

# Financial Modelling

*Avinash Kori / ED15B006*  
*Engineering Design Department,*  
*Indian Institute of Technology, Madras*  
*koriavinash1@gmail.com*

## Contents

<b>Introduction</b>	<b>2</b>
<b>Data</b>	<b>2</b>
<b>Data Analysis</b>	<b>2</b>
Analysis of Alembic Pharmaceuticals Limited (APLLTD.NS) . . . . .	3
Daily Series . . . . .	8
Weekly Series . . . . .	10
Monthly Series . . . . .	12

## 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)

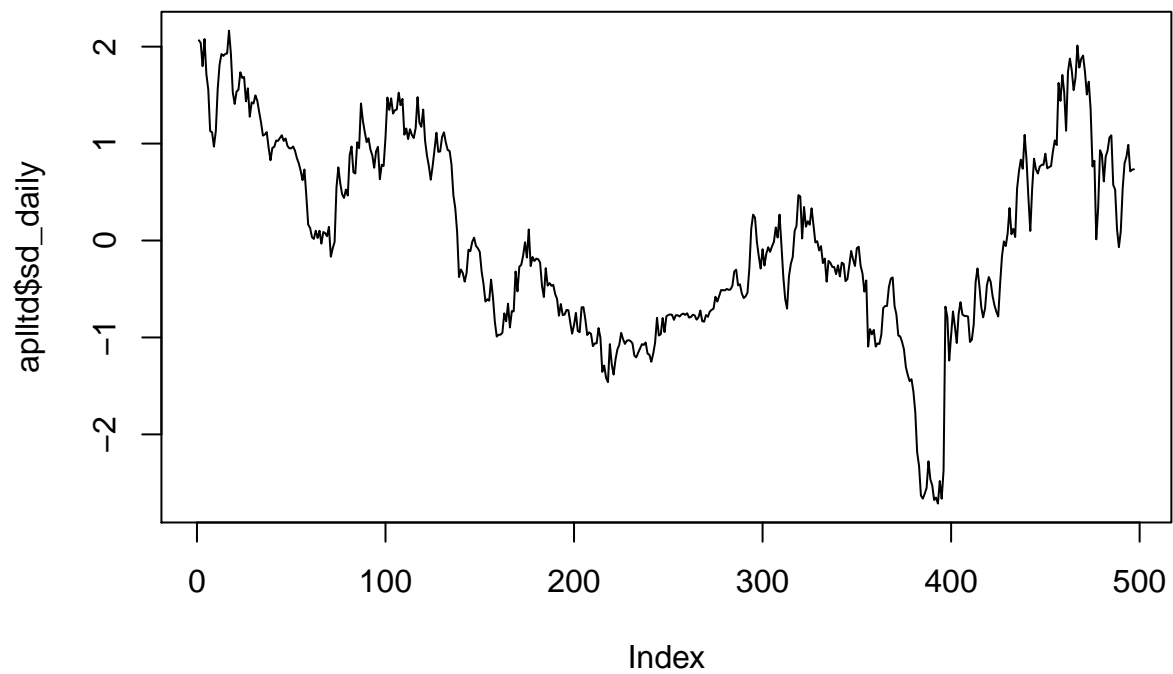
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -2.6640 -0.7536 -0.1326  0.0000  0.8057  1.9800

aplltd$sd_monthly = standardize(aplltd$raw_monthly)

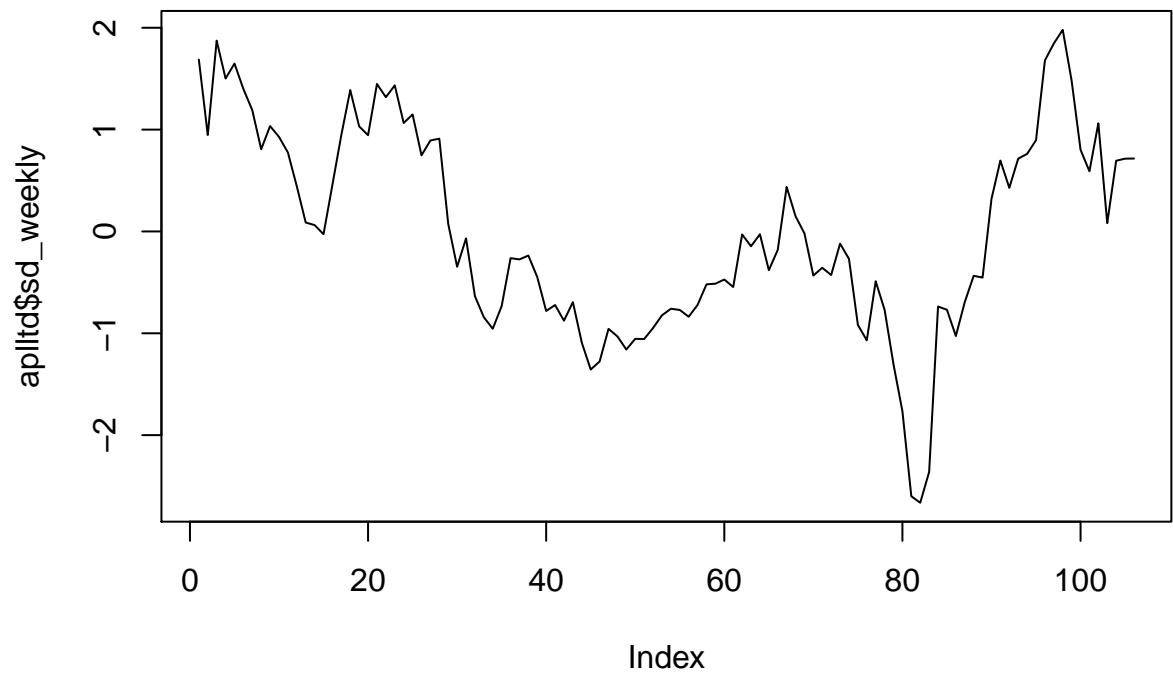
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -2.657000 -0.713800 -0.005926  0.000000  0.793000  1.608000

