Final Project

Joan Zhang

Sunday, November 15, 2015

Objective : Make a prediction for the direction of Dow Jones Average (DJA). The dataset is based upon daily closing value of the DJA from year 2000-2014 taken from yahoo finance. First the dataset is split into two sample training: 2000 -2006 and 2007 - 2012, then use year 2013 for validation and year 2014 for forecasting

```
library(tseries)
```

```
## Warning: package 'tseries' was built under R version 3.2.5
```

```
library(forecast)
```

```
## Warning: package 'forecast' was built under R version 3.2.5
```

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

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

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

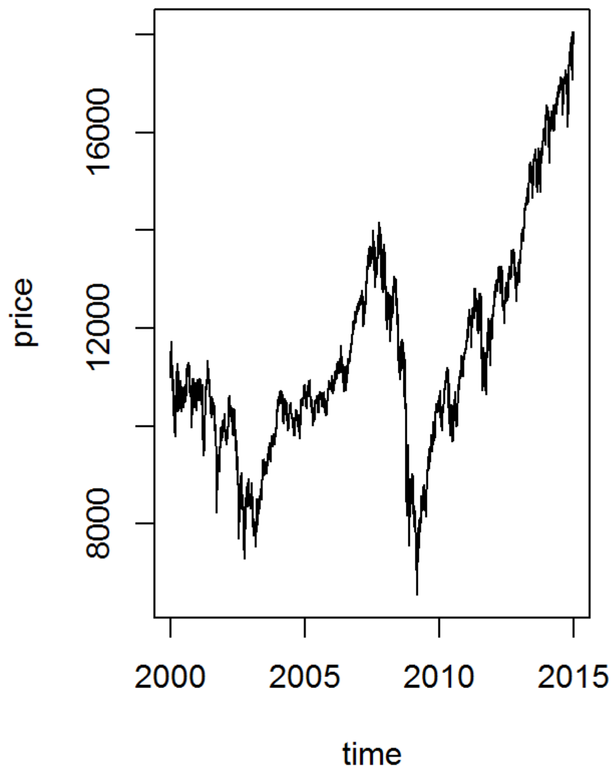
```
## Loading required package: timeDate
```

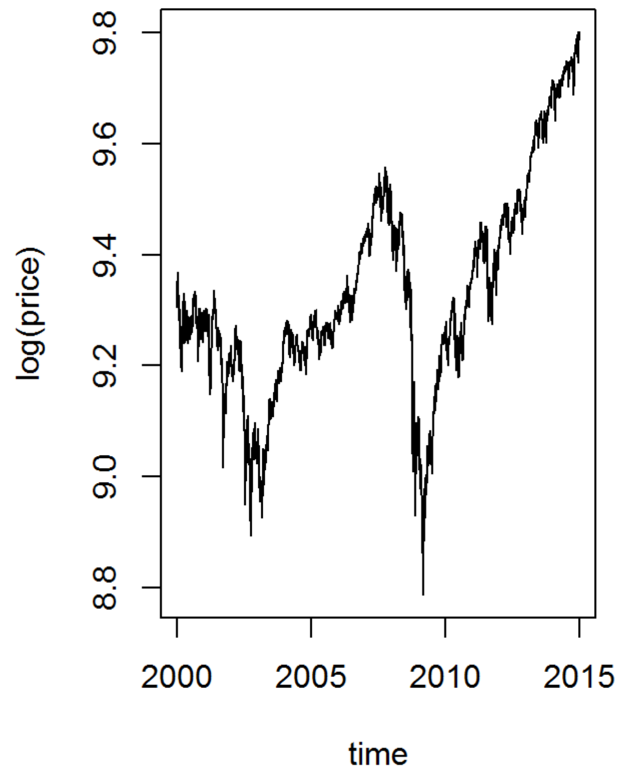
```
## This is forecast 7.1
```

```
library(Metrics)
```

```
## Warning: package 'Metrics' was built under R version 3.2.5
```

```
DJIA <- read.csv(file="C:/Users/jzhanggn/Documents/DJA.csv", header=TRUE, sep=",")
time <- as.Date(DJIA$Date, "%m/%d/%Y")
price <- DJIA$DJIA
par(mfrow=c(1,2))
plot(time, price, type='l'); plot(time, log(price), type='l')
```



