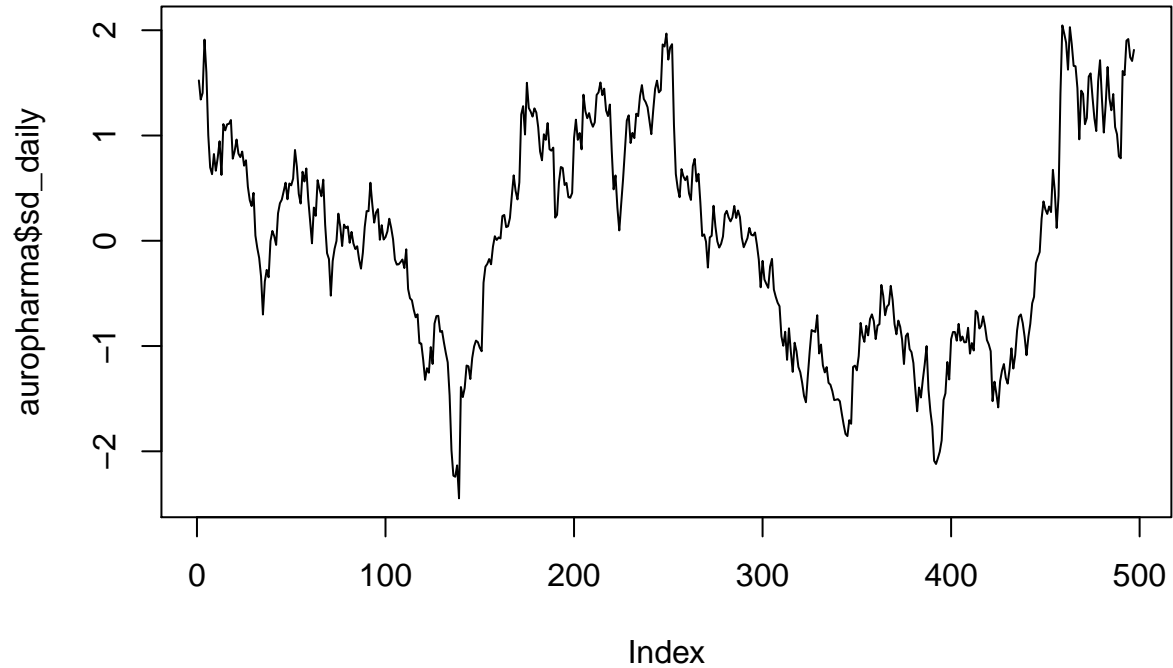
```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -2.1430 -0.8861  0.0139  0.0000  0.7808  1.9560
```

```
auropharma$sd_monthly = standardize(auropharma$raw_monthly)
```

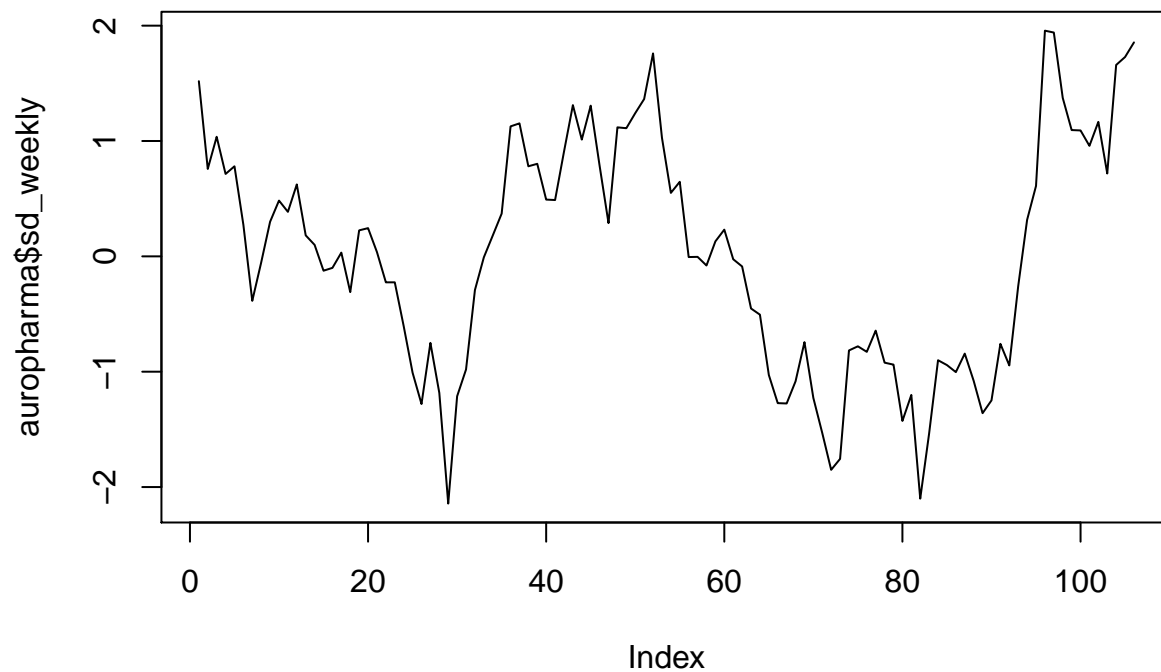
```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -1.67700 -0.86250  0.09762  0.00000  0.61800  1.68700
```

```
# plot all the data
```

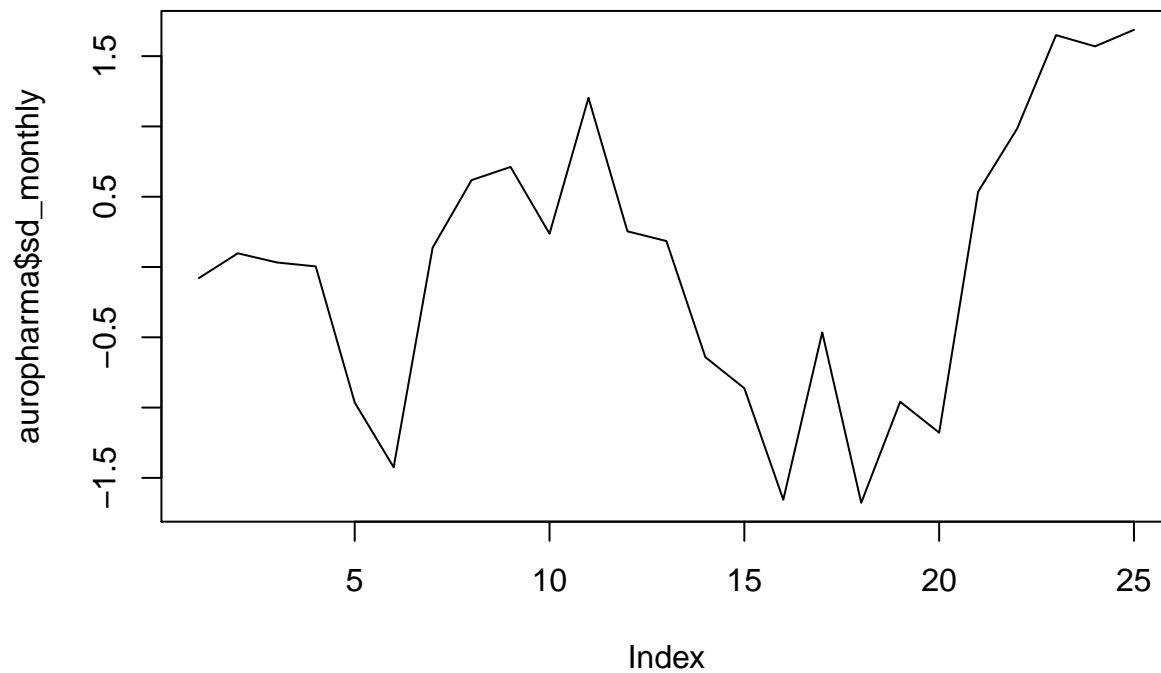
```
plot(auropharma$sd_daily, type='l')
```



```
plot(auropharma$sd_weekly, type='l')
```



```
plot(auropharma$sd_monthly, type='l')
```

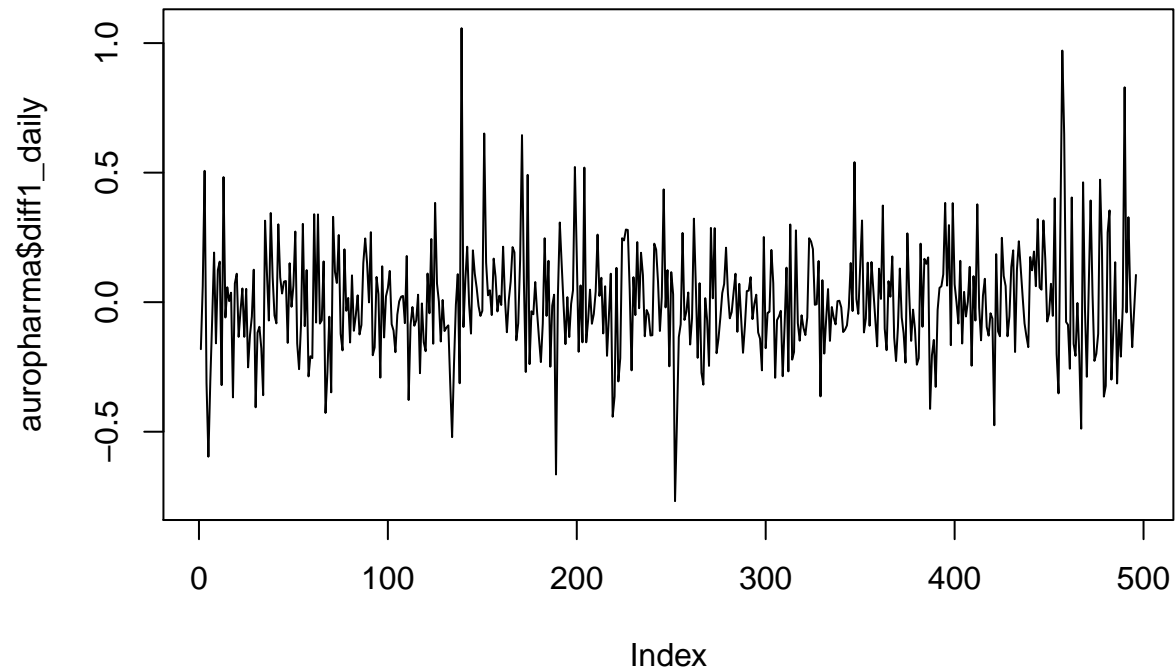


```
# Based on plots we can clearly see that given data is
# non stationary (data has some integrating effect, which should estimated)
# which can be converted to stationary by taking difference of order = n

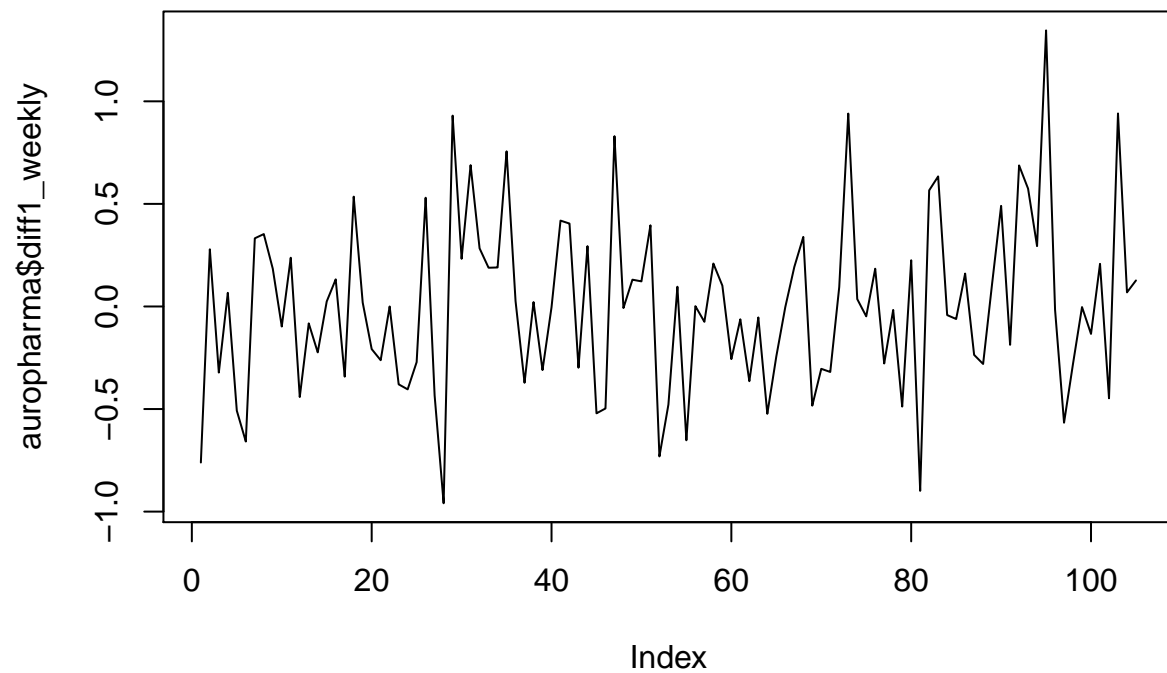
auropharma$diff1_daily = diff(auropharma$sd_daily)
auropharma$diff1_weekly = diff(auropharma$sd_weekly)
auropharma$diff1_monthly = diff(auropharma$sd_monthly)

# Plotting differenced data
```