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

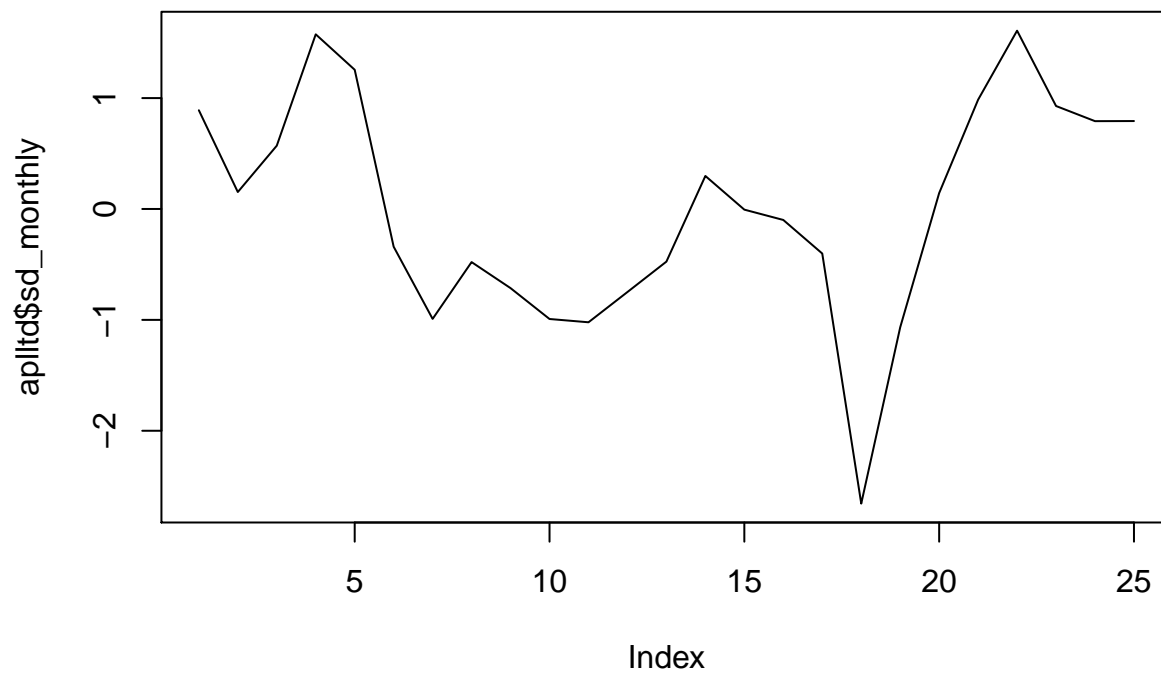
```



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

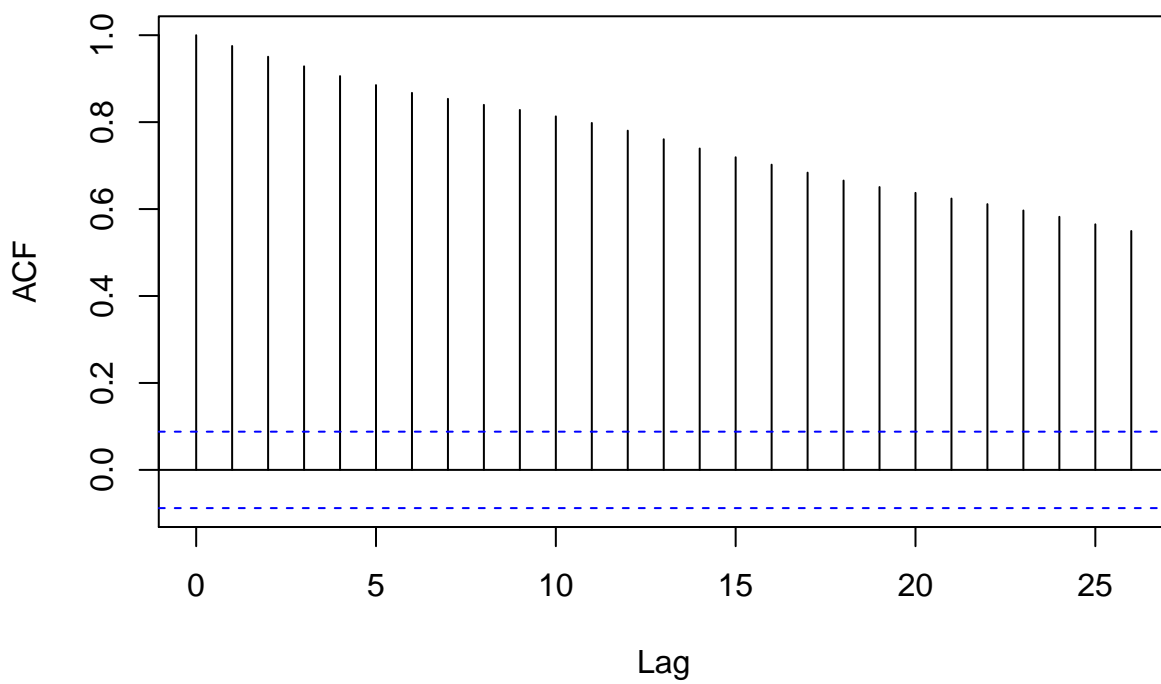