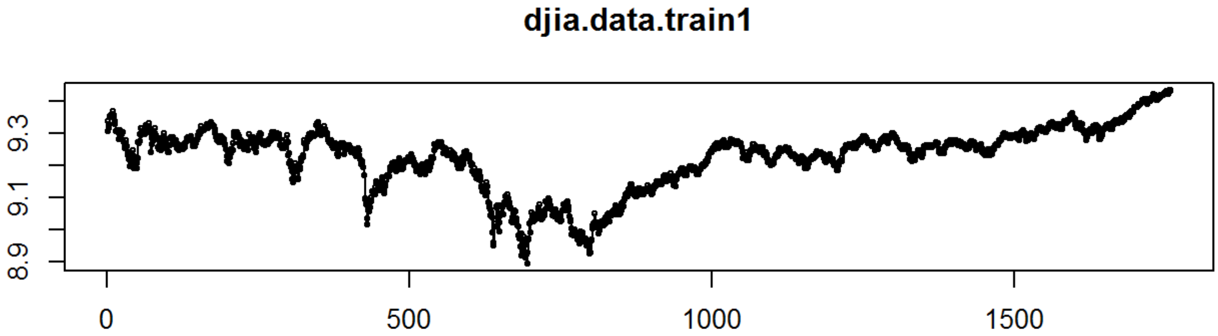


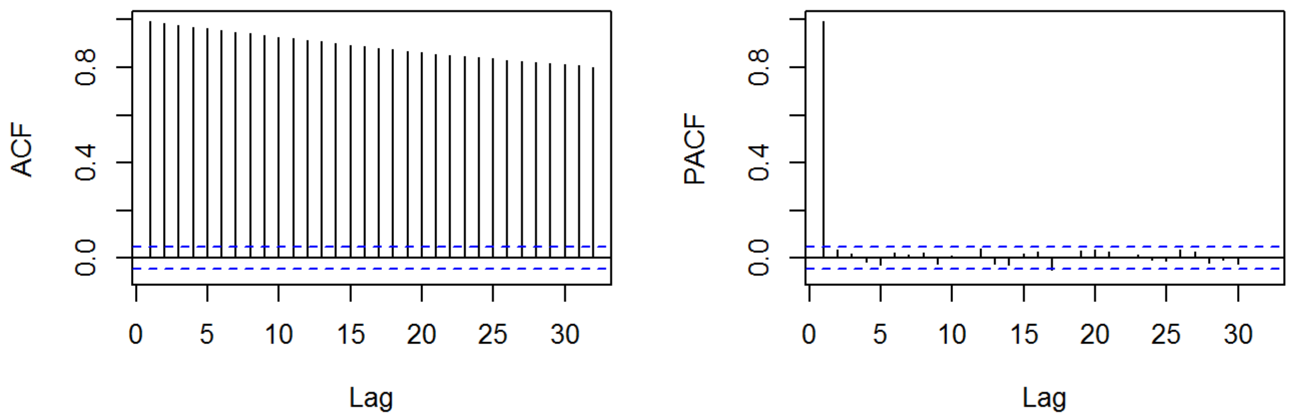

```
DJIA <- as.ts(DJIA)
```

1. Exponential moving average

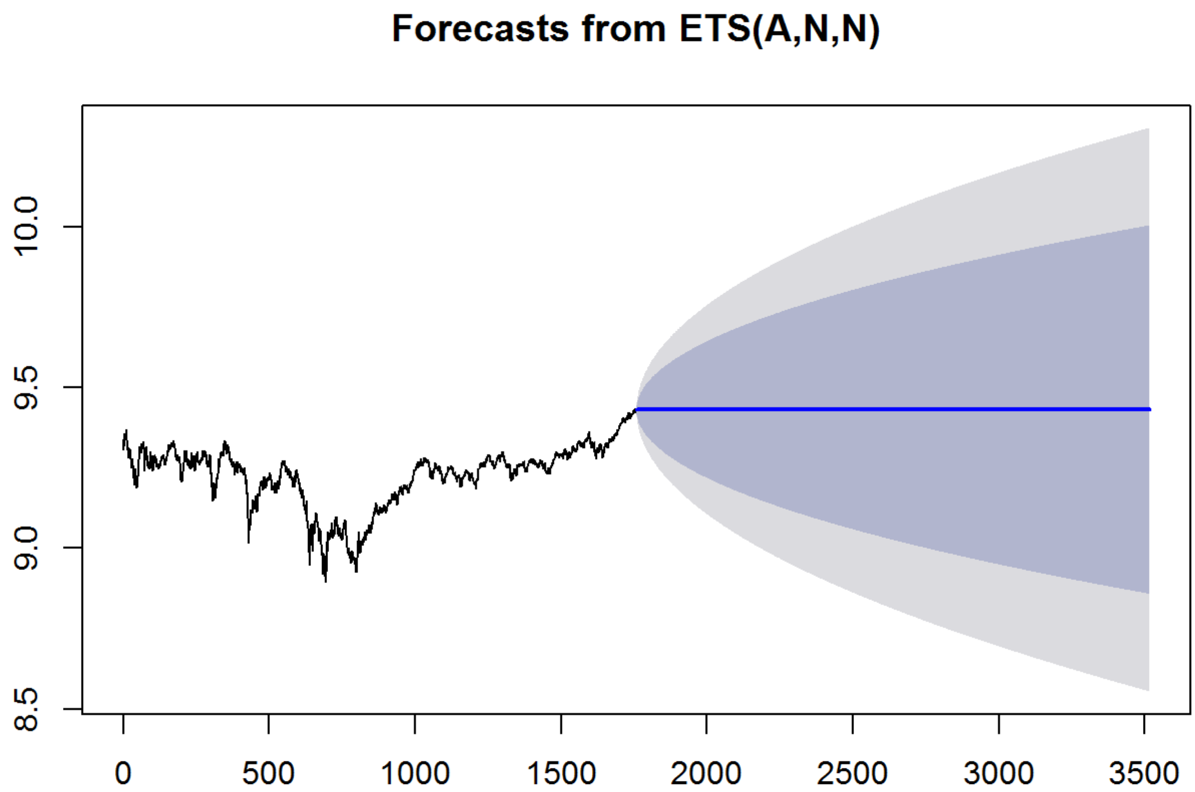
Use Exponential smoothing state space model (ETS). ETS function Automatically chooses a model by default using the AIC, AICc or BIC and can handle any combination of trend, seasonality and damping.

```
#data 2000-2006
DJIA <- as.ts(DJIA)
djia.data.train1 <- window(DJIA,start=1,end=1759)
djia.data.train1 <- log(djia.data.train1[,2])
tsdisplay(djia.data.train1)
```





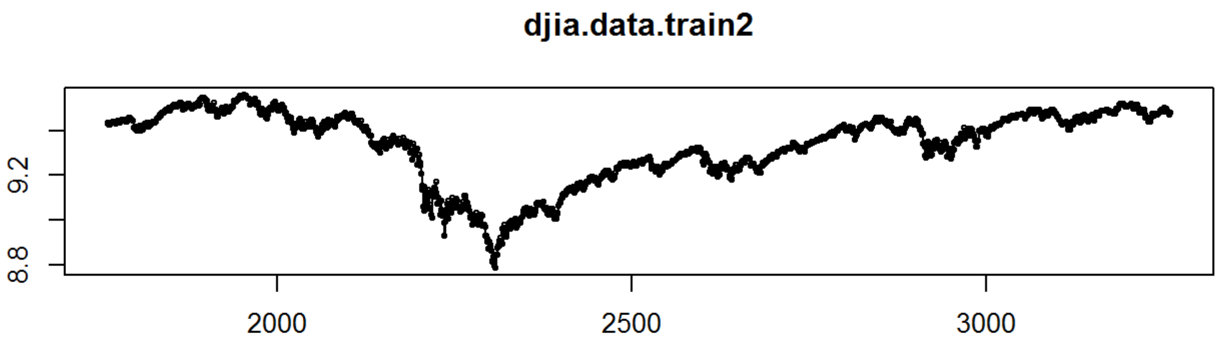

```
fit1 <- ets(djia.data.train1, model="ZZZ")
fcast1 <- forecast(fit1, h=251*7) # forcast 251*7. last 251 is year 2013,
plot(fcast1)
```