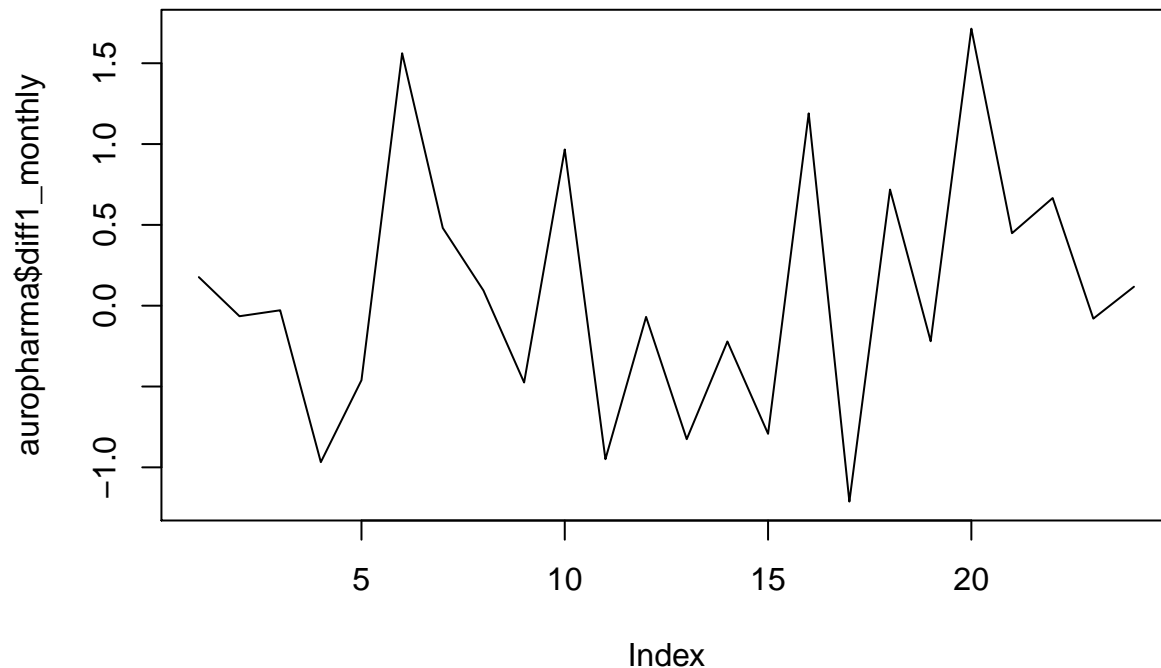
```
plot(auropharma$diff1_daily, type='l')
```



```
plot(auropharma$diff1_weekly, type='l')
```



```
plot(auropharma$diff1_monthly, type='l')
```

Differenced plots seems to be stationary this can also be verified by summary of the data
`print(summary(auropharma$diff1_daily))`

```
##      Min.   1st Qu.   Median     Mean   3rd Qu.     Max.
## -0.767800 -0.127100 -0.018690  0.000584  0.110000  1.057000
```

`print(summary(auropharma$diff1_weekly))`

```
##      Min.   1st Qu.   Median     Mean   3rd Qu.     Max.
## -0.959400 -0.298700 -0.003056  0.003201  0.225300  1.346000
```

`print(summary(auropharma$diff1_monthly))`

```
##      Min.   1st Qu.   Median     Mean   3rd Qu.     Max.
## -1.21200 -0.46450 -0.04666  0.07359  0.52710  1.71400
```

- Actual Raw data is non stationary
- By analysing the data it's clear that some integrating effect exists, which can be removed by taking first order difference of the signal
- Stationary component of the data is estimated using first order difference of the time series
- Resulting plot after removing integrating effect are stationary

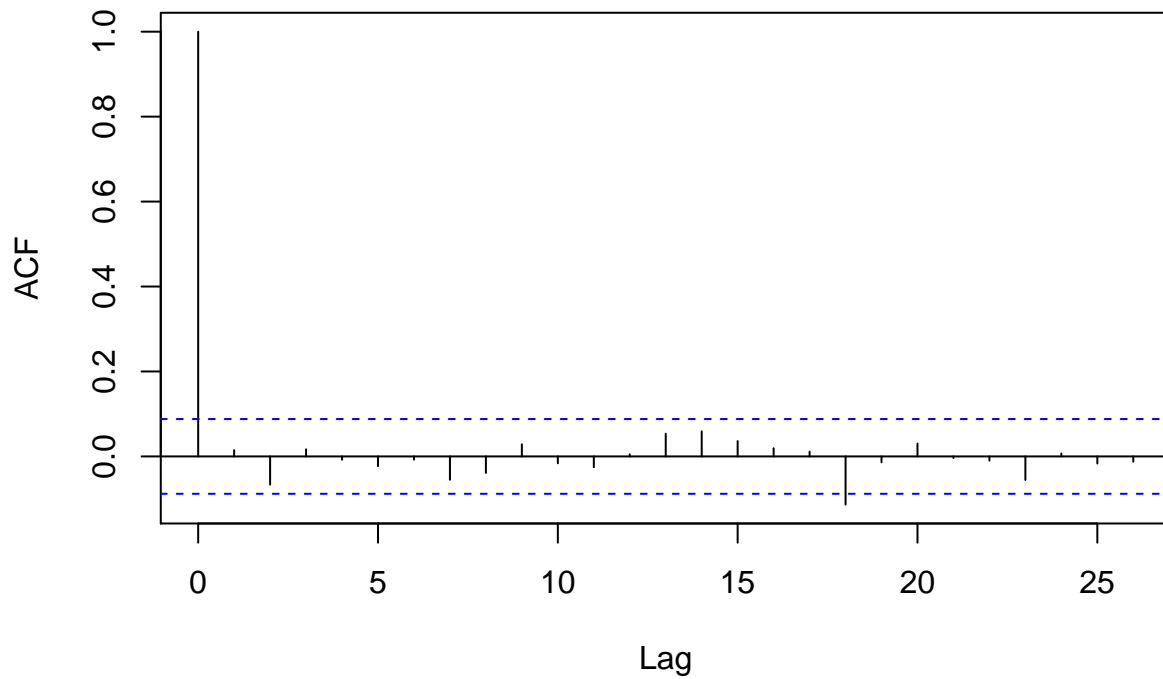
Trend Estimation

In this section we'll try to separate predictable part of the series from random white noise. This is achieved using ACF PACF analysis.

Daily Series

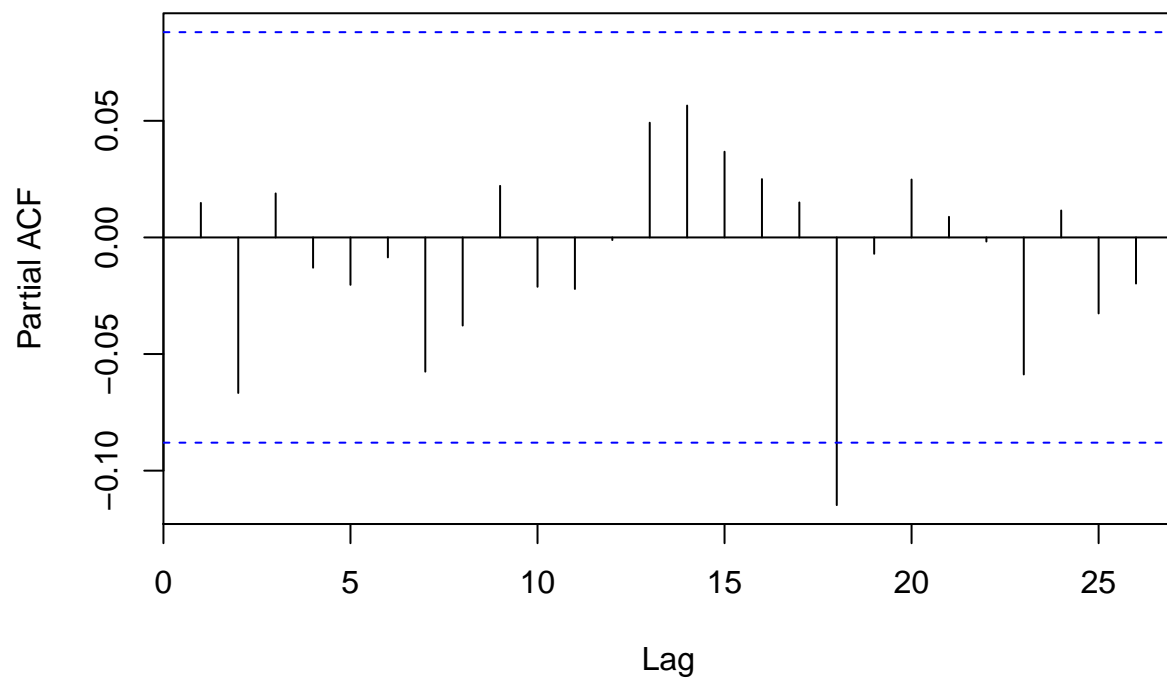
`acf(auropharma$diff1_daily)`

Series auropharma\$diff1_daily



```
pacf(auropharma$diff1_daily)
```

Series auropharma\$diff1_daily

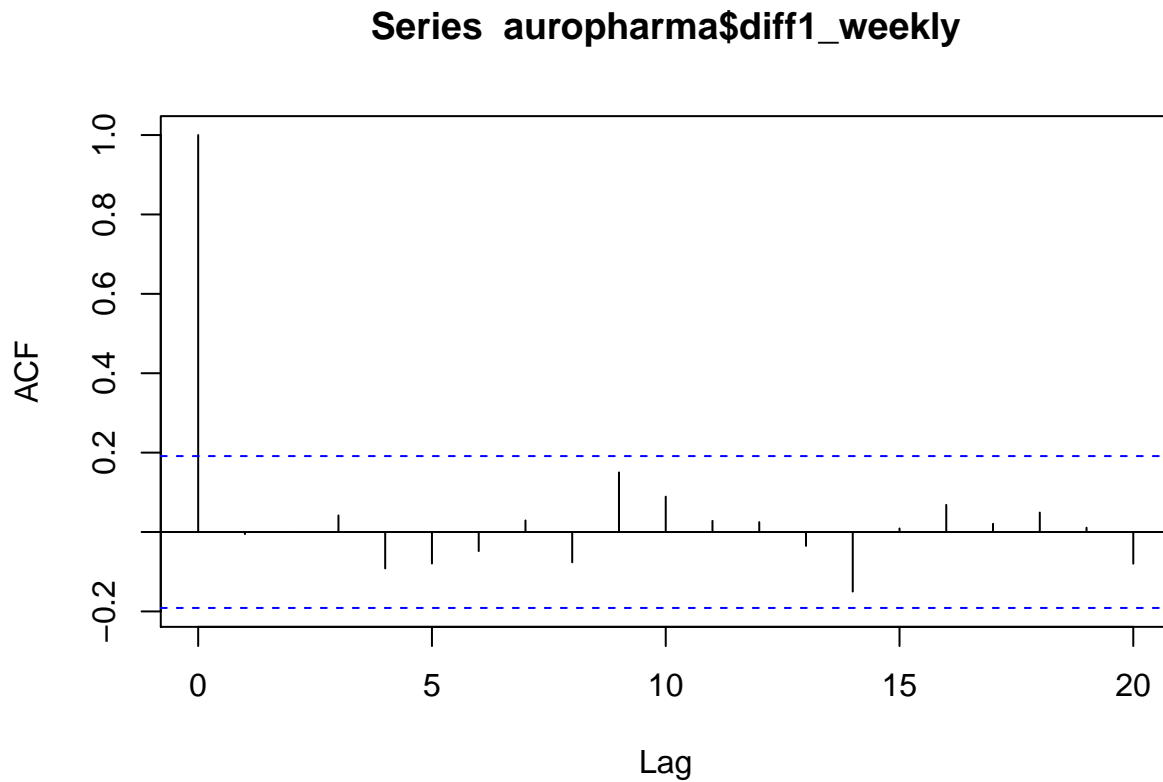


```
# As ACF and PACF are inbetween significant bands, this shows that signal  
# is random (i.e there exists no trend to model) and stationary
```

- As it can be seen that acf at any lag is bounded by significant limits, which means that the stationary series obtained after taking first order difference is white noise.