```
plot(apl1td$sd_monthly, type='l')
```



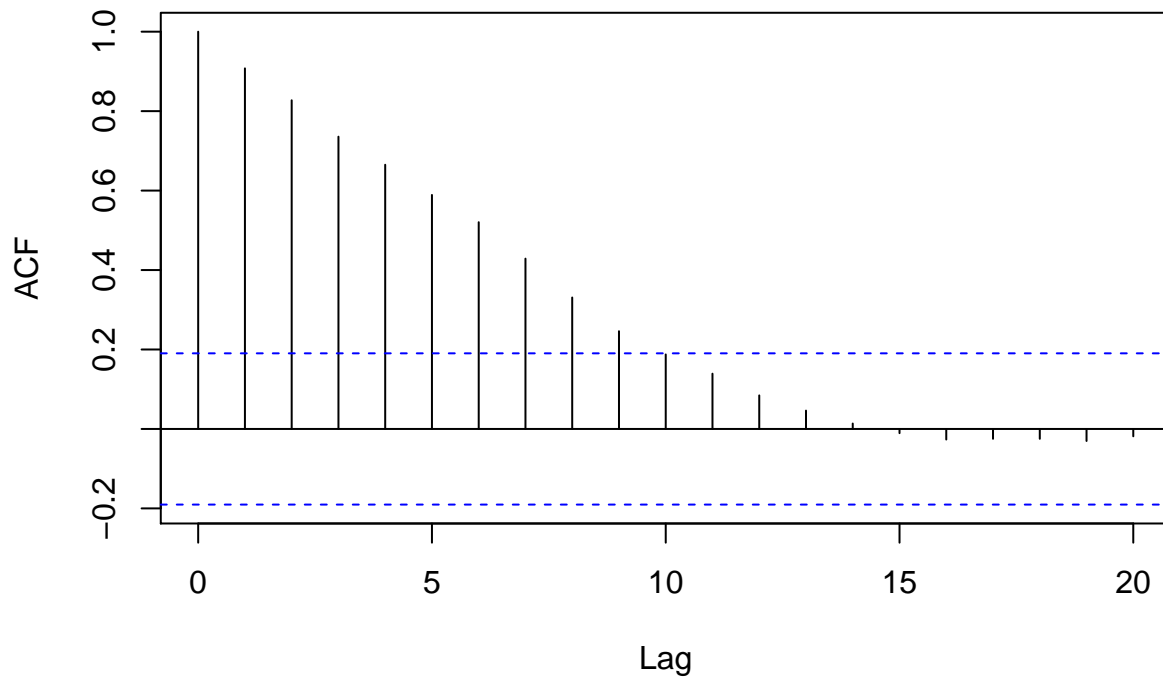
```
# ACF analysis for sd data
acf(aplltd$sd_daily)
```

### Series aplltd\$sd\_daily



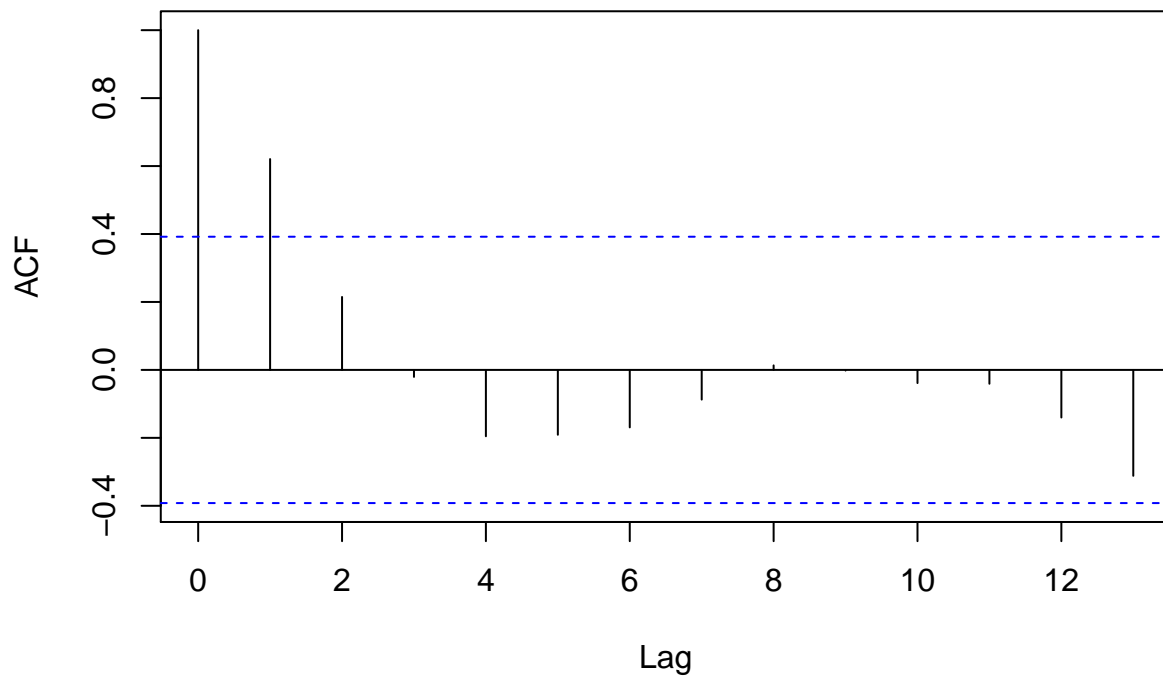
```
acf(aplltd$sd_weekly)
```

### Series aplltd\$sd\_weekly



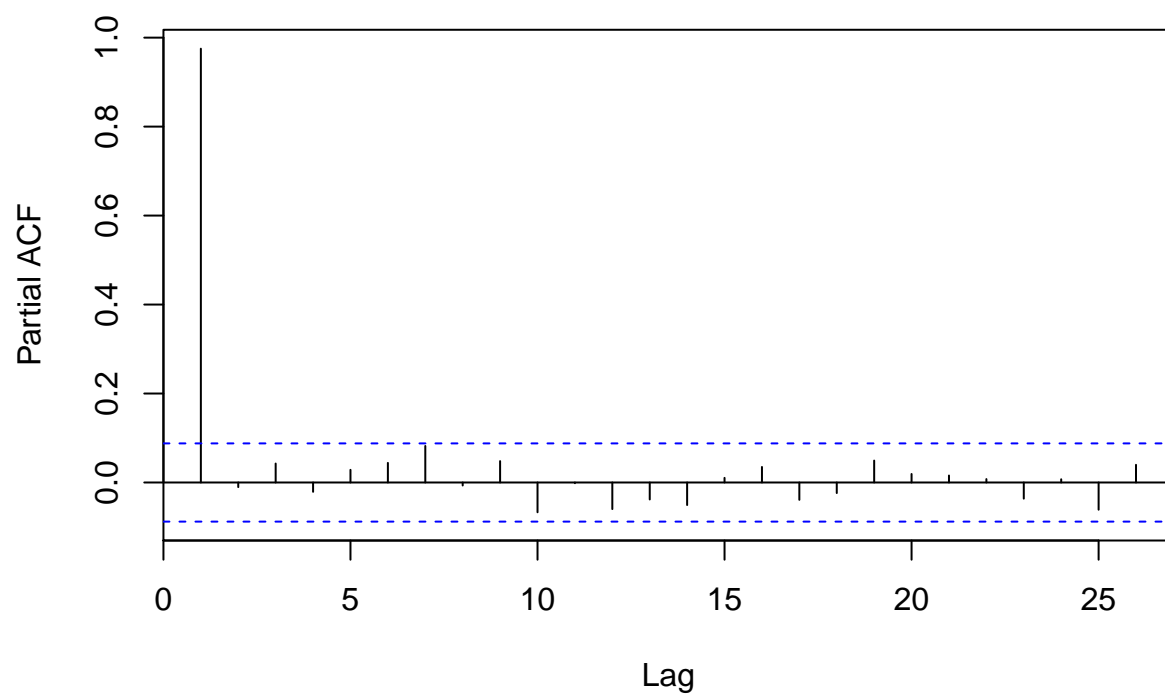
```
acf(aplltd$sd_monthly)
```

### Series aplltd\$sd\_monthly



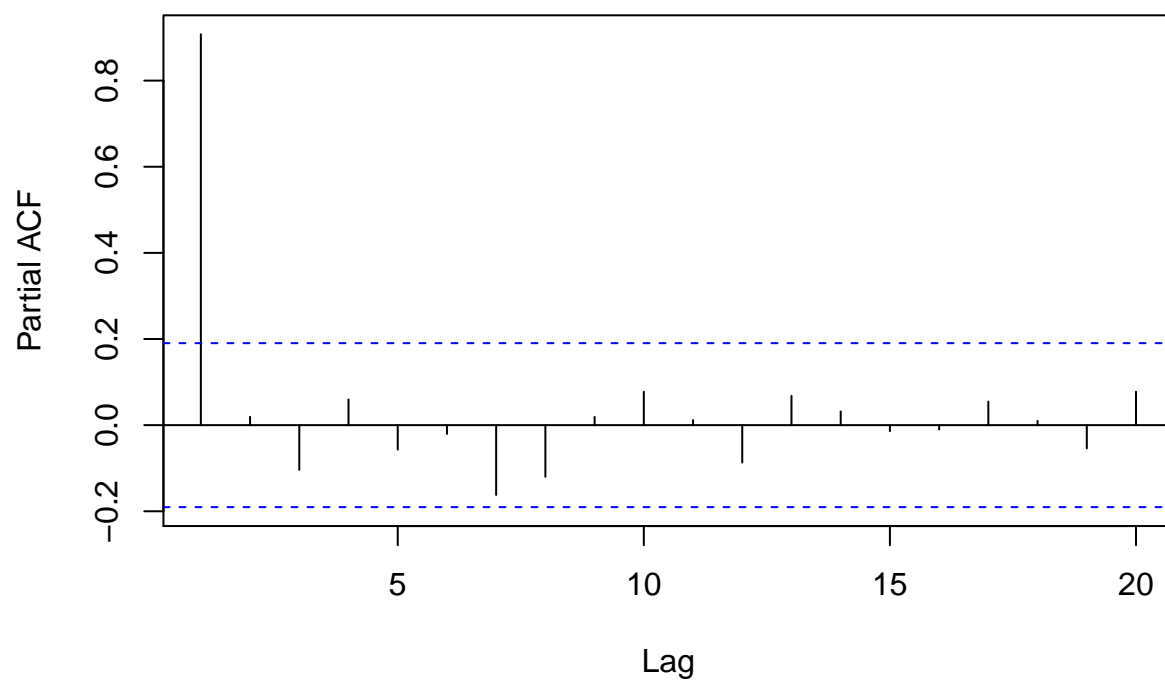
```
# PACF analysis for sd data  
pacf(aplltd$sd_daily)
```

**Series aplltd\$sd\_daily**



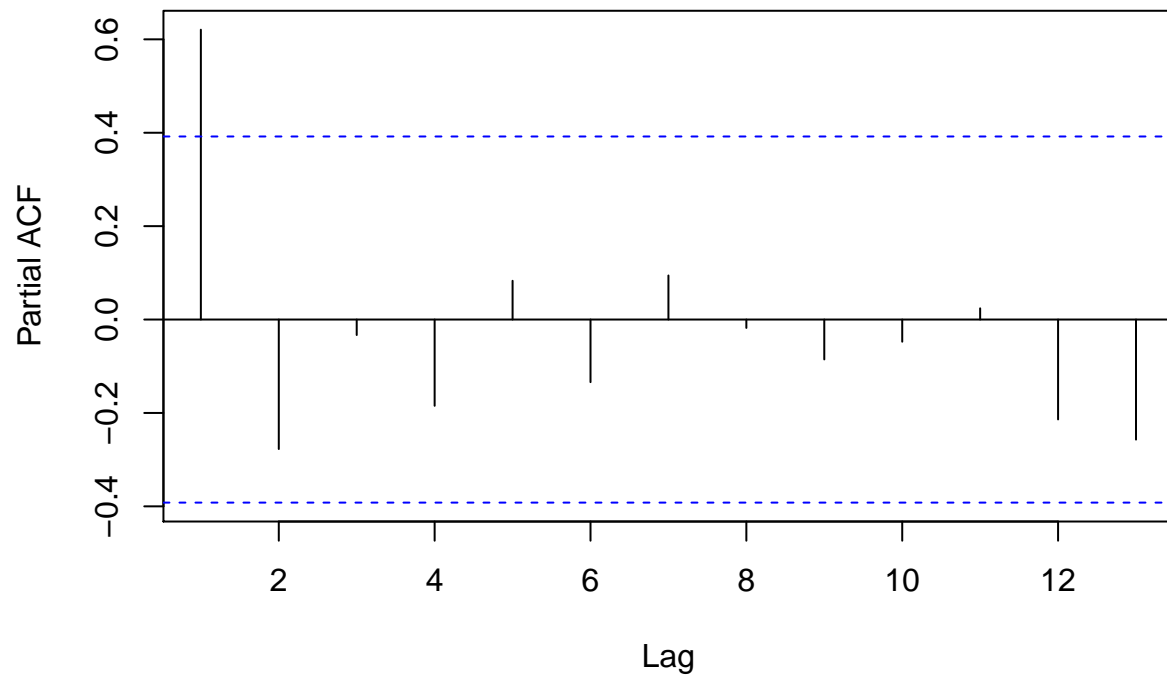
```
pacf(aplltd$sd_weekly)
```

**Series aplltd\$sd\_weekly**