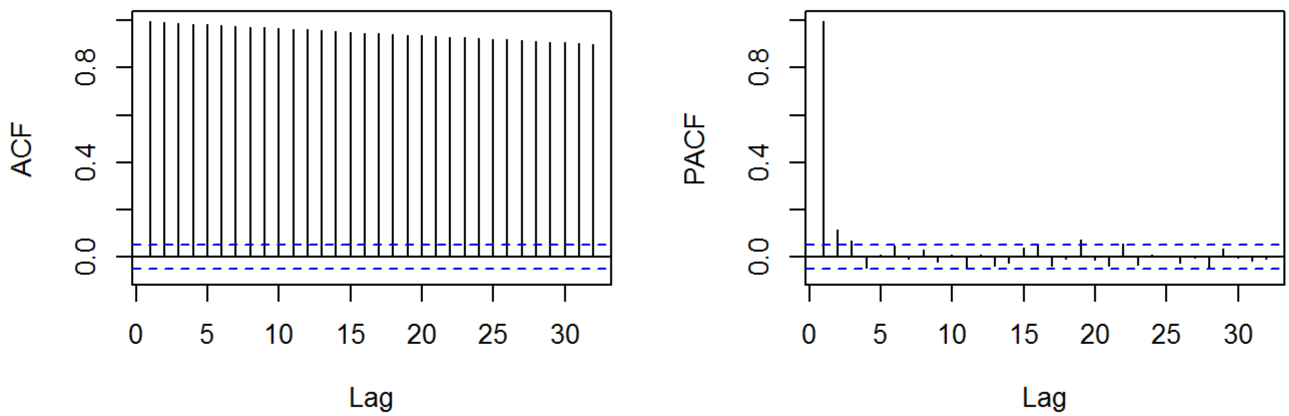



```
fcast1$mean.2013 <- fcast1$mean[1507:1757]
# date from 2007- 2012
djia.data.train2 <- window(DJIA, start=1760, end=3261)
djia.data.train2 <- log(djia.data.train2[,2])
#djia.data.train2 <- diff(djia.data.train2)
adf.test(djia.data.train2)
```

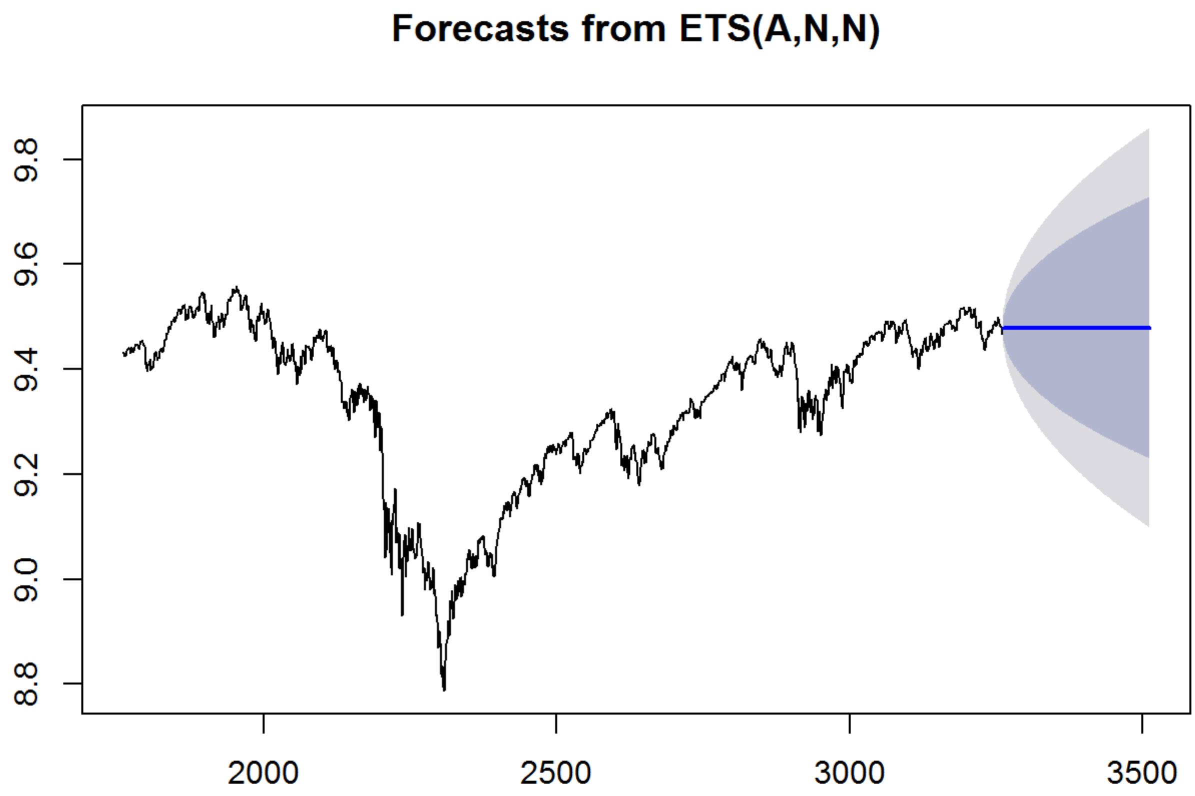
```
##
##  Augmented Dickey-Fuller Test
##
## data:  djia.data.train2
## Dickey-Fuller = -1.4574, Lag order = 11, p-value = 0.808
## alternative hypothesis: stationary
```

```
tsdisplay(djia.data.train2)
```






```
fit2 <- ets(djia.data.train2, model ="ZZZ")
fcast2 <- forecast(fit2, h=251)
plot(fcast2)
```




```
fcast2$mean
```

```
## Time Series:
## Start = 3262
## End = 3512
## Frequency = 1
##   [1] 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917
##   [9] 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917
##  [17] 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917
##  [25] 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917
##  [33] 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917
##  [41] 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917
##  [49] 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917
##  [57] 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917
##  [65] 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917
##  [73] 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917
##  [81] 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917
##  [89] 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917
##  [97] 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917
## [105] 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917
## [113] 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917
## [121] 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917
## [129] 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917
## [137] 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917
## [145] 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917
## [153] 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917
## [161] 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917
## [169] 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917
## [177] 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917
## [185] 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917
## [193] 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917
## [201] 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917
## [209] 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917
## [217] 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917
## [225] 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917
## [233] 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917
## [241] 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917 9.47917
## [249] 9.47917 9.47917 9.47917
```

```
# take mean of two forecast means to get mean
f <- function (x, y) {
  df <- data.frame(x, y)
  ave <- rowMeans(df)
  ave
 }
ave.mean <- f(fcast1$mean.2013, fcast2$mean)

# data 2013
djia.data.valid <- window(DJIA, start=3262, end=3512)
djia.data.valid <- log(djia.data.valid[,2])
exp.s.mv.mse <- mse(djia.data.valid, ave.mean)
exp.s.mv.mse
```

```
## [1] 0.02801211
```

