DaiglePredictionofSocialSecurity.R

daiglechris

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Chris Daigle Prediction of Social Security Awards

```
# Prepare workspace ####
rm(list = ls())
library(tseries)
library(quantmod)
```

```
## Loading required package: xts
```

```
## Loading required package: zoo
```

```
##
## Attaching package: 'zoo'
```

```
## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric
```

```
## Loading required package: TTR
```

```
## Version 0.4-0 included new data defaults. See ?getSymbols.
```

```
library(data.table)
```

```
##
## Attaching package: 'data.table'
```

```
## The following objects are masked from 'package:xts':
##
##     first, last
```

```
library(leaps)
library(plm)
```

```
## Loading required package: Formula
```

```
##
## Attaching package: 'plm'
```

```
## The following object is masked from 'package:data.table':
##
##     between
```

```
library(class)
setwd('~/Git/MachineLearningAndBigDataWithR/Data')
dataName <- 'assembled.csv'
df <- read.csv(dataName, stringsAsFactors = FALSE)
# Summarize and clean data ####
# head(df)
df <- df[-1]
# head(df)
# str(df)
```

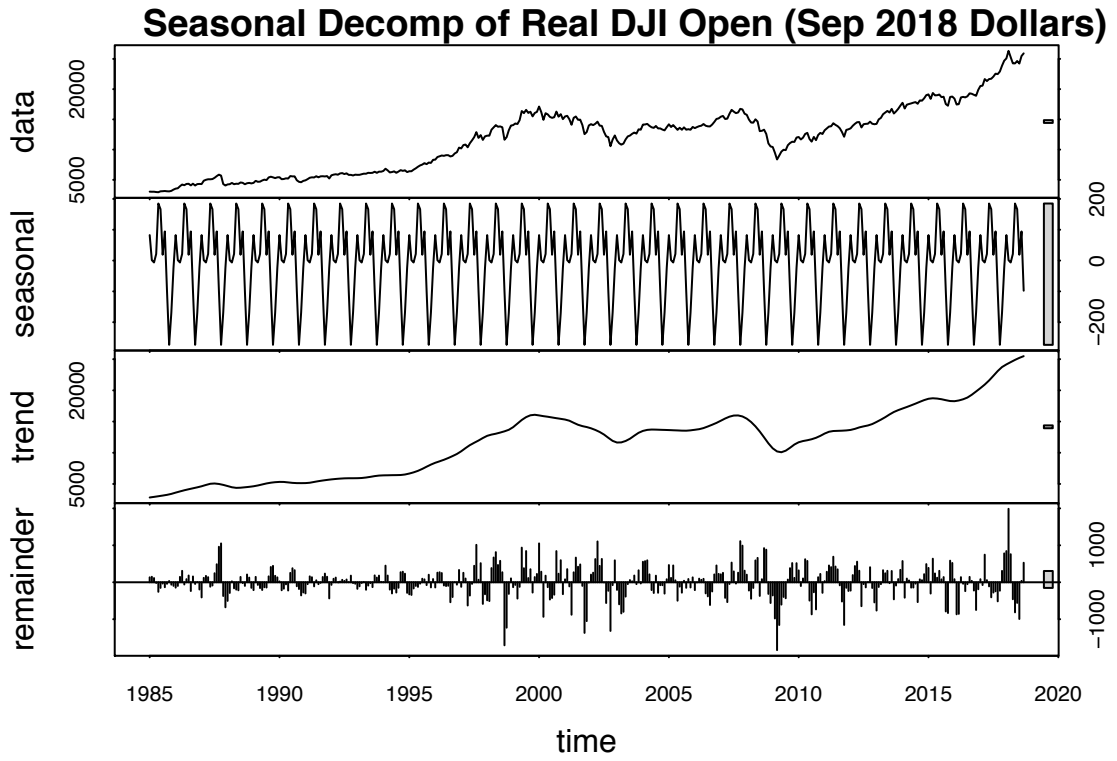
```r
# Variable Manipulation ####
# Set dates
df$date <- as.Date(df$date, "%Y-%m-%d")
# Functions to clean data #
spaceless <- function(x) {
  x <- gsub(" ", ".", x)
  x
}

commaless <- function(x) {
  x <- gsub(",", "", x)
  x
}

dollarless <- function(x) {
  x <- gsub("\\$", "", x)
  x
}

# Loops to apply functions #
for (i in 15:20) {
  df[, i] <- commaless(df[, i])
}
for (i in 15:20) {
  df[, i] <- dollarless(df[, i])
}

# Loop to transform variable types #
for (i in 15:20) {
  df[, i] <- as.numeric(df[, i])
}
# Names with Index ####
# 1 date                      : Date
# 2 DJIopen                   : num
# 3 DJIhigh                   : num
# 4 DJIlow                    : num
# 5 DJIclose                  : num
# 6 DJIadjClose               : num
# 7 DJIvolume                 : num
# 8 SPopen                    : num
# 9 SPhigh                    : num
# 10 SPlow                     : num
# 11 SPclose                   : num
# 12 SPadjClose                : num
# 13 SPvolume                  : num
# 14 fedFundRate               : num
# 15 totalSSRetired            : num
# 16 averageSSRetiredPay       : num
# 17 totalMaleSSRetired        : num
# 18 averageMaleSSRetiredPay   : num
# 19 totalFemaleSSRetired      : num
# 20 averageFemaleSSRetiredPay: num
# 21 cpi                       : num
```

```r
#
# Order Change #
df <- df[, c(1, 15, 17, 19, 21, 14, 7, 13, 2:6, 8:12, 16, 18, 20)]
# 1 date                      : Date
# 2 totalSSRetired            : num
# 3 totalMaleSSRetired        : num
# 4 totalFemaleSSRetired      : num
# 5 cpi                       : num
# 6 fedFundRate               : num
# 7 DJIvolume                 : num
# 8 SPvolume                  : num
# 9 DJIopen                   : num
# 10 DJIhigh                   : num
# 11 DJIlow                    : num
# 12 DJIclose                  : num
# 13 DJIadjClose               : num
# 14 SPopen                    : num
# 15 SPhigh                    : num
# 16 SPlow                     : num
# 17 SPclose                   : num
# 18 SPadjClose                : num
# 19 averageSSRetiredPay       : num
# 20 averageMaleSSRetiredPay   : num
# 21 averageFemaleSSRetiredPay: num
#
# Variable Creation ####
# CPI Inflator
latestDate <- tail(df$date, n = 1)

baseCpi <- df$cpi[df$date == latestDate]
df$inflator <- baseCpi / df$cpi

df <- df[, c(1:6, 22, 7:21)]

realNames <-
  paste('real',
        colnames(df[, 10:22]),
        sep = "")

df[, realNames] <- df$inflator * df[10:22]

# Differences #
diffNames <-
  paste('diff',
        c(colnames(df[10:22]),
          paste('Real',
                colnames(df[10:22]),
                sep = "")),
        sep = "")
df[, diffNames] <- rep(NA, nrow(df))
for (i in 36:61) {
  df[, i][2:nrow(df)] <- diff(df[, i - 26], lag = 1)
}
```

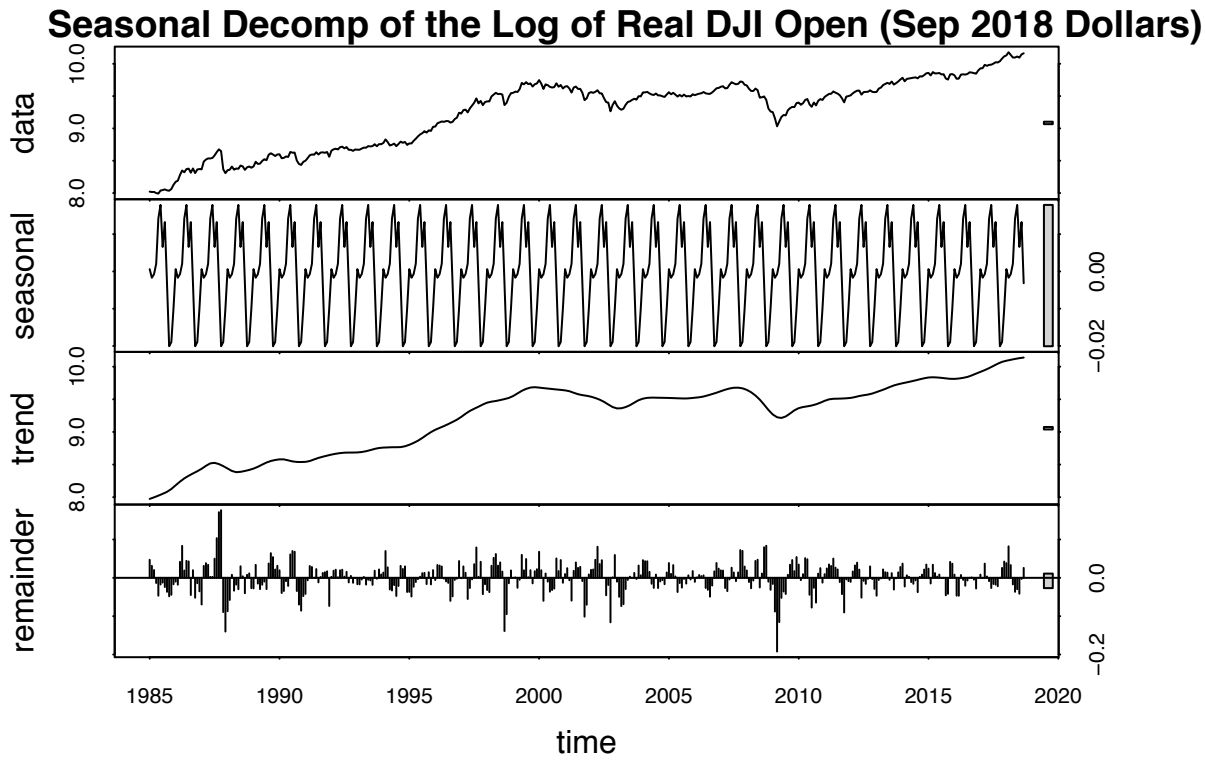
```r
diffTargetNames <-
  paste('diff',
        c(colnames(df[2:4])),
        sep = "")
df[, diffTargetNames] <- rep(NA, nrow(df))
for (i in 62:64) {
  df[, i][2:nrow(df)] <- diff(df[, i - 60], lag = 1)
}

# Positive Indicator #
posNames <-
  paste('pos',
        c(colnames(df[10:22]),
          paste('Real',
                colnames(df[10:22]),
                sep = "")),
        sep = "")
df[, posNames] <- rep(0, nrow(df))
for (i in 65:90) {
  df[, i][df[, i - 20] > 0] <- 1
}

posTargetNames <-
  paste('pos',
        c(colnames(df[2:4])),
        sep = "")
df[, posTargetNames] <- rep(0, nrow(df))
for (i in 91:93) {
  df[, i][df[, i - 29] > 0] <- 1
}

# Percent Changes #
percChangeNames <-
  paste('percChange',
        c(colnames(df[10:22]),
          paste('Real', colnames(df[10:22]), sep = "")),
        sep = "")
df[, percChangeNames] <- rep(NA, nrow(df))

for (i in 94:119) {
  df[, i] <- Delt(df[, i - 84])
}
for (i in 94:119) {
  df[, i] <- as.numeric(df[, i])
}
percChangeTargetNames <-
  paste('percChange',
        c(colnames(df[2:4])),
        sep = "")
df[, percChangeTargetNames] <- rep(NA, nrow(df))
for (i in 120:122) {
  df[, i] <- Delt(df[, i - 118])
}
```

```r
for (i in 120:122) {
  df[, i] <- as.numeric(df[, i])
}

# Place all target variables - totalRetired* - together
df <- df[, c(1:4, 62:64, 91:93, 120:122, 5:61, 65:90, 94:119)]
df1 <- df[complete.cases(df), ]

# Timeseries Evaluation ####
realDJIOpen <-
  ts(
    df$realDJIopen,
    start = c(1985, 1),
    end = c(2018, 9),
    frequency = 12
  )
percRealDJIOpen <-
  ts(
    df1$percChangeRealDJIopen,
    start = c(1985, 2),
    end = c(2018, 9),
    frequency = 12
  )
realSPOpen <-
  ts(
    df$realSPopen,
    start = c(1985, 1),
    end = c(2018, 9),
    frequency = 12
  )
percRealSPOpen <-
  ts(
    df1$percChangeRealSPopen,
    start = c(1985, 2),
    end = c(2018, 9),
    frequency = 12
  )
fedFund <-
  ts(
    df$fedFundRate,
    start = c(1985, 1),
    end = c(2018, 9),
    frequency = 12
  )

totalRetired <-
  ts(
    df$totalSSRetired,
    start = c(1985, 1),
    end = c(2018, 9),
    frequency = 12
  )
```

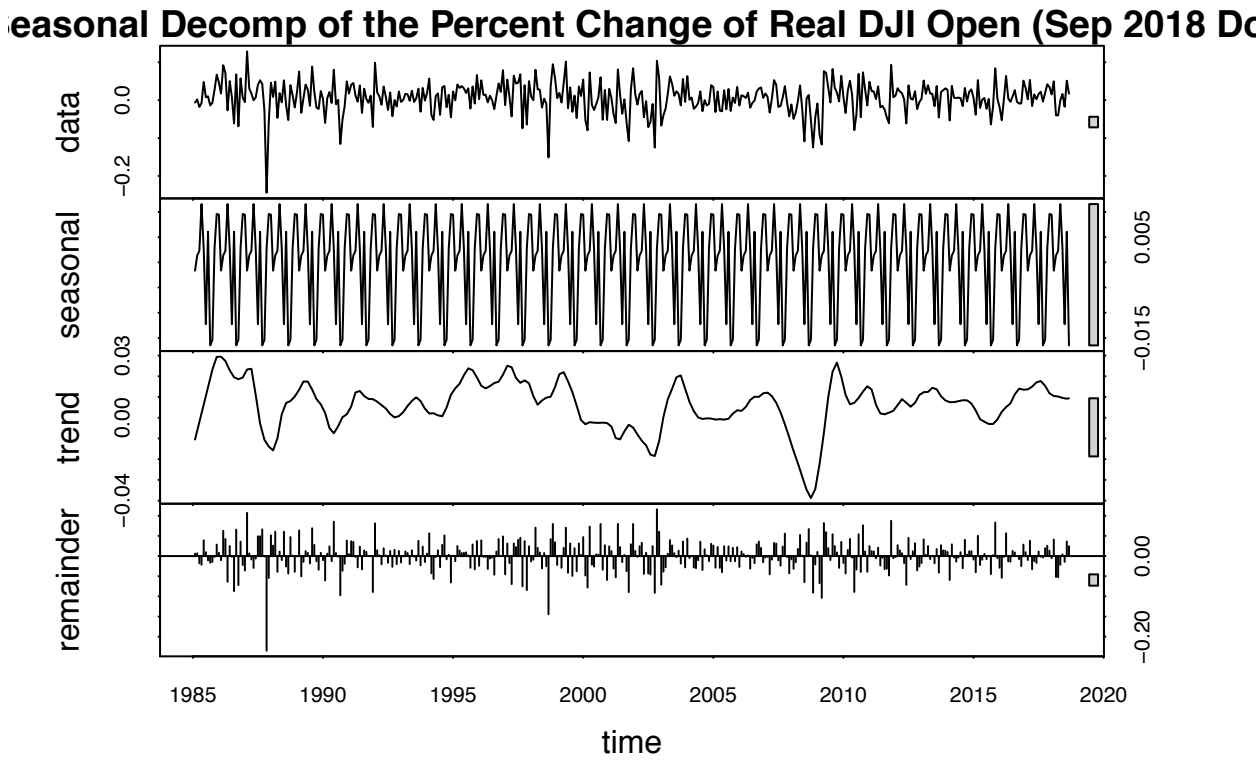
```
plot(stl(realDJIOpen, s.window = "period"), lwd = 1)
title(main = 'Seasonal Decomp of Real DJI Open (Sep 2018 Dollars)')
```



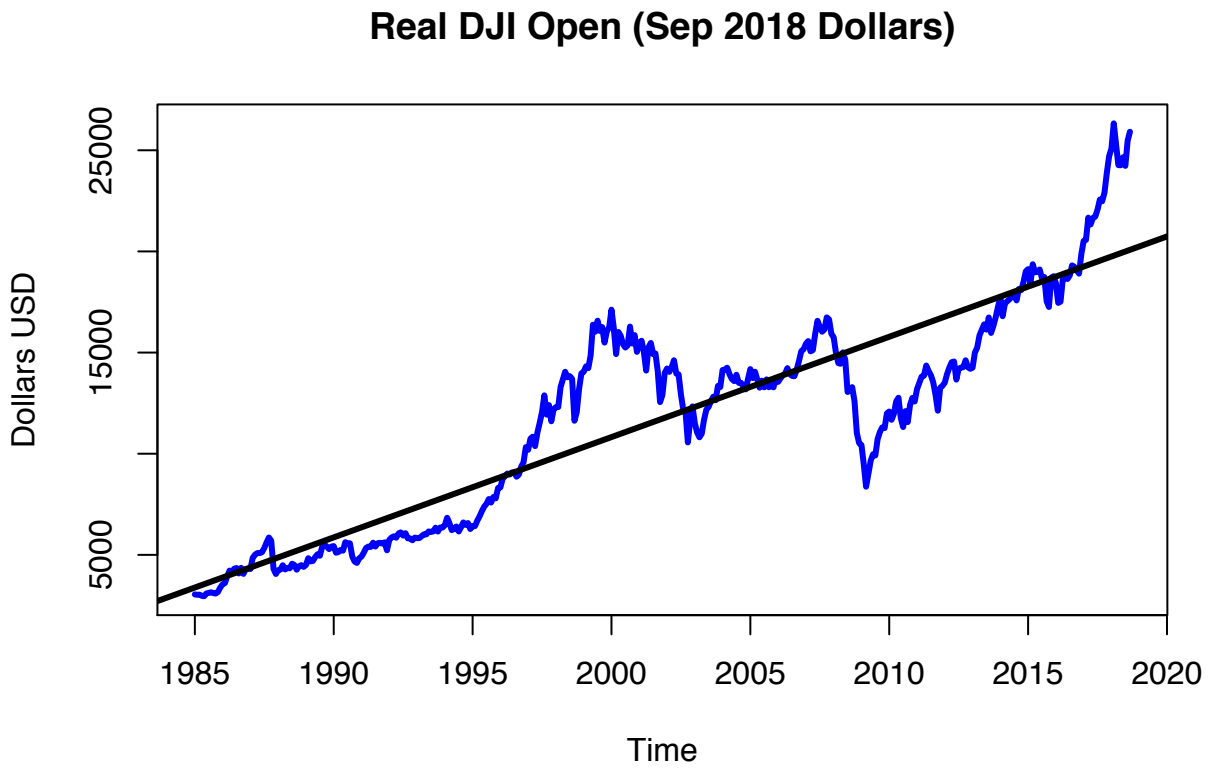

```
plot(stl(log(realDJIOpen), s.window = "period"), lwd = 1)
title(main = 'Seasonal Decomp of the Log of Real DJI Open (Sep 2018 Dollars)')
```



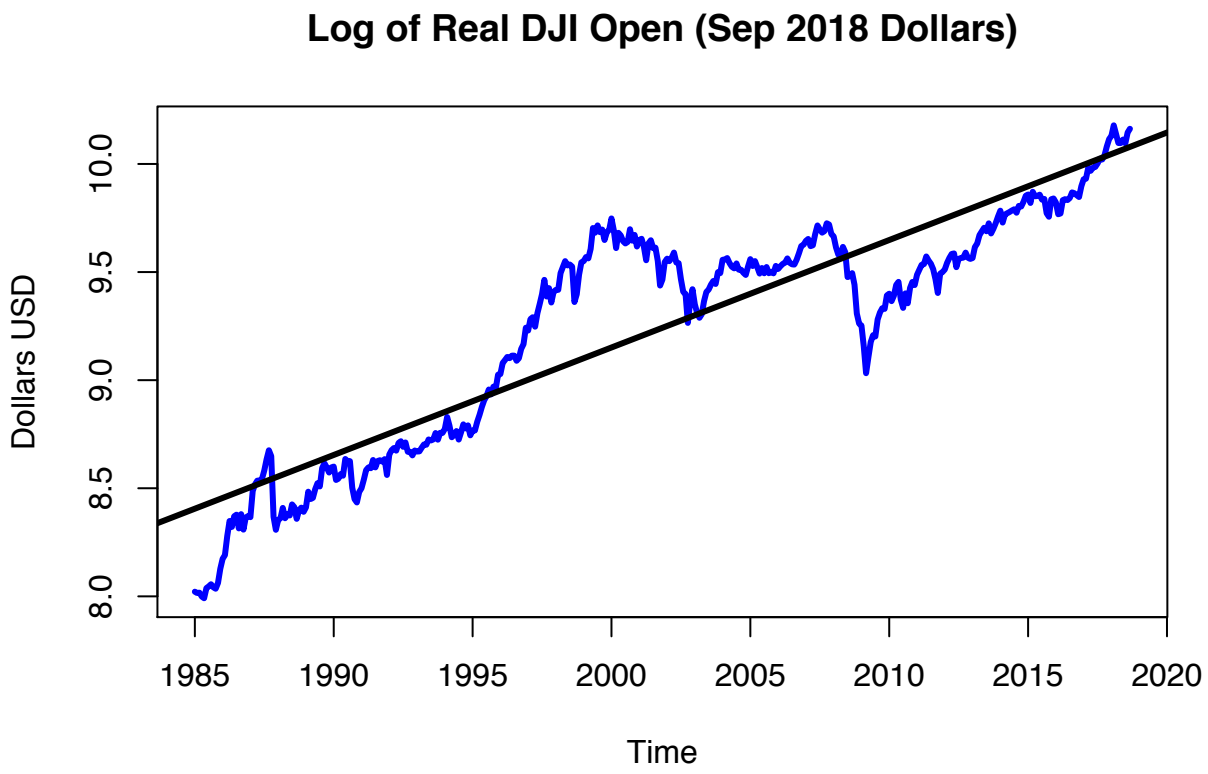
```r
plot(stl(percRealDJIOpen, s.window = "period"), lwd = 1)
title(main = 'Seasonal Decomp of the Percent Change of Real DJI Open (Sep 2018 Dollars)')
```



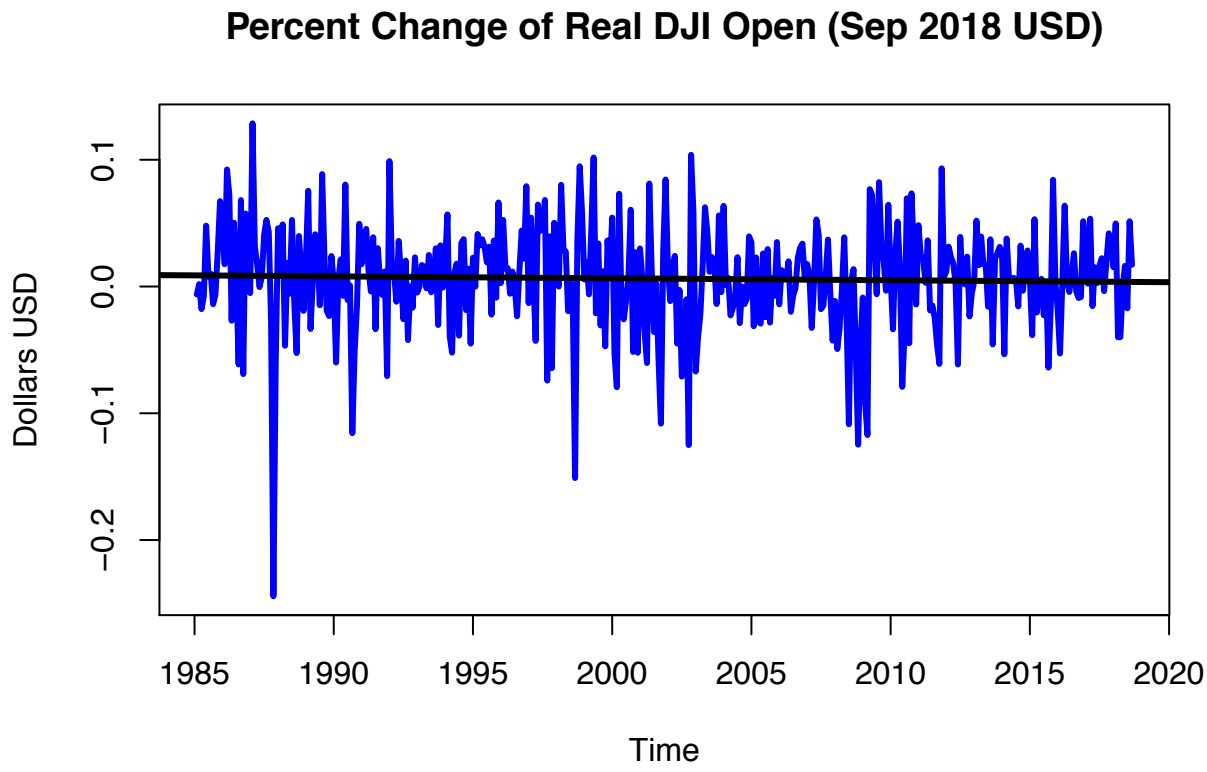

```r
plot(realDJIOpen,
     col = 'blue',
     lwd = 3,
     ylab = 'Dollars USD')
abline(reg = lm(realDJIOpen ~ time(realDJIOpen)), lwd = 3)
title(main = 'Real DJI Open (Sep 2018 Dollars)')
```



