Stat 153 Midterm 2

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Report

Appendix: Code

Establishing working directory:

```
setwd("/Users/sambamamba/Documents/Cal Spring 2017/STAT_153/MT_2/GoogleTimeSeries")
wd <- getwd(); items <- dir()

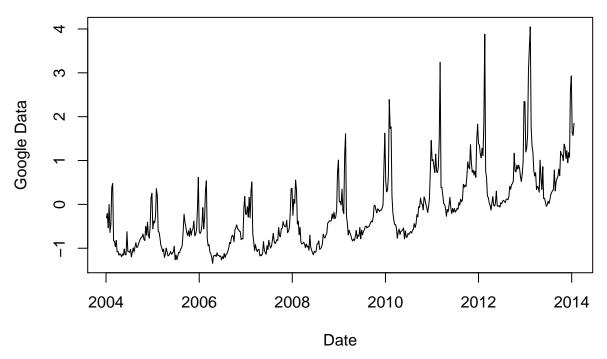
Read in data sets:
readData <- function() { # creates a list of the 5 Google data sets
    dtasets <- items[grep1(".csv", items) == TRUE]
    dataList <- lapply(dtasets, function(dta) read_csv(file.path(wd, dta)))
    names(dataList) <-lapply(1:5, function(x) as.vector(paste0("Q",x,"Train")))
    return(dataList)
}
data <- readData() # where question i can be found by data[[i]] or data$QiTrain</pre>
```

Question 1

Exploratory Data Analysis

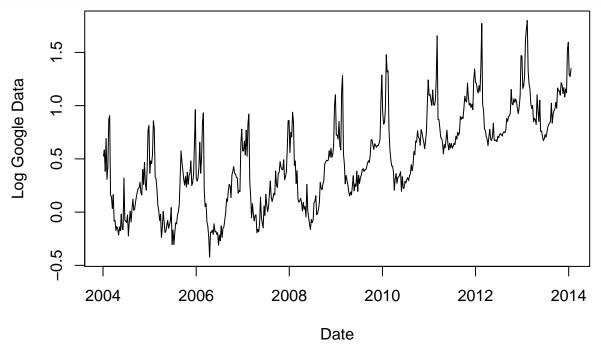
```
Q1Train <- data$Q1Train

plot(Q1Train, type = 'l', xlab = "Date", ylab = "Google Data")
```



There seems to be an increasing linear trend and a clear seasonality in the data set, with a period of around a year. Homoscedasticity in the data set exists. Meaning, as time increases, there seems to be increasing variance in every period. For more convenient analysis and making variance more consistent, we will implement a log transformation of the data. However while log transformation reduces homoskedasticity, logarithms return NaN values with negative data. since the minimum data point in this question is -1.3435, we will shift the data by 2, then perform a log transform, as can be seen in the plot:

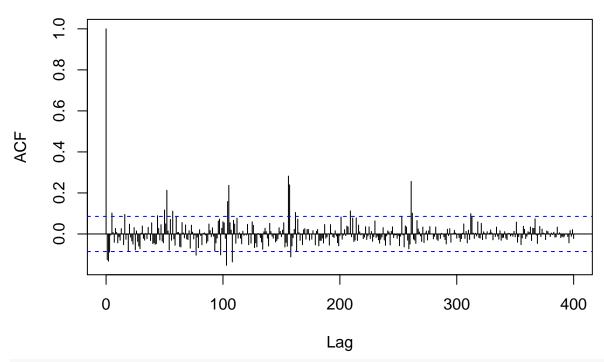
```
Q1Train.Log <- data.frame(Date = Q1Train$Date, Activity = log(Q1Train$activity + 2))
plot(Q1Train.Log, type = 'l', xlab = "Date", ylab = "Log Google Data")
```