2. HoltWinters Method

```
# fit data 2000-2006
fit1 <- HoltWinters(djia.data.train1, beta=TRUE, gamma=FALSE, l.start=9.337634)
fcast1 <- forecast.HoltWinters(fit1, h=251*7)
fcast1$mean.2013 <- fcast1$mean[1507:1757]

#fit data 2007-2012
fit2 <- HoltWinters(djia.data.train2, beta=FALSE, gamma=FALSE, l.start=9.431443)
  fcast2 <- forecast.HoltWinters(fit2, h=251)
  ave.mean <- f(fcast1$mean.2013, fcast2$mean)
  holtwinters.mse <- mse(djia.data.valid, ave.mean)
  holtwinters.mse
```

```
## [1] 0.7114913
```

3. ARIMA

```
fit1 <-auto.arima(djia.data.train1, seasonal=FALSE, max.order=10, stepwise=FALSE,
approximation=FALSE) # auto.arima suggest ARIMA(2,0,2)
fcast1 <- forecast(fit1, h=251*7)
fcast1$mean.2013 <- fcast1$mean[1507:1757]

fit2 <- auto.arima(djia.data.train2, seasonal=FALSE, max.order=10, stepwise=FALSE,
approximation=FALSE) #auto.arima suggest ARIMA(1,0,5)
fcast2 <- forecast(fit2, h=251)
ave.mean <- f(fcast1$mean.2013, fcast2$mean)
arima.mse <- mse(djia.data.valid, ave.mean)
arima.mse
```

```
## [1] 0.02796217
```

Compare three models

```
cbind(exp.s.mv.mse, holtwinters.mse, arima.mse)
```

```
##      exp.s.mv.mse holtwinters.mse  arima.mse
## [1,]   0.02801211       0.7114913 0.02796217
```

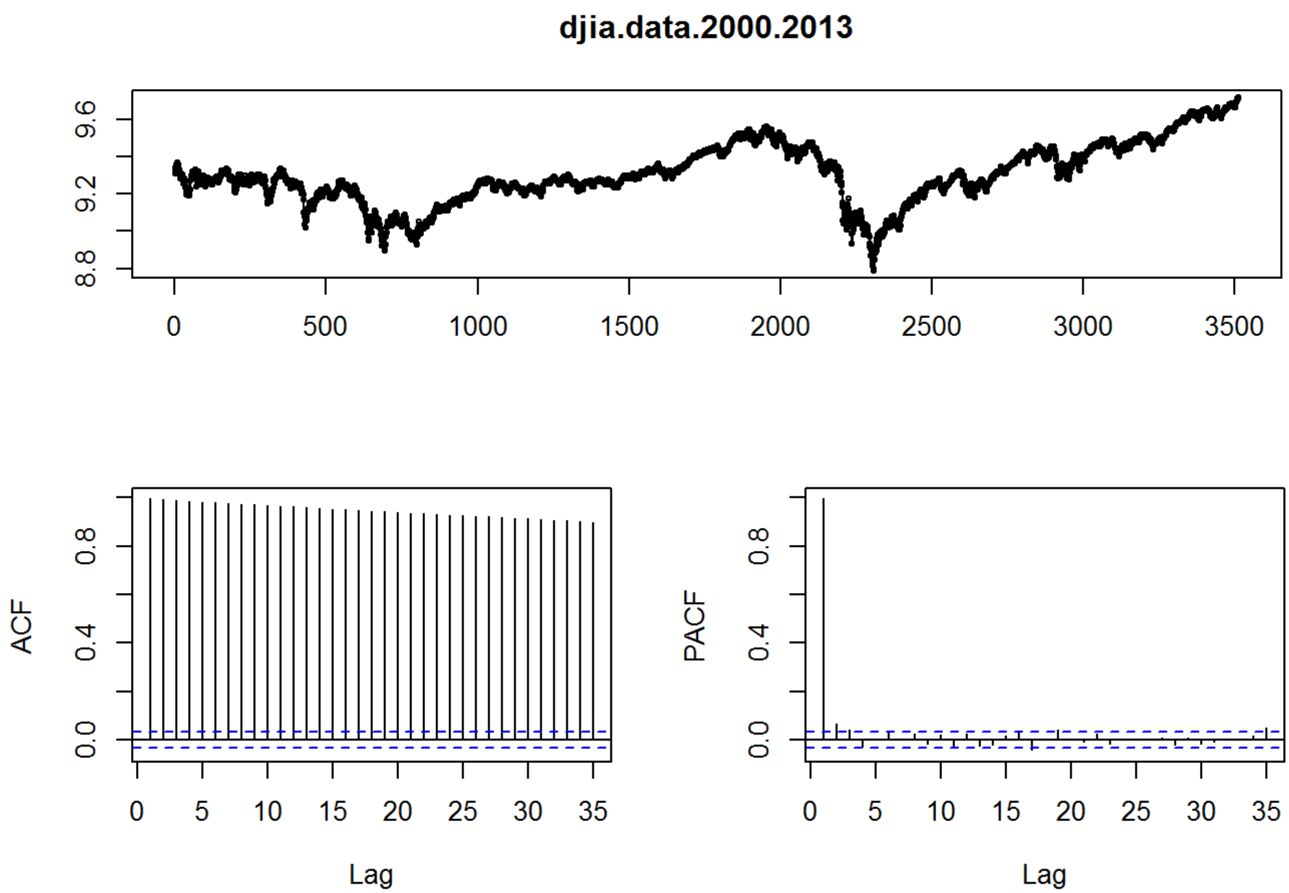
looks like ARIMA fits better with slightly lower MSE