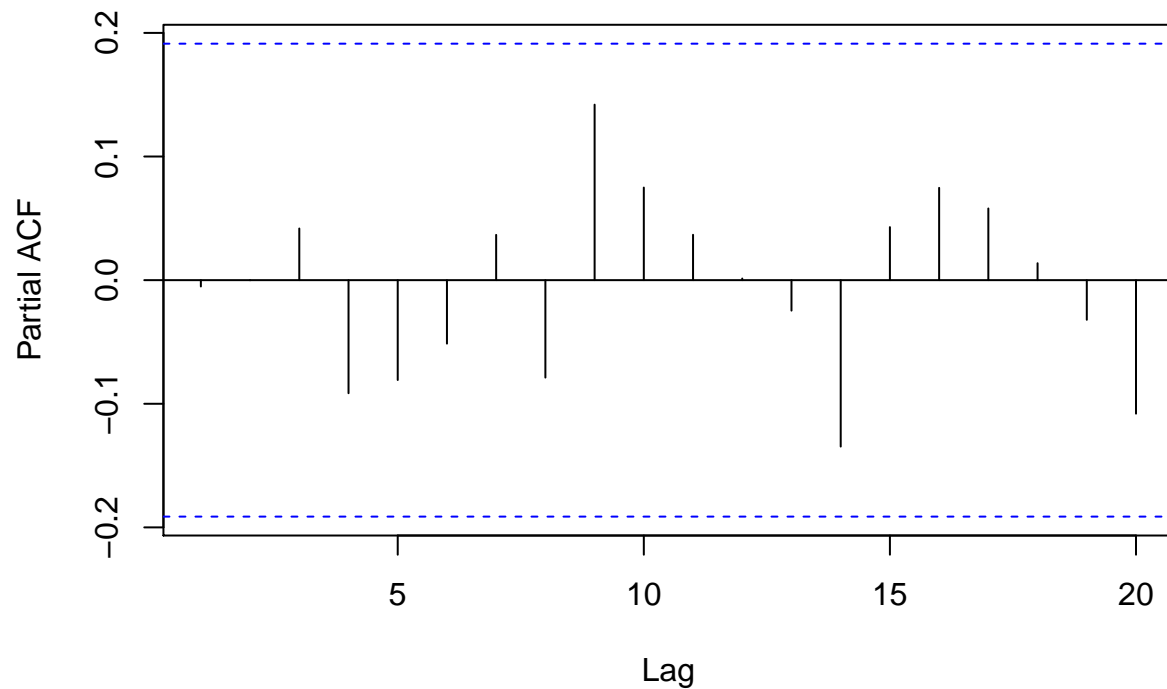
Weekly Series

```
acf(auropharma$diff1_weekly)
```



```
pacf(auropharma$diff1_weekly)
```

Series auropharma\$diff1_weekly



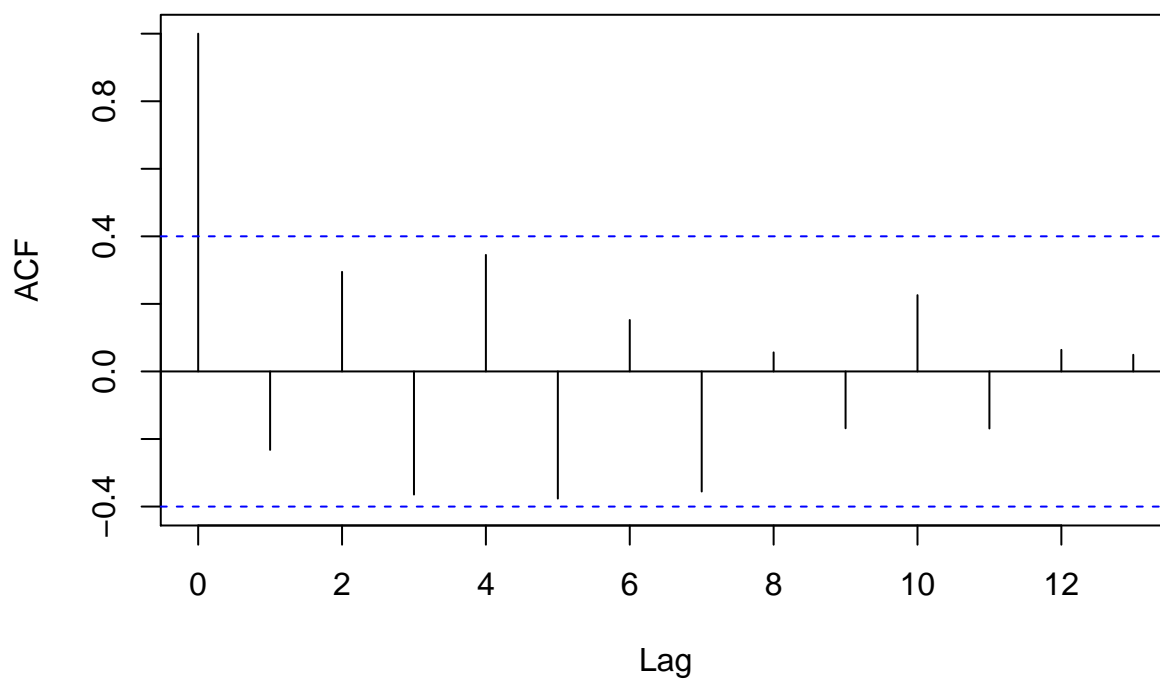
*# As ACF and PACF are inbetween significant bands, this shows that signal
is random (i.e there exists no trend to model) and stationary*

- As it can be seen that acf at any lag is bounded by significant limits, which means that the stationary series obtained after taking first order difference is white noise.

Monthly Series

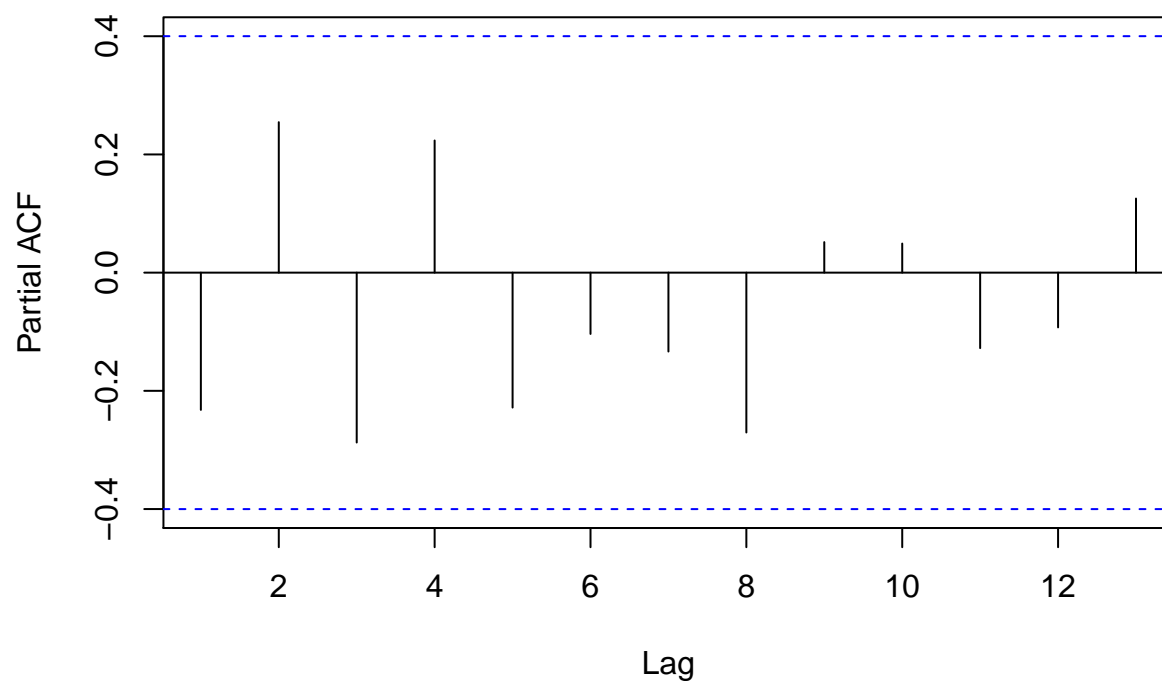
```
acf(auropharma$diff1_monthly)
```

Series auropharma\$diff1_monthly



```
pacf(auropharma$diff1_monthly)
```

Series auropharma\$diff1_monthly



```
# As ACF and PACF are inbetween significant bands, this shows that signal  
# is random (i.e there exists no trend to model) and stationary
```

- As it can be seen that acf at any lag is bounded by significant limits, which means that the stationary series obtained after taking first order difference is white noise.

GlaxoSmithkline Pharmaceuticals Limited (GLAXO.NS)

```
glaxo = NULL
glaxo$raw_daily = loadCSVData('../Data/GLAXO/GLAXO.NS_daily.csv')

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      1044   1216   1272   1308   1366   1795

glaxo$raw_weekly = loadCSVData('../Data/GLAXO/GLAXO.NS_weekly.csv')

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      1044   1220   1271   1311   1369   1749

glaxo$raw_monthly = loadCSVData('../Data/GLAXO/GLAXO.NS_monthly.csv')

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      1044   1230   1273   1313   1372   1714

glaxo$sd_daily = standardize(glaxo$raw_daily)

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -1.9620 -0.6849 -0.2666  0.0000  0.4267  3.6130

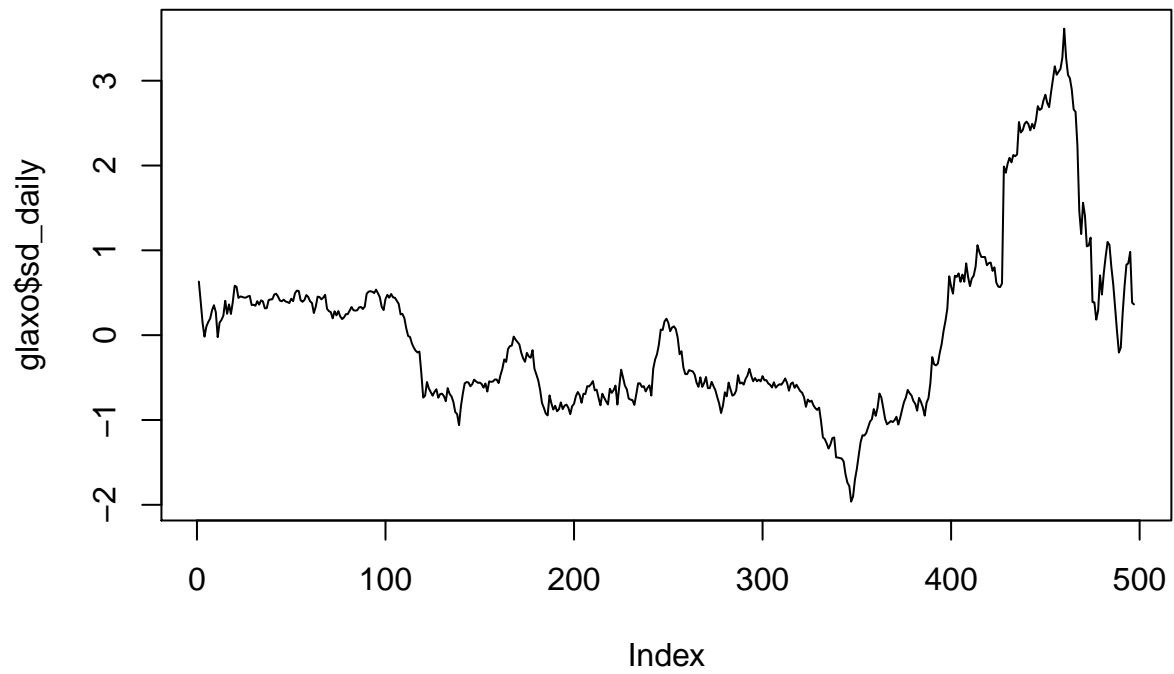
glaxo$sd_weekly = standardize(glaxo$raw_weekly)

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -1.9470 -0.6658 -0.2936  0.0000  0.4184  3.1850

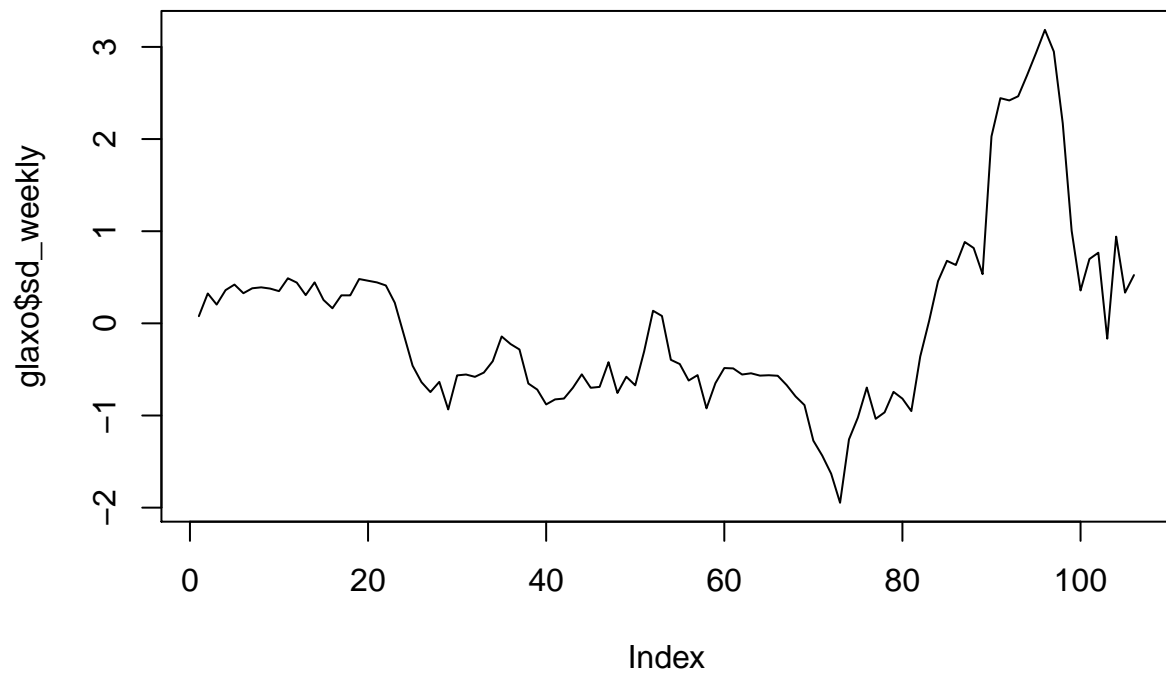
glaxo$sd_monthly = standardize(glaxo$raw_monthly)

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -1.9310 -0.5927 -0.2828  0.0000  0.4269  2.8820

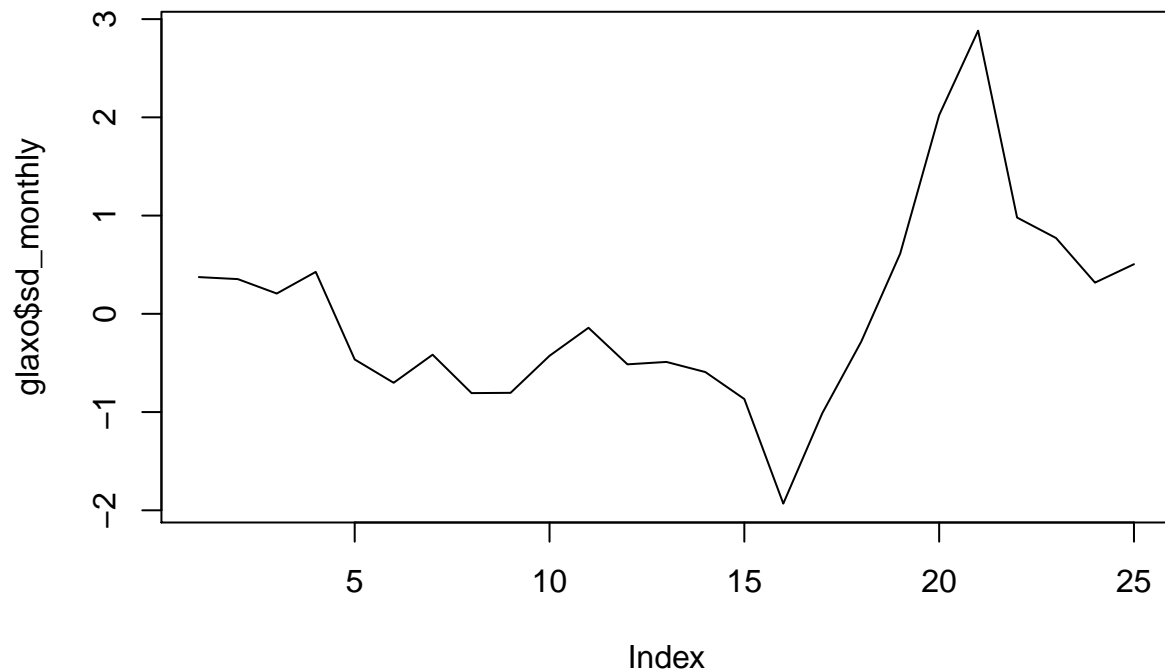
# plot all the data
plot(glaxo$sd_daily, type='l')
```



```
plot(glaxo$sd_weekly, type='l')
```