With the shifted log data at hand, we have reduced homoskedasticity extensively. Now, we must remove the trend by using differencing, aspiring to achieve a stationary data set.

```
q1train.log <- Q1Train.Log$Activity</pre>
#difference <- function(dta, lag.input = 1, order = 1) {
  # Performs differencing for any degree of regular differencing
  #time <- dta[,1]; ts <- dta[,2];
  #ts.out <- diff(ts, lag = lag.input, differences = order)</pre>
  #return(data.frame(Date = time[(order + 1):length(time)], Activity = ts.out))
#}
acfIndex <- function(vec, n.max = 1, mod = NA) {</pre>
  # input : vector of acf values; output : data frame of the top n.max values and their indices
  stopifnot(n.max <= length(vec));</pre>
  val <- rep(NA, n.max); idx <- rep(NA, n.max)</pre>
  for (i in 1:n.max) {
    val[i] <- max(vec); idx[i] <- which.max(vec)</pre>
    vec <- vec[-idx[i]]</pre>
  if (is.na(mod) == FALSE) {
    mod.vec <- idx %% mod</pre>
    return(data.frame(index = idx, value = val, remainder = mod.vec))
  }
  return(data.frame(index = idx, value = val))
# Observe first and second differenced log data
firstdiff <- diff(q1train.log)</pre>
seconddiff <- diff(q1train.log, differences = 2)</pre>
thirddiff <- diff(q1train.log, differences = 3)</pre>
checkSeas <- acfIndex(acf(firstdiff, lag.max = 400)$acf, n.max = 20, mod = 52)</pre>
```

Series firstdiff

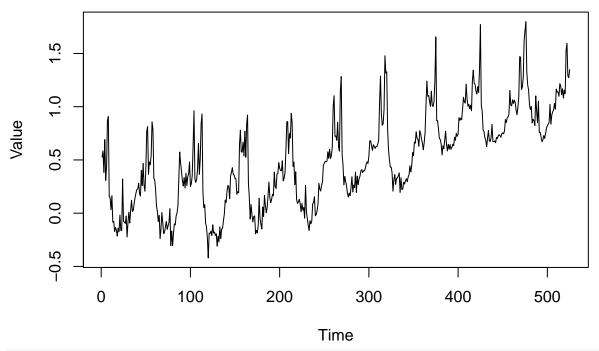


```
# check if yearly
# the acfIndex indicates indices and values of the n highest acf values, and found a lot of them are ye
# seasonal data differencing
print(checkSeas)
```

```
##
                 value remainder
      index
## 1
        1 1.00000000
## 2
        156 0.28215879
                                0
        260 0.25600402
        156 0.23953679
## 4
## 5
        105 0.23686474
## 6
        52 0.21301361
                                0
## 7
        103 0.15798856
                               51
## 8
        50 0.11698184
                               50
        203 0.11235940
## 9
                               47
## 10
        55 0.11112628
                                3
        155 0.10472789
## 11
                               51
## 12
          5 0.10215912
                                5
        251 0.10111736
## 13
                               43
        300 0.09900733
## 14
                               40
## 15
         15 0.09504322
                               15
## 16
         42 0.08916602
                               42
        241 0.08642917
                               33
## 17
## 18
        297 0.08526497
                               37
## 19
        190 0.08322715
                               34
         54 0.08272026
firstdiff.52 <- diff(firstdiff, lag = 52)</pre>
```

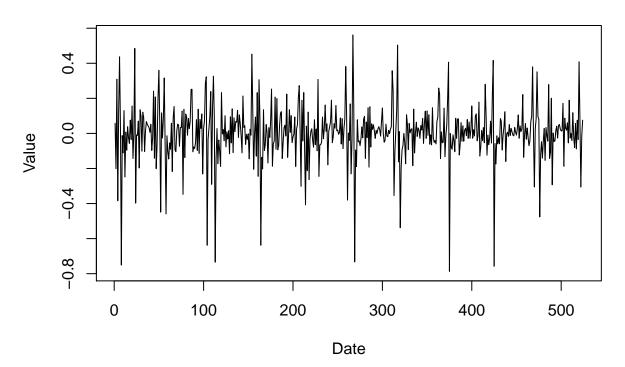
```
# Observe differenced data of orders 1,2
#par(mfrow = c(2,1))
plot(q1train.log, type = 'l', xlab = "Time", ylab = "Value", main = "Undifferenced Google Data")
```