Use ARIMA method to predicate 2014

```
djia.data.2000.2013 <- window(DJIA, start =1, end = 3512) # data 2000-2013
djia.data.2000.2013 <- log(djia.data.2000.2013[,2])
#djia.data.2000.2013 <- diff(djia.data.2000.2013)
adf.test(djia.data.2000.2013)
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  djia.data.2000.2013
## Dickey-Fuller = -2.0307, Lag order = 15, p-value = 0.5653
## alternative hypothesis: stationary
```

```
tsdisplay(djia.data.2000.2013)
```




```
fit.arima <- auto.arima(djia.data.2000.2013, seasonal=FALSE, max.order=10, stepwise=FALSE, appro
ximation=FALSE)
fit.arima
```

```
## Series: djia.data.2000.2013
## ARIMA(4,1,3)
##
## Coefficients:
```

```
## Warning in sqrt(diag(x$var.coef)): NaNs produced
```

```
##          ar1      ar2     ar3     ar4      ma1     ma2      ma3
##       0.0243  -0.3778  0.7713  0.0424  -0.1079  0.3537  -0.7935
## s.e.     NaN      NaN     NaN     NaN      NaN     NaN      NaN
##
## sigma^2 estimated as 0.00015:  log likelihood=10479.26
## AIC=-20942.51   AICc=-20942.47   BIC=-20893.2
```

```
fcast.arima <- forecast(fit.arima, h=251)
djia.data.test <- window(DJIA, start=3513, end=3762) # year 2014 data
djia.data.test.2014 <- log(djia.data.test[,2])
djia.data.test.2014.mse <- mse(djia.data.test.2014, fcast.arima$mean)
djia.data.test.2014.mse
```

```
## [1] 0.00127234
```

```
djia.data.test.2014.mae <- mae(djia.data.test.2014, fcast.arima$mean)
djia.data.test.2014.mae
```

```
## [1] 0.02743191
```

The MSE for 2014 is: 0.00127234

4. Fit intervention model. On Oct-06-2008, DJA drops from 10325.38 to 9955.5 pre-intervention series (2000-Jan-1 to 008-Oct-06)

```
library(tseries)
library(forecast)
library(TSA)
```

```
## Warning: package 'TSA' was built under R version 3.2.5
```

```
## Loading required package: leaps
```

```
## Loading required package: locfit
```

```
## Warning: package 'locfit' was built under R version 3.2.5
```

```
## locfit 1.5-9.1    2013-03-22
```

```
## Loading required package: mgcv
```

```
## Loading required package: nlme
```

```
##
## Attaching package: 'nlme'
```

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

```
## This is mgcv 1.8-9. For overview type 'help("mgcv-package")'.
```

```
##
## Attaching package: 'TSA'
```

```
## The following objects are masked from 'package:forecast':
##
##     fitted.Arima, plot.Arima
```

```
## The following objects are masked from 'package:timeDate':
##
##     kurtosis, skewness
```

```
## The following objects are masked from 'package:stats':
##
##     acf, arima
```

```
## The following object is masked from 'package:utils':
##
##     tar
```

```
djia.data.preinterv <- window(DJIA, start=1,end= 2202) # before 6, Oct 2008
auto.arima(log(djia.data.preinterv[,2]), seasonal=FALSE, trace=TRUE, stepwise=FALSE, approximati
on=FALSE) # return (2,1,2)
```

```
##
##  ARIMA(0,1,0)                    : -13449.84
##  ARIMA(0,1,0) with drift         : -13447.87
##  ARIMA(0,1,1)                    : -13460.11
##  ARIMA(0,1,1) with drift         : -13458.14
##  ARIMA(0,1,2)                    : -13461.13
##  ARIMA(0,1,2) with drift         : -13459.16
##  ARIMA(0,1,3)                    : -13460.06
##  ARIMA(0,1,3) with drift         : -13458.08
##  ARIMA(0,1,4)                    : -13458.51
##  ARIMA(0,1,4) with drift         : -13456.53
##  ARIMA(0,1,5)                    : -13459.43
##  ARIMA(0,1,5) with drift         : -13457.45
##  ARIMA(1,1,0)                    : -13459.08
##  ARIMA(1,1,0) with drift         : -13457.11
##  ARIMA(1,1,1)                    : -13459.96
##  ARIMA(1,1,1) with drift         : -13457.98
##  ARIMA(1,1,2)                    : -13459.52
##  ARIMA(1,1,2) with drift         : -13457.54
##  ARIMA(1,1,3)                    : -13458.13
##  ARIMA(1,1,3) with drift         : -13456.17
##  ARIMA(1,1,4)                    : -13457.12
##  ARIMA(1,1,4) with drift         : -13460.43
##  ARIMA(2,1,0)                    : -13461.72
##  ARIMA(2,1,0) with drift         : -13459.75
##  ARIMA(2,1,1)                    : -13459.76
##  ARIMA(2,1,1) with drift         : -13457.93
##  ARIMA(2,1,2)                    : -13468.37
##  ARIMA(2,1,2) with drift         : -13466.38
##  ARIMA(2,1,3)                    : -13468.04
##  ARIMA(2,1,3) with drift         : -13466.06
##  ARIMA(3,1,0)                    : -13460.12
##  ARIMA(3,1,0) with drift         : -13458.15
##  ARIMA(3,1,1)                    : -13457.73
##  ARIMA(3,1,1) with drift         : -13456.32
##  ARIMA(3,1,2)                    : -13467.95
##  ARIMA(3,1,2) with drift         : -13465.98
##  ARIMA(4,1,0)                    : -13459.24
##  ARIMA(4,1,0) with drift         : -13457.26
##  ARIMA(4,1,1)                    : -13457.6
##  ARIMA(4,1,1) with drift         : -13455.67
##  ARIMA(5,1,0)                    : -13458.53
##  ARIMA(5,1,0) with drift         : -13456.55
```