```
pacf(aplltd$sd_monthly)
```

## Series aplltd\$sd\_monthly

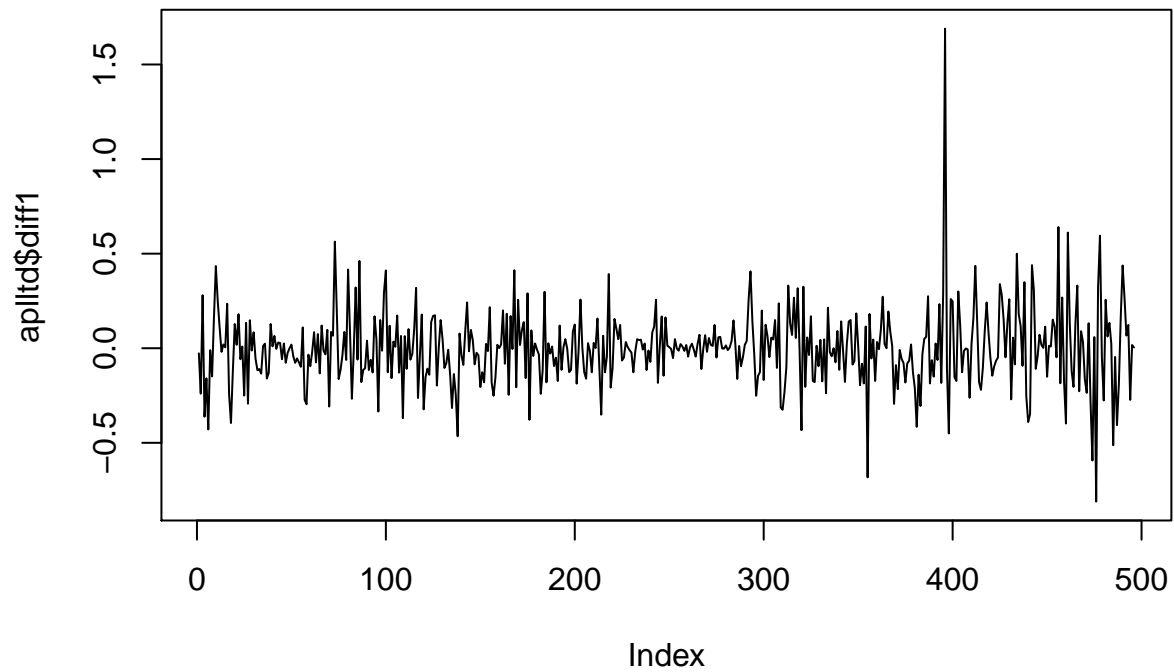


- By analysing acf plot it's clear that daily data has some integrating effect which can be removed by taking first order difference of the signal.
- Weekly Data can be modelled using Moving Average model with lag=9
- Monthly Data can be modelled using MA model with lag = 1

### Daily Series

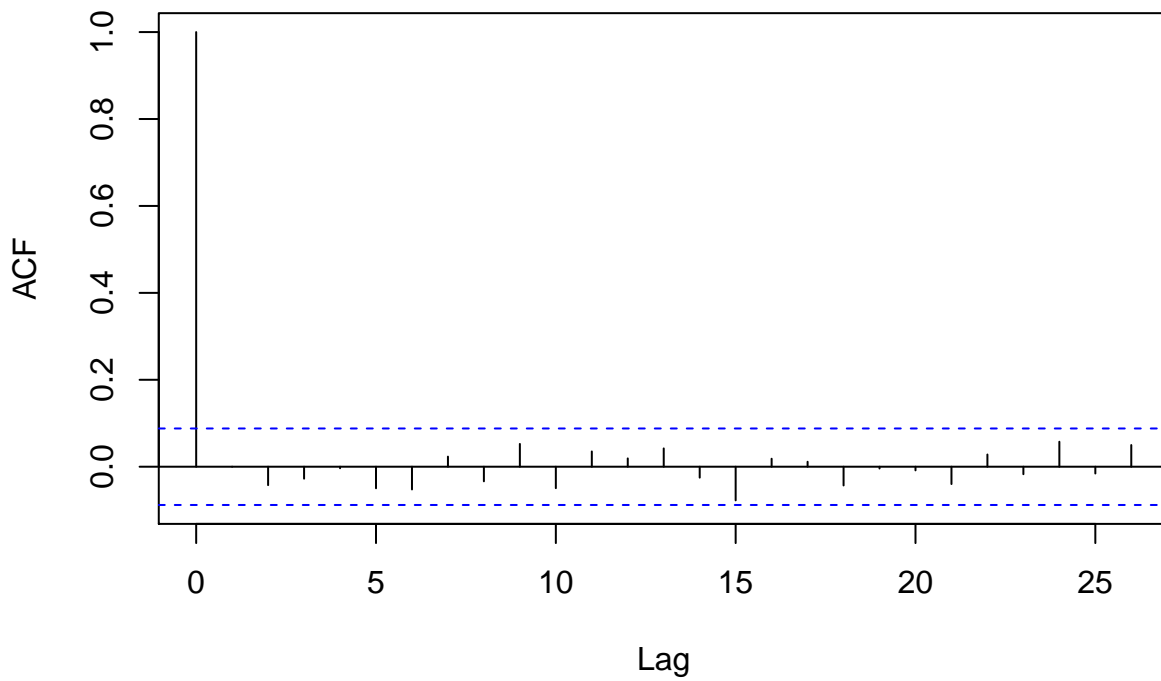
```
aplltd$diff1 = diff(aplltd$sd_daily)
plot(aplltd$diff1, type='l')
```





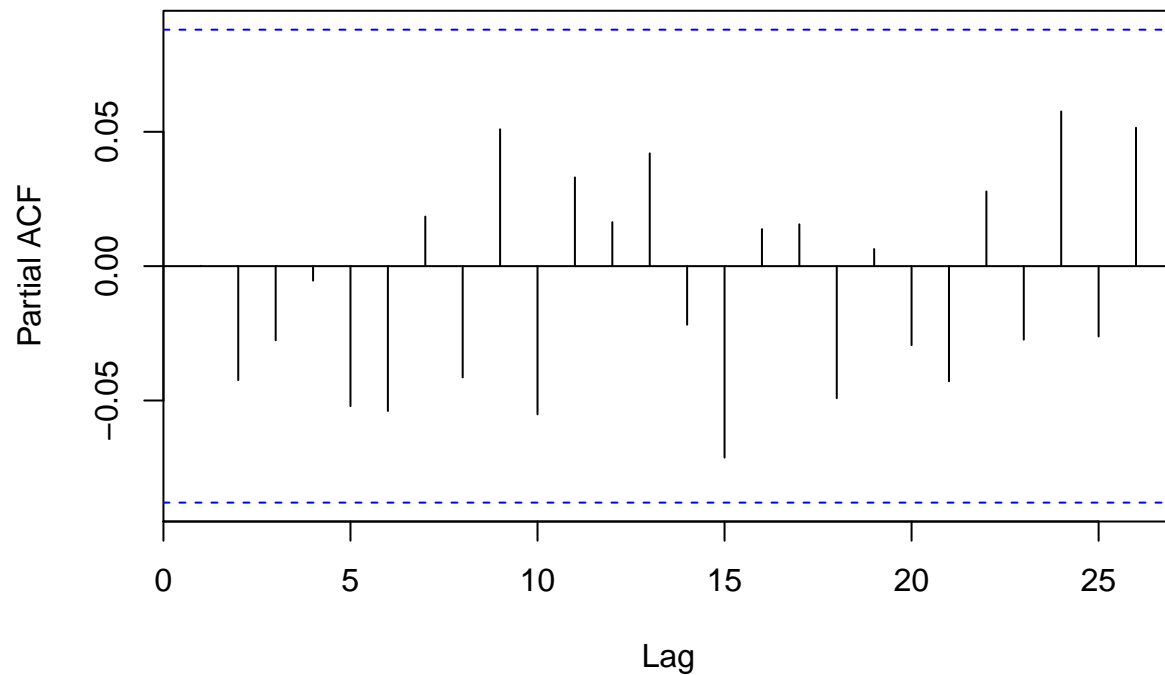
```
# plot visually seems to be random stationary signal which can be  
# therotically proved by plotting acf and pacf of signal  
acf(aplltd$diff1)
```

**Series aplltd\$diff1**