Undifferenced Google Data

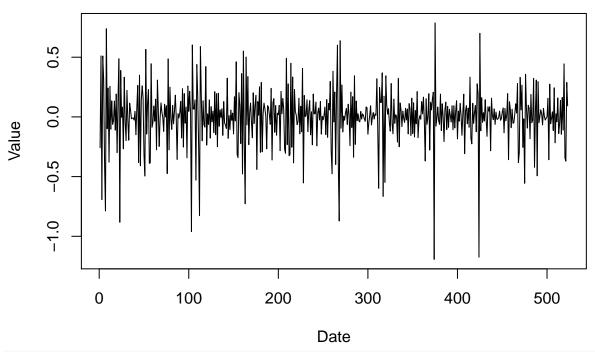


plot(firstdiff, type = 'l', xlab = "Date", ylab = "Value", main = "1st Diff Google Data");

1st Diff Google Data

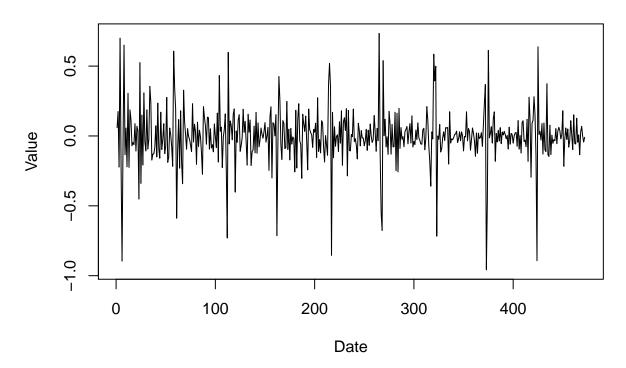


2nd Diff Google Data

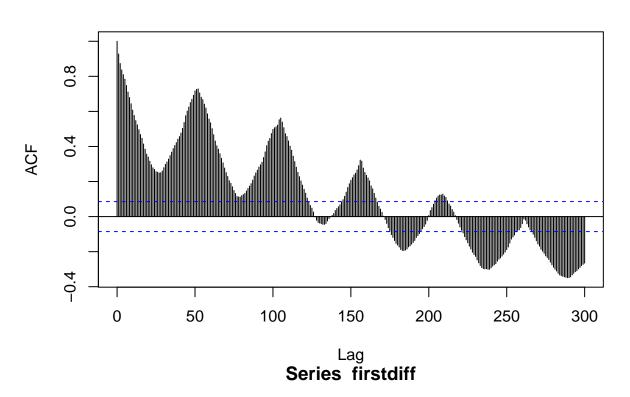


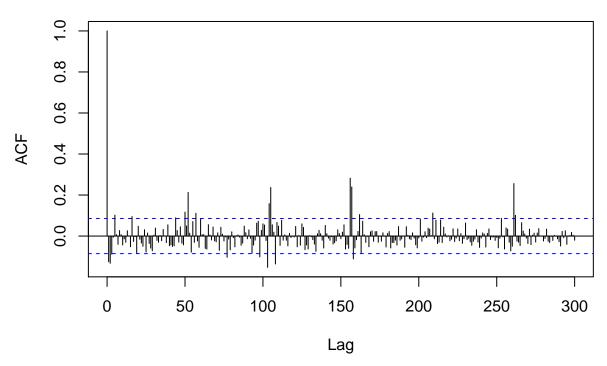
plot(firstdiff.52, type = 'l', xlab = "Date", ylab = "Value", main = "1st Diff and 1st Seasonal Diff