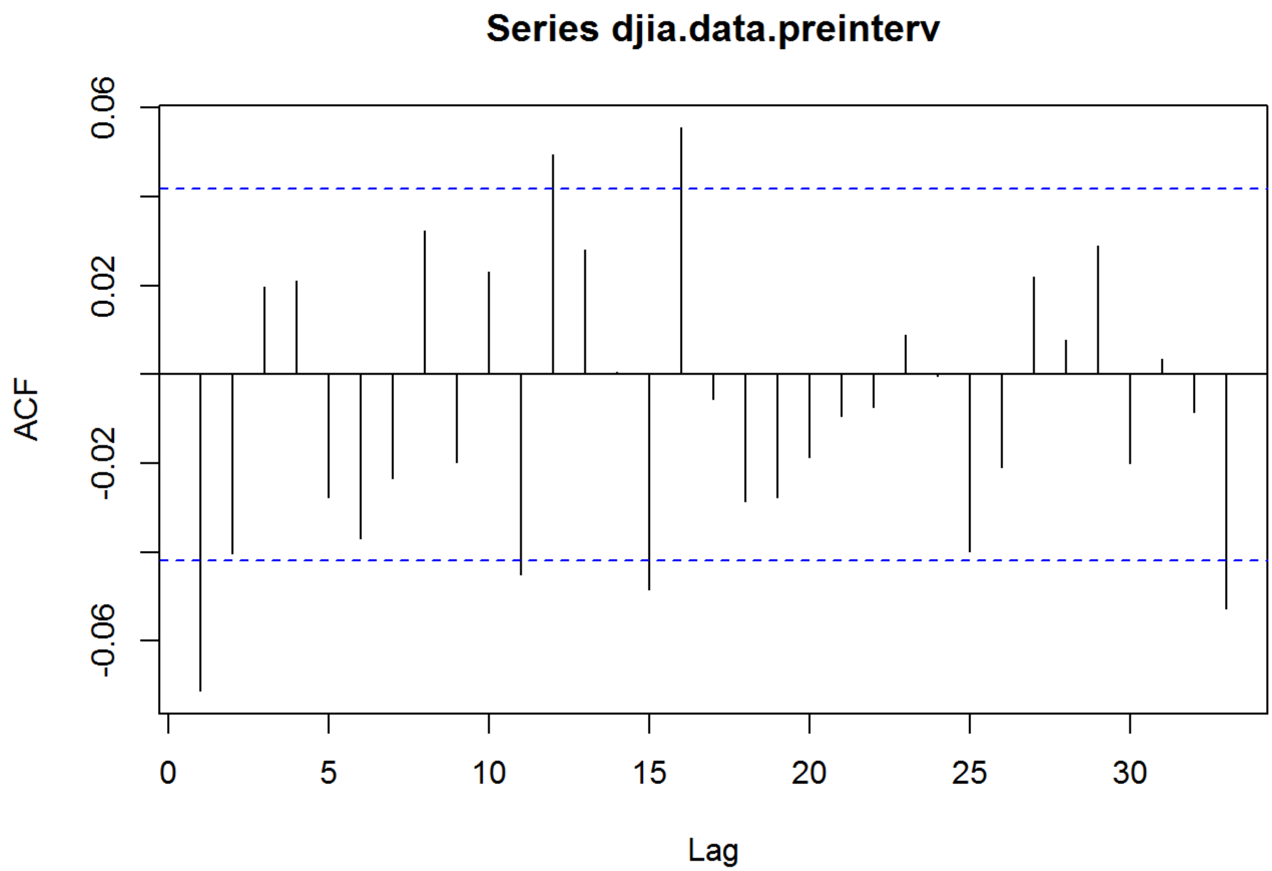
```
## Series: log(djia.data.preinterv[, 2])
## ARIMA(2,1,2)
##
## Coefficients:
##          ar1      ar2      ma1     ma2
##       0.3387  -0.8615  -0.3942  0.8583
## s.e.  0.0590   0.0612   0.0570  0.0642
##
## sigma^2 estimated as 0.0001285:  log likelihood=6739.2
## AIC=-13468.39   AICc=-13468.37   BIC=-13439.91
```

```
djia.data.preinterv <- diff(log(djia.data.preinterv[,2]))
adf.test(djia.data.preinterv) # p-value = 0.01 reject H0, stationary
```