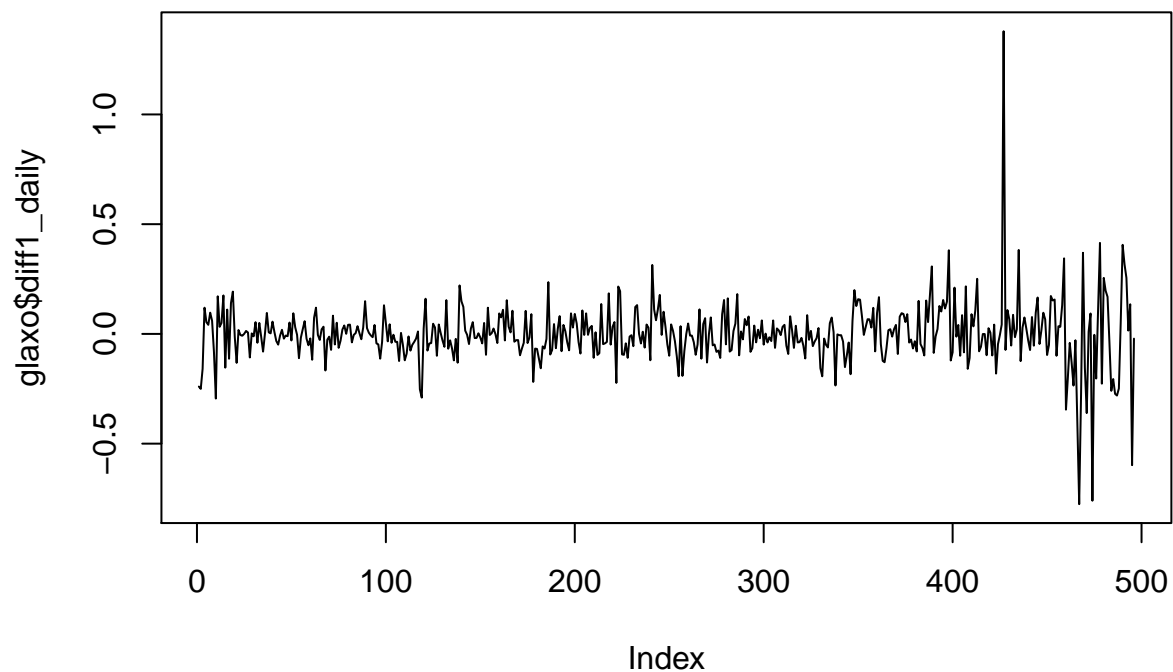
```
plot(glaxo$sd_monthly, type='l')
```



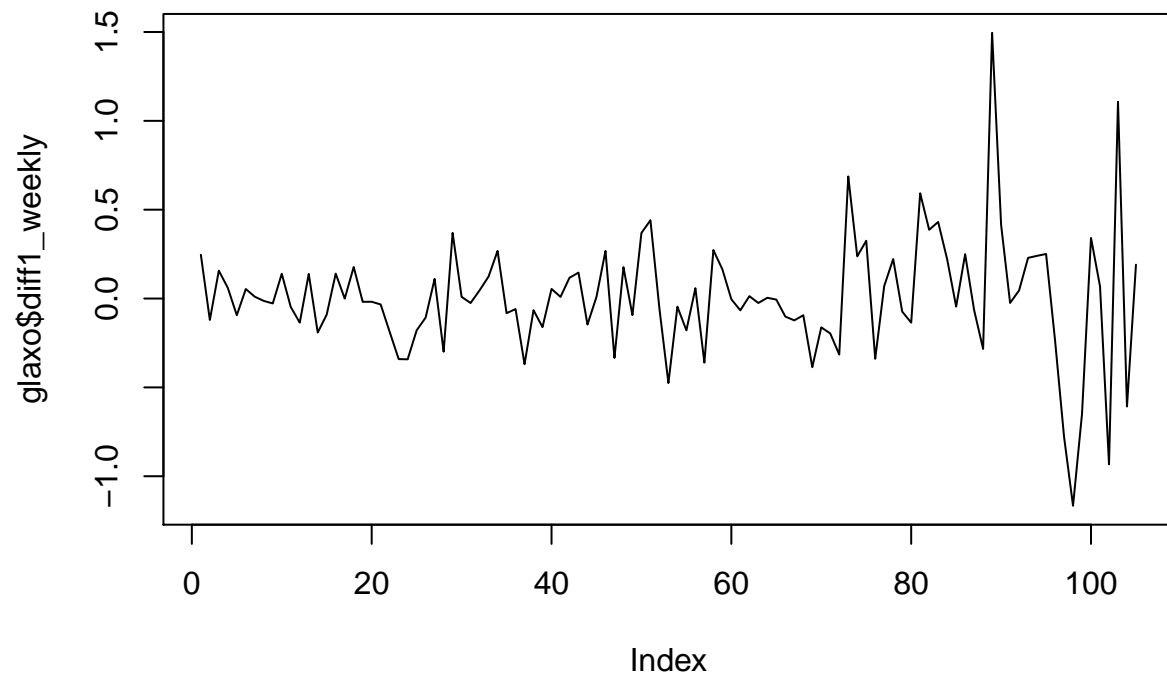
```
# Based on plots we can clearly see that given data is
# non stationary (data has some integrating effect, which should estimated)
# which can be converted to stationary by taking difference of order = n
```

```
glaxo$diff1_daily = diff(glaxo$sd_daily)
glaxo$diff1_weekly = diff(glaxo$sd_weekly)
glaxo$diff1_monthly = diff(glaxo$sd_monthly)
```

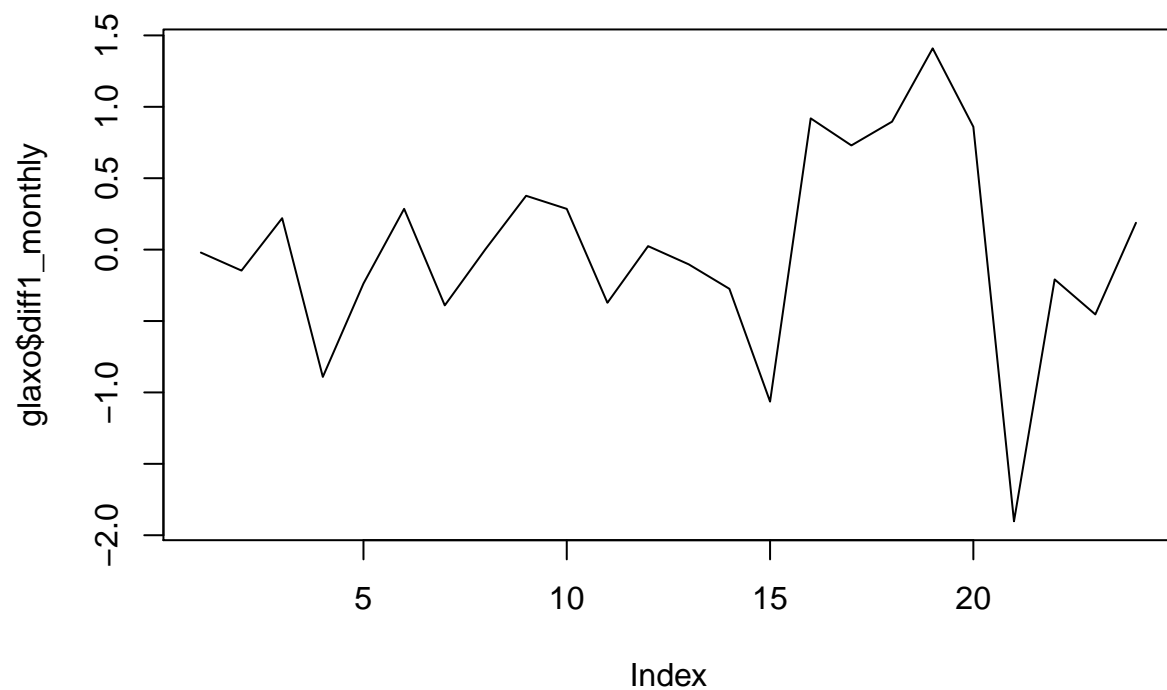
```
# Plotting differenced data
plot(glaxo$diff1_daily, type='l')
```




```
plot(glaxo$diff1_weekly, type='l')
```



```
plot(glaxo$diff1_monthly, type='l')
```



Differenced plots seems to be stationary this can also be verified by summary of the data

```
print(summary(glaxo$diff1_daily))
```

```
##      Min.      1st Qu.      Median      Mean      3rd Qu.      Max.
## -0.7756000 -0.0572600 -0.0045650 -0.0005432  0.0537000  1.3790000
```

```
print(summary(glaxo$diff1_weekly))
```

```
##      Min.   1st Qu.   Median     Mean   3rd Qu.     Max.
## -1.166000 -0.135500 -0.013330  0.004248  0.164700  1.495000
```

```
print(summary(glaxo$diff1_monthly))
```

```
##      Min.   1st Qu.   Median     Mean   3rd Qu.     Max.
## -1.902000 -0.298900 -0.008869  0.005476  0.308500  1.409000
```