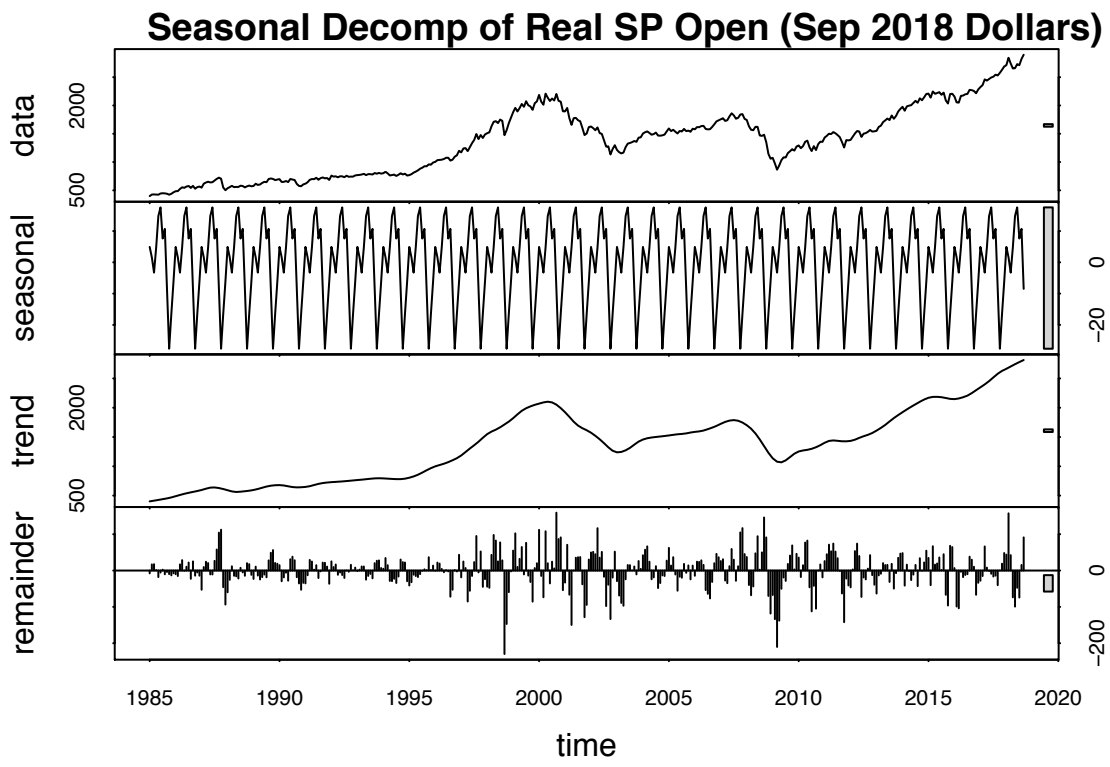

```
plot(log(realDJIOpen),
     col = 'blue',
     lwd = 3,
     ylab = 'Dollars USD')
abline(reg = lm(log(realDJIOpen) ~ time(log(realDJIOpen))), lwd = 3)
title(main = 'Log of Real DJI Open (Sep 2018 Dollars)')
```



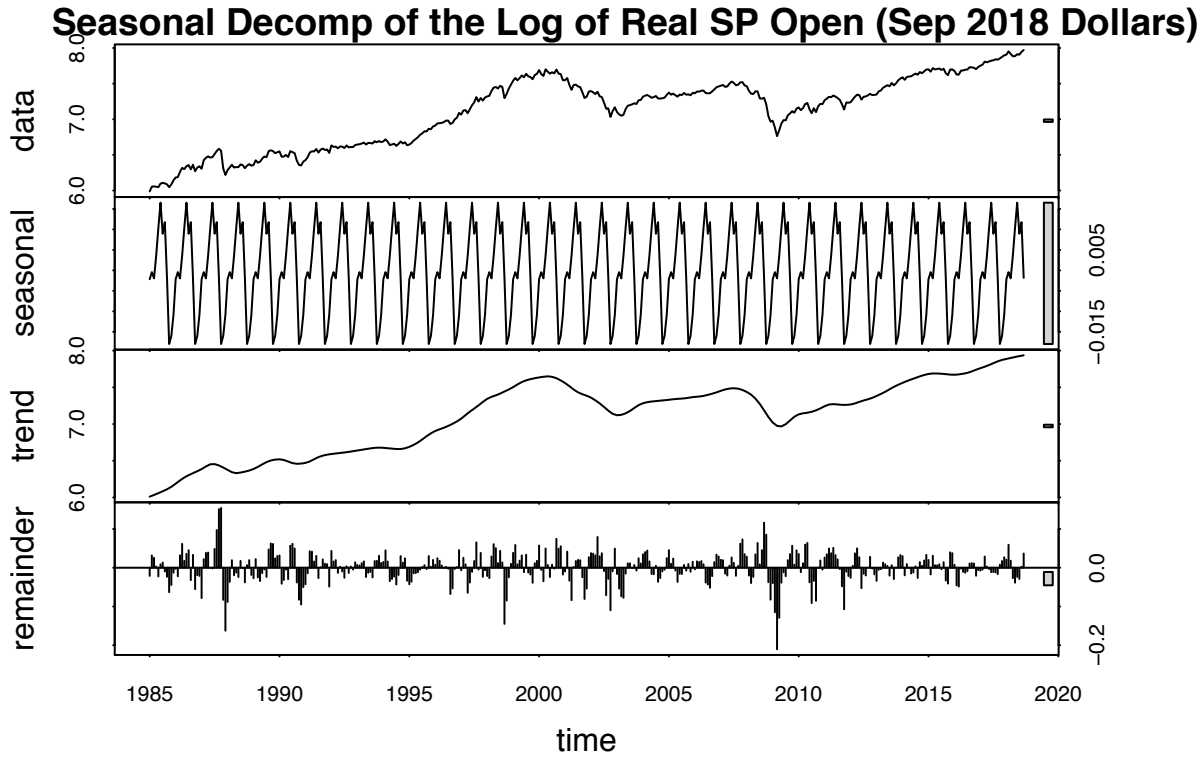

```
plot(percRealDJIOpen,
     col = 'blue',
     lwd = 3,
     ylab = 'Dollars USD')
abline(reg = lm(percRealDJIOpen ~ time(percRealDJIOpen)), lwd = 3)
title(main = 'Percent Change of Real DJI Open (Sep 2018 USD)')
```



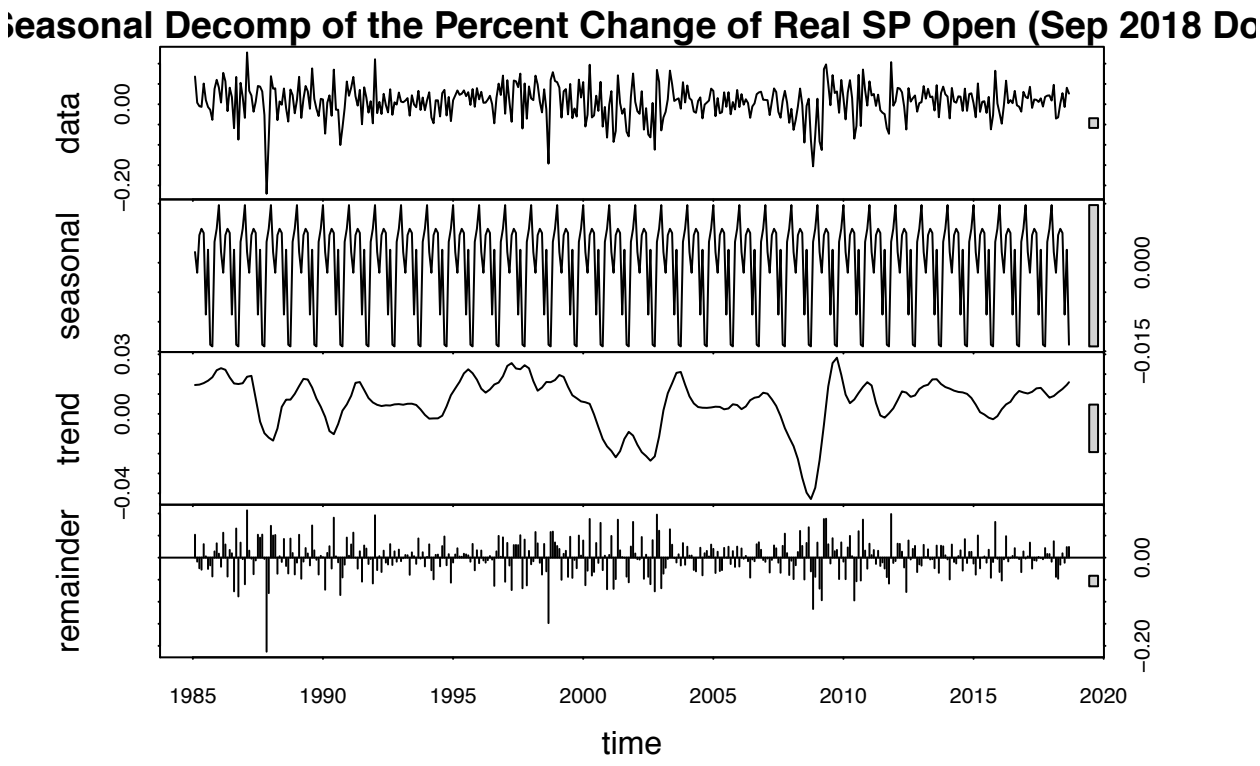

```
plot(stl(realSPOpen, s.window = "period"), lwd = 1)
title(main = 'Seasonal Decomp of Real SP Open (Sep 2018 Dollars)')
```




```
plot(stl(log(realSPOpen), s.window = "period"), lwd = 1)
title(main = 'Seasonal Decomp of the Log of Real SP Open (Sep 2018 Dollars)')
```

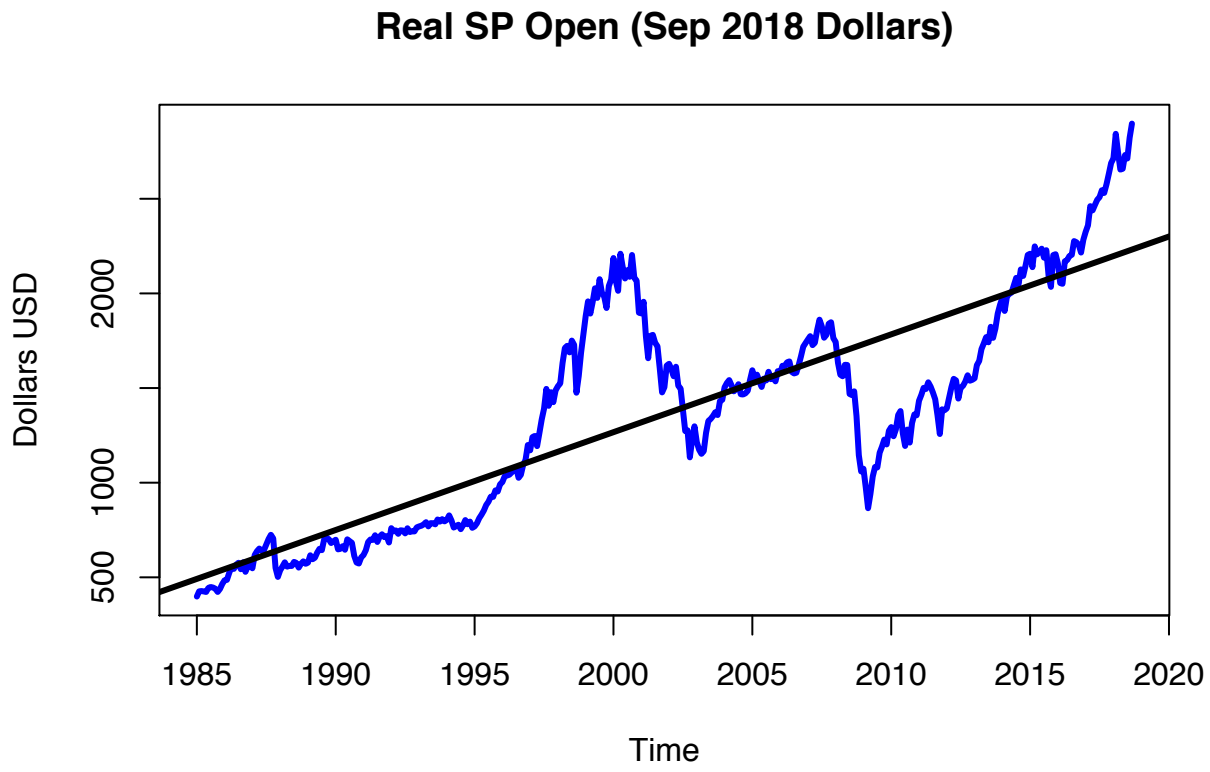



```
plot(stl(percRealSPOpen, s.window = "period"), lwd = 1)
title(main = 'Seasonal Decomp of the Percent Change of Real SP Open (Sep 2018 Dollars)')
```

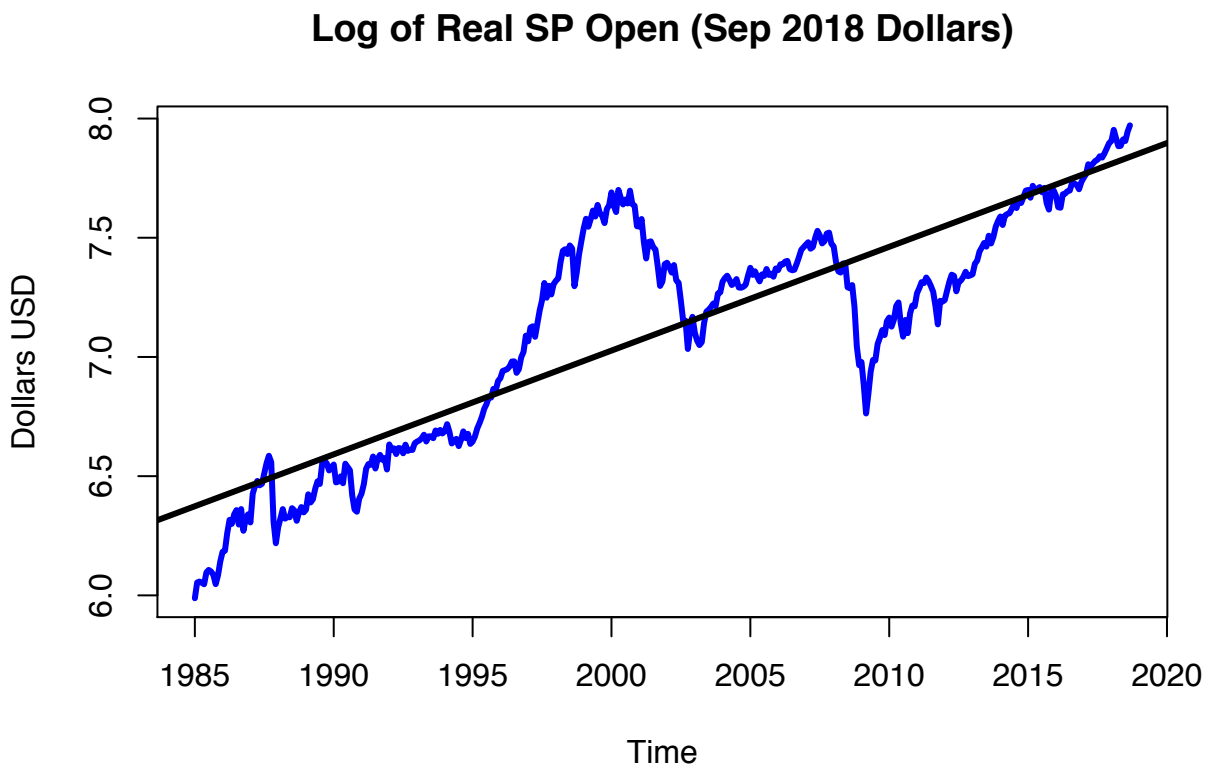



```
plot(realSPOpen,
     col = 'blue',
     lwd = 3,
```

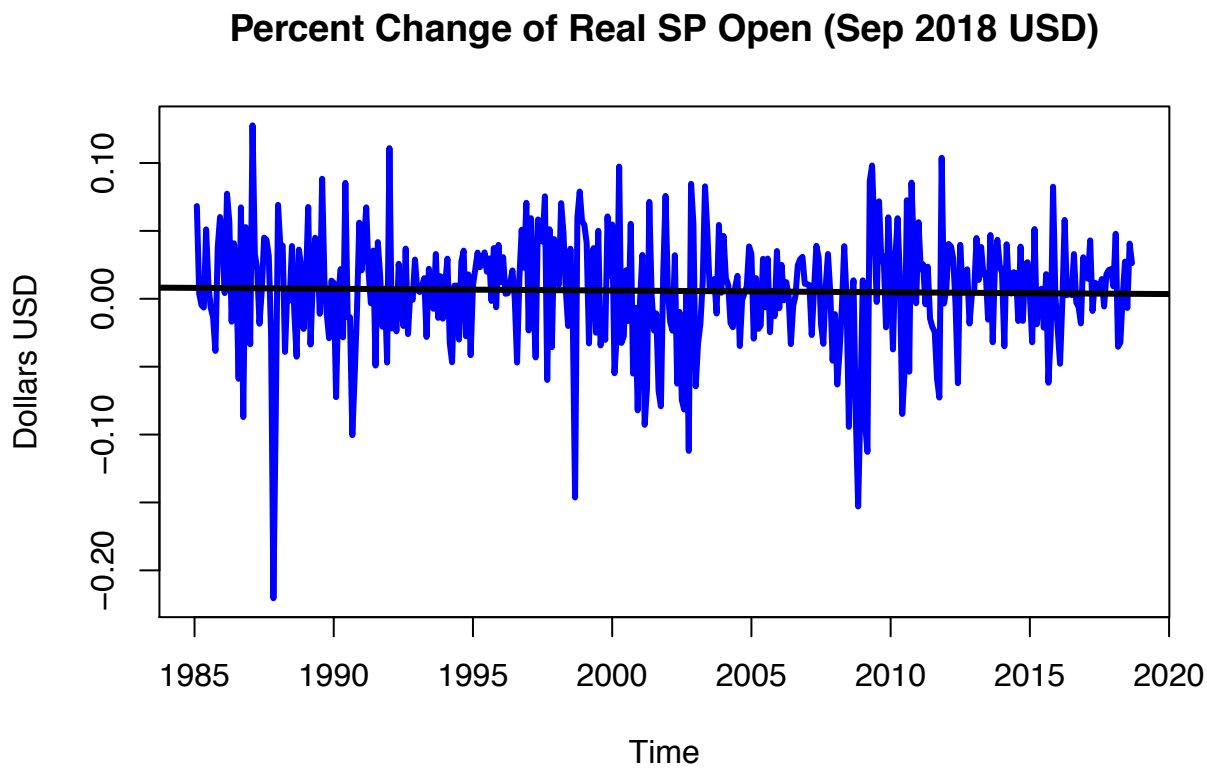
```
     ylab = 'Dollars USD')
abline(reg = lm(realSPOpen ~ time(realSPOpen)), lwd = 3)
title(main = 'Real SP Open (Sep 2018 Dollars)')
```



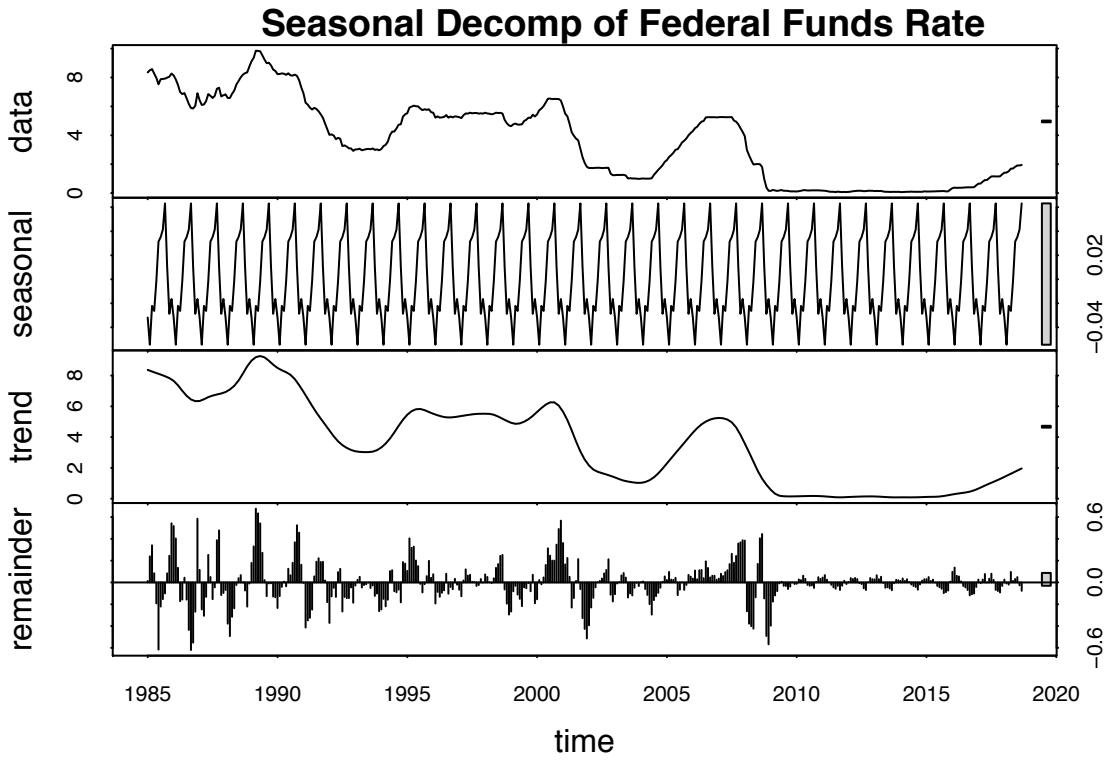

```
plot(log(realSPOpen),
     col = 'blue',
     lwd = 3,
     ylab = 'Dollars USD')
abline(reg = lm(log(realSPOpen) ~ time(log(realSPOpen))), lwd = 3)
title(main = 'Log of Real SP Open (Sep 2018 Dollars)')
```




```
plot(percRealSPOpen,
     col = 'blue',
     lwd = 3,
     ylab = 'Dollars USD')
abline(reg = lm(percRealSPOpen ~ time(percRealSPOpen)), lwd = 3)
title(main = 'Percent Change of Real SP Open (Sep 2018 USD)')
```

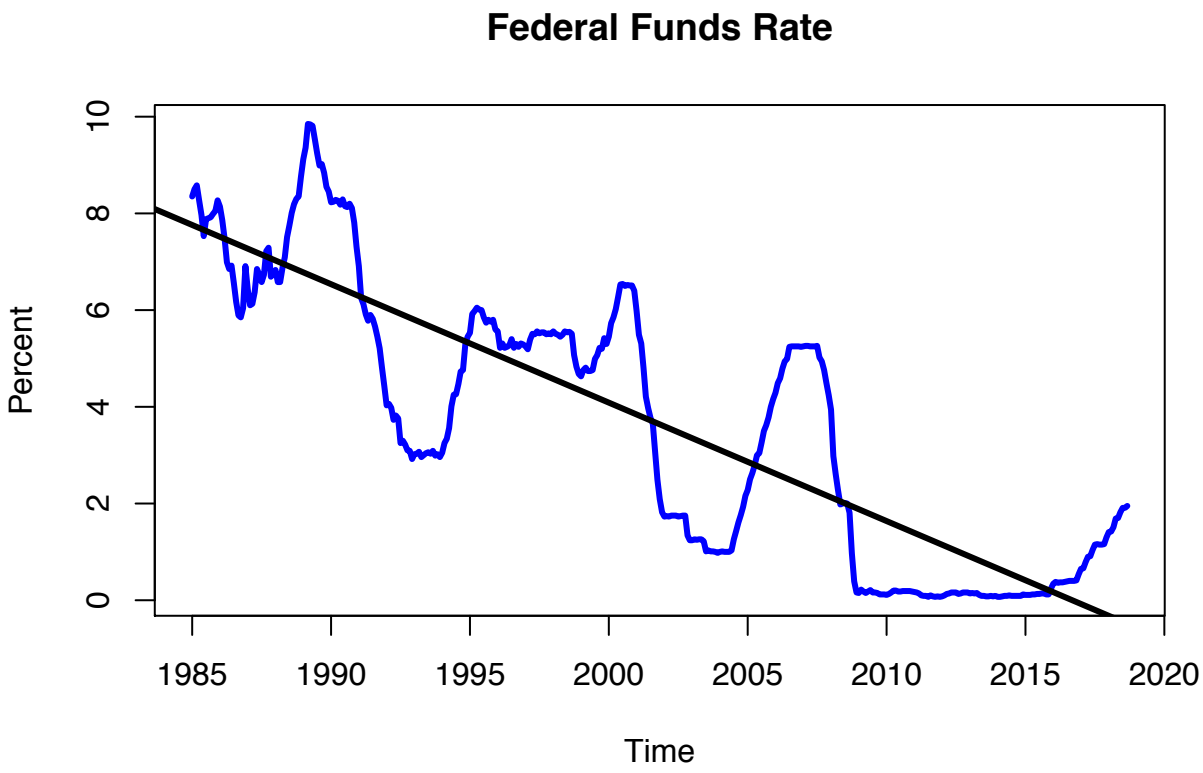



```
plot(stl(fedFund, s.window = "period"), lwd = 1)
title(main = 'Seasonal Decomp of Federal Funds Rate')
```