1st Diff and 1st Seasonal Diff Google Data

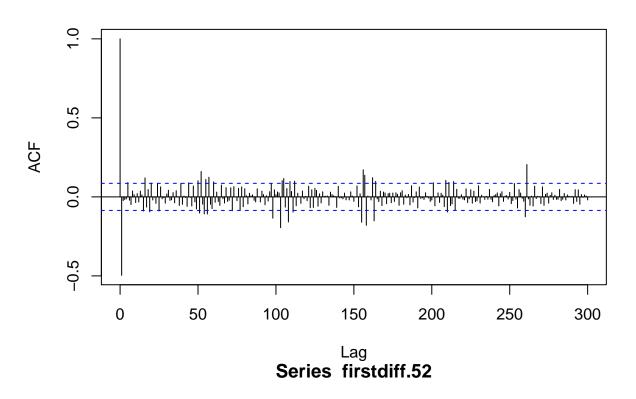


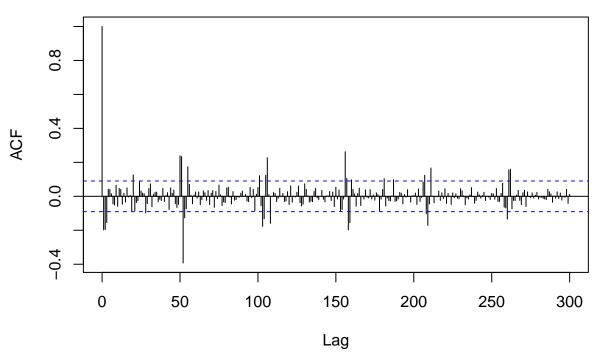
Series q1train.log





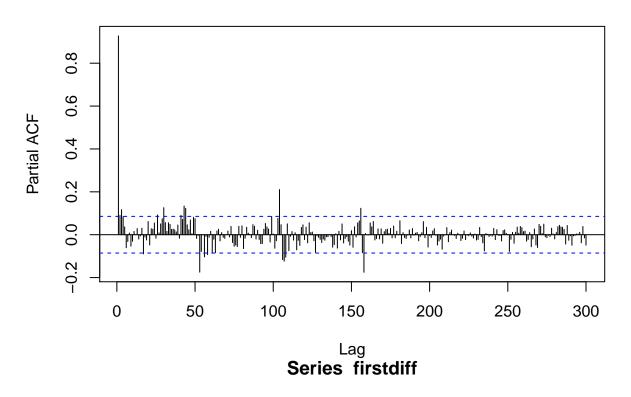
Series seconddiff

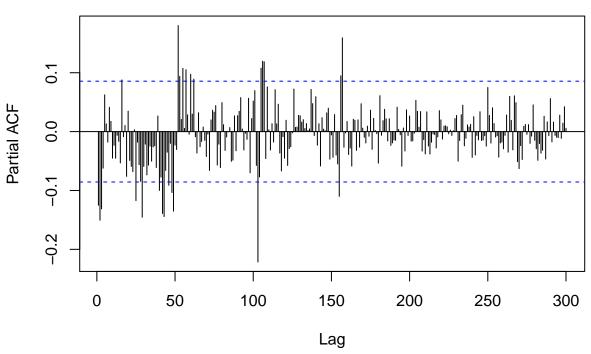




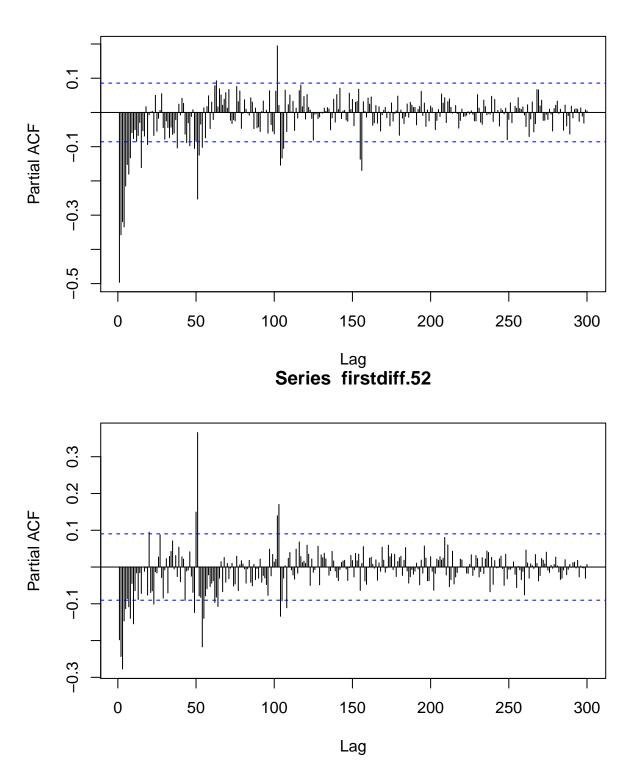
pacf(q1train.log, lag.max = 300); pacf(firstdiff, lag.max = 300); pacf(seconddiff, lag.max = 300); pacf