```
pacf(aplltd$diff1)
```

## Series aplltd\$diff1



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

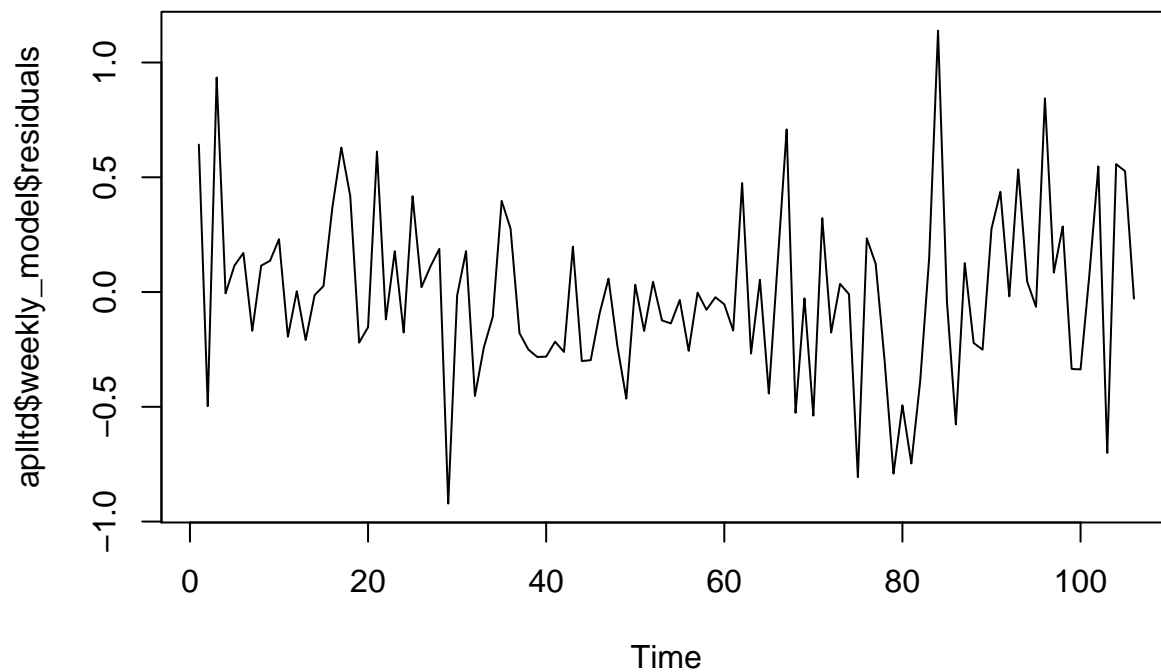
Daily data has no trend to exploit, Signal can be transformed to stationary signal by taking first order difference, which is illustrated in above plots.

## Weekly Series