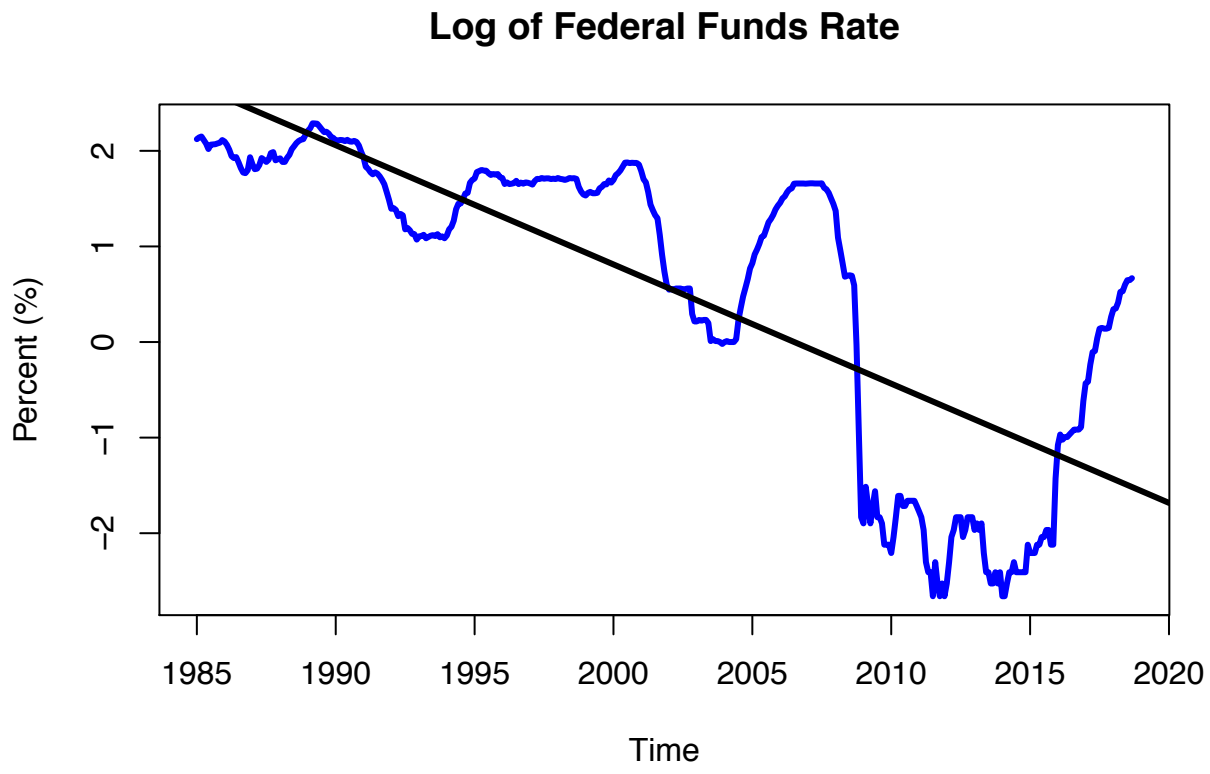



```
plot(fedFund,
     col = 'blue',
     lwd = 3,
```

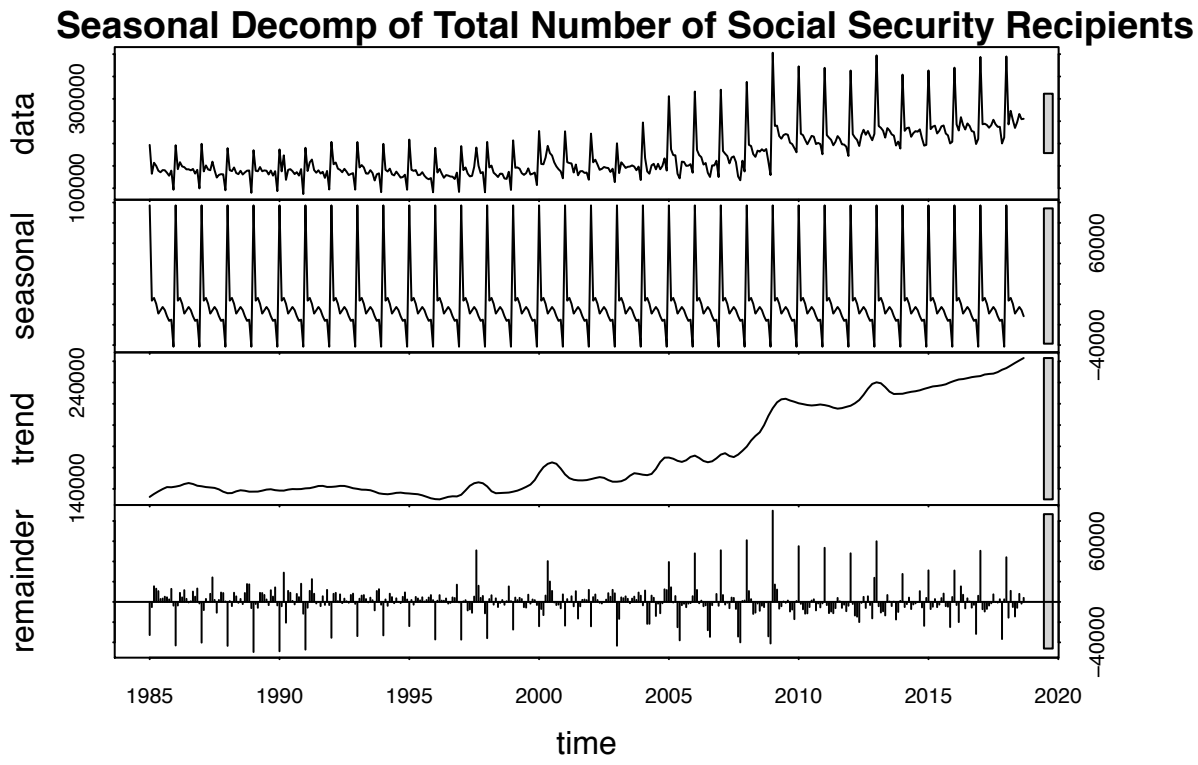
```
     ylab = 'Percent')
abline(reg = lm(fedFund ~ time(fedFund)), lwd = 3)
title(main = 'Federal Funds Rate')
```




```
plot(log(fedFund),
     col = 'blue',
     lwd = 3,
     ylab = 'Percent (%)')
abline(reg = lm(log(fedFund) ~ time(log(fedFund))), lwd = 3)
title(main = 'Log of Federal Funds Rate')
```

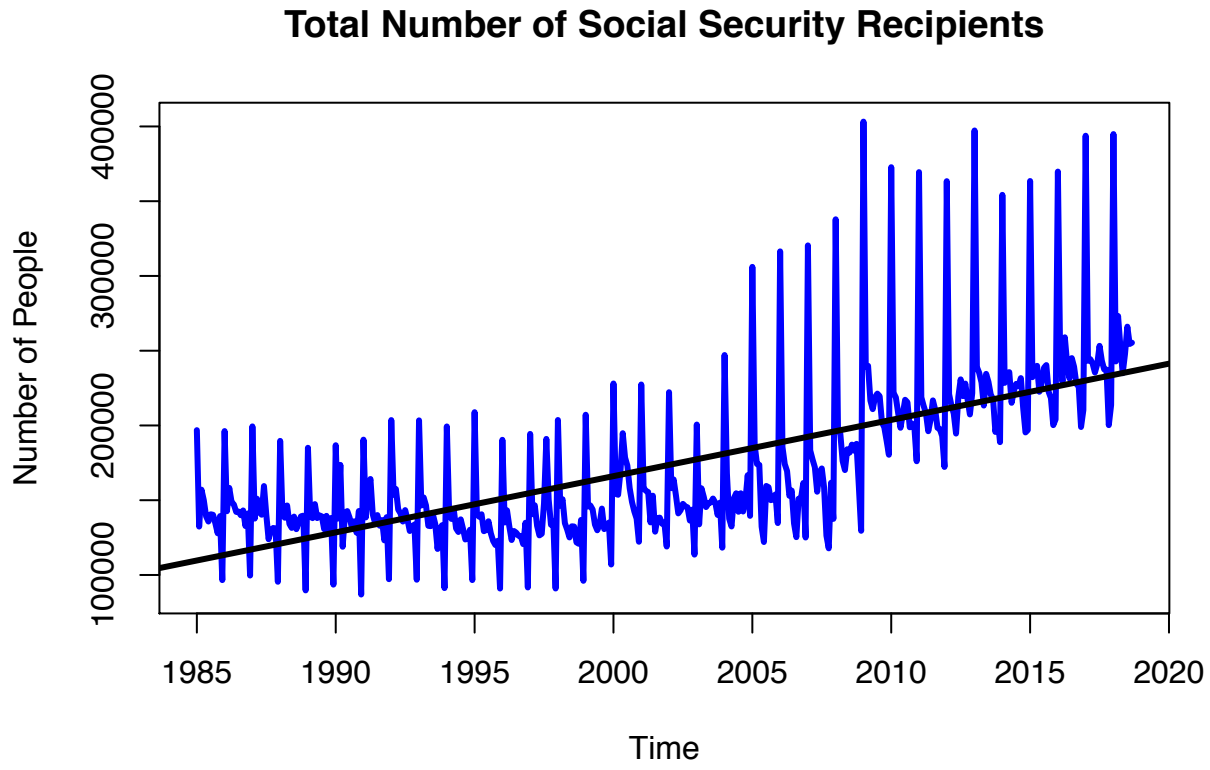



```
plot(stl(totalRetired, s.window = "period"), lwd = 1)
title(main = 'Seasonal Decomp of Total Number of Social Security Recipients')
```

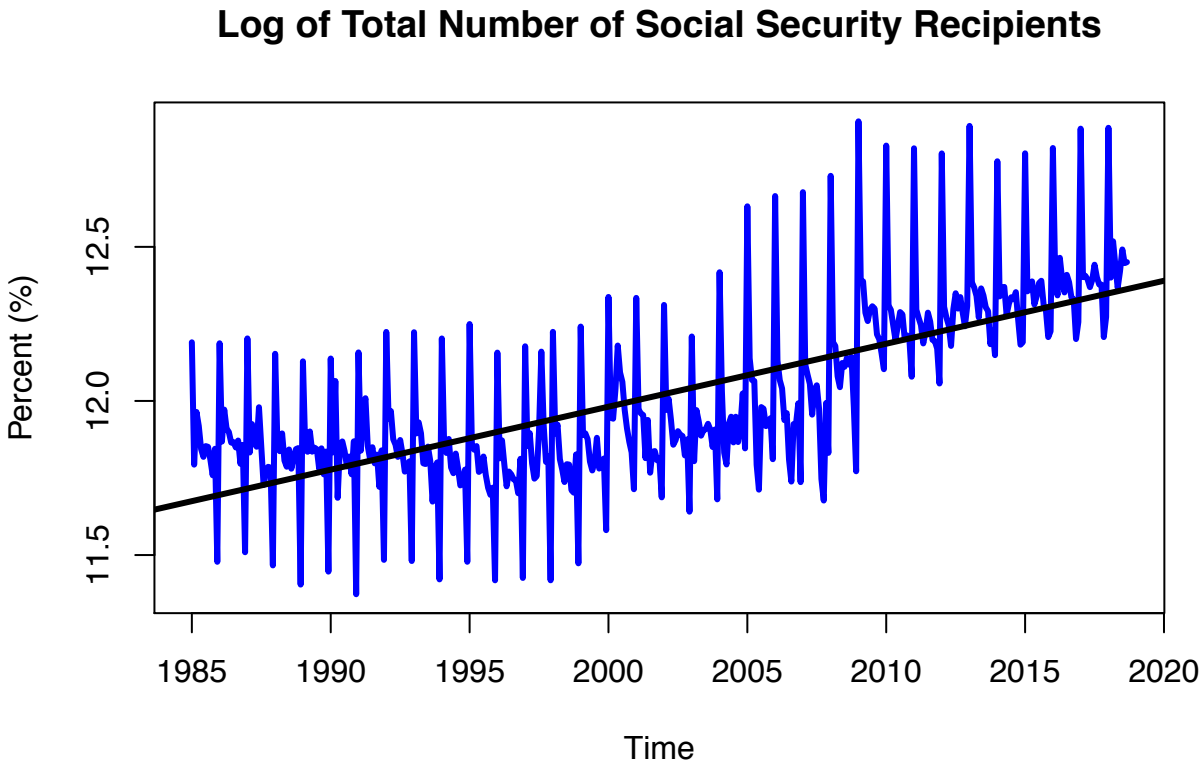



```
plot(totalRetired,
     col = 'blue',
     lwd = 3,
```

```
     ylab = 'Number of People')
abline(reg = lm(totalRetired ~ time(totalRetired)), lwd = 3)
title(main = 'Total Number of Social Security Recipients')
```




```
plot(log(totalRetired),
     col = 'blue',
     lwd = 3,
     ylab = 'Percent (%)')
abline(reg = lm(log(totalRetired) ~ time(log(totalRetired))), lwd = 3)
title(main = 'Log of Total Number of Social Security Recipients')
```




```
# Remove nominal values aside indicators of positive change
df2 <- df1[, c(1, 8:10, 11:18, 32:44, 58:96, 110:122)]
# remove components of the total SS Retirees (male + female = total) and percent increases and decrease
df3 <- df2[, c(1:2, 8:9, 13:77)]

# Hypothesis Tests ####
# Stationarity Loop Testing
statVars <- matrix(data = NA, nrow = 68, ncol = 2)
df3TS <- ts(
  df3,
  start = c(1985, 12),
  end = c(2018, 9),
  frequency = 12
)
for (i in c(1:68)) {
  statVars[i,1] <- i+1
  statVars[i,2] <- adf.test(df3TS[,i+1], alternative = 'stationary')[[4]]
}
```

```
## Warning in adf.test(df3TS[, i + 1], alternative = "stationary"): p-value
## smaller than printed p-value

## Warning in adf.test(df3TS[, i + 1], alternative = "stationary"): p-value
## smaller than printed p-value

## Warning in adf.test(df3TS[, i + 1], alternative = "stationary"): p-value
## smaller than printed p-value

## Warning in adf.test(df3TS[, i + 1], alternative = "stationary"): p-value
## smaller than printed p-value
```

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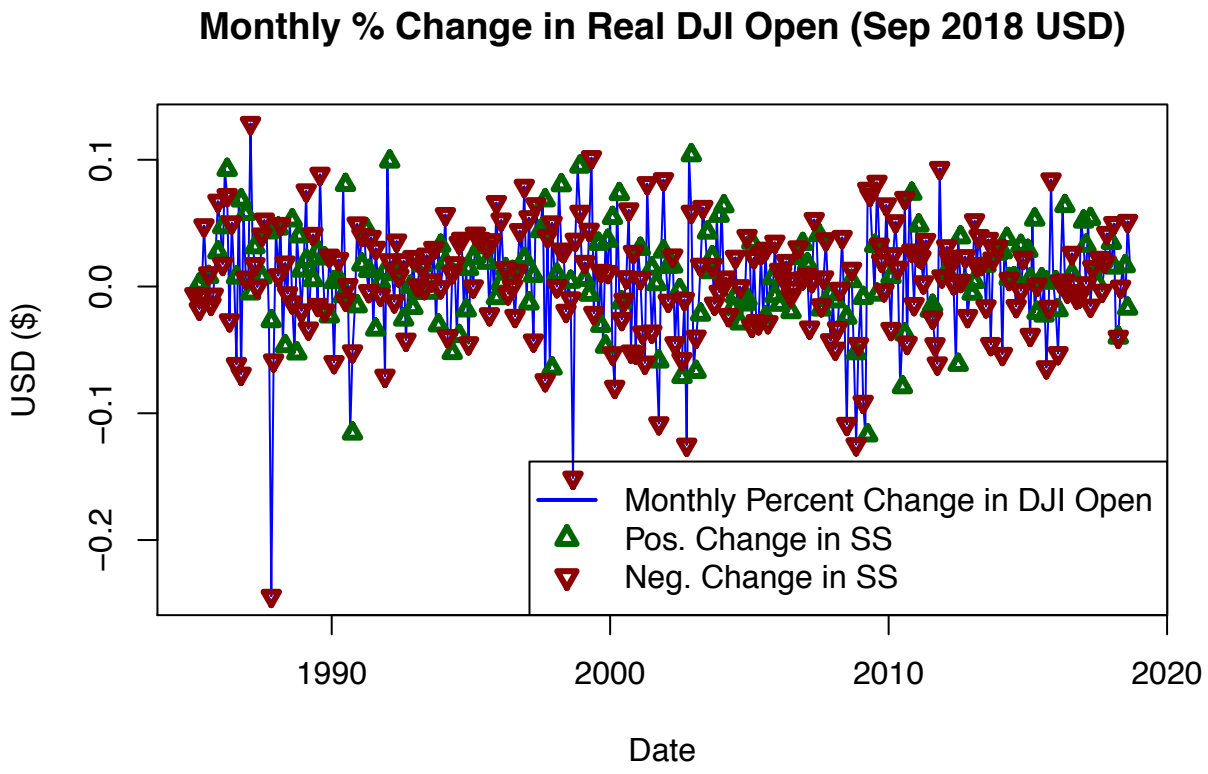
## smaller than printed p-value

## Warning in adf.test(df3TS[, i + 1], alternative = "stationary"): p-value
## smaller than printed p-value
```

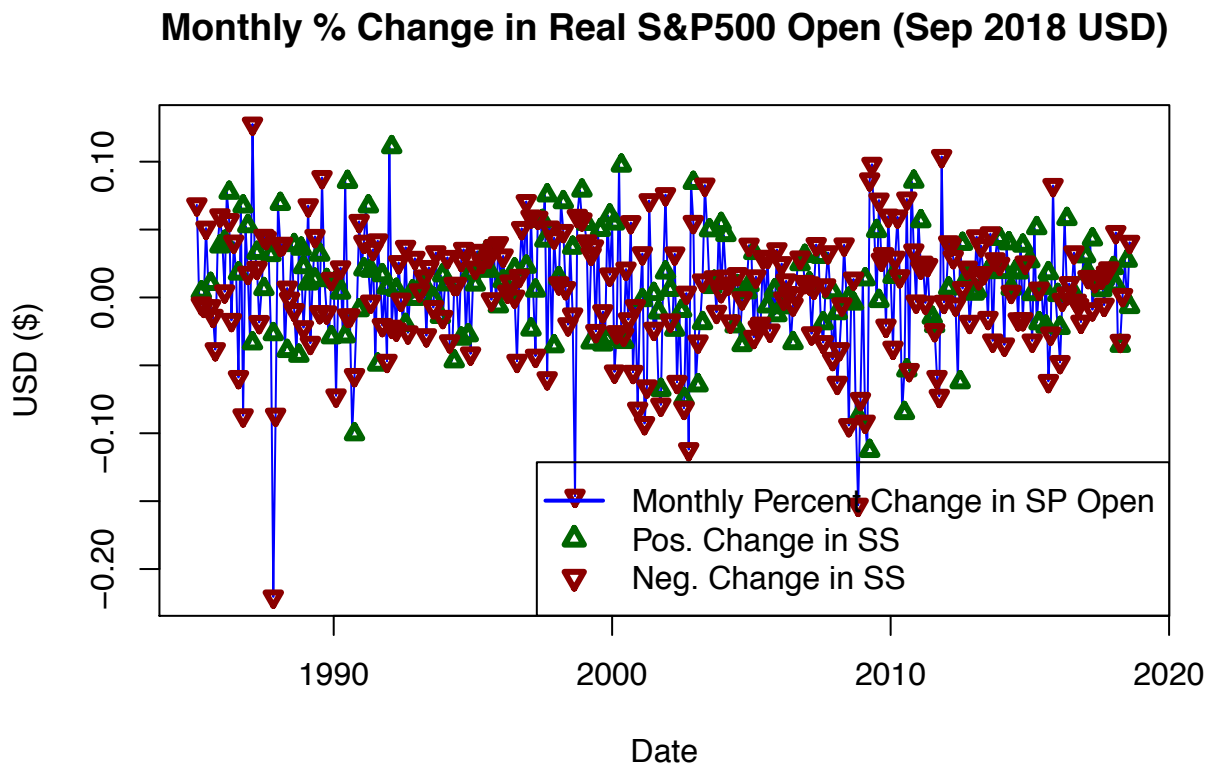
```
# Reject the null when p < 0.05. So, the variables associated with this are
# likely stationary and useful for prediction of time series
dfStatSelect<- statVars[,1][statVars[,2] < 0.05]
dfStationary<- df3[,c(1,dfStatSelect)]
```

```r
# Visualizations ####
plot(
  x = dfStationary$date,
  y = dfStationary$percChangeRealDJIopen,
  col = 'blue',
  lwd = 1,
  type = 'l',
  ylab = 'USD ($)',
  xlab = 'Date'
)
points(
  x = dfStationary$date[df$postotalSSRetired == 1],
  y = dfStationary$percChangeRealDJIopen[dfStationary$postotalSSRetired == 1],
  pch = 24,
  col = 'darkgreen',
  cex = 0.8,
  lwd = 3
)
points(
  x = dfStationary$date[dfStationary$postotalSSRetired == 0],
  y = dfStationary$percChangeRealDJIopen[dfStationary$postotalSSRetired == 0],
  pch = 25,
  col = 'darkred',
  cex = 0.8,
  lwd = 3
)
legend(
  'bottomright',
  legend = c(
    'Monthly Percent Change in DJI Open',
    c('Pos. Change in SS', 'Neg. Change in SS')
  ),
  lty = c(1, c(NA, NA)),
  pch = c(NA, c(24, 25)),
  col = c('blue', c('darkgreen', 'darkred')),
  bg = c(NA, c('darkgreen', 'darkred')),
  lwd = c(2, c(3, 3))
)
title(main = 'Monthly % Change in Real DJI Open (Sep 2018 USD)')
```



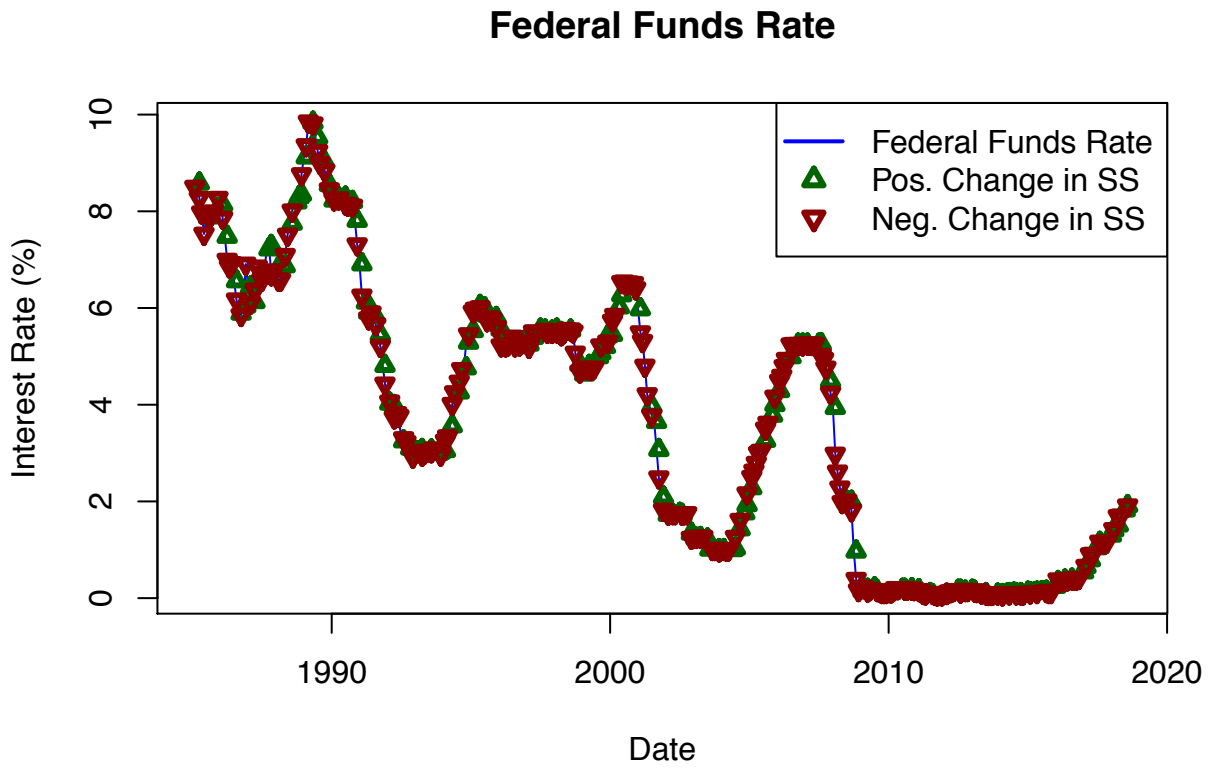