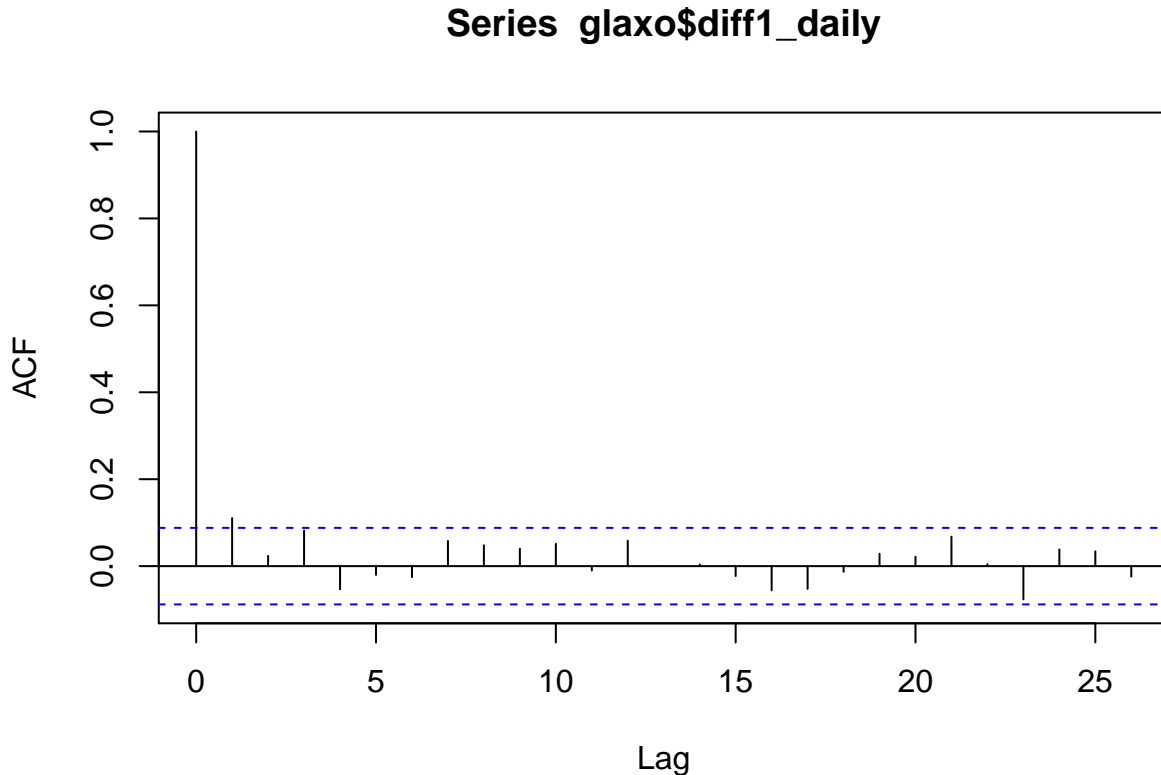
- Actual Raw data is non stationary
- By analysing the data it's clear that some integrating effect exists, which can be removed by taking first order difference of the signal
- Stationary component of the data is estimated using first order difference of the time series
- Resulting plot after removing integrating effect are stationary

Trend Estimation

In this section we'll try to separate predictable part of the series from random white noise. This is achieved using ACF PACF analysis.

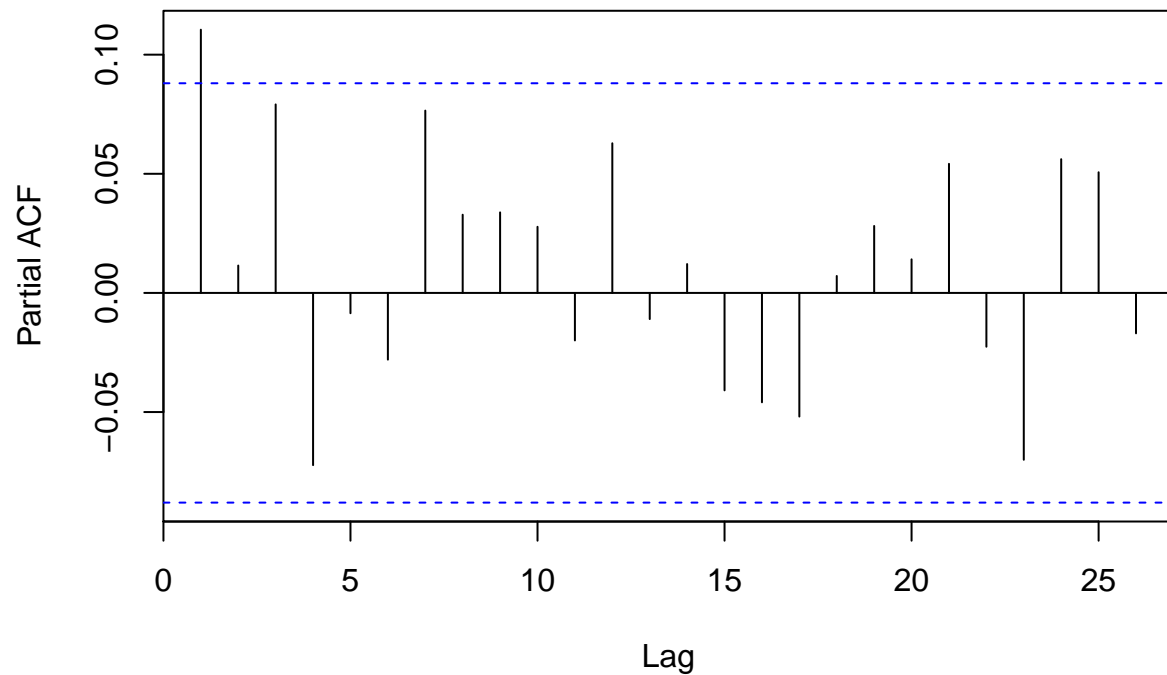
Daily Series

```
acf(glaxo$diff1_daily)
```



```
pacf(glaxo$diff1_daily)
```

Series glaxo\$diff1_daily



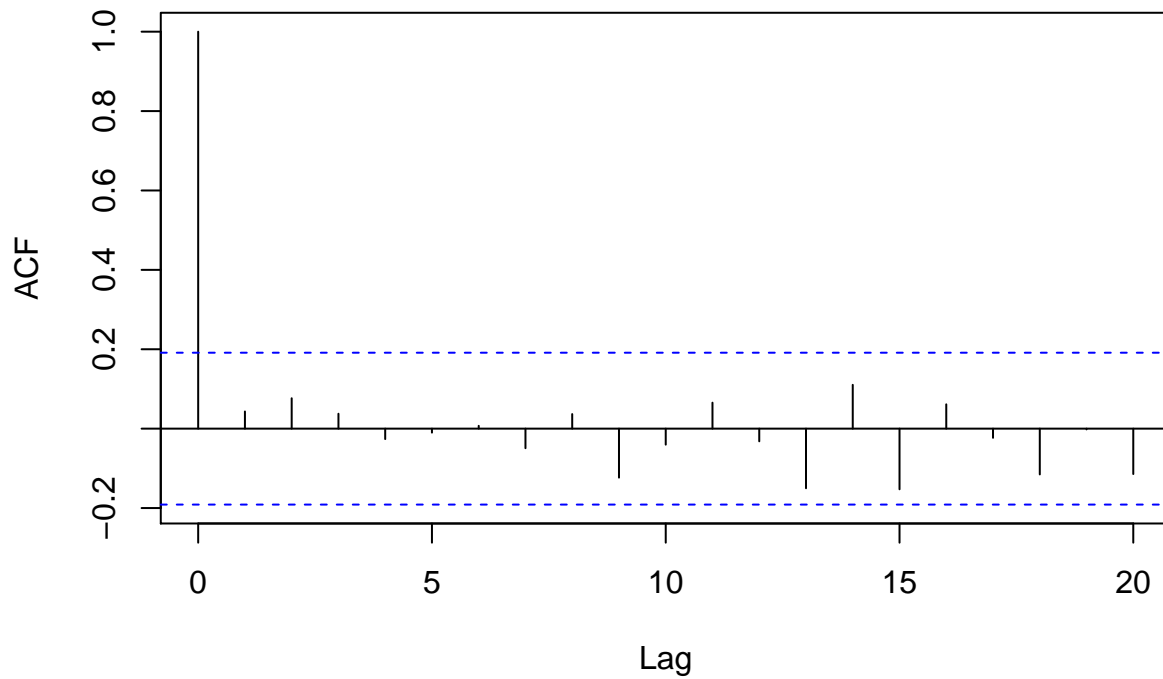
*# As ACF and PACF are inbetween significant bands, this shows that signal
is random (i.e there exists no trend to model) and stationary*

- As it can be seen that acf at any lag is bounded by significant limits, which means that the stationary series obtained after taking first order difference is white noise.

Weekly Series

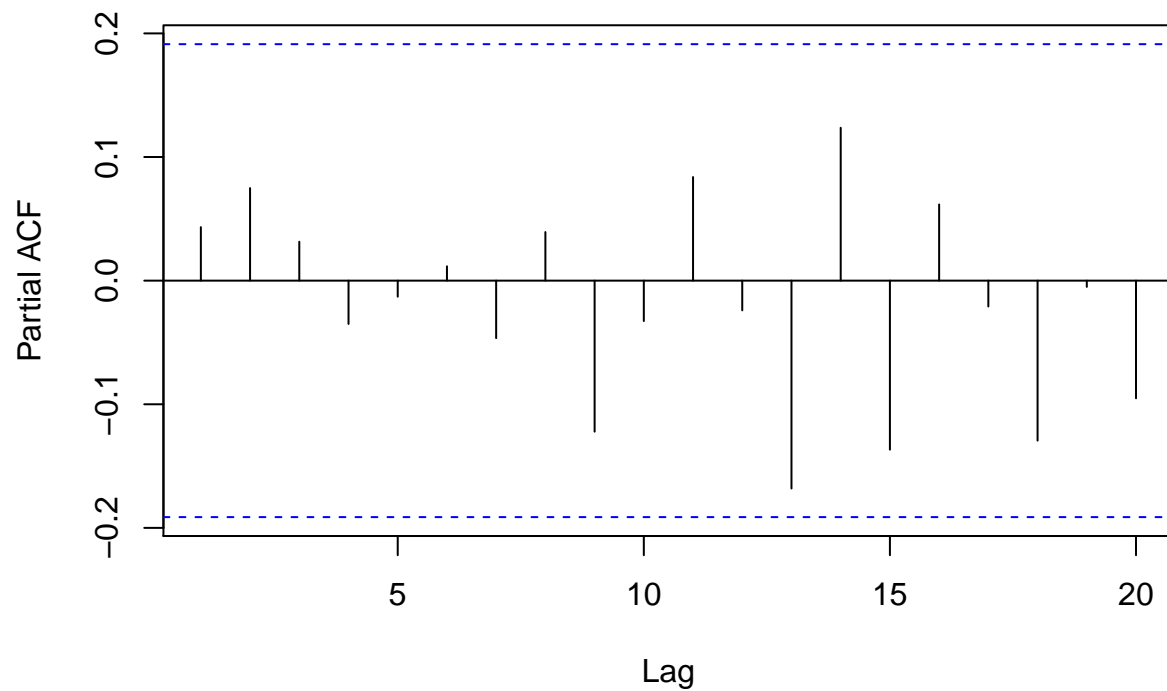
```
acf(glaxo$diff1_weekly)
```

Series glaxo\$diff1_weekly



```
pacf(glaxo$diff1_weekly)
```

Series glaxo\$diff1_weekly

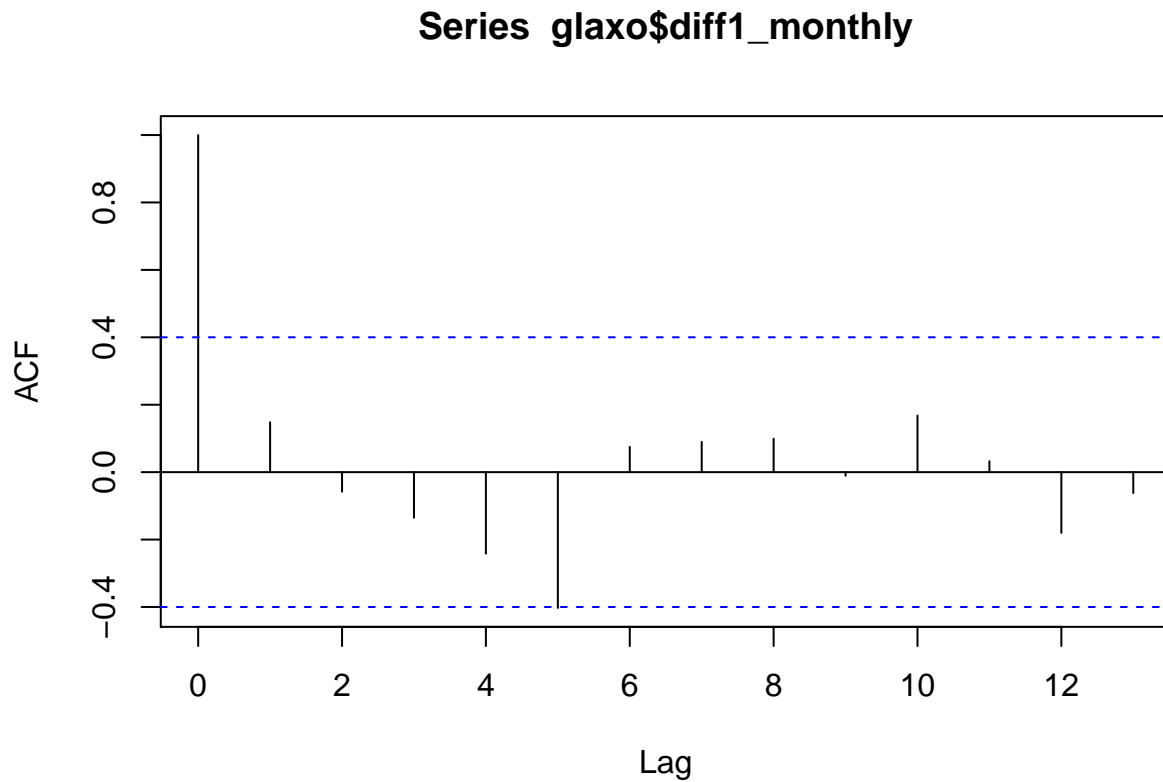


```
# As ACF and PACF are inbetween significant bands, this shows that signal  
# is random (i.e there exists no trend to model) and stationary
```

- As it can be seen that acf at any lag is bounded by significant limits, which means that the stationary series obtained after taking first order difference is white noise.