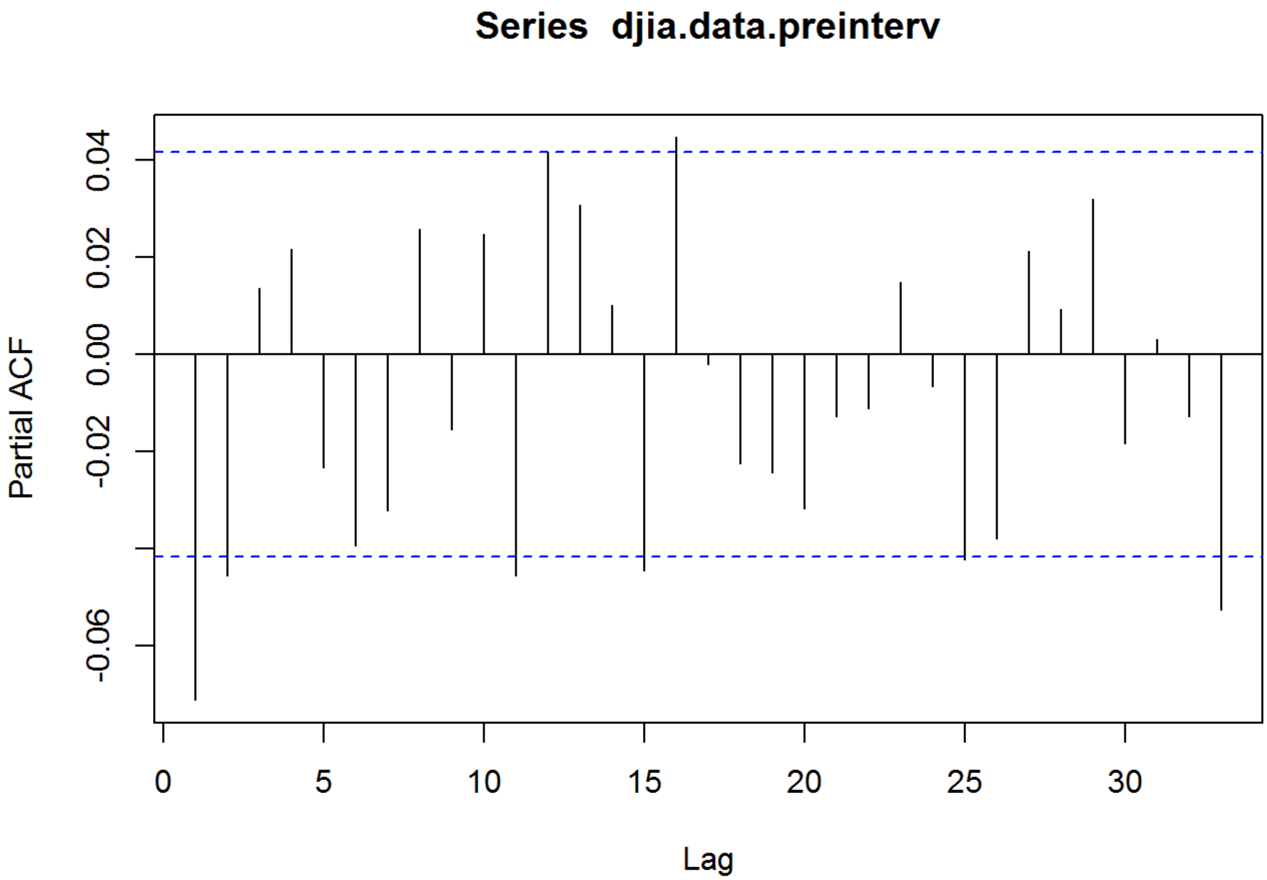
```
## Warning in adf.test(djia.data.preinterv): p-value smaller than printed p-
## value
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  djia.data.preinterv
## Dickey-Fuller = -12.149, Lag order = 13, p-value = 0.01
## alternative hypothesis: stationary
```

```
acf(djia.data.preinterv) # shows lag1 spike MA(1)
```




```
pacf(djia.data.preinterv)
```




```
price.2000.2003 <- window(DJIA, start =1, end = 3512)
price.2000.2003 <- log(price.2000.2003[,2])

fit.interv <- arimax(price.2000.2003, order=c(2,1,2), xtransf=data.frame(I.1=1*(seq(price.2000.2
003)==2203), I.0=1*(seq(price.2000.2003)==2203)), transfer=list(c(0,0),c(1,0)),  method='ML')
fit.interv
```

```
##
## Call:
## arimax(x = price.2000.2003, order = c(2, 1, 2), method = "ML", xtransf = data.frame(I.1 = 1 *

##     (seq(price.2000.2003) == 2203), I.0 = 1 * (seq(price.2000.2003) == 2203)),
##     transfer = list(c(0, 0), c(1, 0)))
##
## Coefficients:
##           ar1      ar2     ma1     ma2  I.1-MA0  I.0-AR1  I.0-MA0
##       -0.3126  -0.3772  0.2272  0.3045  -0.0252  -0.3999   0.0294
## s.e.   0.2211   0.1233  0.2257  0.1309   0.0384   0.2728   0.0340
##
## sigma^2 estimated as 0.0001503:  log likelihood = 10471.16,  aic = -20928.32
```

```
summary(fit.interv)
```