```
aplltd$weekly_model = arima (aplltd$sd_weekly, order = c(0,0,9), include.mean = T)
print(summary(aplltd$weekly_model))
```

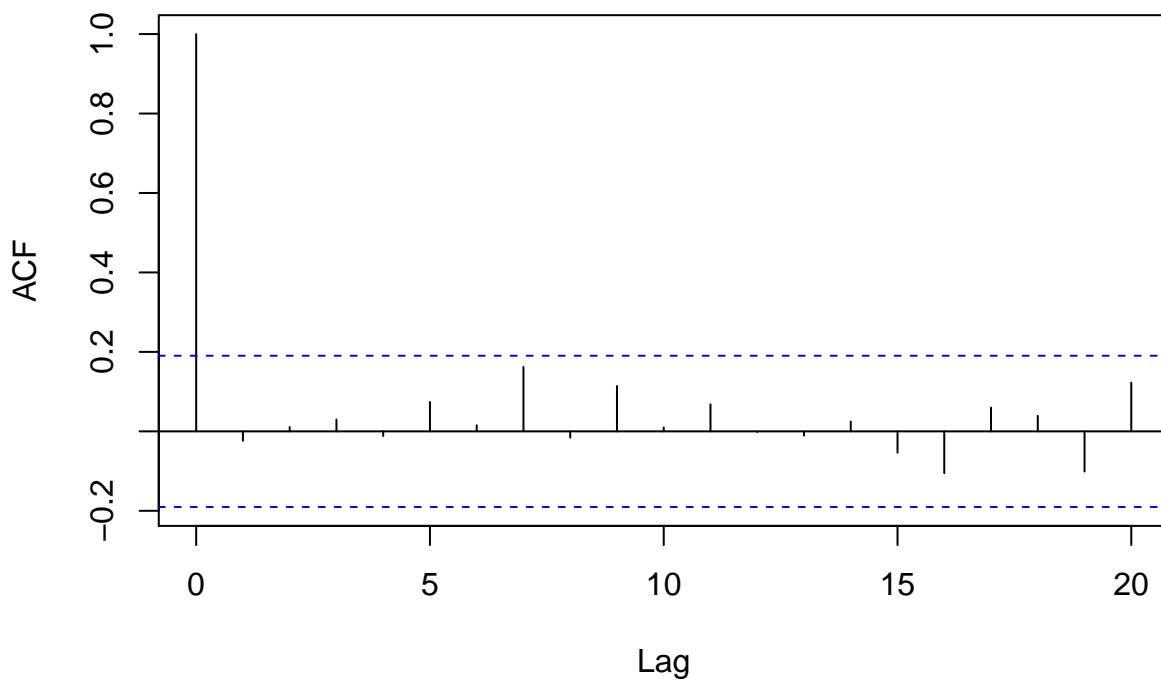
```
##          Length Class  Mode
## coef         10  -none- numeric
## sigma2         1  -none- numeric
## var.coef      100  -none- numeric
## mask          10  -none- logical
## loglik         1  -none- numeric
## aic            1  -none- numeric
## arma           7  -none- numeric
## residuals    106   ts      numeric
## call          4  -none- call
## series        1  -none- character
## code          1  -none- numeric
## n.cond        1  -none- numeric
## nob           1  -none- numeric
## model         10  -none- list
```