```
plot(
  x = dfStationary$date,
  y = dfStationary$percChangeRealSPopen,
  col = 'blue',
  lwd = 1,
  type = 'l',
  ylab = 'USD ($)',
  xlab = 'Date'
)
points(
  x = dfStationary$date[df$postotalSSRetired == 1],
  y = dfStationary$percChangeRealSPopen[dfStationary$postotalSSRetired == 1],
  pch = 24,
  col = 'darkgreen',
  cex = 0.8,
  lwd = 3
)
points(
  x = dfStationary$date[dfStationary$postotalSSRetired == 0],
  y = dfStationary$percChangeRealSPopen[dfStationary$postotalSSRetired == 0],
  pch = 25,
  col = 'darkred',
  cex = 0.8,
  lwd = 3
)
legend(
  'bottomright',
  legend = c(
    'Monthly Percent Change in SP Open',
    c('Pos. Change in SS', 'Neg. Change in SS')
```

```
  ),
  lty = c(1, c(NA, NA)),
  pch = c(NA, c(24, 25)),
  col = c('blue', c('darkgreen', 'darkred')),
  bg = c(NA, c('darkgreen', 'darkred')),
  lwd = c(2, c(3, 3))
)
title(main = 'Monthly % Change in Real S&P500 Open (Sep 2018 USD)')
```



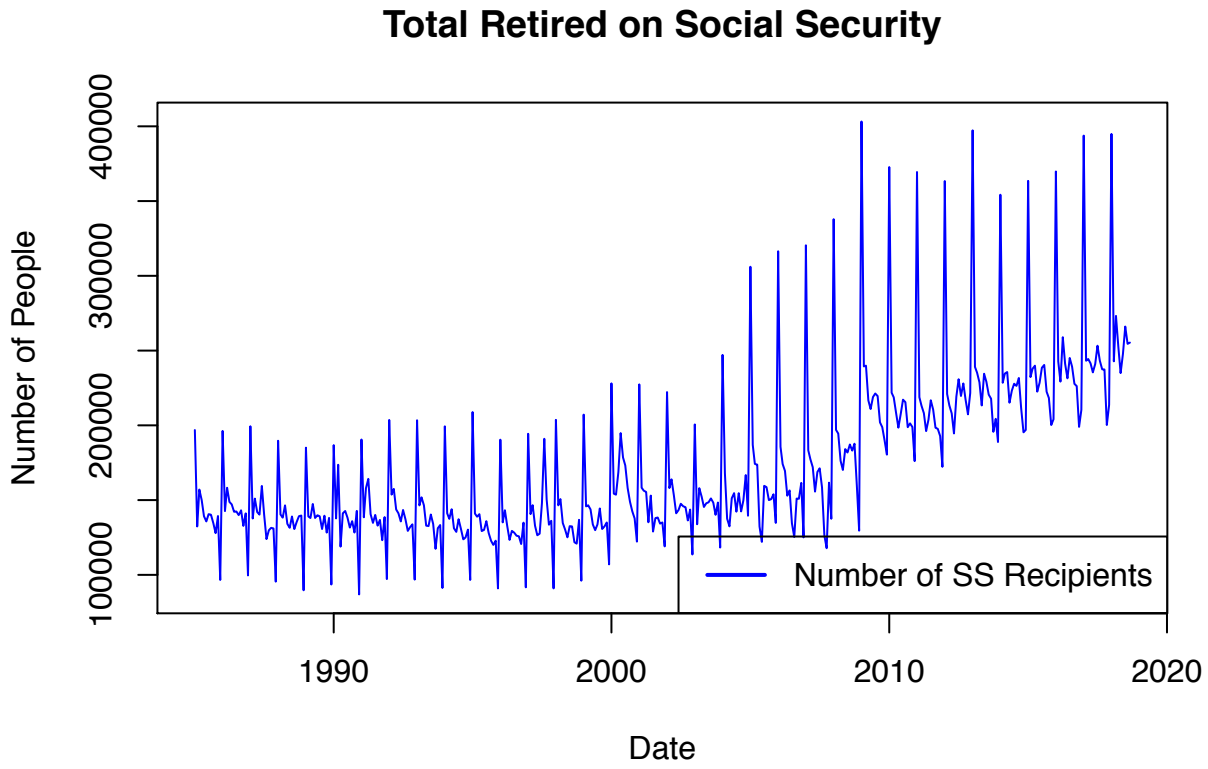

```
plot(
  x = dfStationary$date,
  y = dfStationary$fedFundRate,
  col = 'blue',
  lwd = 1,
  type = 'l',
  ylab = 'Interest Rate (%)',
  xlab = 'Date'
)
points(
  x = dfStationary$date[df$postotalSSRetired == 1],
  y = dfStationary$fedFundRate[dfStationary$postotalSSRetired == 1],
  pch = 24,
  col = 'darkgreen',
  cex = 0.8,
  lwd = 3
)
points(
  x = dfStationary$date[dfStationary$postotalSSRetired == 0],
  y = dfStationary$fedFundRate[dfStationary$postotalSSRetired == 0],
```

```
  pch = 25,
  col = 'darkred',
  cex = 0.8,
  lwd = 3
)
legend(
  'topright',
  legend = c('Federal Funds Rate',
             c('Pos. Change in SS', 'Neg. Change in SS')),
  lty = c(1, c(NA, NA)),
  pch = c(NA, c(24, 25)),
  col = c('blue', c('darkgreen', 'darkred')),
  bg = c(NA, c('darkgreen', 'darkred')),
  lwd = c(2, c(3, 3))
)
title(main = 'Federal Funds Rate')
```




```
plot(
  x = df$date,
  y = df$totalSSRetired,
  col = 'blue',
  lwd = 1,
  type = 'l',
  ylab = 'Number of People',
  xlab = 'Date'
)
legend(
  'bottomright',
  legend = c('Number of SS Recipients'),
  lty = c(1),
```

```
  col = c('blue'),
  lwd = c(2)
)
title(main = 'Total Retired on Social Security')
```




```
# Selection ####
# Set a few dataframes for different variables
dfDiff <- dfStationary[,c(2:5,7:19)]
dfPosChange <- dfStationary[,c(2:5, 20:45)]
dfPerc <- dfStationary[,c(2:5, 46:58)]
# Run the selections
# Differences ####
# SeqRep
regFitSelect <- regsubsets(
  postotalSSRetired~.,
  data=dfDiff,
  method= 'seqrep',
  nvmax=17)
```

```
## Warning in leaps.setup(x, y, wt = wt, nbest = nbest, nvmax = nvmax,
## force.in = force.in, : 2 linear dependencies found
```

```
## Reordering variables and trying again:
```

```
regSummary <- summary(regFitSelect)
names(regSummary)
```

```
## [1] "which"  "rsq"    "rss"    "adjr2"  "cp"     "bic"    "outmat" "obj"
```

```
regSummary$rsq
```

```
##  [1] 0.1731698 0.1779456 0.1839180 0.2391592 0.2410517 0.2463118 0.2466627
```

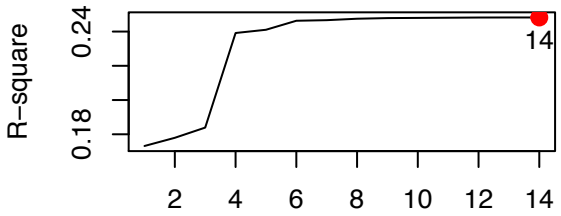
```
##  [8] 0.2474956 0.2478743 0.2479814 0.2480829 0.2481942 0.2482266 0.2482272
```

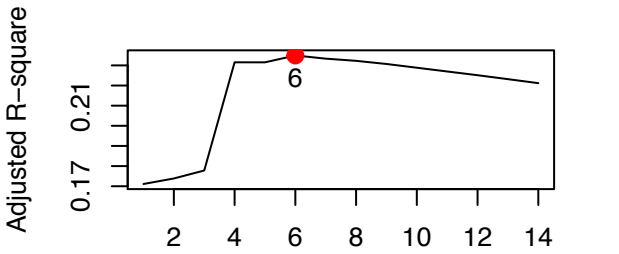
```
regSummary$adjr2
```

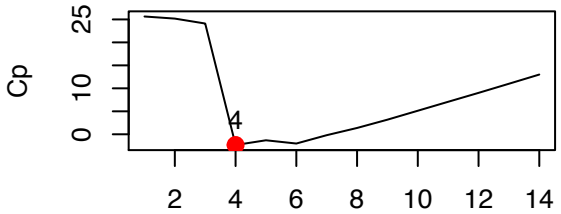
```
##  [1] 0.1711130 0.1738456 0.1777974 0.2315317 0.2315172 0.2349210 0.2333461
##  [8] 0.2322550 0.2306938 0.2288461 0.2269832 0.2251209 0.2231675 0.2211711
```

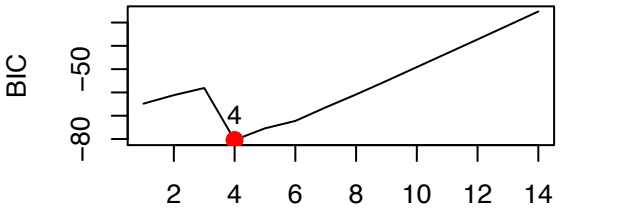
```
par(mfrow=c(2,2))
aRSQ <- which.max(regSummary$rsq)
aARSQ <- which.max(regSummary$adjr2)
aCP <- which.min(regSummary$cp)
aBIC <- which.min(regSummary$bic)
aRSS <- which.min(regSummary$rss)

par(mfrow = c(2, 2))

plot(
  regSummary$rsq,
  xlab = "Number of regressors - SeqRep - Differences",
  ylab = "R-square",
  type = "l"
)
points(
  aRSQ,
  regSummary$rsq[aRSQ],
  col = "red",
  cex = 2,
  pch = 20
)
text(aRSQ,
     regSummary$rsq[aRSQ],
     labels = aRSQ,
     pos = 1)

plot(
  regSummary$adjr2,
  xlab = "Number of regressors - SeqRep - Differences",
  ylab = "Adjusted R-square",
  type = "l"
)
points(
  aARSQ,
  regSummary$adjr2[aARSQ],
  col = "red",
  cex = 2,
  pch = 20
)
text(aARSQ,
     regSummary$adjr2[aARSQ],
     labels = aARSQ,
     pos = 1)

plot(regSummary$cp,
     xlab = "Number of regressors - SeqRep - Differences",
     ylab = "Cp",
```

```
     type = "l")
points(
  aCP,
  regSummary$cp[aCP],
  col = "red",
  cex = 2,
  pch = 20
)
text(aCP,
     regSummary$cp[aCP],
     labels = aCP,
     pos = 3)

plot(
  regSummary$bic,
  xlab = "Number of regressors - SeqRep - Differences",
  ylab = "BIC",
  type = "l"
)
points(
  aBIC,
  regSummary$bic[aBIC],
  col = "red",
  cex = 2,
  pch = 20
)
text(aBIC,
     regSummary$bic[aBIC],
     labels = aBIC,
     pos = 3)
```

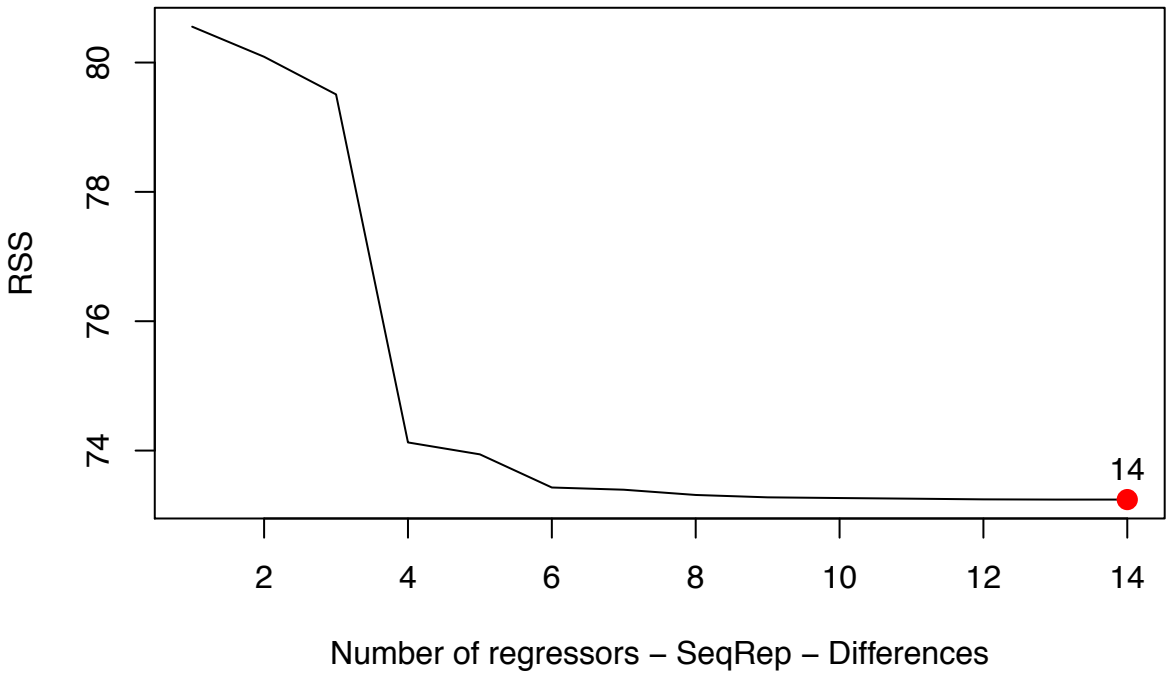




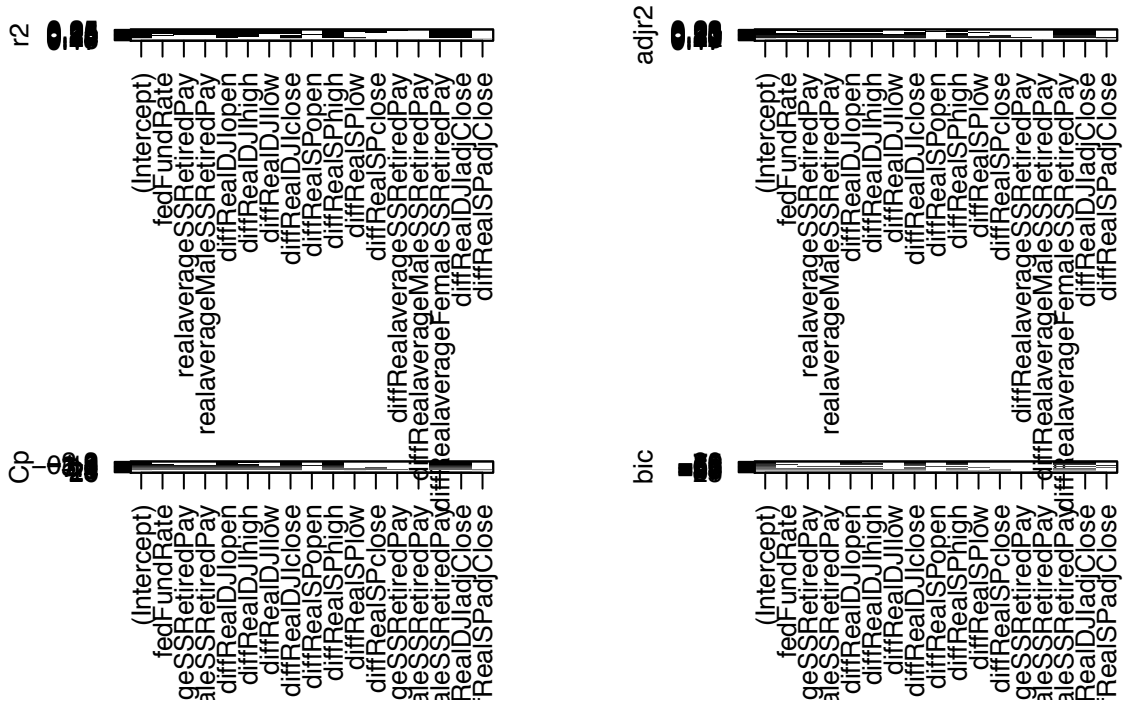





```r
par(mfrow = c(1, 1))
plot(
  regSummary$rss,
  xlab = "Number of regressors - SeqRep - Differences",
  ylab = "RSS",
  type = "l"
)
points(
  aRSS,
  regSummary$rss[aRSS],
  col = "red",
  cex = 2,
  pch = 20
)
text(aRSS,
     regSummary$rss[aRSS],
     labels = aRSS,
     pos = 3)
```




```
par(mfrow = c(2, 2))
plot(regFitSelect, scale = "r2")
plot(regFitSelect, scale = "adjr2")
plot(regFitSelect, scale = "Cp")
plot(regFitSelect, scale = "bic")
```




```
valuesSeqRep <- c(names(coef(regFitSelect, id = 4))[-1])
# Forward
regFitSelect <- regsubsets(
  postotalSSRetired~.,
```

```
  data=dfDiff,
  method= 'forward',
  nvmax=17)
```

```
## Warning in leaps.setup(x, y, wt = wt, nbest = nbest, nvmax = nvmax,
## force.in = force.in, : 2 linear dependencies found
```

```
## Reordering variables and trying again:
```

```
## Warning in rval$lopt[] <- rval$vorder[rval$lopt]: number of items to
## replace is not a multiple of replacement length
```

```
regSummary <- summary(regFitSelect)
names(regSummary)
```

```
## [1] "which"  "rsq"    "rss"    "adjr2"  "cp"     "bic"    "outmat" "obj"
```

```
regSummary$rsq
```

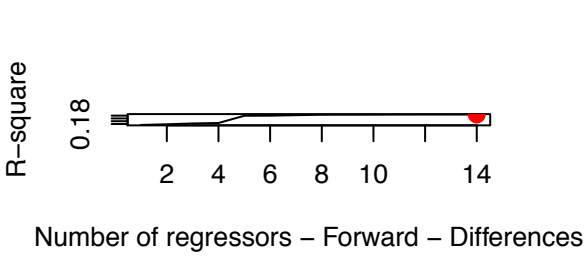
```
##  [1] 0.1731698 0.1779456 0.1839180 0.1871817 0.2391704 0.2399022 0.2433283
##  [8] 0.2463473 0.2466978 0.2469470 0.2479080 0.2480453 0.2481380 0.2482272
```

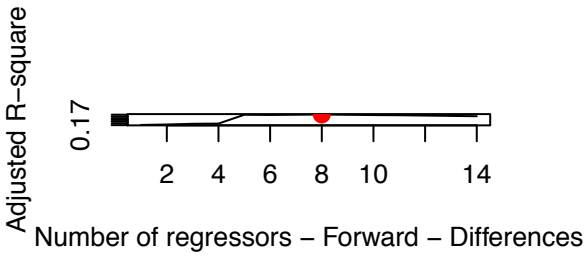
```
regSummary$adjr2
```

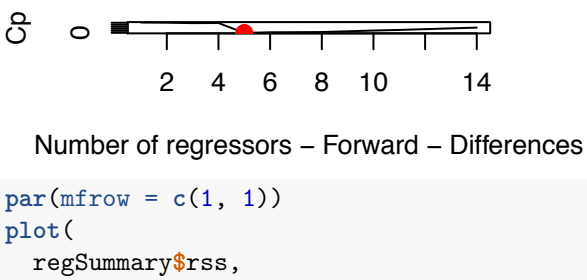
```
##  [1] 0.1711130 0.1738456 0.1777974 0.1790331 0.2296123 0.2284146 0.2299528
##  [8] 0.2310835 0.2294904 0.2277853 0.2268034 0.2249674 0.2230759 0.2211711
```

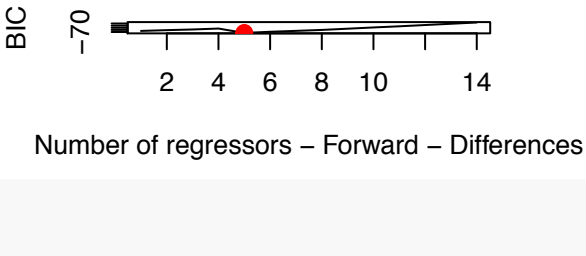
```
par(mfrow=c(2,2))
aRSQ <- which.max(regSummary$rsq)
aARSQ <- which.max(regSummary$adjr2)
aCP <- which.min(regSummary$cp)
aBIC <- which.min(regSummary$bic)
aRSS <- which.min(regSummary$rss)

par(mfrow = c(2, 2))

plot(
  regSummary$rsq,
  xlab = "Number of regressors - Forward - Differences",
  ylab = "R-square",
  type = "l"
)
points(
  aRSQ,
  regSummary$rsq[aRSQ],
  col = "red",
  cex = 2,
  pch = 20
)
text(aRSQ,
     regSummary$rsq[aRSQ],
     labels = aRSQ,
     pos = 1)

plot(
  regSummary$adjr2,
  xlab = "Number of regressors - Forward - Differences",
```

```
  ylab = "Adjusted R-square",
  type = "l"
)
points(
  aARSQ,
  regSummary$adjr2[aARSQ],
  col = "red",
  cex = 2,
  pch = 20
)
text(aARSQ,
     regSummary$adjr2[aARSQ],
     labels = aARSQ,
     pos = 1)

plot(regSummary$cp,
     xlab = "Number of regressors - Forward - Differences",
     ylab = "Cp",
     type = "l")
points(
  aCP,
  regSummary$cp[aCP],
  col = "red",
  cex = 2,
  pch = 20
)
text(aCP,
     regSummary$cp[aCP],
     labels = aCP,
     pos = 3)

plot(
  regSummary$bic,
  xlab = "Number of regressors - Forward - Differences",
  ylab = "BIC",
  type = "l"
)
points(
  aBIC,
  regSummary$bic[aBIC],
  col = "red",
  cex = 2,
  pch = 20
)
text(aBIC,
     regSummary$bic[aBIC],
     labels = aBIC,
     pos = 3)
```

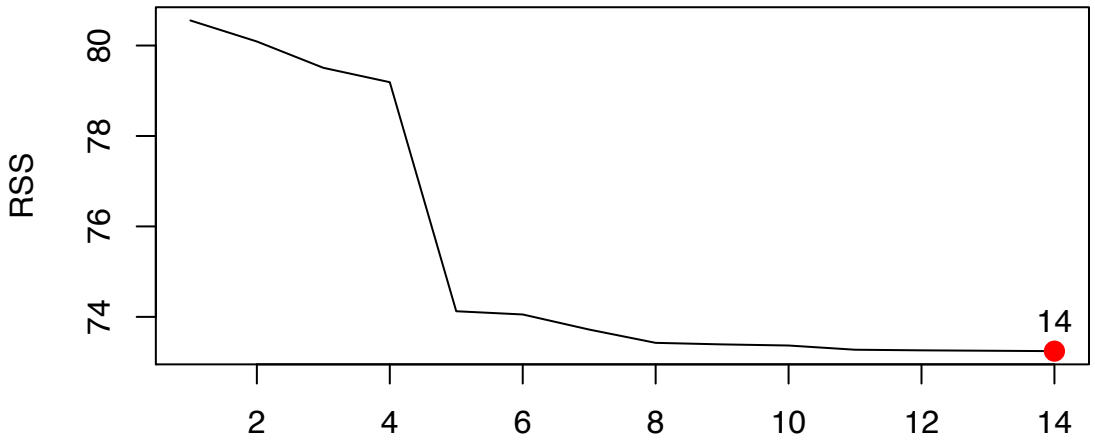






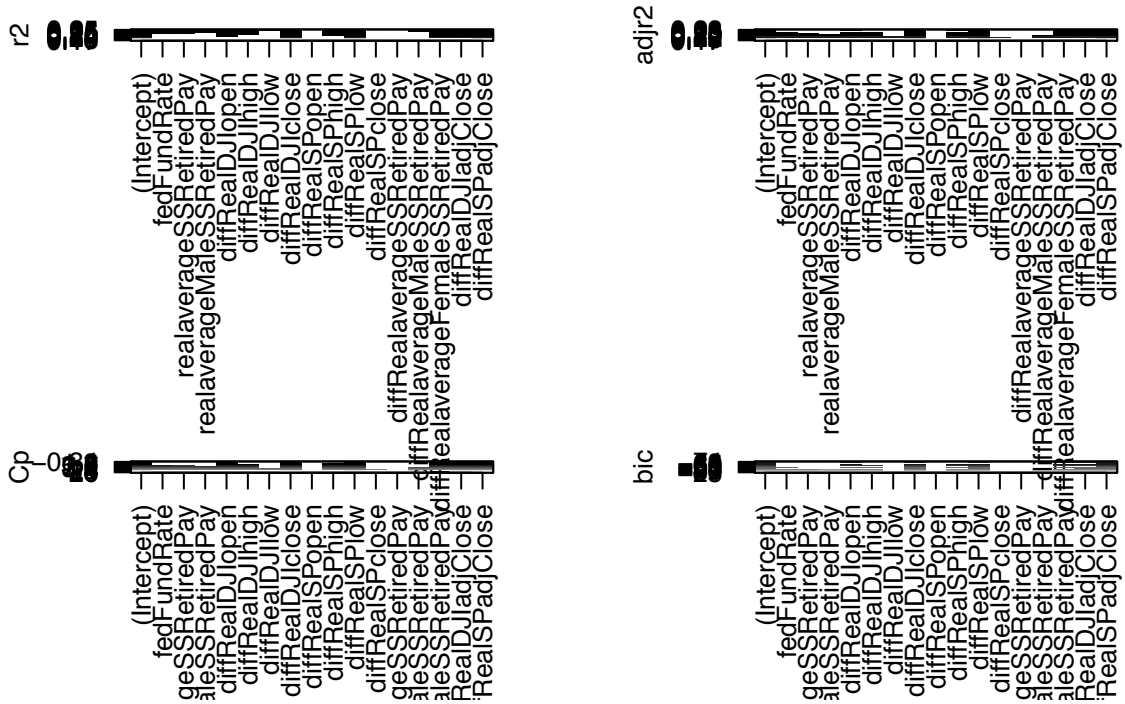