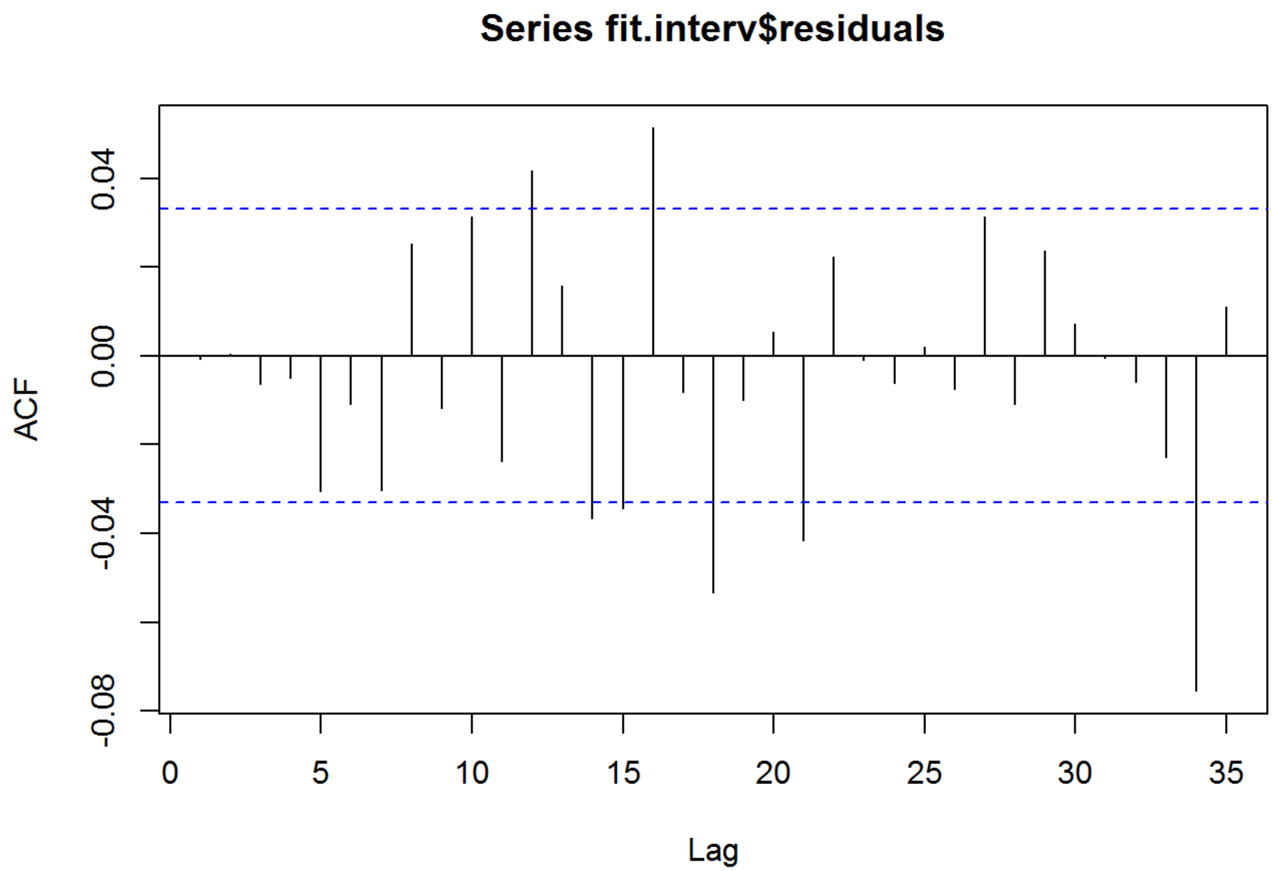
```
##
## Call:
## arimax(x = price.2000.2003, order = c(2, 1, 2), method = "ML", xtransf = data.frame(I.1 = 1 *

##     (seq(price.2000.2003) == 2203), I.0 = 1 * (seq(price.2000.2003) == 2203)),
##     transfer = list(c(0, 0), c(1, 0)))
##
## Coefficients:
##           ar1      ar2     ma1     ma2  I.1-MA0  I.0-AR1  I.0-MA0
##       -0.3126  -0.3772  0.2272  0.3045  -0.0252  -0.3999   0.0294
## s.e.   0.2211   0.1233  0.2257  0.1309   0.0384   0.2728   0.0340
##
## sigma^2 estimated as 0.0001503:  log likelihood = 10471.16,  aic = -20928.32
##
## Training set error measures:
##                        ME       RMSE         MAE         MPE       MAPE
## Training set 0.0001213312 0.01226032 0.008295931 0.001176996 0.08970643
##                   MASE          ACF1
## Training set 0.9969304 -0.0008066632
```

```
#Test residual -portmanteau' tests
Box.test(residuals(fit.interv), lag=48, type="Ljung") #  failed to reject H0-0 autocorrelation
```

```
##
##  Box-Ljung test
##
## data:  residuals(fit.interv)
## X-squared = 114.17, df = 48, p-value = 2.581e-07
```

```
acf(fit.interv$residuals)
```



The Ljung box test failed to reject H0 of independency, but we don't see significant spikes on lag1. Althought there are few spikes exceed bounds. that might be due to chance

Compare with Holtwinter model using SSE

```
cbind(fit.arima$loglik, fit.interv$loglik)
```

```
##          [,1]     [,2]
## [1,] 10479.26 10471.16
```

```
cbind(fit.arima$aic, fit.interv$aic)
```

```
##           [,1]      [,2]
## [1,] -20942.51 -20928.32
```

```
fit.arima.mae = 0.0082958
fit.interv.mae = 0.008305585
```

looks like that arima fits better even with intervention added in

Future Work

```
detectAO(fit.interv, robust=F); detectIO(fit.interv, robust=F)
```

```
##             [,1]       [,2]       [,3]       [,4]       [,5]        [,6]
## ind     73.00000 427.000000 638.000000 641.000000 686.000000 2198.000000
## lambda2 -4.70692  -5.980335  -4.360481   4.908215   4.744066   -5.434128
##                [,7]        [,8]        [,9]       [,10]       [,11]
## ind     2206.000000 2208.000000 2210.000000 2215.000000 2219.000000
## lambda2   -5.642978    7.955783   -6.194112   -5.082575    8.161684
##               [,12]       [,13]      [,14]      [,15]       [,16]
## ind     2225.000000 2235.000000 2237.00000 2238.00000 2242.000000
## lambda2   -4.353159   -4.455457    4.67717    4.47162   -5.917519
##               [,17]       [,18]       [,19]
## ind     2309.000000 2318.000000 2914.000000
## lambda2    4.821204    5.042813   -4.835103
```

```
##              [,1]      [,2]       [,3]       [,4]        [,5]        [,6]
## ind     73.000000 427.00000 641.000000 686.000000 2198.000000 2206.000000
## lambda1 -4.965143  -6.07189   4.985771   5.160104   -5.778937   -6.008619
##                [,7]        [,8]        [,9]       [,10]       [,11]
## ind     2208.000000 2210.000000 2215.000000 2219.000000 2231.000000
## lambda1    8.341065   -6.205401   -4.966892    8.070278    4.791764
##               [,12]       [,13]       [,14]      [,15]       [,16]
## ind     2236.000000 2237.000000 2242.000000 2309.00000 2318.000000
## lambda1   -4.761923    4.469385   -6.284452    4.64674    5.164824
##               [,17]
## ind     2914.000000
## lambda1   -4.802836
```

There are significant outliers out there, so we could add these outliers to improve model for a better fit