Series q1train.log





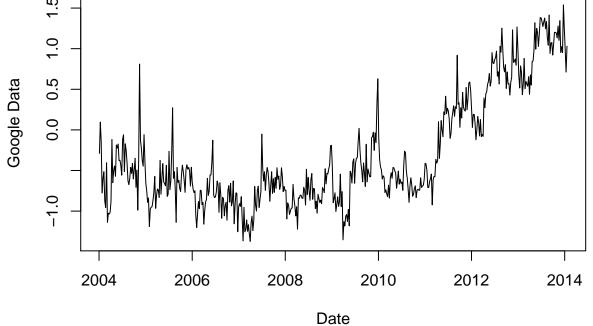
Series seconddiff



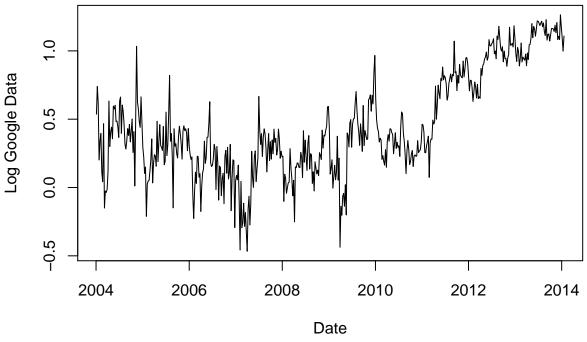
From the plots above, observe that with the second-order differenced data, there is significantly more higher magnitude of lags than the first-order differenced data. As such, we assume that the second-order differencing over-differences the data due to an increase in the breadth of lags with higher magnitudes, and also the existence of lags with higher than -0.5 magnitudes, not seen in the first-order plot. Also, notice that since the lag-1 acf signal is negative (slightly less than -0.5), we have a non-zero degree MA component to our model.

- residuals of plot
- doing adjusted R^2, AIC, BIC, differencing
- polynomial, exponential fit

Question 4



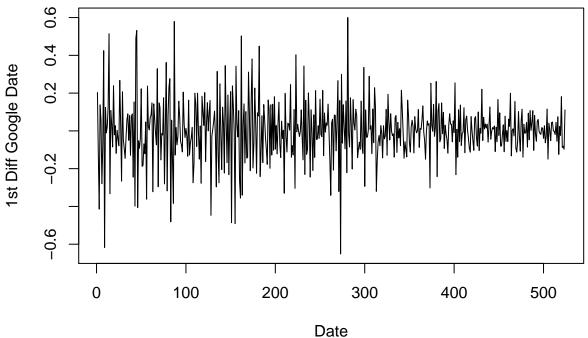
Q4Train.Log <- data.frame(Date = Q4Train\$Date, Activity = log(Q4Train\$activity + 2))
plot(Q4Train.Log, type = 'l', xlab = "Date", ylab = "Log Google Data")



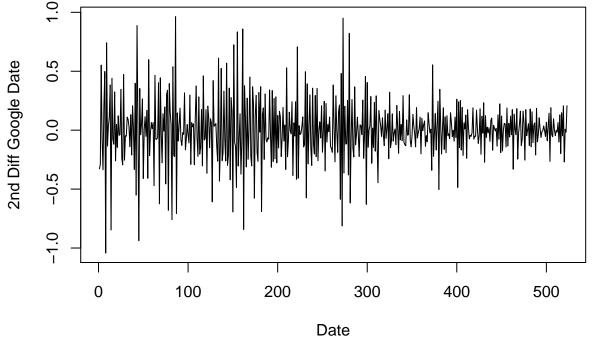
```
q4train.log <- Q4Train.Log$Activity

# Observe first and second differenced log data
q4firstdiff <- diff(q4train.log)
q4seconddiff <- diff(diff(q4train.log))

# Observe differenced data of orders 1,2
plot(q4firstdiff, type = 'l', xlab = "Date", ylab = "1st Diff Google Date");</pre>
```