```r
par(mfrow = c(1, 1))
plot(
  regSummary$rss,
  xlab = "Number of regressors - Forward - Differences",
  ylab = "RSS",
  type = "l"
)
points(
  aRSS,
  regSummary$rss[aRSS],
  col = "red",
  cex = 2,
  pch = 20
)
text(aRSS,
     regSummary$rss[aRSS],
     labels = aRSS,
     pos = 3)
```



Number of regressors – Forward – Differences

```
par(mfrow = c(2, 2))
plot(regFitSelect, scale = "r2")
plot(regFitSelect, scale = "adjr2")
plot(regFitSelect, scale = "Cp")
plot(regFitSelect, scale = "bic")
```




```
valuesForward <- c(names(coef(regFitSelect, id = 5))[-1])
# Backward
regFitSelect <- regsubsets(
  postotalSSRetired~.,
  data=dfDiff,
  method= 'backward',
  nvmax=17)
```

```
## Warning in leaps.setup(x, y, wt = wt, nbest = nbest, nvmax = nvmax,
```

```
## force.in = force.in, : 2 linear dependencies found
```

```
## Reordering variables and trying again:
```

```
## Warning in rval$lopt[] <- rval$vorder[rval$lopt]: number of items to
## replace is not a multiple of replacement length
```

```
regSummary <- summary(regFitSelect)
names(regSummary)
```

```
## [1] "which"  "rsq"    "rss"    "adjr2"  "cp"     "bic"    "outmat" "obj"
```

```
regSummary$rsq
```

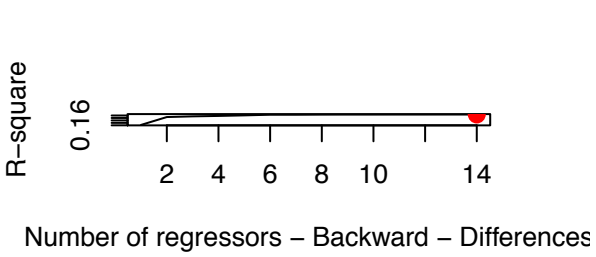
```
##  [1] 0.1630296 0.2273926 0.2330672 0.2364933 0.2410517 0.2463118 0.2464133
##  [8] 0.2474956 0.2478743 0.2479814 0.2480829 0.2481942 0.2482266 0.2482272
```

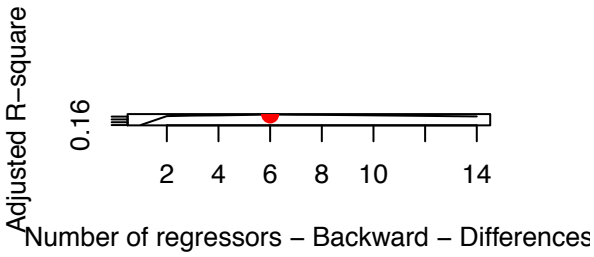
```
regSummary$adjr2
```

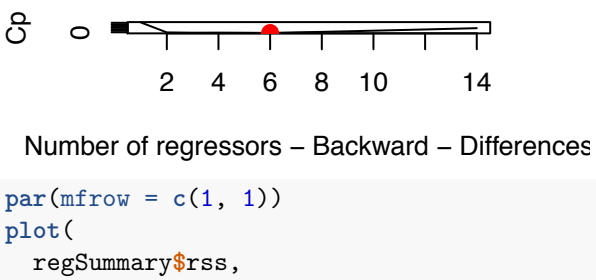
```
##  [1] 0.1609476 0.2235392 0.2273153 0.2288391 0.2315172 0.2349210 0.2330923
##  [8] 0.2322550 0.2306938 0.2288461 0.2269832 0.2251209 0.2231675 0.2211711
```

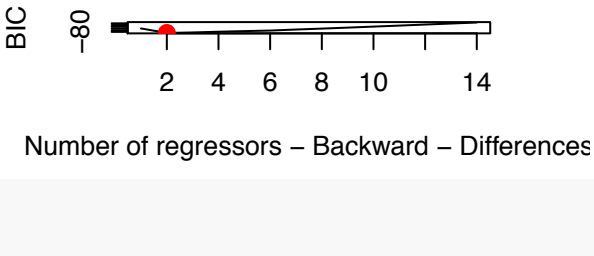
```
par(mfrow=c(2,2))
aRSQ <- which.max(regSummary$rsq)
aARSQ <- which.max(regSummary$adjr2)
aCP <- which.min(regSummary$cp)
aBIC <- which.min(regSummary$bic)
aRSS <- which.min(regSummary$rss)

par(mfrow = c(2, 2))

plot(
  regSummary$rsq,
  xlab = "Number of regressors - Backward - Differences",
  ylab = "R-square",
  type = "l"
)
points(
  aRSQ,
  regSummary$rsq[aRSQ],
  col = "red",
  cex = 2,
  pch = 20
)
text(aRSQ,
     regSummary$rsq[aRSQ],
     labels = aRSQ,
     pos = 1)

plot(
  regSummary$adjr2,
  xlab = "Number of regressors - Backward - Differences",
  ylab = "Adjusted R-square",
  type = "l"
)
points(
  aARSQ,
  regSummary$adjr2[aARSQ],
```

```
  col = "red",
  cex = 2,
  pch = 20
)
text(aARSQ,
     regSummary$adjr2[aARSQ],
     labels = aARSQ,
     pos = 1)

plot(regSummary$cp,
     xlab = "Number of regressors - Backward - Differences",
     ylab = "Cp",
     type = "l")
points(
  aCP,
  regSummary$cp[aCP],
  col = "red",
  cex = 2,
  pch = 20
)
text(aCP,
     regSummary$cp[aCP],
     labels = aCP,
     pos = 3)

plot(
  regSummary$bic,
  xlab = "Number of regressors - Backward - Differences",
  ylab = "BIC",
  type = "l"
)
points(
  aBIC,
  regSummary$bic[aBIC],
  col = "red",
  cex = 2,
  pch = 20
)
text(aBIC,
     regSummary$bic[aBIC],
     labels = aBIC,
     pos = 3)
```

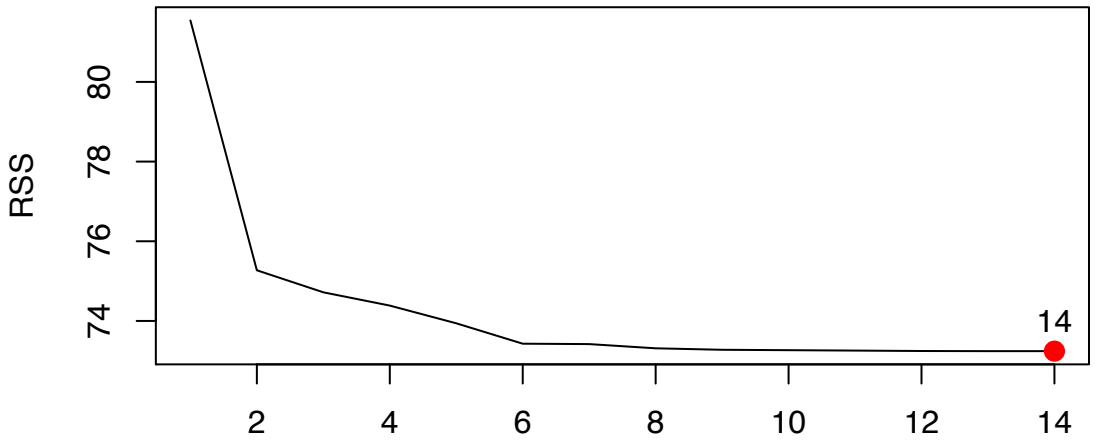




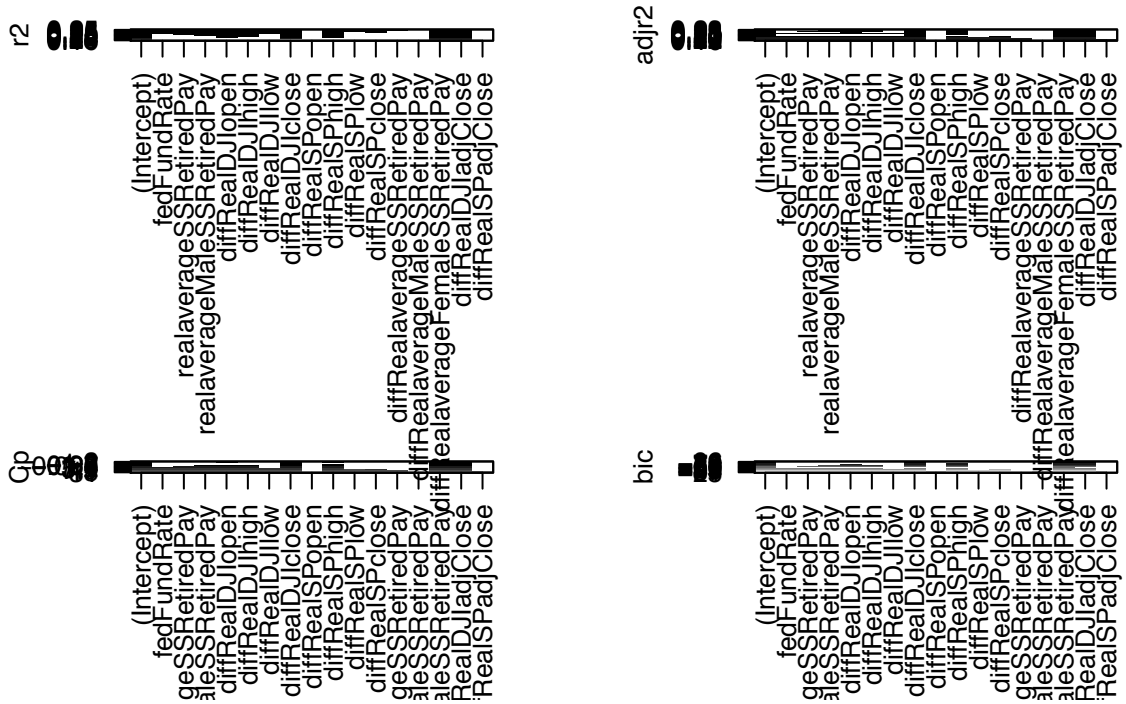





```r
par(mfrow = c(1, 1))
plot(
  regSummary$rss,
  xlab = "Number of regressors - Backward - Differences",
  ylab = "RSS",
  type = "l"
)
points(
  aRSS,
  regSummary$rss[aRSS],
  col = "red",
  cex = 2,
  pch = 20
)
text(aRSS,
     regSummary$rss[aRSS],
     labels = aRSS,
     pos = 3)
```




```
par(mfrow = c(2, 2))
plot(regFitSelect, scale = "r2")
plot(regFitSelect, scale = "adjr2")
plot(regFitSelect, scale = "Cp")
plot(regFitSelect, scale = "bic")
```




```
valuesBackward <- c(names(coef(regFitSelect, id = 6))[-1])
# Exhaustive
regFitSelect <- regsubsets(
  postotalSSRetired~.,
  data=dfDiff,
  method= 'exhaustive',
  nvmax=17)
```

```
## Warning in leaps.setup(x, y, wt = wt, nbest = nbest, nvmax = nvmax,
```

```
## force.in = force.in, : 2 linear dependencies found
```

```
## Reordering variables and trying again:
```

```
regSummary <- summary(regFitSelect)
names(regSummary)
```

```
## [1] "which"  "rsq"    "rss"    "adjr2"  "cp"     "bic"    "outmat" "obj"
```

```
regSummary$rsq
```

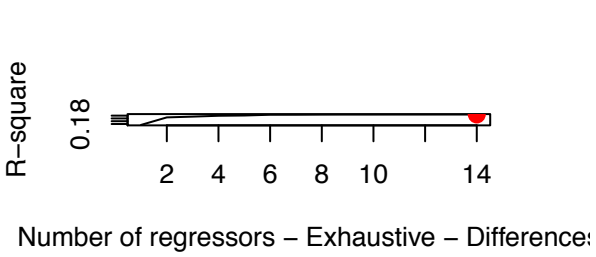
```
##  [1] 0.1731698 0.2273926 0.2330672 0.2391592 0.2410517 0.2463118 0.2466627
##  [8] 0.2474956 0.2478743 0.2479814 0.2480829 0.2481942 0.2482266 0.2482272
```

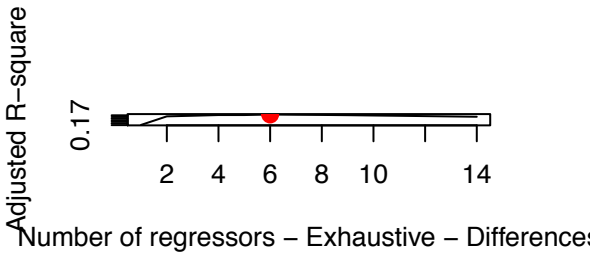
```
regSummary$adjr2
```

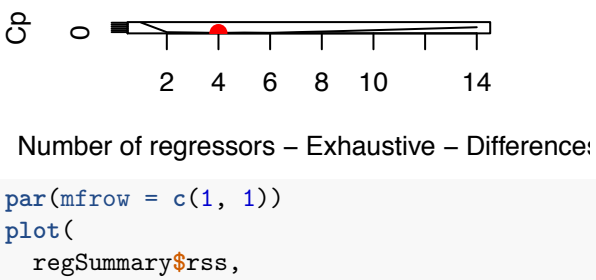
```
##  [1] 0.1711130 0.2235392 0.2273153 0.2315317 0.2315172 0.2349210 0.2333461
##  [8] 0.2322550 0.2306938 0.2288461 0.2269832 0.2251209 0.2231675 0.2211711
```

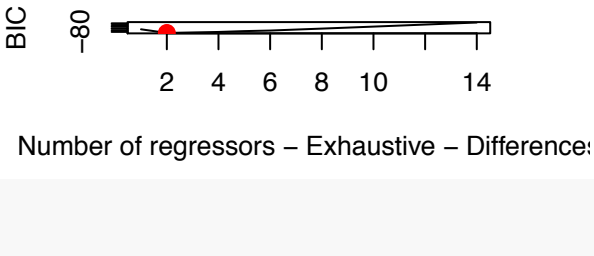
```
par(mfrow=c(2,2))
aRSQ <- which.max(regSummary$rsq)
aARSQ <- which.max(regSummary$adjr2)
aCP <- which.min(regSummary$cp)
aBIC <- which.min(regSummary$bic)
aRSS <- which.min(regSummary$rss)

par(mfrow = c(2, 2))

plot(
  regSummary$rsq,
  xlab = "Number of regressors - Exhaustive - Differences",
  ylab = "R-square",
  type = "l"
)
points(
  aRSQ,
  regSummary$rsq[aRSQ],
  col = "red",
  cex = 2,
  pch = 20
)
text(aRSQ,
     regSummary$rsq[aRSQ],
     labels = aRSQ,
     pos = 1)

plot(
  regSummary$adjr2,
  xlab = "Number of regressors - Exhaustive - Differences",
  ylab = "Adjusted R-square",
  type = "l"
)
points(
  aARSQ,
  regSummary$adjr2[aARSQ],
  col = "red",
  cex = 2,
```

```
  pch = 20
)
text(aARSQ,
     regSummary$adjr2[aARSQ],
     labels = aARSQ,
     pos = 1)

plot(regSummary$cp,
     xlab = "Number of regressors - Exhaustive - Differences",
     ylab = "Cp",
     type = "l")
points(
  aCP,
  regSummary$cp[aCP],
  col = "red",
  cex = 2,
  pch = 20
)
text(aCP,
     regSummary$cp[aCP],
     labels = aCP,
     pos = 3)

plot(
  regSummary$bic,
  xlab = "Number of regressors - Exhaustive - Differences",
  ylab = "BIC",
  type = "l"
)
points(
  aBIC,
  regSummary$bic[aBIC],
  col = "red",
  cex = 2,
  pch = 20
)
text(aBIC,
     regSummary$bic[aBIC],
     labels = aBIC,
     pos = 3)
```

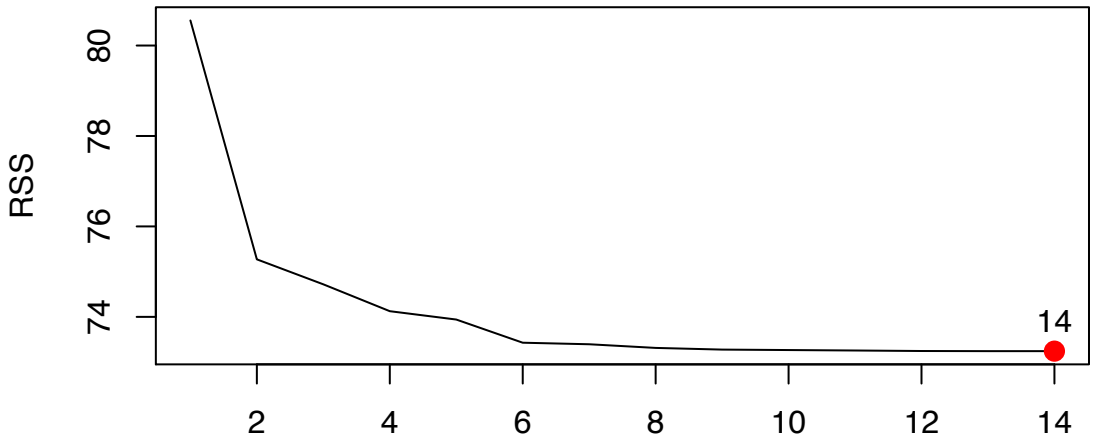






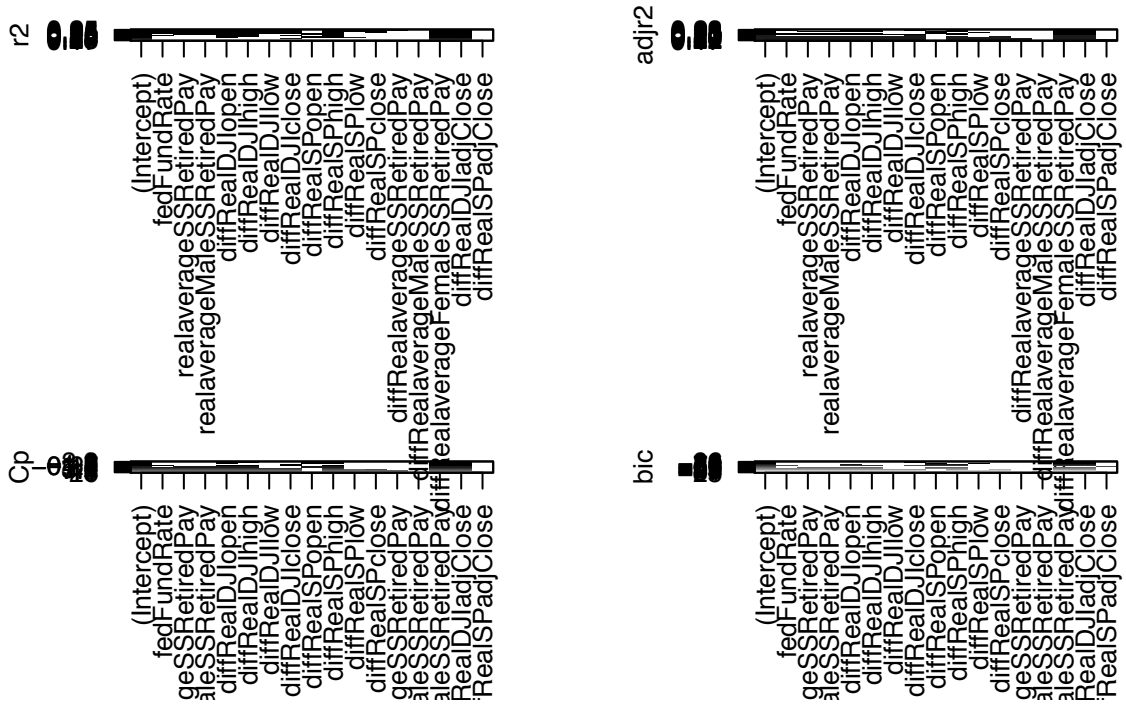



```
par(mfrow = c(1, 1))
plot(
  regSummary$rss,
  xlab = "Number of regressors - Exhaustive - Differences",
  ylab = "RSS",
  type = "l"
)
points(
  aRSS,
  regSummary$rss[aRSS],
  col = "red",
  cex = 2,
  pch = 20
)
text(aRSS,
     regSummary$rss[aRSS],
     labels = aRSS,
     pos = 3)
```



Number of regressors – Exhaustive – Differences

```
par(mfrow = c(2, 2))
plot(regFitSelect, scale = "r2")
plot(regFitSelect, scale = "adjr2")
plot(regFitSelect, scale = "Cp")
plot(regFitSelect, scale = "bic")
```




```
valuesExhaustive <- c(names(coef(regFitSelect, id = 4))[-1])

# Percentages - Fairly low value, not going to use ####
regFitSelect <- regsubsets(
  postotalSSRetired~.,
  data=dfPerc,
  nvmax=17)
```

```
## Warning in leaps.setup(x, y, wt = wt, nbest = nbest, nvmax = nvmax,
```

```
## force.in = force.in, : 2 linear dependencies found
```

```
## Reordering variables and trying again:
```

```
regSummary <- summary(regFitSelect)
names(regSummary)
```

```
## [1] "which"  "rsq"    "rss"    "adjr2"  "cp"     "bic"    "outmat" "obj"
```