```
# residual analysis
plot(aplltd$weekly_model$residuals)
```



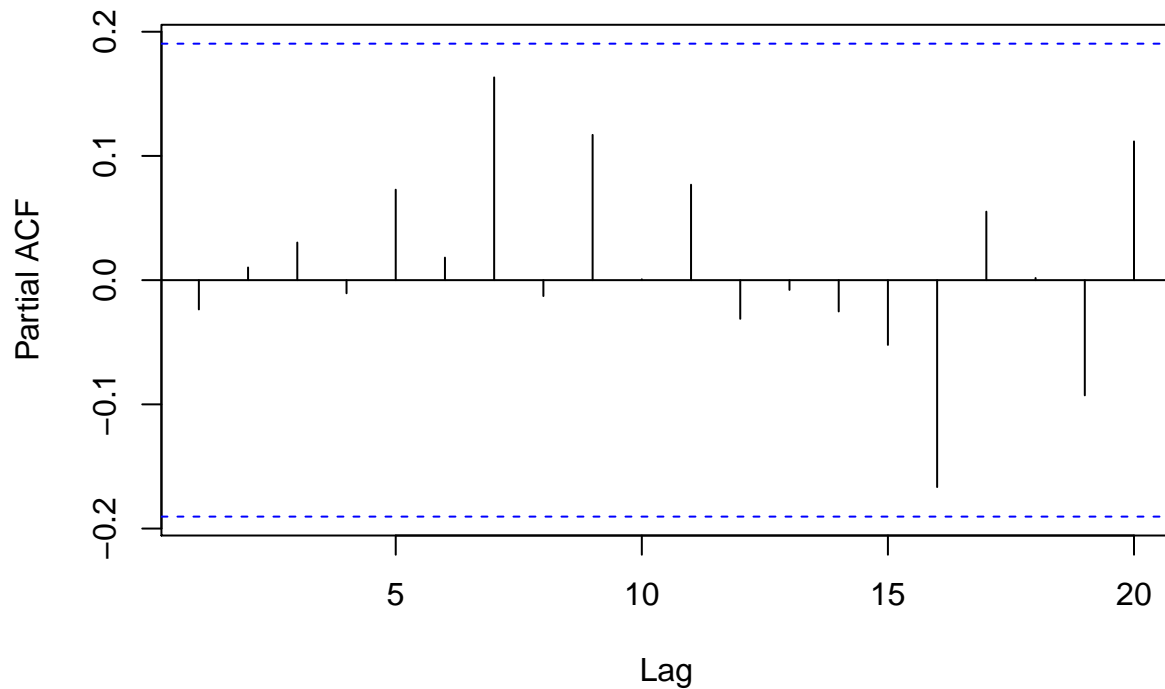
```
# plot visually seems to be random stationary signal which can be  
# therotically proved by plotting acf and pacf of signal  
acf(apl1td$weekly_model$residuals)
```

### Series apl1td\$weekly\_model\$residuals



```
pacf(apl1td$weekly_model$residuals)
```

## Series aplltd\$weekly\_model\$residuals



*# As ACF and PACF are inbetween significant bands shows that residual signal stationary*

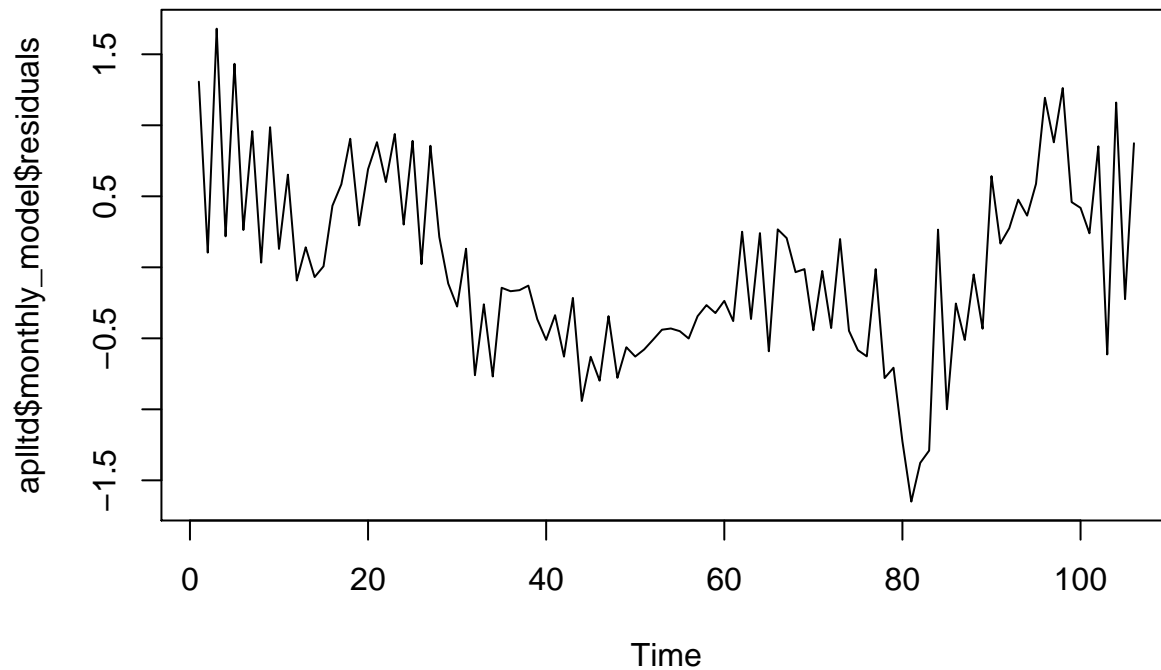
Weekly data has moving average (lag=9) trend which can be exploited, MA residuals form a stationary signal

## Monthly Series