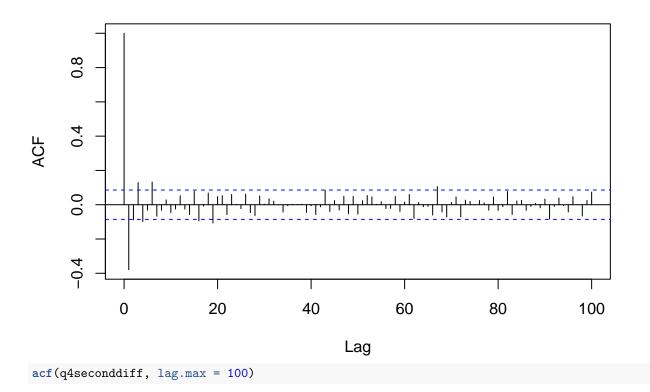




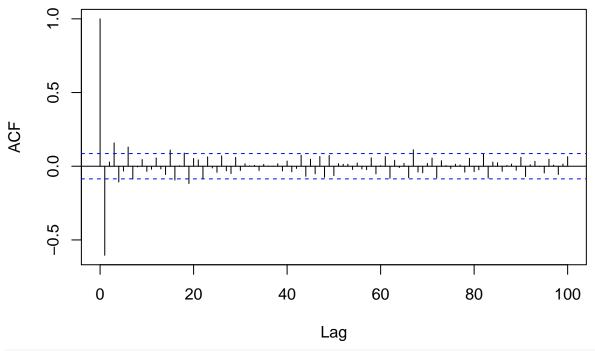


```
# Observe acf of data of orders 1, 2
#par(mfrow = c(2,1))
acf(q4firstdiff, lag.max = 100)
```

Series q4firstdiff

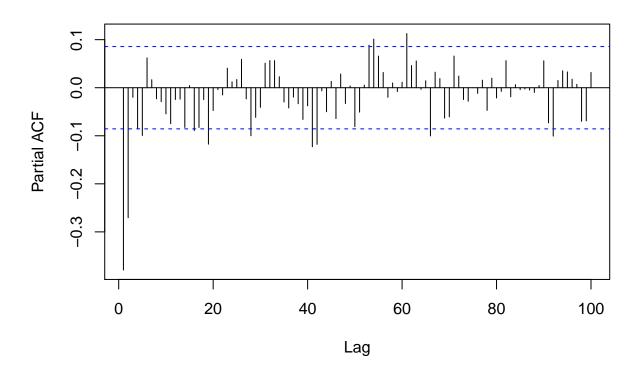


Series q4seconddiff



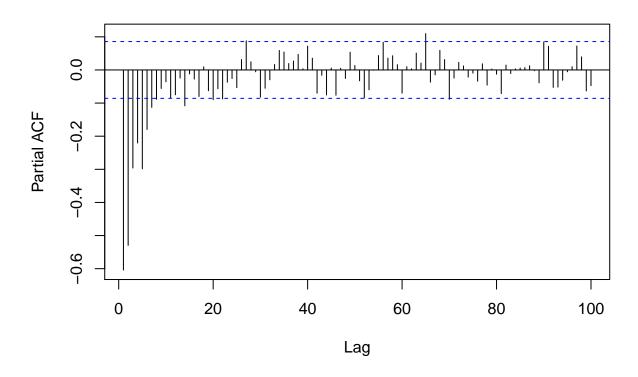
#par(mfrow = c(2,1))
pacf(q4firstdiff, lag.max = 100)

Series q4firstdiff



```
pacf(q4seconddiff, lag.max = 100)
```

Series q4seconddiff



Creating the Submission File