```
regSummary$rsq
```

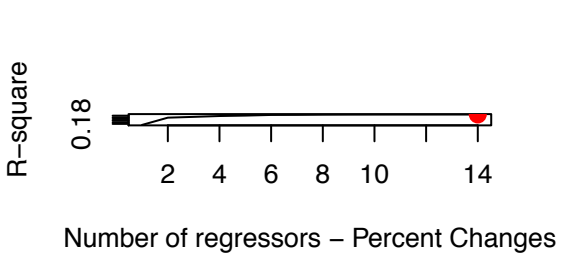
```
##  [1] 0.1734833 0.2178484 0.2228415 0.2279842 0.2305041 0.2344034 0.2348847
##  [8] 0.2361503 0.2366112 0.2368900 0.2370863 0.2371085 0.2371529 0.2371530
```

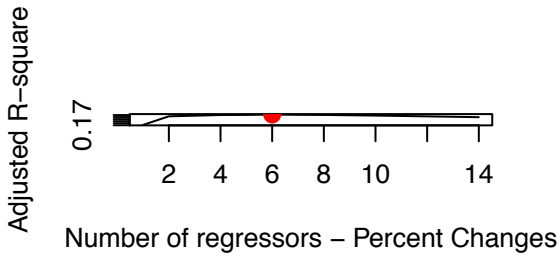
```
regSummary$adjr2
```

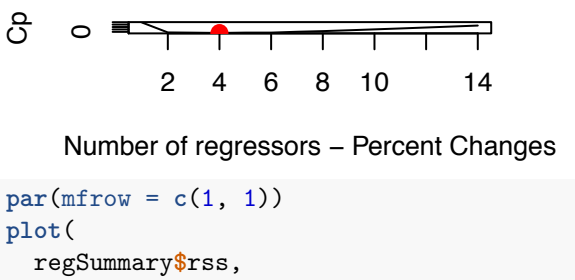
```
##  [1] 0.1714273 0.2139474 0.2170129 0.2202447 0.2208371 0.2228327 0.2213599
##  [8] 0.2206799 0.2191734 0.2174725 0.2156780 0.2136949 0.2117246 0.2096984
```

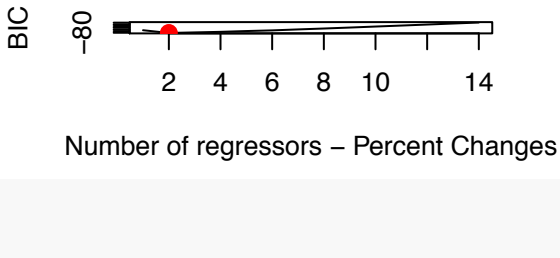
```
par(mfrow=c(2,2))
aRSQ <- which.max(regSummary$rsq)
aARSQ <- which.max(regSummary$adjr2)
aCP <- which.min(regSummary$cp)
aBIC <- which.min(regSummary$bic)
aRSS <- which.min(regSummary$rss)

par(mfrow = c(2, 2))

plot(
  regSummary$rsq,
  xlab = "Number of regressors - Percent Changes",
  ylab = "R-square",
  type = "l"
)
points(
  aRSQ,
  regSummary$rsq[aRSQ],
  col = "red",
  cex = 2,
  pch = 20
)
text(aRSQ,
     regSummary$rsq[aRSQ],
     labels = aRSQ,
     pos = 1)

plot(
  regSummary$adjr2,
  xlab = "Number of regressors - Percent Changes",
  ylab = "Adjusted R-square",
  type = "l"
)
points(
  aARSQ,
  regSummary$adjr2[aARSQ],
  col = "red",
  cex = 2,
```

```
  pch = 20
)
text(aARSQ,
     regSummary$adjr2[aARSQ],
     labels = aARSQ,
     pos = 1)

plot(regSummary$cp,
     xlab = "Number of regressors - Percent Changes",
     ylab = "Cp",
     type = "l")
points(
  aCP,
  regSummary$cp[aCP],
  col = "red",
  cex = 2,
  pch = 20
)
text(aCP,
     regSummary$cp[aCP],
     labels = aCP,
     pos = 3)

plot(
  regSummary$bic,
  xlab = "Number of regressors - Percent Changes",
  ylab = "BIC",
  type = "l"
)
points(
  aBIC,
  regSummary$bic[aBIC],
  col = "red",
  cex = 2,
  pch = 20
)
text(aBIC,
     regSummary$bic[aBIC],
     labels = aBIC,
     pos = 3)
```

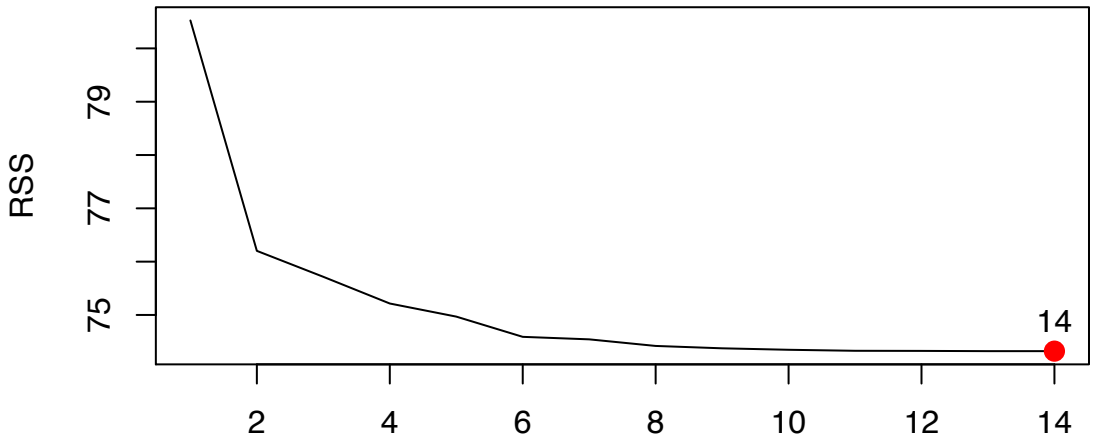




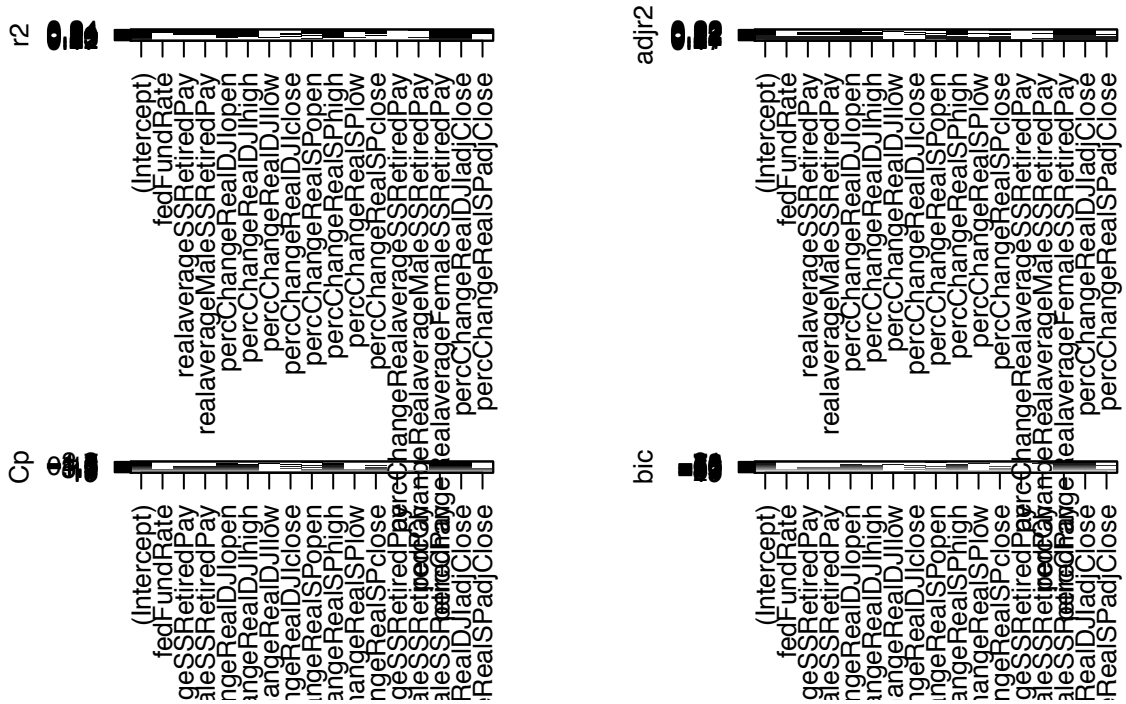





```
par(mfrow = c(1, 1))
plot(
  regSummary$rss,
  xlab = "Number of regressors - Percent Changes",
  ylab = "RSS",
  type = "l"
)
points(
  aRSS,
  regSummary$rss[aRSS],
  col = "red",
  cex = 2,
  pch = 20
)
text(aRSS,
     regSummary$rss[aRSS],
     labels = aRSS,
     pos = 3)
```




```
par(mfrow = c(2, 2))
plot(regFitSelect, scale = "r2")
plot(regFitSelect, scale = "adjr2")
plot(regFitSelect, scale = "Cp")
plot(regFitSelect, scale = "bic")
```




```
# All Data Selection ####
# Exhaustive - All Data
regFitSelect <- regsubsets(
  postotalSSRetired~.,
  data=dfStationary[-1],
  method= 'exhaustive',
  really.big = TRUE,
  nvmax=56)
```

```
## Warning in leaps.setup(x, y, wt = wt, nbest = nbest, nvmax = nvmax,
## force.in = force.in, : 12 linear dependencies found
```

```
## Reordering variables and trying again:
```

```
regSummary <- summary(regFitSelect)
```

```
## Warning in log(vr): NaNs produced
```

```
names(regSummary)
```

```
## [1] "which"  "rsq"    "rss"    "adjr2"  "cp"     "bic"    "outmat" "obj"
```

```
regSummary$rsq
```

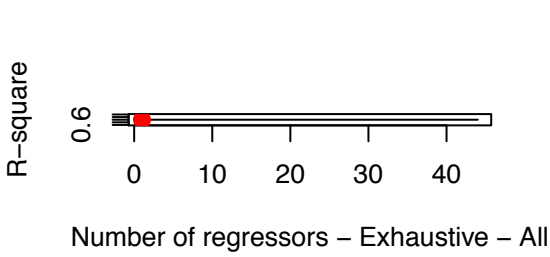
```
##  [1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [36] 1 1 1 1 1 1 1 1 1
```

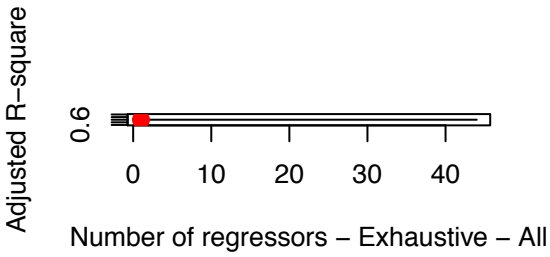
```
regSummary$adjr2
```

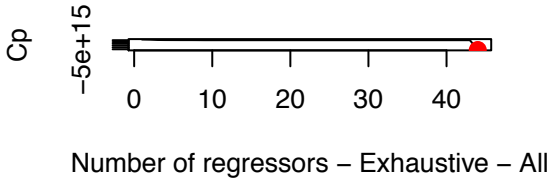
```
##  [1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [36] 1 1 1 1 1 1 1 1 1
```

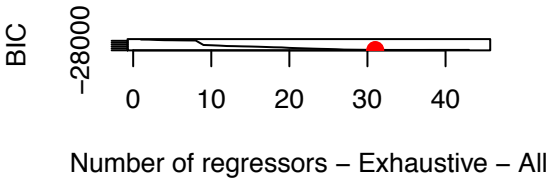
```
par(mfrow=c(2,2))
aRSQ <- which.max(regSummary$rsq)
aARSQ <- which.max(regSummary$adjr2)
aCP <- which.min(regSummary$cp)
aBIC <- which.min(regSummary$bic)
aRSS <- which.min(regSummary$rss)

par(mfrow = c(2, 2))

plot(
  regSummary$rsq,
  xlab = "Number of regressors - Exhaustive - All",
  ylab = "R-square",
  type = "l"
)
points(
  aRSQ,
  regSummary$rsq[aRSQ],
  col = "red",
  cex = 2,
  pch = 20
)
text(aRSQ,
     regSummary$rsq[aRSQ],
     labels = aRSQ,
     pos = 1)

plot(
  regSummary$adjr2,
  xlab = "Number of regressors - Exhaustive - All",
  ylab = "Adjusted R-square",
  type = "l"
)
points(
  aARSQ,
```

```
  regSummary$adjr2[aARSQ],
  col = "red",
  cex = 2,
  pch = 20
)
text(aARSQ,
     regSummary$adjr2[aARSQ],
     labels = aARSQ,
     pos = 1)

plot(regSummary$cp,
     xlab = "Number of regressors - Exhaustive - All",
     ylab = "Cp",
     type = "l")
points(
  aCP,
  regSummary$cp[aCP],
  col = "red",
  cex = 2,
  pch = 20
)
text(aCP,
     regSummary$cp[aCP],
     labels = aCP,
     pos = 3)

plot(
  regSummary$bic,
  xlab = "Number of regressors - Exhaustive - All",
  ylab = "BIC",
  type = "l"
)
points(
  aBIC,
  regSummary$bic[aBIC],
  col = "red",
  cex = 2,
  pch = 20
)
text(aBIC,
     regSummary$bic[aBIC],
     labels = aBIC,
     pos = 3)
```

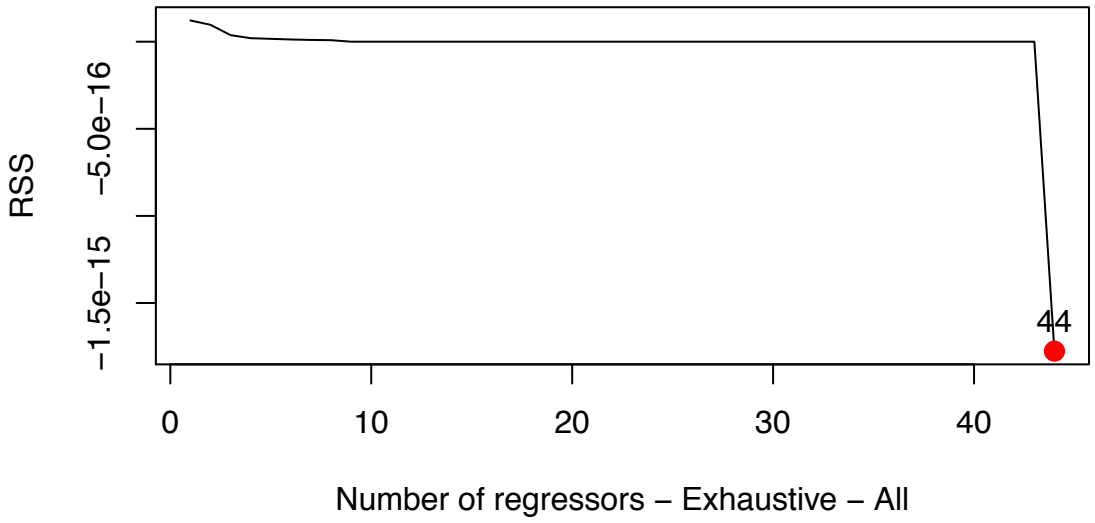









```r
par(mfrow = c(1, 1))
plot(
  regSummary$rss,
  xlab = "Number of regressors - Exhaustive - All",
  ylab = "RSS",
  type = "l"
)
points(
  aRSS,
  regSummary$rss[aRSS],
  col = "red",
  cex = 2,
  pch = 20
)
text(aRSS,
     regSummary$rss[aRSS],
     labels = aRSS,
     pos = 3)
```




```
par(mfrow = c(2, 2))
plot(regFitSelect, scale = "r2")
```

```
## Warning in log(vr): NaNs produced
```

```
plot(regFitSelect, scale = "adjr2")
```

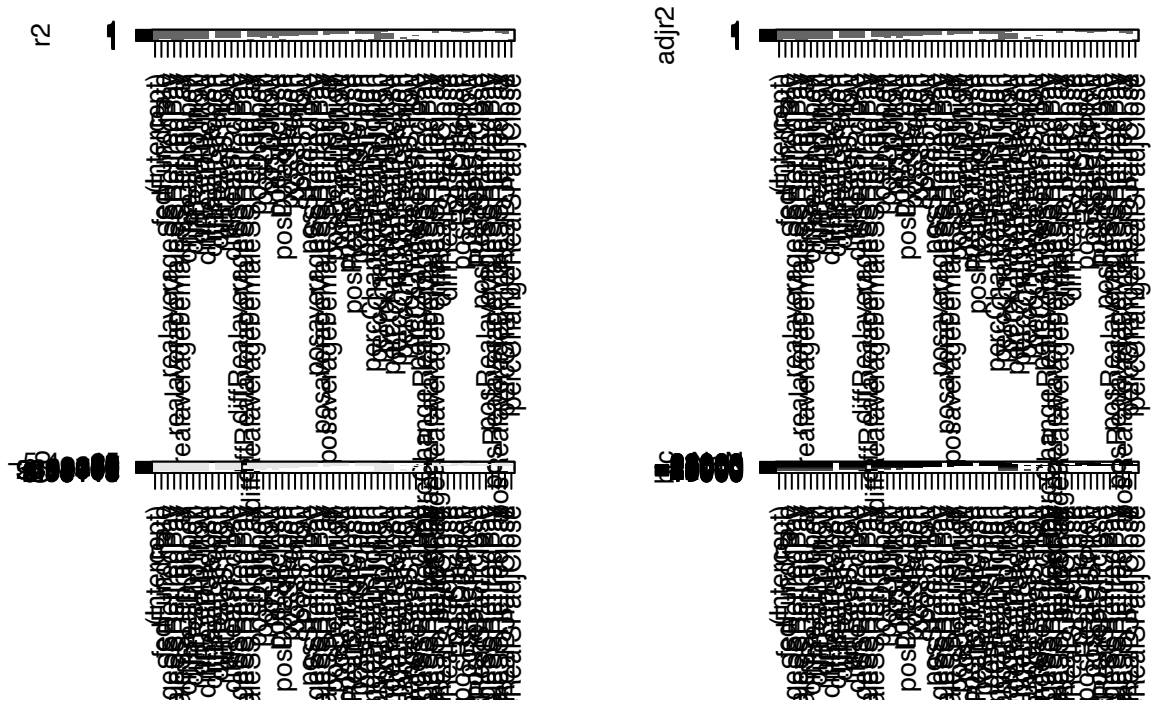
```
## Warning in log(vr): NaNs produced
```

```
plot(regFitSelect, scale = "Cp")
```

```
## Warning in log(vr): NaNs produced
```

```
plot(regFitSelect, scale = "bic")
```

```
## Warning in log(vr): NaNs produced
```



```
valuesStatExhaustive <- c(names(coef(regFitSelect, id = 31))[-1])
```

```
## Warning in log(vr): NaNs produced
```

```
# Backward
regFitSelect <- regsubsets(
  postotalSSRetired~.,
  data=dfStationary[-1],
  method= 'backward',
  really.big = TRUE,
  nvmax=55)
```

```
## Warning in leaps.setup(x, y, wt = wt, nbest = nbest, nvmax = nvmax,
## force.in = force.in, : 12 linear dependencies found
```

```
## Reordering variables and trying again:
```

```
## Warning in rval$lopt[] <- rval$vorder[rval$lopt]: number of items to
## replace is not a multiple of replacement length
```

```
regSummary <- summary(regFitSelect)
names(regSummary)
```

```
## [1] "which"  "rsq"    "rss"    "adjr2"  "cp"     "bic"    "outmat" "obj"
```

```
regSummary$rsq
```

```
##  [1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [36] 1 1 1 1 1 1 1 1 1
```

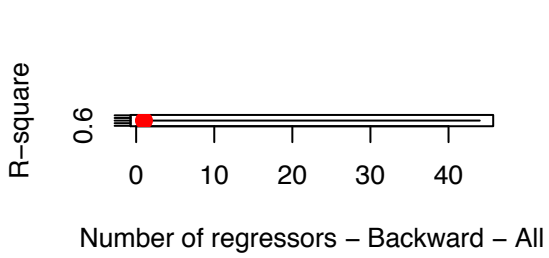
```
regSummary$adjr2
```

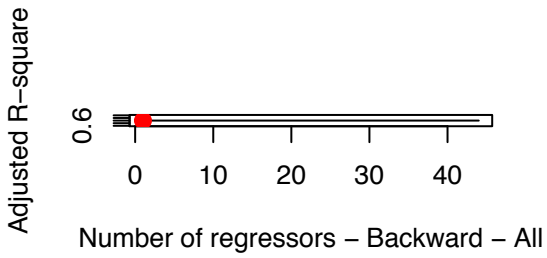
```
##  [1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [36] 1 1 1 1 1 1 1 1 1
```

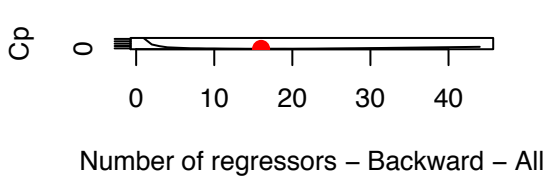
```
par(mfrow=c(2,2))
aRSQ <- which.max(regSummary$rsq)
aARSQ <- which.max(regSummary$adjr2)
aCP <- which.min(regSummary$cp)
aBIC <- which.min(regSummary$bic)
aRSS <- which.min(regSummary$rss)

par(mfrow = c(2, 2))

plot(
  regSummary$rsq,
  xlab = "Number of regressors - Backward - All",
  ylab = "R-square",
  type = "l"
)
points(
  aRSQ,
  regSummary$rsq[aRSQ],
  col = "red",
  cex = 2,
  pch = 20
)
text(aRSQ,
```

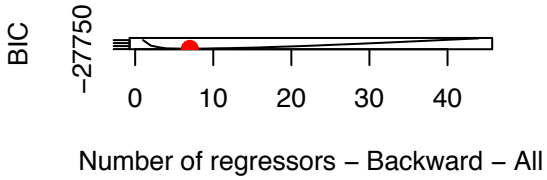
```
     regSummary$rsq[aRSQ],
     labels = aRSQ,
     pos = 1)

plot(
  regSummary$adjr2,
  xlab = "Number of regressors - Backward - All",
  ylab = "Adjusted R-square",
  type = "l"
)
points(
  aARSQ,
  regSummary$adjr2[aARSQ],
  col = "red",
  cex = 2,
  pch = 20
)
text(aARSQ,
     regSummary$adjr2[aARSQ],
     labels = aARSQ,
     pos = 1)

plot(regSummary$cp,
     xlab = "Number of regressors - Backward - All",
     ylab = "Cp",
     type = "l")
points(
  aCP,
  regSummary$cp[aCP],
  col = "red",
  cex = 2,
  pch = 20
)
text(aCP,
     regSummary$cp[aCP],
     labels = aCP,
     pos = 3)

plot(
  regSummary$bic,
  xlab = "Number of regressors - Backward - All",
  ylab = "BIC",
  type = "l"
)
points(
  aBIC,
  regSummary$bic[aBIC],
  col = "red",
  cex = 2,
  pch = 20
)
text(aBIC,
     regSummary$bic[aBIC],
```

```
     labels = aBIC,
     pos = 3)
```

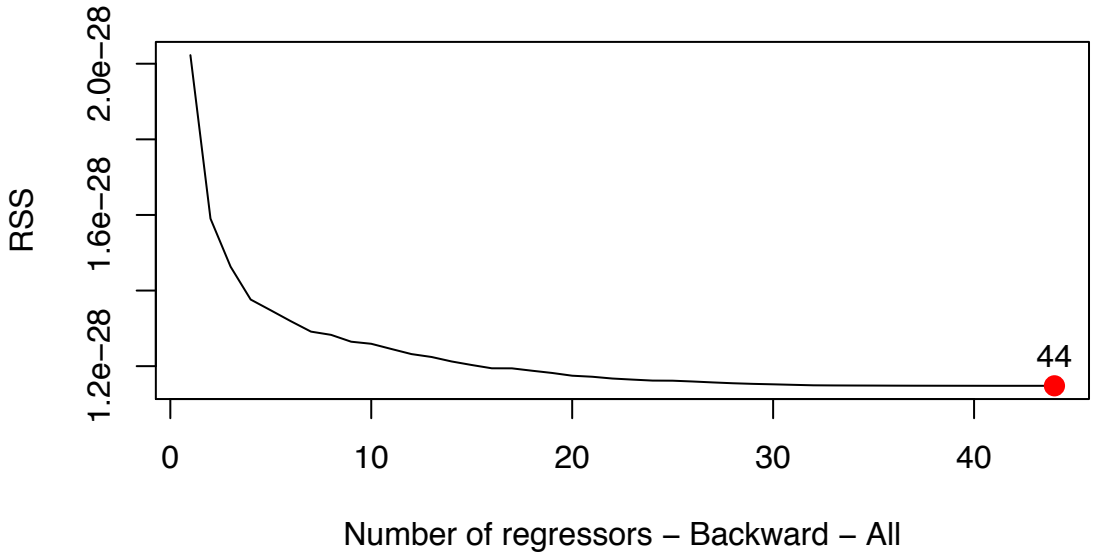




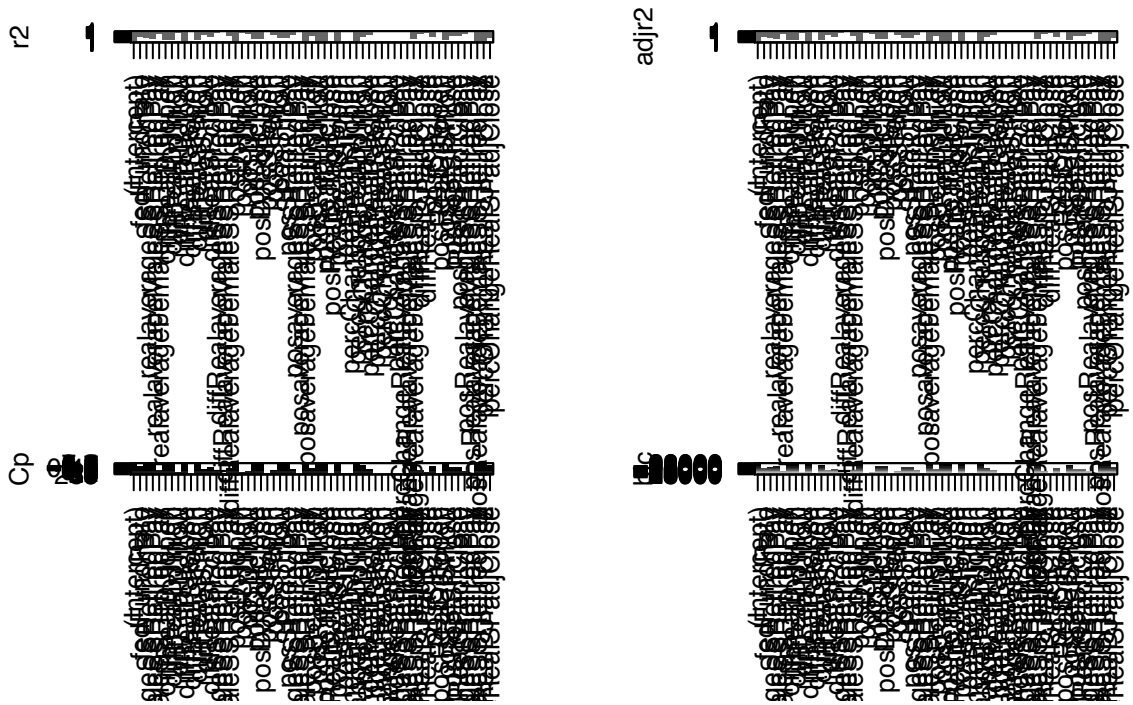