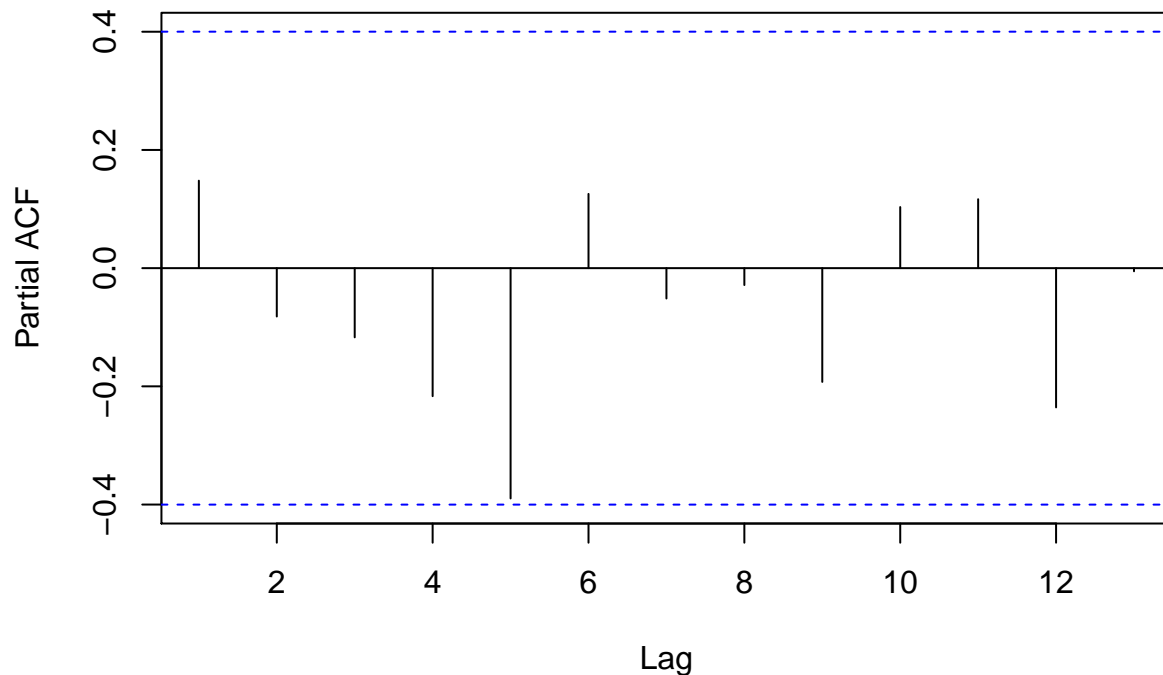
Monthly Series

```
acf(glaxo$diff1_monthly)
```



```
pacf(glaxo$diff1_monthly)
```

Series glaxo\$diff1_monthly



*# As ACF and PACF are inbetween significant bands, this shows that signal
is random (i.e there exists no trend to model) and stationary*

- As it can be seen that acf at any lag is bounded by significant limits, which means that the stationary series obtained after taking first order difference is white noise.

Glenmark Pharmaceuticals Limited (GLENMARK.NS)

```
glenmark = NULL
glenmark$raw_daily = loadCSVData('../Data/GLENMARK/GLENMARK.NS_daily.csv')

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  500.6   581.3   616.3   675.8   853.8   959.3

glenmark$raw_weekly = loadCSVData('../Data/GLENMARK/GLENMARK.NS_weekly.csv')

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  500.6   582.7   618.6   674.5   749.0   953.2

glenmark$raw_monthly = loadCSVData('../Data/GLENMARK/GLENMARK.NS_monthly.csv')

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  526.3   583.0   621.5   663.9   665.7   925.5

glenmark$sd_daily = standardize(glenmark$raw_daily)

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -1.2750 -0.6876 -0.4329  0.0000  1.2950  2.0630
```

```
glenmark$sd_weekly = standardize(glenmark$raw_weekly)
```

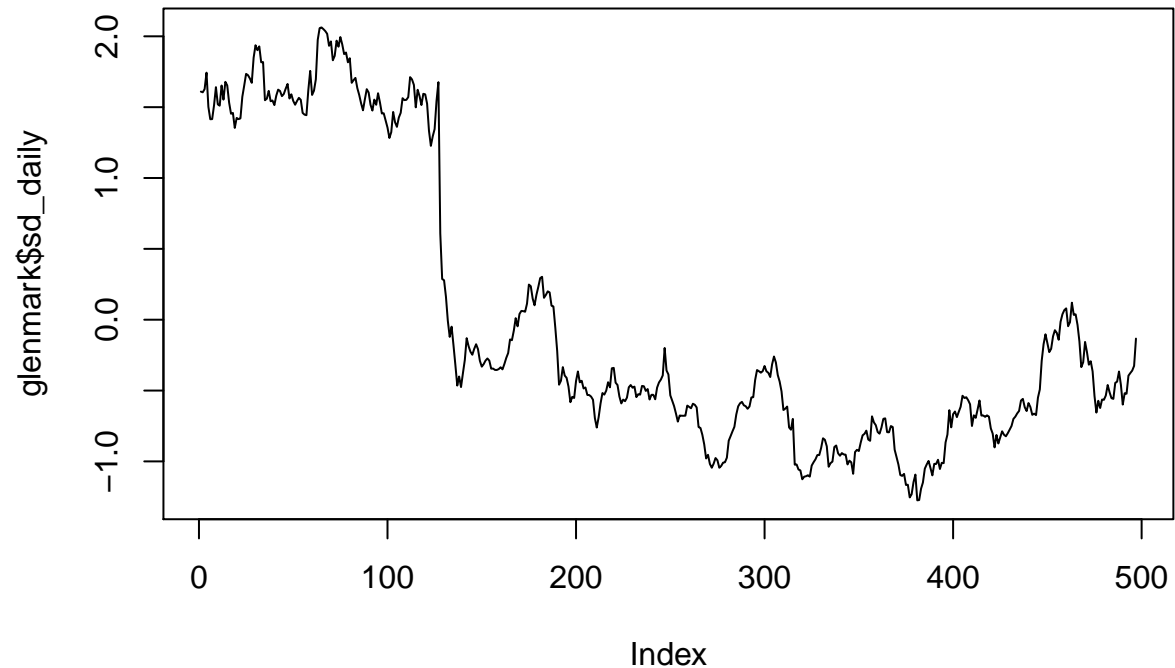
```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -1.2750 -0.6731 -0.4098  0.0000  0.5461  2.0430
```

```
glenmark$sd_monthly = standardize(glenmark$raw_monthly)
```

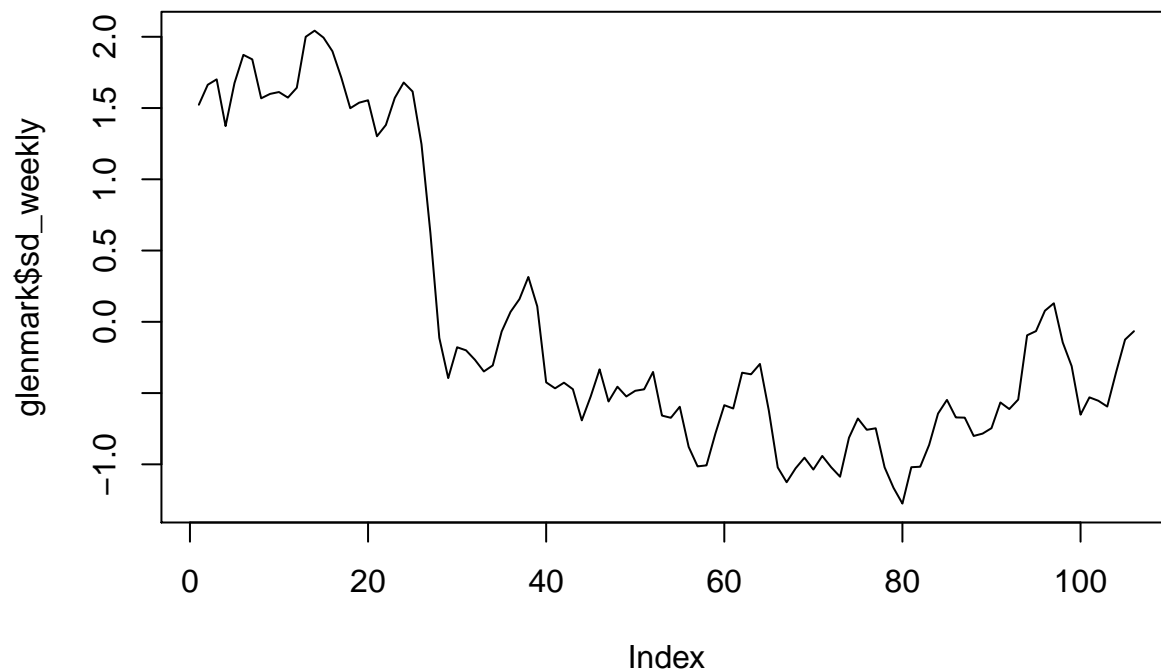
```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -1.1160 -0.6554 -0.3437  0.0000  0.0143  2.1210
```

```
# plot all the data
```

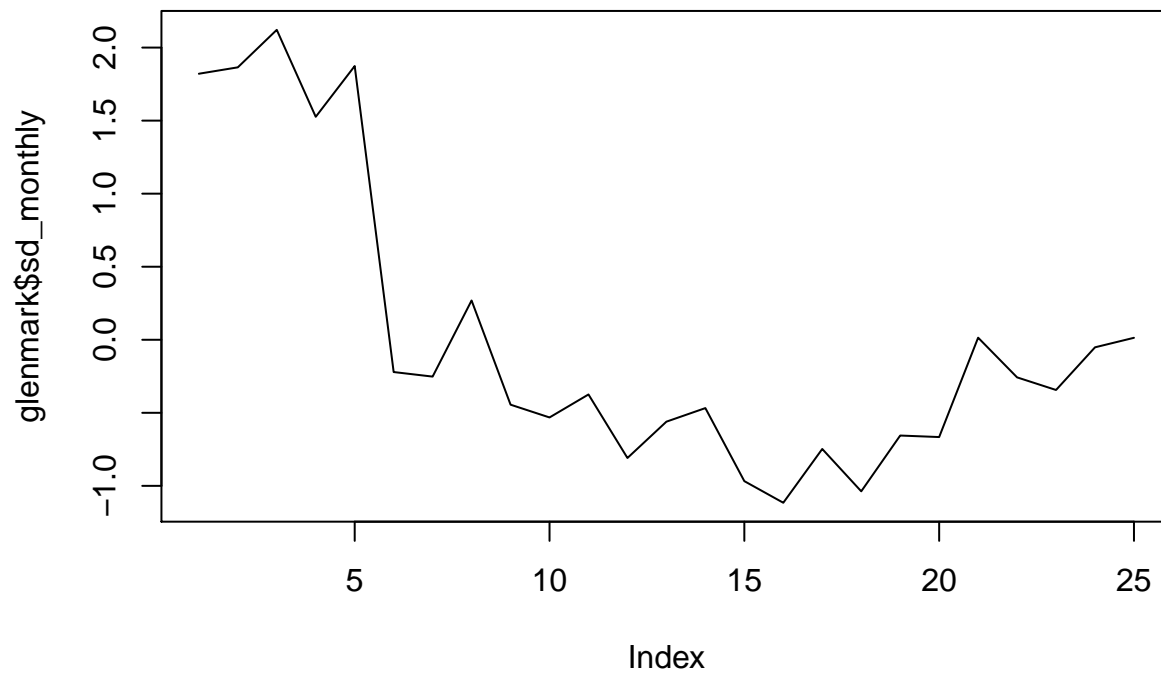
```
plot(glenmark$sd_daily, type='l')
```



```
plot(glenmark$sd_weekly, type='l')
```



```
plot(glenmark$sd_monthly, type='l')
```