```
aplltd$monthly_model = arima (aplltd$sd_weekly, order = c(0,0,1), include.mean = T)
print(summary(aplltd$monthly_model))
```

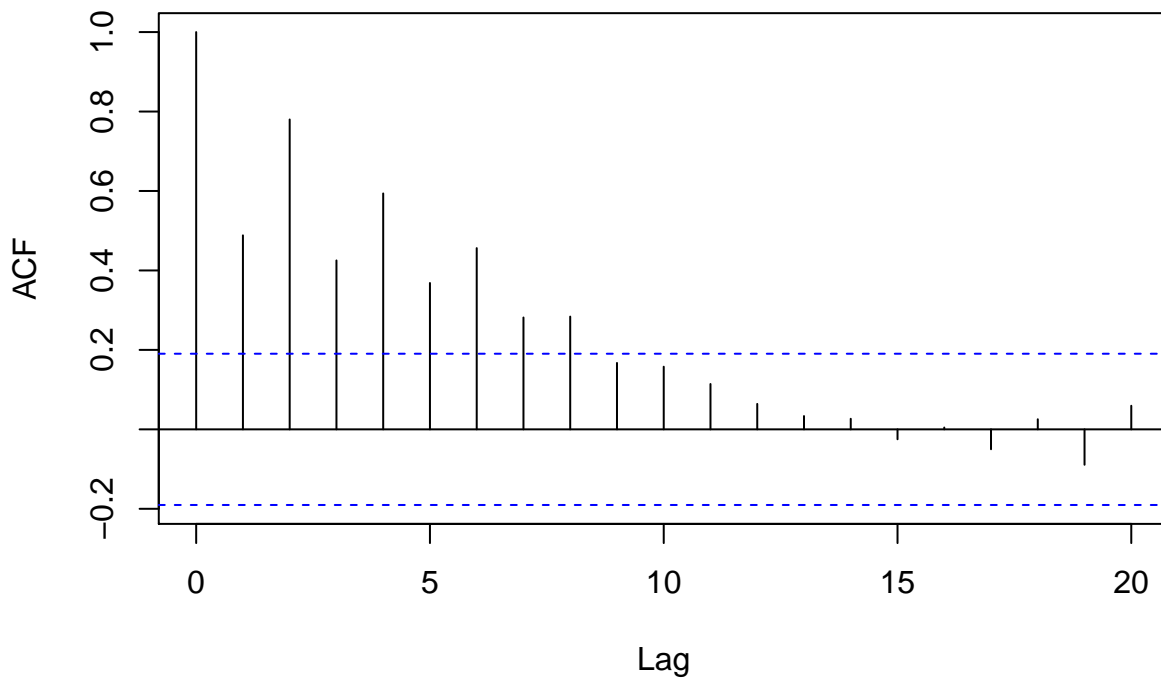
```
##          Length Class  Mode
## coef          2  -none- numeric
## sigma2        1  -none- numeric
## var.coef      4  -none- numeric
## mask          2  -none- logical
## loglik        1  -none- numeric
## aic           1  -none- numeric
## arma          7  -none- numeric
## residuals 106   ts      numeric
## call          4  -none- call
## series        1  -none- character
## code          1  -none- numeric
## n.cond        1  -none- numeric
## nob           1  -none- numeric
## model         10  -none- list
```

```
# residual analysis
plot(aplltd$monthly_model$residuals)
```



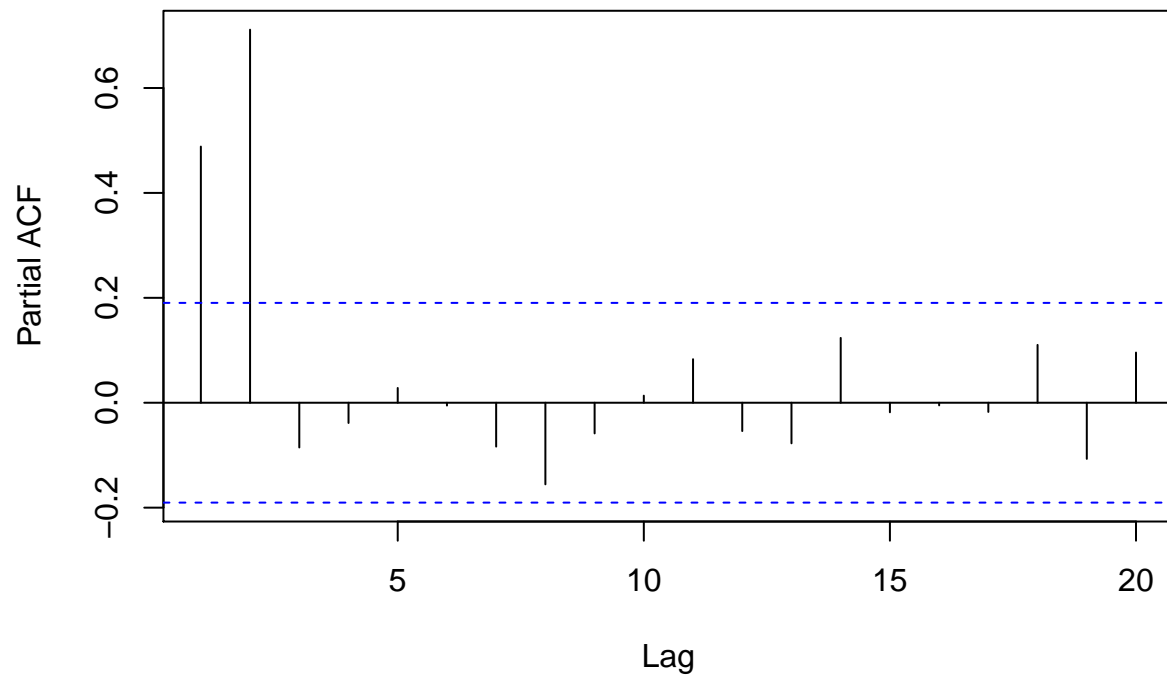
```
# plot visually seems to be random stationary signal which can be  
# therotically proved by plotting acf and pacf of signal  
acf(apl1td$monthly_model$residuals)
```

### Series apl1td\$monthly\_model\$residuals



```
pacf(apl1td$monthly_model$residuals)
```

### Series aplltd\$monthly\_model\$residuals



*# As ACF and PACF are inbetween significant bands shows that residual signal stationary*

Monthly data has moving average (lag=1) trend which can be exploited, MA residuals form a stationary signal