```
par(mfrow = c(1, 1))
plot(
  regSummary$rss,
  xlab = "Number of regressors - Backward - All",
  ylab = "RSS",
  type = "l"
)
points(
  aRSS,
  regSummary$rss[aRSS],
  col = "red",
  cex = 2,
  pch = 20
)
text(aRSS,
     regSummary$rss[aRSS],
     labels = aRSS,
     pos = 3)
```




```
par(mfrow = c(2, 2))
plot(regFitSelect, scale = "r2")
plot(regFitSelect, scale = "adjr2")
plot(regFitSelect, scale = "Cp")
plot(regFitSelect, scale = "bic")
```




```
valuesStatBackward <- c(names(coef(regFitSelect, id = 7))[-1])

# Forward
regFitSelect <- regsubsets(
  postotalSSRetired~.,
  data=dfStationary[-1],
  method= 'forward',
  really.big = TRUE,
```

```
  nvmax=55)
```

```
## Warning in leaps.setup(x, y, wt = wt, nbest = nbest, nvmax = nvmax,
## force.in = force.in, : 12 linear dependencies found
```

```
## Reordering variables and trying again:
```

```
## Warning in rval$lopt[] <- rval$vorder[rval$lopt]: number of items to
## replace is not a multiple of replacement length
```

```
regSummary <- summary(regFitSelect)
names(regSummary)
```

```
## [1] "which"  "rsq"    "rss"    "adjr2"  "cp"     "bic"    "outmat" "obj"
```

```
regSummary$rsq
```

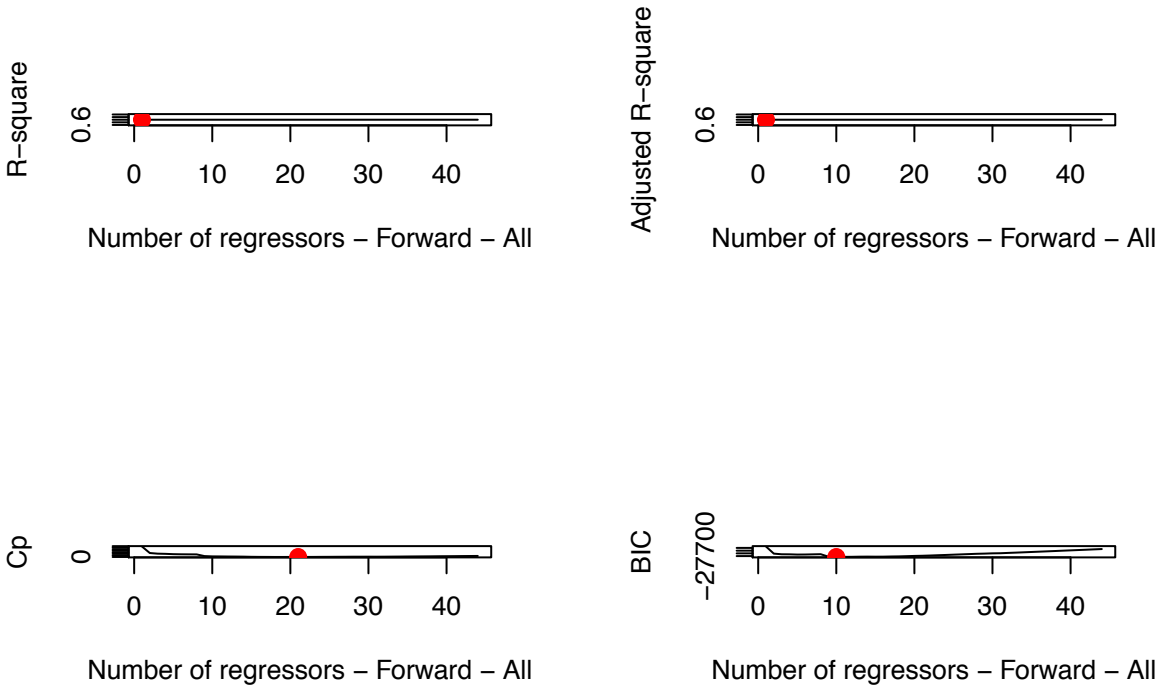
```
##  [1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [36] 1 1 1 1 1 1 1 1 1
```

```
regSummary$adjr2
```

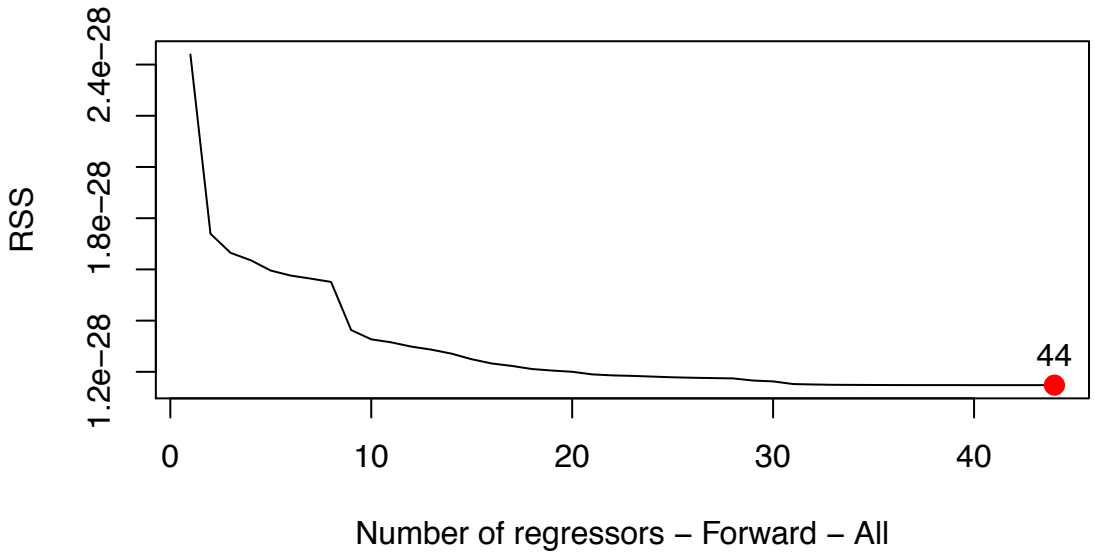
```
##  [1] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
## [36] 1 1 1 1 1 1 1 1 1
```

```
par(mfrow=c(2,2))
aRSQ <- which.max(regSummary$rsq)
aARSQ <- which.max(regSummary$adjr2)
aCP <- which.min(regSummary$cp)
aBIC <- which.min(regSummary$bic)
aRSS <- which.min(regSummary$rss)

par(mfrow = c(2, 2))

plot(
  regSummary$rsq,
  xlab = "Number of regressors - Forward - All",
  ylab = "R-square",
  type = "l"
)
points(
  aRSQ,
  regSummary$rsq[aRSQ],
  col = "red",
  cex = 2,
  pch = 20
)
text(aRSQ,
     regSummary$rsq[aRSQ],
     labels = aRSQ,
     pos = 1)

plot(
  regSummary$adjr2,
  xlab = "Number of regressors - Forward - All",
  ylab = "Adjusted R-square",
  type = "l"
```

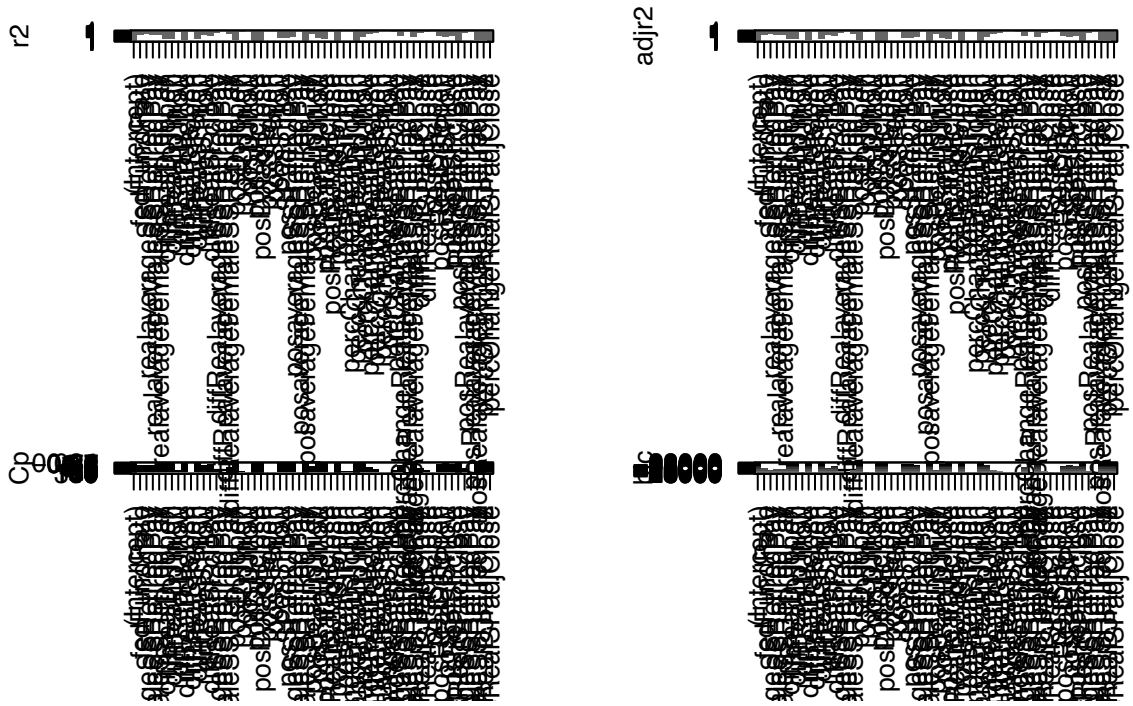
```
)
points(
  aARSQ,
  regSummary$adjr2[aARSQ],
  col = "red",
  cex = 2,
  pch = 20
)
text(aARSQ,
     regSummary$adjr2[aARSQ],
     labels = aARSQ,
     pos = 1)

plot(regSummary$cp,
     xlab = "Number of regressors - Forward - All",
     ylab = "Cp",
     type = "l")
points(
  aCP,
  regSummary$cp[aCP],
  col = "red",
  cex = 2,
  pch = 20
)
text(aCP,
     regSummary$cp[aCP],
     labels = aCP,
     pos = 3)

plot(
  regSummary$bic,
  xlab = "Number of regressors - Forward - All",
  ylab = "BIC",
  type = "l"
)
points(
  aBIC,
  regSummary$bic[aBIC],
  col = "red",
  cex = 2,
  pch = 20
)
text(aBIC,
     regSummary$bic[aBIC],
     labels = aBIC,
     pos = 3)
```




```
par(mfrow = c(1, 1))
plot(
  regSummary$rss,
  xlab = "Number of regressors - Forward - All",
  ylab = "RSS",
  type = "l"
)
points(
  aRSS,
  regSummary$rss[aRSS],
  col = "red",
  cex = 2,
  pch = 20
)
text(aRSS,
     regSummary$rss[aRSS],
     labels = aRSS,
     pos = 3)
```




```
par(mfrow = c(2, 2))
plot(regFitSelect, scale = "r2")
plot(regFitSelect, scale = "adjr2")
plot(regFitSelect, scale = "Cp")
plot(regFitSelect, scale = "bic")
```




```
valuesStatForward <- c(names(coef(regFitSelect, id = 10))[-1])

# Sequential - Too long, don't use
# regFitSelect <- regsubsets(
#   postotalSSRetired~.,
#   data=dfStationary[-1],
#   method= 'seqrep',
#   really.big = TRUE,
```

```
#   nvmax=55)
# regSummary <- summary(regFitSelect)
# names(regSummary)
# regSummary$rsq
# regSummary$adjr2
#
# par(mfrow=c(2,2))
# aRSQ <- which.max(regSummary$rsq)
# aARSQ <- which.max(regSummary$adjr2)
# aCP <- which.min(regSummary$cp)
# aBIC <- which.min(regSummary$bic)
# aRSS <- which.min(regSummary$rss)
#
# par(mfrow = c(2, 2))
#
# plot(
#   regSummary$rsq,
#   xlab = "Number of regressors - Sequential - All",
#   ylab = "R-square",
#   type = "l"
# )
# points(
#   aRSQ,
#   regSummary$rsq[aRSQ],
#   col = "red",
#   cex = 2,
#   pch = 20
# )
# text(aRSQ,
#      regSummary$rsq[aRSQ],
#      labels = aRSQ,
#      pos = 1)
#
# plot(
#   regSummary$adjr2,
#   xlab = "Number of regressors - Sequential - All",
#   ylab = "Adjusted R-square",
#   type = "l"
# )
# points(
#   aARSQ,
#   regSummary$adjr2[aARSQ],
#   col = "red",
#   cex = 2,
#   pch = 20
# )
# text(aARSQ,
#      regSummary$adjr2[aARSQ],
#      labels = aARSQ,
#      pos = 1)
#
# plot(regSummary$cp,
#      xlab = "Number of regressors - Sequential - All",
```

```
#      ylab = "Cp",
#      type = "l")
# points(
#   aCP,
#   regSummary$cp[aCP],
#   col = "red",
#   cex = 2,
#   pch = 20
# )
# text(aCP,
#      regSummary$cp[aCP],
#      labels = aCP,
#      pos = 3)
#
# plot(
#   regSummary$bic,
#   xlab = "Number of regressors - Sequential - All",
#   ylab = "BIC",
#   type = "l"
# )
# points(
#   aBIC,
#   regSummary$bic[aBIC],
#   col = "red",
#   cex = 2,
#   pch = 20
# )
# text(aBIC,
#      regSummary$bic[aBIC],
#      labels = aBIC,
#      pos = 3)
#
# par(mfrow = c(1, 1))
# plot(
#   regSummary$rss,
#   xlab = "Number of regressors - Sequential - All",
#   ylab = "RSS",
#   type = "l"
# )
# points(
#   aRSS,
#   regSummary$rss[aRSS],
#   col = "red",
#   cex = 2,
#   pch = 20
# )
# text(aRSS,
#      regSummary$rss[aRSS],
#      labels = aRSS,
#      pos = 3)
#
# par(mfrow = c(2, 2))
# plot(regFitSelect, scale = "r2")
```

```r
# plot(regFitSelect, scale = "adjr2")
# plot(regFitSelect, scale = "Cp")
# plot(regFitSelect, scale = "bic")
#
# valuesStatSeq <- c(names(coef(regFitSelect, id = 10))[-1])


# Model ####
# Setting train/test split
set.seed(1)
trainSample <- sample(1:nrow(dfStationary), round(nrow(dfStationary)/2), replace = F)
trainData <- dfStationary[trainSample,]
testData <- dfStationary[-trainSample,]

trainX <- trainData[,c(1, 3:58)]
trainY <- trainData[,c(1:2)]
testX <- testData[,c(1, 3:58)]
trainY <- testData[,c(1:2)]

# Logistic ####
#fmlaSeq <- as.formula(paste("postotalSSRetired ~ ", paste(valuesSeqRep, collapse= "+")))
fmlaForward <- as.formula(paste("postotalSSRetired ~ ", paste(valuesStatForward, collapse= "+")))
fmlaBackward <- as.formula(paste("postotalSSRetired ~ ", paste(valuesStatBackward, collapse= "+")))
fmlaExhaust <- as.formula(paste("postotalSSRetired ~ ", paste(valuesStatExhaustive, collapse= "+")))

# Exhaustive Selected model
logFit <- glm(fmlaExhaust,
              family = binomial,
              data = dfStationary)
```

```
## Warning: glm.fit: algorithm did not converge
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```r
summary(logFit, diagnostics=TRUE)
```

```
##
## Call:
## glm(formula = fmlaExhaust, family = binomial, data = dfStationary)
##
## Deviance Residuals:
##       Min         1Q     Median         3Q        Max
## -6.65e-05  -2.10e-08  -2.10e-08   2.10e-08   7.67e-05
##
## Coefficients:
##                                  Estimate Std. Error z value Pr(>|z|)
## (Intercept)                    -3.740e+02  2.429e+06   0.000    1.000
## fedFundRate                    -1.826e+00  5.610e+04   0.000    1.000
## realaverageSSRetiredPay         4.457e-01  3.568e+03   0.000    1.000
## realaverageMaleSSRetiredPay     3.177e-01  1.549e+03   0.000    1.000
## realaverageFemaleSSRetiredPay  -7.487e-01  1.798e+03   0.000    1.000
## diffRealDJIopen                 8.708e-02  2.692e+02   0.000    1.000
## diffRealDJIhigh                -9.536e-02  3.648e+02   0.000    1.000
## diffRealDJIlow                 -9.996e-02  2.308e+02   0.000    1.000
## diffRealDJIclose                1.026e-01  2.825e+02   0.000    1.000
```

```
## diffRealSPhigh                    -5.578e-02  9.441e+02   0.000    1.000
## diffRealSPlow                      9.387e-01  2.054e+03   0.000    1.000
## diffRealSPclose                   -8.024e-01  1.307e+03  -0.001    1.000
## diffRealaverageSSRetiredPay       -2.077e+00  1.769e+03  -0.001    0.999
## diffRealaverageFemaleSSRetiredPay  2.315e+00  2.784e+03   0.001    0.999
## posDJIopen                        -8.073e+00  3.913e+05   0.000    1.000
## posDJIhigh                         8.907e+01  1.074e+05   0.001    0.999
## posDJIlow                         -7.844e+00  1.396e+05   0.000    1.000
## posDJIclose                       -8.014e+01  1.063e+05  -0.001    0.999
## posDJIadjClose                     4.842e+01  8.540e+04   0.001    1.000
## posSPopen                         -9.421e+00  1.519e+05   0.000    1.000
## posSPhigh                         -5.175e+00  7.073e+04   0.000    1.000
## posSPlow                           1.310e+01  3.304e+05   0.000    1.000
## posSPadjClose                     -5.501e+01  8.350e+04  -0.001    0.999
## posaverageSSRetiredPay             1.374e+01  1.007e+05   0.000    1.000
## posaverageFemaleSSRetiredPay      -6.536e+01  2.678e+05   0.000    1.000
## posRealDJIhigh                    -1.473e+00  8.302e+04   0.000    1.000
## posRealDJIlow                     -1.582e+01  1.677e+05   0.000    1.000
## posRealDJIclose                    4.006e+01  6.266e+04   0.001    0.999
## posRealSPopen                      1.578e+02  5.881e+04   0.003    0.998
## posRealSPhigh                      9.575e+01  3.884e+04   0.002    0.998
## percChangeRealDJIopen             -1.179e+03  4.426e+06   0.000    1.000
## percChangeRealDJIhigh              1.768e+03  5.401e+06   0.000    1.000
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 5.4568e+02  on 403  degrees of freedom
## Residual deviance: 4.0544e-08  on 372  degrees of freedom
## AIC: 64
##
## Number of Fisher Scoring iterations: 25
```

```
confint(logFit)
```

```
## Waiting for profiling to be done...
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
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## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

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## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

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## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: algorithm did not converge
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
##                                         2.5 %       97.5 %
## (Intercept)                                NA 252002.49723
## fedFundRate                      -3.983147e+03   4703.37124
## realaverageSSRetiredPay          -2.546648e+02    268.77575
## realaverageMaleSSRetiredPay      -8.577694e+01     77.87345
## realaverageFemaleSSRetiredPay    -9.572672e+01     76.17133
## diffRealDJIopen                  -9.242949e+00      8.84281
## diffRealDJIhigh                  -1.829923e+01     16.61109
## diffRealDJIlow                   -1.504885e+01     16.18882
## diffRealDJIclose                 -1.549278e+01     15.26941
## diffRealSPhigh                   -8.653673e+01     94.17654
## diffRealSPlow                    -9.404891e+01     84.85045
## diffRealSPclose                  -5.913237e+01     52.72950
## diffRealaverageSSRetiredPay      -6.627266e+01     70.74603
## diffRealaverageFemaleSSRetiredPay -1.311546e+02    162.12368
## posDJIopen                       -2.341307e+04  26188.87448
## posDJIhigh                       -3.817369e+03   4672.39169
## posDJIlow                        -6.241243e+03   5712.80741
## posDJIclose                      -8.751598e+03   8591.31205
## posDJIadjClose                   -4.072687e+03   4000.15889
## posSPopen                        -6.995852e+03   8452.16400
## posSPhigh                        -3.335126e+03   3324.77570
## posSPlow                         -1.239607e+04  15042.40911
## posSPadjClose                    -3.586792e+03   3898.06575
## posaverageSSRetiredPay           -3.065634e+03   3148.67282
## posaverageFemaleSSRetiredPay     -1.515226e+04  16011.10232
## posRealDJIhigh                   -6.244430e+03   5933.91934
## posRealDJIlow                    -8.292697e+03   6536.94787
## posRealDJIclose                  -5.699962e+03   6294.56015
## posRealSPopen                    -1.457712e+03   1784.94750
## posRealSPhigh                    -1.023044e+03   1260.88953
## percChangeRealDJIopen            -1.509047e+05 150183.97188
## percChangeRealDJIhigh            -2.276793e+05 227418.56595
```

```
logProbs <- predict(logFit, type = 'response')
logProbs[1:10]
```

```
##            2            3            4            5            6
## 2.220446e-16 1.000000e+00 2.220446e-16 2.220446e-16 2.220446e-16
##            7            8            9           10           11
## 1.000000e+00 4.891675e-10 2.220446e-16 2.220446e-16 1.000000e+00
```

```
logPred <- rep(NA, dim(dfStationary)[2])
logPred[logProbs > 0.5] <- 1
logPred[logProbs < 0.5] = 0

table(logPred)
```

```
## logPred
##   0   1
## 240 164
```

```
table(logPred, dfStationary[,2])
```

```
##
## logPred   0   1
##       0 240   0
##       1   0 164
```

```
mean(logPred == dfStationary[,2])
```

```
## [1] 1
```

```
# Testing Prediction
train <- subset(dfStationary, dfStationary$date < as.Date('2010-04-08'))
test3rdQuart <- subset(dfStationary, dfStationary$date >= as.Date('2010-04-08'))

logFit1 <- glm(fmlaExhaust,
               family = binomial,
               data = train)
```

```
## Warning: glm.fit: algorithm did not converge
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
logProbs1 <- predict(logFit1, test3rdQuart, type = 'response') # setting prediction for the testing set

logPred1 <- rep(NA, dim(train)[2])
logPred1[logProbs1 >= 0.5] = 1
logPred1[logProbs1 < 0.5] = 0

table(logPred1, test3rdQuart$postotalSSRetired)
```

```
##
## logPred1  0  1
##        0 58  5
##        1  1 37
```

```
mean(logPred1 == test3rdQuart$postotalSSRetired)
```

```
## [1] 0.9405941
```

Predicition accuracy is approximately 94% with a train/test split at the 3rd quartile mark of the dates. Positive class prediction: 37/5; 88% Negative Class prediction: 58/1; 98.3%

```r
# Backard Selected model
logFit <- glm(fmlaBackward,
              family = binomial,
              data = dfStationary)
summary(logFit, diagnostics=TRUE)
```