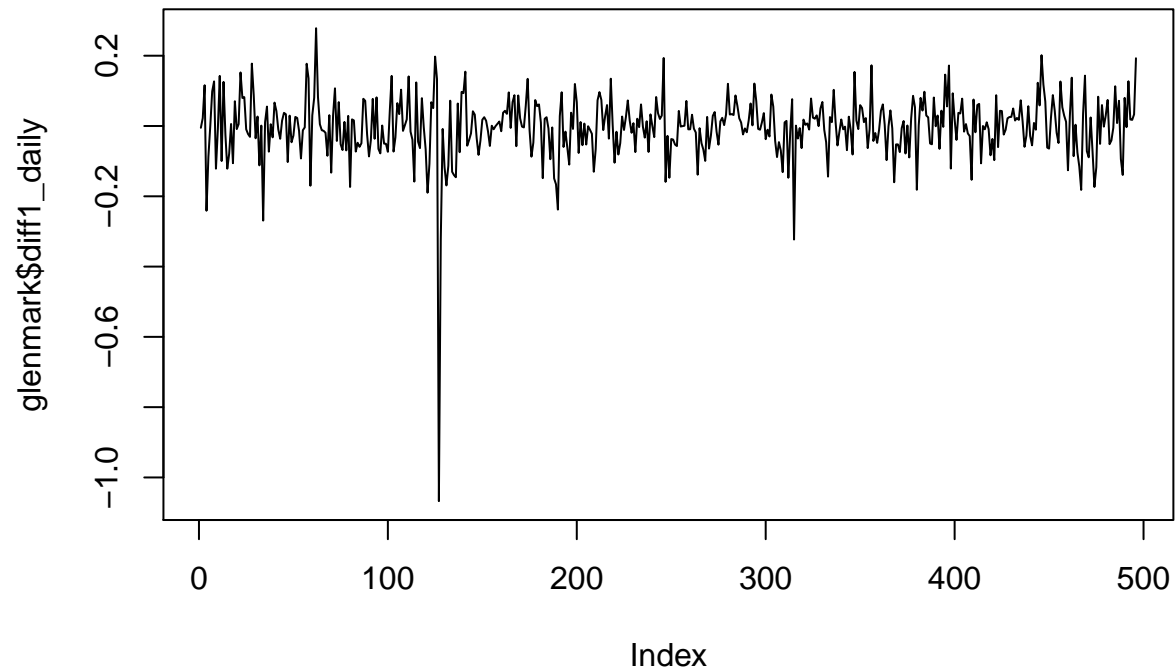
```
# Based on plots we can clearly see that given data is
# non stationary (data has some integrating effect, which should estimated)
# which can be converted to stationary by taking difference of order = n

glenmark$diff1_daily = diff(glenmark$sd_daily)
glenmark$diff1_weekly = diff(glenmark$sd_weekly)
glenmark$diff1_monthly = diff(glenmark$sd_monthly)

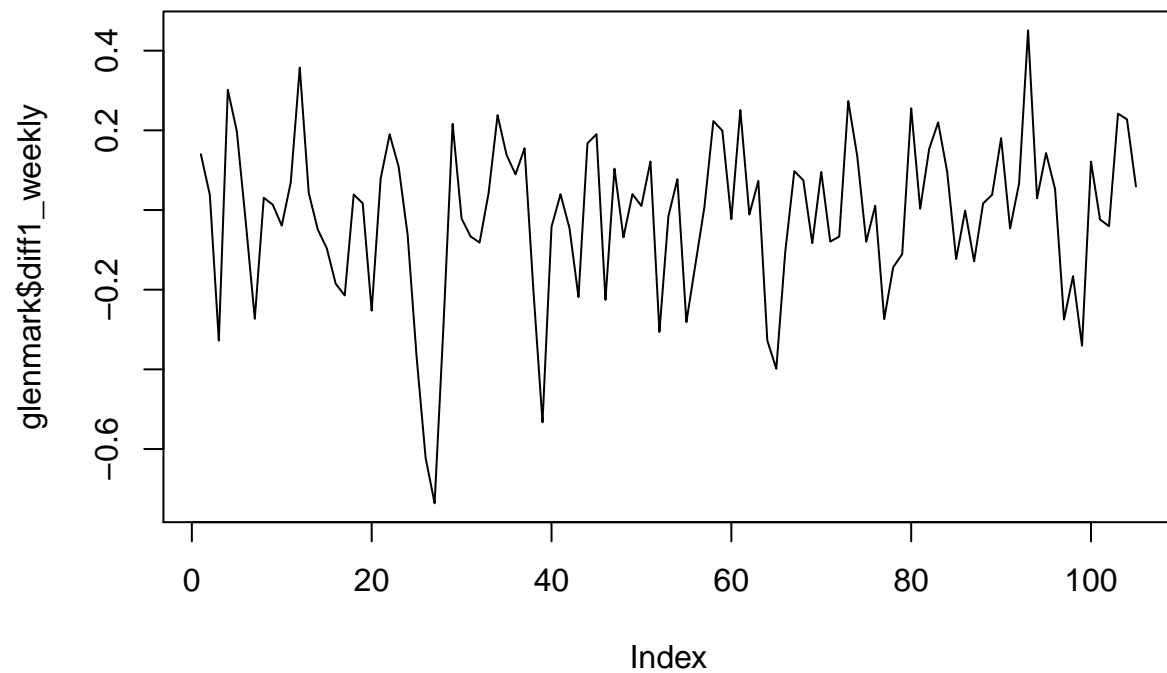
# Plotting differenced data
```



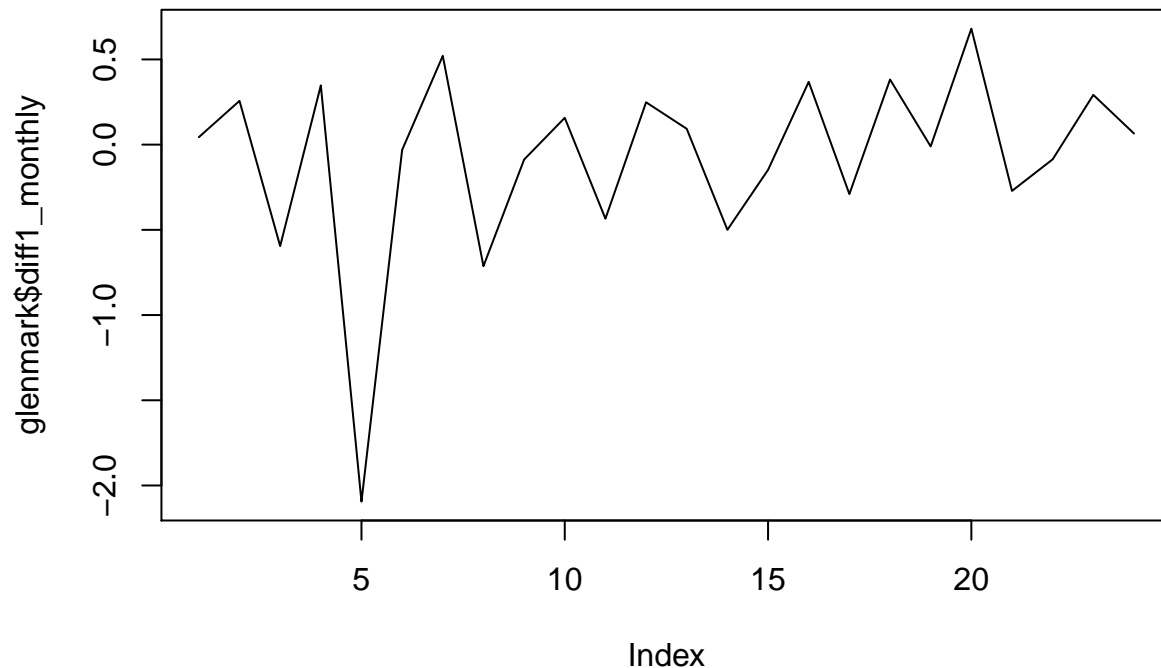
```
plot(glenmark$diff1_daily, type='l')
```



```
plot(glenmark$diff1_weekly, type='l')
```



```
plot(glenmark$diff1_monthly, type='l')
```



Differenced plots seems to be stationary this can also be verified by summary of the data
`print(summary(glenmark$diff1_daily))`

```
##      Min.      1st Qu.      Median      Mean      3rd Qu.      Max.
## -1.0670000 -0.0477400  0.0007278 -0.0035140  0.0420100  0.2783000
```

`print(summary(glenmark$diff1_weekly))`

```
##      Min. 1st Qu.  Median      Mean 3rd Qu.      Max.
## -0.73610 -0.10410  0.01063 -0.01514  0.10810  0.45090
```

`print(summary(glenmark$diff1_monthly))`

```
##      Min. 1st Qu.  Median      Mean 3rd Qu.      Max.
## -2.09400 -0.27620  0.01662 -0.07531  0.26540  0.68030
```

- Actual Raw data is non stationary
- By analysing the data it's clear that some integrating effect exists, which can be removed by taking first order difference of the signal
- Stationary component of the data is estimated using first order difference of the time series
- Resulting plot after removing integrating effect are stationary

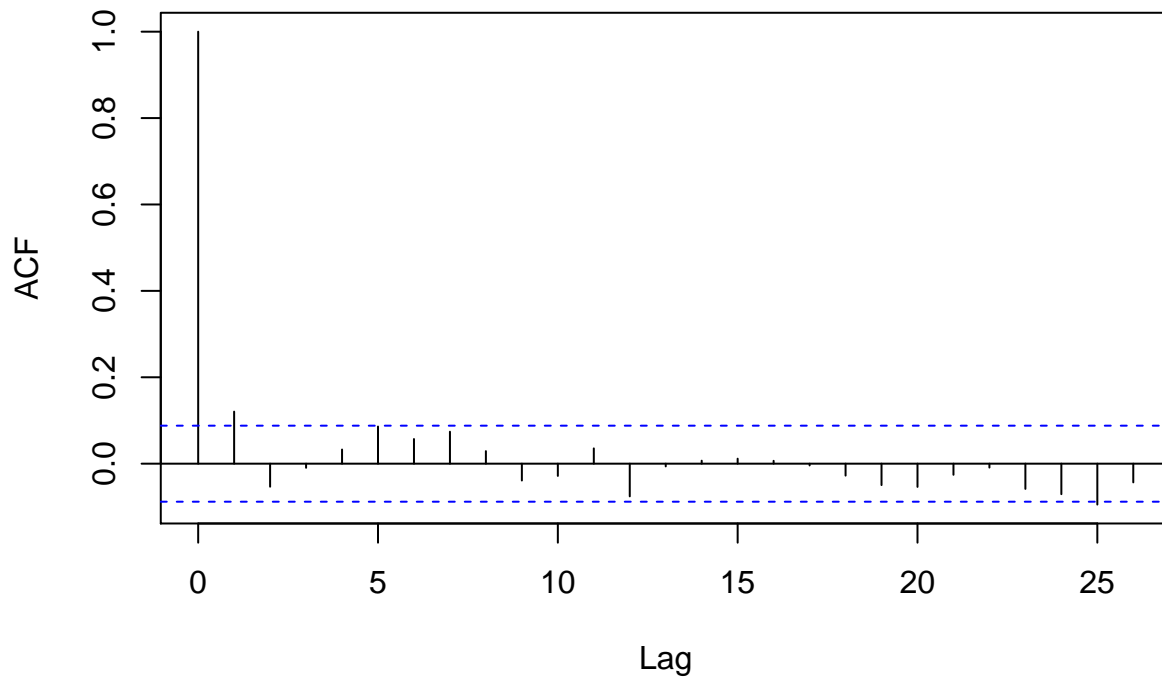
Trend Estimation

In this section we'll try to separate predictable part of the series from random white noise. This is achieved using ACF PACF analysis.