```
##
## Call:
## glm(formula = fmlaBackward, family = binomial, data = dfStationary)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -2.87722  -0.16582  -0.06502   0.14678   2.93502
##
## Coefficients:
##                                  Estimate Std. Error z value Pr(>|z|)
## (Intercept)                       -3.9626     0.8825  -4.490 7.12e-06 ***
## posDJIopen                         1.0262     1.2013   0.854 0.392953
## posaverageFemaleSSRetiredPay      -2.3635     1.2734  -1.856 0.063449 .
## posRealDJIlow                      2.6609     0.7858   3.386 0.000708 ***
## posRealSPopen                      7.6607     0.8839   8.667  < 2e-16 ***
## percChangeRealDJIhigh             31.9746    16.1912   1.975 0.048290 *
## posRealaverageFemaleSSRetiredPay  -1.3853     0.8903  -1.556 0.119728
## percChangeRealDJIadjClose         -1.6774    11.0572  -0.152 0.879418
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 545.68  on 403  degrees of freedom
## Residual deviance: 109.01  on 396  degrees of freedom
## AIC: 125.01
##
## Number of Fisher Scoring iterations: 7
```

```r
confint(logFit)
```

```
## Waiting for profiling to be done...
```

```
##                                      2.5 %     97.5 %
## (Intercept)                       -6.017531 -2.4528686
## posDJIopen                        -1.605622  3.2647653
## posaverageFemaleSSRetiredPay      -4.803546  0.3041155
## posRealDJIlow                      1.316928  4.5526627
## posRealSPopen                      6.175544  9.7417619
## percChangeRealDJIhigh              1.004724 64.9354675
## posRealaverageFemaleSSRetiredPay  -3.220072  0.3118396
## percChangeRealDJIadjClose        -23.719774 19.5259955
```

```r
logProbs <- predict(logFit, type = 'response')
logProbs[1:10]
```

```
##           2           3           4           5           6           7
## 0.004460318 0.974363975 0.011132525 0.002320106 0.001827138 0.996462622
##           8           9          10          11
## 0.014180239 0.012967488 0.002486971 0.955606920
```

```
logPred <- rep(0, dim(dfStationary)[2])
logPred[logProbs >= 0.5] <- 1
logPred[logProbs < 0.5] <- 0

table(logPred)
```

```
## logPred
##   0   1
## 235 169
```

```
table(logPred, dfStationary[,2])
```

```
##
## logPred   0   1
##       0 229   6
##       1  11 158
```

```
mean(logPred == dfStationary[,2])
```

```
## [1] 0.9579208
```

```
# Testing Prediction
train <- subset(dfStationary, dfStationary$date < as.Date('2010-04-08'))
test3rdQuart <- subset(dfStationary, dfStationary$date >= as.Date('2010-04-08'))

logFit1 <- glm(fmlaBackward,
               family = binomial,
               data = train)
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
logProbs1 <- predict(logFit1, test3rdQuart, type = 'response') # setting prediction for the testing set

logPred1 <- rep(NA, dim(train)[2])
logPred1[logProbs1 >= 0.5] = 1
logPred1[logProbs1 < 0.5] = 0

table(logPred1, test3rdQuart$postotalSSRetired)
```

```
##
## logPred1  0  1
##        0 53  3
##        1  6 39
```

```
mean(logPred1 == test3rdQuart$postotalSSRetired)
```

```
## [1] 0.9108911
```

Predicition accuracy is approximately 91% with a train/test split at the 3rd quartile mark of the dates. Positive class prediction: 39/3; 92.8% Negative Class prediction: 53/6; 89.8%

```
# Forward Selected model - Best Model
logFit <- glm(fmlaForward,
              family = binomial,
              data = dfStationary)
summary(logFit, diagnostics=TRUE)
```

```
##
## Call:
```

```
## glm(formula = fmlaForward, family = binomial, data = dfStationary)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -2.99923  -0.14379  -0.04962   0.11169   2.37220
##
## Coefficients:
##                                 Estimate Std. Error z value Pr(>|z|)
## (Intercept)                      -5.6618     1.1726  -4.828 1.38e-06 ***
## posDJIopen                        0.9537     1.1957   0.798   0.4251
## posDJIclose                       1.6413     0.9356   1.754   0.0794 .
## posDJIadjClose                    1.5744     0.7340   2.145   0.0320 *
## posaverageFemaleSSRetiredPay     -2.0477     1.2833  -1.596   0.1106
## posRealSPopen                     8.2310     1.0236   8.041 8.90e-16 ***
## percChangeRealDJIhigh            16.2008    16.7530   0.967   0.3335
## posRealSPadjClose                 1.7653     0.9697   1.821   0.0687 .
## posRealaverageFemaleSSRetiredPay -1.7625     0.9146  -1.927   0.0540 .
## percChangeRealDJIadjClose        14.8932    25.1203   0.593   0.5533
## percChangeRealSPadjClose         -8.7965    24.4464  -0.360   0.7190
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 545.68  on 403  degrees of freedom
## Residual deviance: 100.23  on 393  degrees of freedom
## AIC: 122.23
##
## Number of Fisher Scoring iterations: 8
```

```
confint(logFit)
```

```
## Waiting for profiling to be done...
```

```
##                                       2.5 %      97.5 %
## (Intercept)                      -8.27635780 -3.59826504
## posDJIopen                       -1.69547870  3.16467729
## posDJIclose                      -0.01687701  3.75337299
## posDJIadjClose                    0.17531940  3.08661477
## posaverageFemaleSSRetiredPay     -4.52081970  0.63960043
## posRealSPopen                     6.52290072 10.62645641
## percChangeRealDJIhigh           -15.07388172 50.55178323
## posRealSPadjClose                 0.02995487  3.92774639
## posRealaverageFemaleSSRetiredPay -3.65209872 -0.02327801
## percChangeRealDJIadjClose       -34.39831275 64.32052832
## percChangeRealSPadjClose        -56.69350534 38.92640439
```

```
logProbs <- predict(logFit, type = 'response')
logProbs[1:10]
```

```
##            2            3            4            5            6
## 0.0009492249 0.9960759029 0.0024526558 0.0003439175 0.0380386988
##            7            8            9           10           11
## 0.9981604947 0.0134793360 0.0036100750 0.0019040660 0.9981081640
```

```
logPred <- rep(NA, dim(dfStationary)[2])
logPred[logProbs > 0.5] <- 1
logPred[logProbs < 0.5] = 0


table(logPred)
```

```
## logPred
##   0   1
## 236 168
```

```
table(logPred, dfStationary[,2])
```

```
##
## logPred   0   1
##       0 230   6
##       1  10 158
```

```
mean(logPred == dfStationary[,2])
```

```
## [1] 0.960396
```

```
# Testing Prediction
train <- subset(dfStationary, dfStationary$date < as.Date('2010-04-08'))
test3rdQuart <- subset(dfStationary, dfStationary$date >= as.Date('2010-04-08'))

logFit1 <- glm(fmlaForward,
               family = binomial,
               data = train)
logProbs1 <- predict(logFit1, test3rdQuart, type = 'response') # setting prediction for the testing set

logPred1 <- rep(NA, dim(train)[2])
logPred1[logProbs1 >= 0.5] = 1
logPred1[logProbs1 < 0.5] = 0

table(logPred1, test3rdQuart$postotalSSRetired)
```

```
##
## logPred1  0  1
##        0 54  2
##        1  5 40
```

```
mean(logPred1 == test3rdQuart$postotalSSRetired)
```

```
## [1] 0.9306931
```

Predicition accuracy is approximately 93% with a train/test split at the 3rd quartile mark of the dates. Positive class prediction: 40/2; 95% Negative Class prediction: 54/5; 91.5% This is the best model.

```
# Check only those with good statistical significance
logFit <- glm(postotalSSRetired ~ posDJIclose + posDJIadjClose + posRealSPopen  + posRealSPadjClose + po
              family = binomial,
              data = dfStationary)
summary(logFit, diagnostics=TRUE)
```

```
##
## Call:
## glm(formula = postotalSSRetired ~ posDJIclose + posDJIadjClose +
```

```
##     posRealSPopen + posRealSPadjClose + posRealaverageFemaleSSRetiredPay,
##     family = binomial, data = dfStationary)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -3.06535  -0.13360  -0.05683   0.13530   2.48559
##
## Coefficients:
##                                  Estimate Std. Error z value Pr(>|z|)
## (Intercept)                       -6.4278     1.0182  -6.313 2.74e-10 ***
## posDJIclose                        1.5484     0.9552   1.621  0.10501
## posDJIadjClose                     1.7133     0.6531   2.623  0.00871 **
## posRealSPopen                      7.7315     0.9048   8.545  < 2e-16 ***
## posRealSPadjClose                  1.8369     0.9750   1.884  0.05956 .
## posRealaverageFemaleSSRetiredPay  -1.0678     0.6117  -1.746  0.08090 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 545.68  on 403  degrees of freedom
## Residual deviance: 104.59  on 398  degrees of freedom
## AIC: 116.59
##
## Number of Fisher Scoring iterations: 7
```

```
confint(logFit)
```

```
## Waiting for profiling to be done...
```

```
##                                      2.5 %     97.5 %
## (Intercept)                     -8.7614151 -4.6808299
## posDJIclose                     -0.1244147  3.6921985
## posDJIadjClose                   0.4920897  3.0838235
## posRealSPopen                    6.2167780  9.8785185
## posRealSPadjClose                0.1224186  4.0102672
## posRealaverageFemaleSSRetiredPay -2.3042923  0.1182437
```

```
logProbs <- predict(logFit, type = 'response')
logProbs[1:10]
```

```
##            2            3            4            5            6
## 0.0016134028 0.9897014801 0.0016134028 0.0005552172 0.0834023010
##            7            8            9           10           11
## 0.9952008178 0.0088844333 0.0016134028 0.0034749324 0.9952008178
```

```
logPred <- rep(0, dim(dfStationary)[2])
logPred[logProbs > 0.5] <- 1
table(logPred)
```

```
## logPred
##   0   1
##  34 169
```

```
table(logPred, dfStationary[,2])
```

```
##
```

```
## logPred   0   1
##       0  33   1
##       1  11 158
```

```
mean(logPred == dfStationary[,2])
```

```
## [1] NA
```

```
# Testing Prediction
train <- subset(dfStationary, dfStationary$date < as.Date('2010-04-08'))
test3rdQuart <- subset(dfStationary, dfStationary$date >= as.Date('2010-04-08'))

logFit1 <- glm(postotalSSRetired ~ posDJIclose + posDJIadjClose + posRealSPopen  + posRealSPadjClose + p
               family = binomial,
               data = train)
logProbs1 <- predict(logFit1, test3rdQuart, type = 'response') # setting prediction for the testing set

logPred1 <- rep(NA, dim(train)[2])
logPred1[logProbs1 >= 0.5] = 1
logPred1[logProbs1 < 0.5] = 0

table(logPred1, test3rdQuart$postotalSSRetired)
```

```
##
## logPred1  0  1
##        0 54  2
##        1  5 40
```

```
mean(logPred1 == test3rdQuart$postotalSSRetired)
```

```
## [1] 0.9306931
```

Predicition accuracy is approximately 93% with a train/test split at the 3rd quartile mark of the dates. Positive class prediction: 40/2; 95% Negative Class prediction: 54/5; 91.5% There is no change, but we have reduced the number of regressors by half, from 10 to 5.

```
# Subset this further by selecting only those with statistical significance from this model
logFit <- glm(postotalSSRetired ~  posDJIadjClose + posRealSPopen  + posRealSPadjClose + posRealaverageF
               family = binomial,
               data = dfStationary)
summary(logFit, diagnostics=TRUE)
```

```
##
## Call:
## glm(formula = postotalSSRetired ~ posDJIadjClose + posRealSPopen +
##     posRealSPadjClose + posRealaverageFemaleSSRetiredPay, family = binomial,
##     data = dfStationary)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -2.95006  -0.14982  -0.06188   0.16107   2.60136
##
## Coefficients:
##                                 Estimate Std. Error z value Pr(>|z|)
## (Intercept)                      -6.2573     0.9852  -6.351 2.14e-10 ***
## posDJIadjClose                    1.9282     0.6514   2.960 0.003077 **
## posRealSPopen                     7.6875     0.8767   8.768  < 2e-16 ***
```

```
## posRealSPadjClose                   2.9082     0.7852   3.704 0.000212 ***
## posRealaverageFemaleSSRetiredPay  -1.1351     0.6097  -1.862 0.062626 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 545.68  on 403  degrees of freedom
## Residual deviance: 107.82  on 399  degrees of freedom
## AIC: 117.82
##
## Number of Fisher Scoring iterations: 7
```

```
confint(logFit)
```

```
## Waiting for profiling to be done...
```

```
##                                       2.5 %      97.5 %
## (Intercept)                      -8.4911635 -4.55434311
## posDJIadjClose                    0.7088555  3.29449737
## posRealSPopen                     6.2092825  9.74742204
## posRealSPadjClose                 1.5701719  4.80067290
## posRealaverageFemaleSSRetiredPay -2.3670651  0.04756246
```

```
logProbs <- predict(logFit, type = 'response')
logProbs[1:10]
```

```
##            2            3            4            5            6
## 0.0019128306 0.9663798429 0.0019128306 0.0006155424 0.0720274306
##            7            8            9           10           11
## 0.9941271498 0.0130086210 0.0019128306 0.0111603749 0.9941271498
```

```
logPred <- rep(0, dim(dfStationary)[2])
logPred[logProbs > 0.5] <- 1
table(logPred)
```

```
## logPred
##   0   1
##  34 169
```

```
table(logPred, dfStationary[,2])
```

```
##
## logPred   0   1
##       0  33   1
##       1  11 158
```

```
mean(logPred == dfStationary[,2])
```

```
## [1] NA
```

```
# Testing Prediction
train <- subset(dfStationary, dfStationary$date < as.Date('2010-04-08'))
test3rdQuart <- subset(dfStationary, dfStationary$date >= as.Date('2010-04-08'))

logFit1 <- glm(postotalSSRetired ~ posDJIadjClose + posRealSPopen  + posRealSPadjClose + posRealaverageF
               family = binomial,
               data = train)
logProbs1 <- predict(logFit1, test3rdQuart, type = 'response') # setting prediction for the testing set
```

```
logPred1 <- rep(NA, dim(train)[2])
logPred1[logProbs1 >= 0.5] = 1
logPred1[logProbs1 < 0.5] = 0

table(logPred1, test3rdQuart$postotalSSRetired)
```

```
##
## logPred1  0  1
##        0 54  2
##        1  5 40
```

```
mean(logPred1 == test3rdQuart$postotalSSRetired)
```

```
## [1] 0.9306931
```

Predicition accuracy is approximately 93% with a train/test split at the 3rd quartile mark of the dates. Positive class prediction: 40/2; 95% Negative Class prediction: 54/5; 91.5% There is no change, but we have reduced the number of regressors from 5 to 4.

```
# Subset once more based on those with statistical significance better than 0.05
logFit <- glm(postotalSSRetired ~  posDJIadjClose + posRealSPopen  + posRealSPadjClose,
              family = binomial,
              data = dfStationary)
summary(logFit, diagnostics=TRUE)
```

```
##
## Call:
## glm(formula = postotalSSRetired ~ posDJIadjClose + posRealSPopen +
##     posRealSPadjClose, family = binomial, data = dfStationary)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.7339  -0.1139  -0.0556   0.2196   2.7439
##
## Coefficients:
##                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)        -6.4717     0.9659  -6.700 2.08e-11 ***
## posDJIadjClose      1.4368     0.5820   2.469 0.013560 *
## posRealSPopen       7.4540     0.8341   8.936  < 2e-16 ***
## posRealSPadjClose   2.7306     0.7696   3.548 0.000388 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 545.68  on 403  degrees of freedom
## Residual deviance: 111.36  on 400  degrees of freedom
## AIC: 119.36
##
## Number of Fisher Scoring iterations: 7
```

```
confint(logFit)
```

```
## Waiting for profiling to be done...
```

```
##                       2.5 %    97.5 %
```

```
## (Intercept)       -8.6700560 -4.804306
## posDJIadjClose     0.3477433  2.669307
## posRealSPopen      6.0508612  9.436552
## posRealSPadjClose  1.4244555  4.600410
```

```
logProbs <- predict(logFit, type = 'response')
logProbs[1:10]
```

```
##           2           3           4           5           6           7
## 0.001544224 0.918271072 0.001544224 0.001544224 0.090771223 0.994232497
##           8           9          10          11
## 0.006464772 0.001544224 0.023179357 0.994232497
```

```
logPred <- rep(0, dim(dfStationary)[2])
logPred[logProbs > 0.5] <- 1
table(logPred)
```

```
## logPred
##   0   1
##  34 169
```

```
table(logPred, dfStationary[,2])
```

```
##
## logPred   0   1
##       0  33   1
##       1  11 158
```

```
mean(logPred == dfStationary[,2])
```

```
## [1] NA
```

```
# Testing Prediction
train <- subset(dfStationary, dfStationary$date < as.Date('2010-04-08'))
test3rdQuart <- subset(dfStationary, dfStationary$date >= as.Date('2010-04-08'))

logFit1 <- glm(postotalSSRetired ~ posDJIadjClose + posRealSPopen  + posRealSPadjClose,
               family = binomial,
               data = train)
logProbs1 <- predict(logFit1, test3rdQuart, type = 'response') # setting prediction for the testing set

logPred1 <- rep(NA, dim(train)[2])
logPred1[logProbs1 >= 0.5] = 1
logPred1[logProbs1 < 0.5] = 0

table(logPred1, test3rdQuart$postotalSSRetired)
```

```
##
## logPred1  0  1
##        0 54  2
##        1  5 40
```

```
mean(logPred1 == test3rdQuart$postotalSSRetired)
```

```
## [1] 0.9306931
```

Predicition accuracy is approximately 93% with a train/test split at the 3rd quartile mark of the dates. Positive class prediction: 40/2; 95% Negative Class prediction: 54/5; 91.5% There is no change, but we have reduced the number of regressors from 4 to 3. All factors are statisticall siginificant.

```
predForm <- as.formula(postotalSSRetired ~ posDJIadjClose + posRealSPopen  + posRealSPadjClose)
```

Switch up the train/test split to account for about 80% of the data

```
train80 <- subset(dfStationary, dfStationary$date < as.Date(dfStationary$date[round(nrow(dfStationary)
test20 <- subset(dfStationary, dfStationary$date >= as.Date(dfStationary$date[round(nrow(dfStationary)

logFit <- glm(predForm,
              family = binomial,
              data = dfStationary)
summary(logFit, diagnostics=TRUE)
```

```
##
## Call:
## glm(formula = predForm, family = binomial, data = dfStationary)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.7339  -0.1139  -0.0556   0.2196   2.7439
##
## Coefficients:
##                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)        -6.4717     0.9659  -6.700 2.08e-11 ***
## posDJIadjClose      1.4368     0.5820   2.469 0.013560 *
## posRealSPopen       7.4540     0.8341   8.936  < 2e-16 ***
## posRealSPadjClose   2.7306     0.7696   3.548 0.000388 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 545.68  on 403  degrees of freedom
## Residual deviance: 111.36  on 400  degrees of freedom
## AIC: 119.36
##
## Number of Fisher Scoring iterations: 7
```

```
confint(logFit)
```

```
## Waiting for profiling to be done...
```

```
##                       2.5 %    97.5 %
## (Intercept)       -8.6700560 -4.804306
## posDJIadjClose     0.3477433  2.669307
## posRealSPopen      6.0508612  9.436552
## posRealSPadjClose  1.4244555  4.600410
```

```
logProbs <- predict(logFit, type = 'response')
logProbs[1:10]
```

```
##           2           3           4           5           6           7
## 0.001544224 0.918271072 0.001544224 0.001544224 0.090771223 0.994232497
##           8           9          10          11
## 0.006464772 0.001544224 0.023179357 0.994232497
```

```
logPred <- rep(0, dim(dfStationary)[2])
logPred[logProbs > 0.5] <- 1
```

```
table(logPred)
```

```
## logPred
##   0   1
##  34 169
```

```
table(logPred, dfStationary[,2])
```

```
##
## logPred   0   1
##       0  33   1
##       1  11 158
```

```
mean(logPred == dfStationary[,2])
```

```
## [1] NA
```

```
# Testing Prediction
logFit1 <- glm(predForm,
               family = binomial,
               data = train80)
logProbs1 <- predict(logFit1, test20, type = 'response') # setting prediction for the testing set FROM

logPred1 <- rep(NA, dim(train80)[2])
logPred1[logProbs1 >= 0.5] = 1
logPred1[logProbs1 < 0.5] = 0

table(logPred1, test20$postotalSSRetired)
```

```
##
## logPred1  0  1
##        0 43  1
##        1  3 35
```

```
mean(logPred1 == test20$postotalSSRetired)
```

```
## [1] 0.9512195
```

```
# Tests for exogeneity ####
```

Predicition accuracy is approximately 95% with a train/test split of 80/20. Positive class prediction: 43/3; 93.4% Negative Class prediction: 35/36; 97.2%. Let's check how probit fits the data

```
# Probit ####
```

As the variable of interest is generated from the differences in Total SS Recipients, which appears about normally distributed, a probit model may be more appropriate.

```
probFit <- glm(predForm,
               family = binomial(link = "probit"),
               data = dfStationary)
summary(probFit, diagnostics=TRUE)
```

```
##
## Call:
## glm(formula = predForm, family = binomial(link = "probit"), data = dfStationary)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
```

```
## -2.67493  -0.09598  -0.02853   0.23807   2.79822
##
## Coefficients:
##                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)        -3.3480     0.4453  -7.519 5.50e-14 ***
## posDJIadjClose      0.7431     0.2886   2.575     0.01 *
## posRealSPopen       3.9669     0.3551  11.170  < 2e-16 ***
## posRealSPadjClose   1.2930     0.3300   3.918 8.91e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 545.68  on 403  degrees of freedom
## Residual deviance: 110.30  on 400  degrees of freedom
## AIC: 118.3
##
## Number of Fisher Scoring iterations: 8
```

```
confint(probFit)
```

```
## Waiting for profiling to be done...
```

```
##                        2.5 %    97.5 %
## (Intercept)       -4.3500091 -2.558896
## posDJIadjClose     0.1993879  1.337637
## posRealSPopen      3.3429631  4.773703
## posRealSPadjClose  0.7017883  2.036072
```

```
probProbs <- predict(probFit, type = 'response')
probProbs[1:10]
```

```
##            2            3            4            5            6
## 0.0004069635 0.9134087643 0.0004069635 0.0004069635 0.0947859691
##            7            8            9           10           11
## 0.9960355244 0.0045953487 0.0004069635 0.0199403179 0.9960355244
```

```
probPred <- rep(NA, dim(dfStationary)[2])
probPred[probProbs >= 0.5] <- 1
probPred[probProbs < 0.5] <- 0

table(probPred)
```

```
## probPred
##   0   1
## 235 169
```

```
table(probPred, dfStationary$postotalSSRetired)
```

```
##
## probPred   0   1
##        0 229   6
##        1  11 158
```

```
mean(probPred == dfStationary$postotalSSRetired)
```

```
## [1] 0.9579208
```

```r
# Testing Prediction
probFit1 <- glm(predForm,
                family = binomial(link = "probit"),
                data = train)
probProbs1 <- predict(probFit1, test3rdQuart, type = 'response') # setting prediction for the testing s

probPred1 <- rep(0, dim(train)[2])
probPred1[probProbs1 >= 0.5] <- 1
probPred1[probProbs1 < 0.5] <- 0

table(probPred1, test3rdQuart$postotalSSRetired)
```

```
##
## probPred1  0  1
##         0 54  2
##         1  5 40
```

```r
mean(probPred1 == test3rdQuart$postotalSSRetired)
```

```
## [1] 0.9306931
```

Predicition accuracy is approximately 93% with a train/test split at the 3rd quartile mark of the dates. Positive class prediction: 40/2; 95.2% Negative Class prediction: 54/5; 91.5%.

```r
# Test it at the 80/20 split
train80 <- subset(dfStationary, dfStationary$date < as.Date(dfStationary$date[round(nrow(dfStationary)
test20 <- subset(dfStationary, dfStationary$date >= as.Date(dfStationary$date[round(nrow(dfStationary)

probFit1 <- glm(predForm,
                family = binomial(link = "probit"),
                data = train)
probProbs1 <- predict(probFit1, test20, type = 'response') # setting prediction for the testing set FRO

probPred1 <- rep(0, dim(train80)[2])
probPred1[probProbs1 >= 0.5] <- 1
probPred1[probProbs1 < 0.5] <- 0

table(probPred1, test20$postotalSSRetired)
```

```
##
## probPred1  0  1
##         0 43  1
##         1  3 35
```

```r
mean(probPred1 == test20$postotalSSRetired)
```

```
## [1] 0.9512195
```

Predicition accuracy is approximately 95% with a train/test split of 80/20. Positive class prediction: 43/3; 93.4% Negative Class prediction: 35/1; 97.2% This prediction accuracy is the same as the logit model

```r
# XGboost ####
# train <- as.matrix(train)
# test3rdQuart <- as.matrix(test3rdQuart)
# bstSparse <- xgboost(data = train[-c(1:2)],
#                      label = train[2],
#                      max.depth = 2,
```

```
#                       eta = 1,
#                       nthread = 2,
#                       nrounds = 2,
#                       objective = "binary:logistic")
```