Daily Series

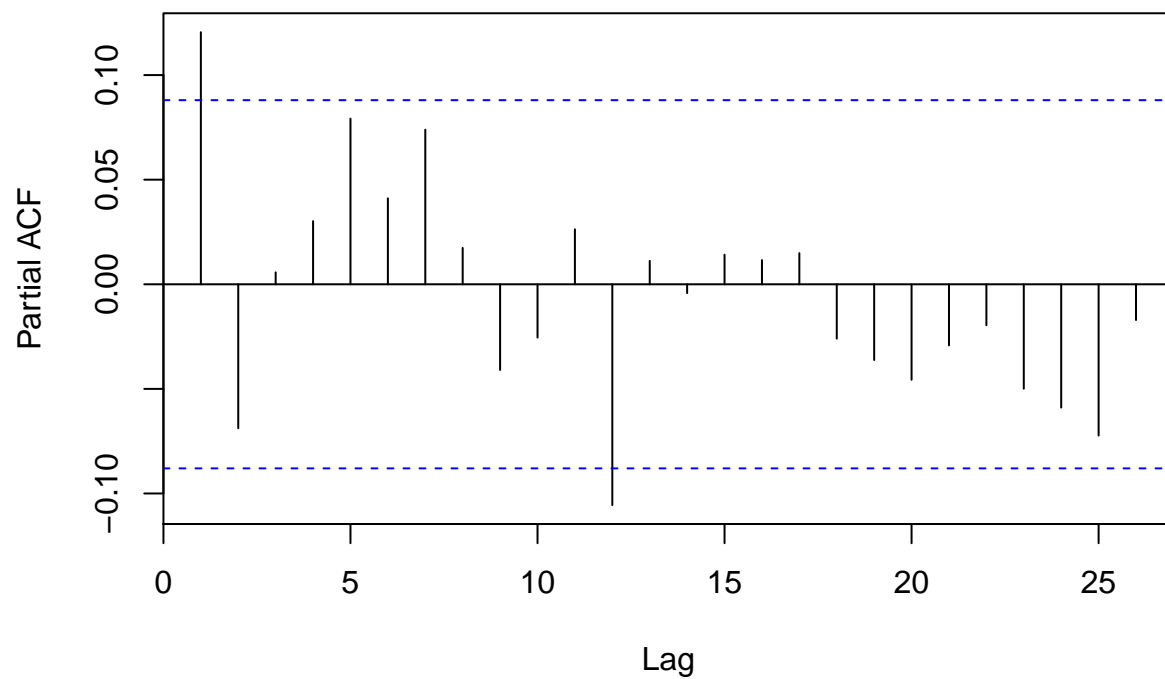
`acf(glenmark$diff1_daily)`

Series glenmark\$diff1_daily



```
pacf(glenmark$diff1_daily)
```

Series glenmark\$diff1_daily

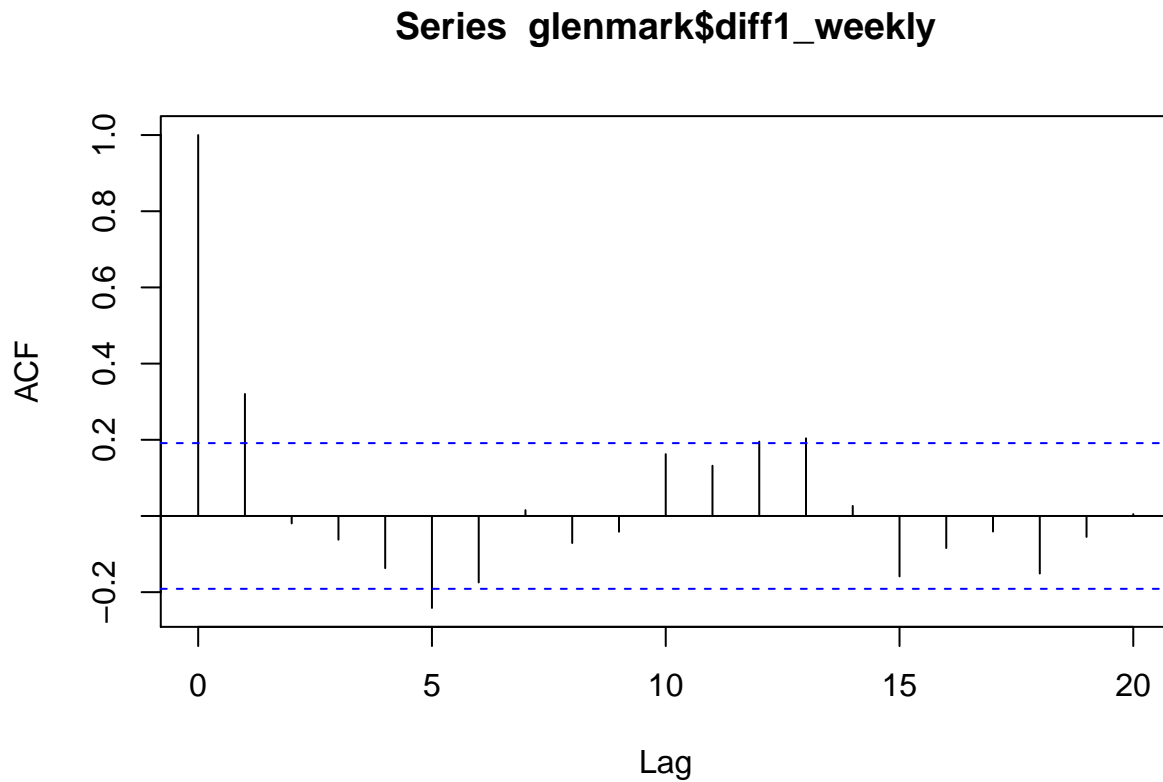


*# As ACF and PACF are inbetween significant bands, this shows that signal
is random (i.e there exists no trend to model) and stationary*

- As it can be seen that acf at any lag is bounded by significant limits, which means that the stationary series obtained after taking first order difference is white noise.

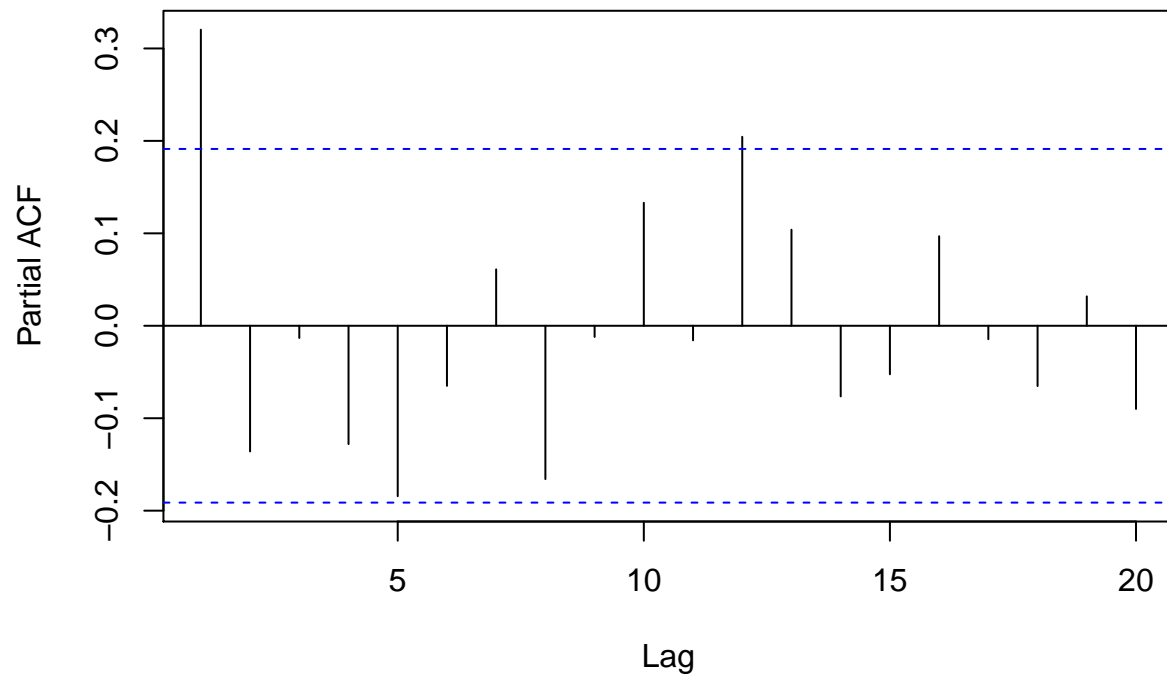
Weekly Series

```
acf(glenmark$diff1_weekly)
```



```
pacf(glenmark$diff1_weekly)
```

Series glenmark\$diff1_weekly



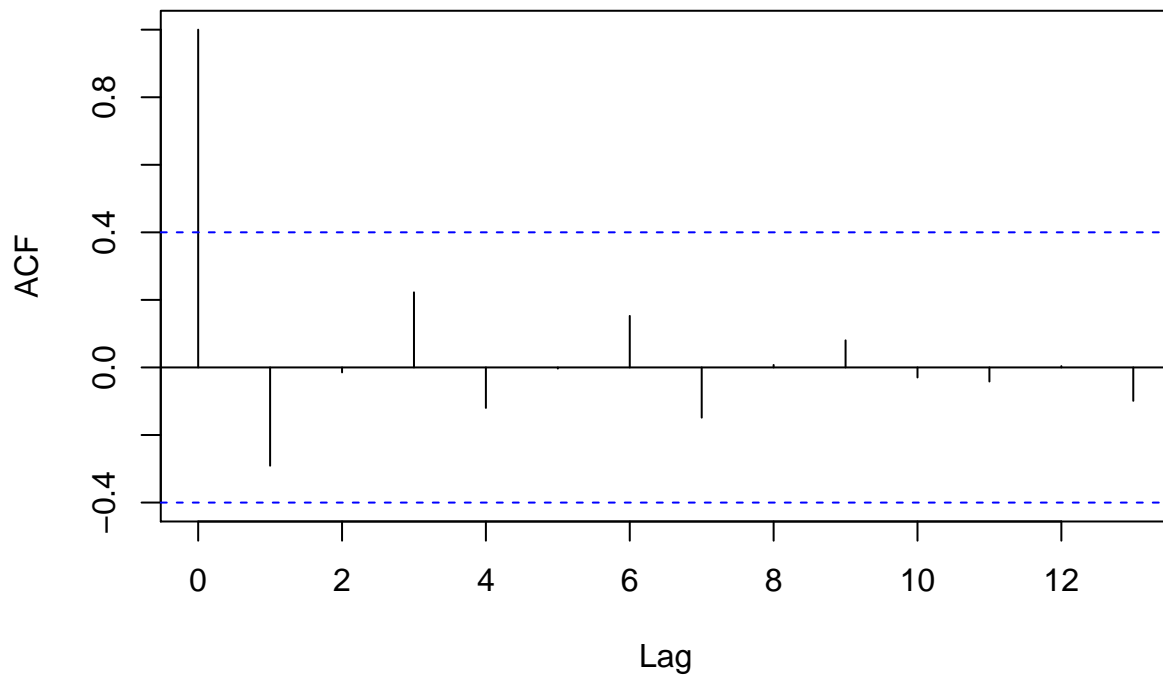
*# As ACF and PACF are inbetween significant bands, this shows that signal
is random (i.e there exists no trend to model) and stationary*

- As it can be seen that acf at any lag is bounded by significant limits, which means that the stationary series obtained after taking first order difference is white noise.

Monthly Series

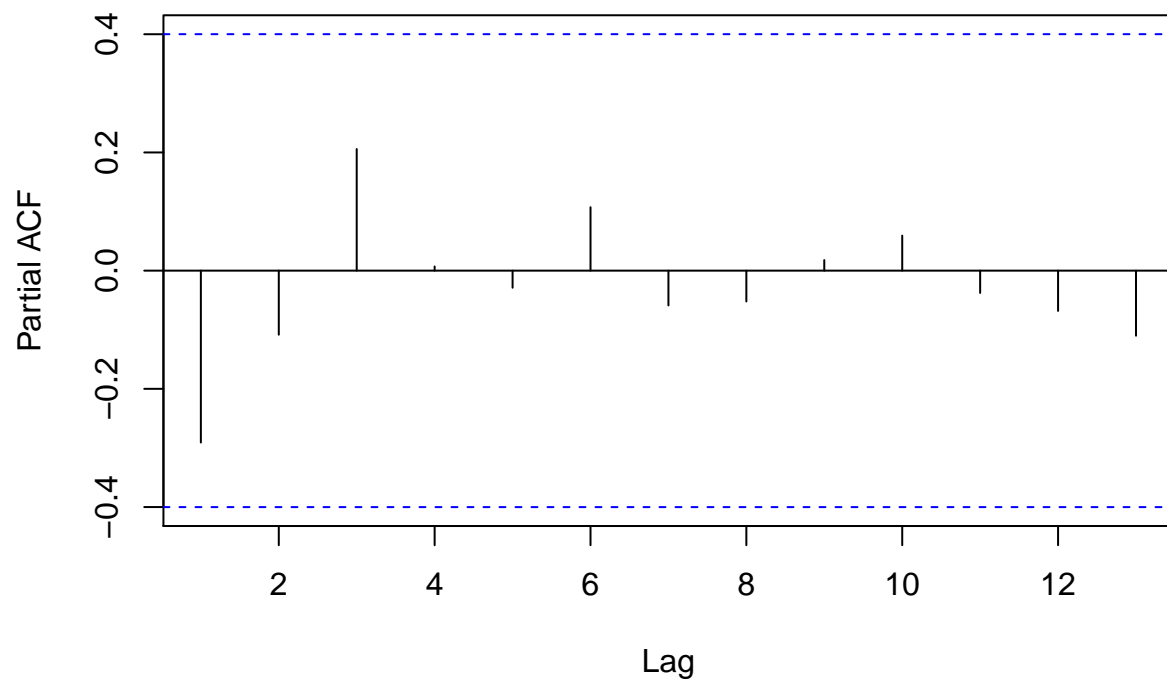
```
acf(glenmark$diff1_monthly)
```

Series glenmark\$diff1_monthly



```
pacf(glenmark$diff1_monthly)
```

Series glenmark\$diff1_monthly



```
# As ACF and PACF are inbetween significant bands, this shows that signal  
# is random (i.e there exists no trend to model) and stationary
```

- As it can be seen that acf at any lag is bounded by significant limits, which means that the stationary series obtained after taking first order difference is white noise.