274 Final Project

Bochen Wang

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1. Abstract

This times series project is about studying and predicting the data of US monthly gas supply from Jan. 1992 to Dec. 2007.In this data prediction, I have used the modeling processes of SARIMA models to fit the data and utilized it for predictions. By analyzing the acf/pacf, comparing AICcs, analysis of residuals, I selected the best model for prediction, and the results are looking great for the prediction outcomes. I also did the spectral analysis for the periodicity checking. The conclusion is that our model prediction power is fine with all the predicted two years of data lies inside the confidance interval.

2. Introduction

Project interest details:

In this project, I plan to analyze the monthly gas supply data in the US from 1992.1 to 2007.12 for the gas time series data prediction. In this case, I will use the data from 1992.1 to 2005.12 for training the model and use the 2006.1 to 2007.12 data for validation and prediction. Due to recent feelings about the increasing prices of gas money has brought to many people’s attention. I decided to analyze the supply side of amount of gas data to study its trend and give people insights of supply side of data.

Techniques and Results:

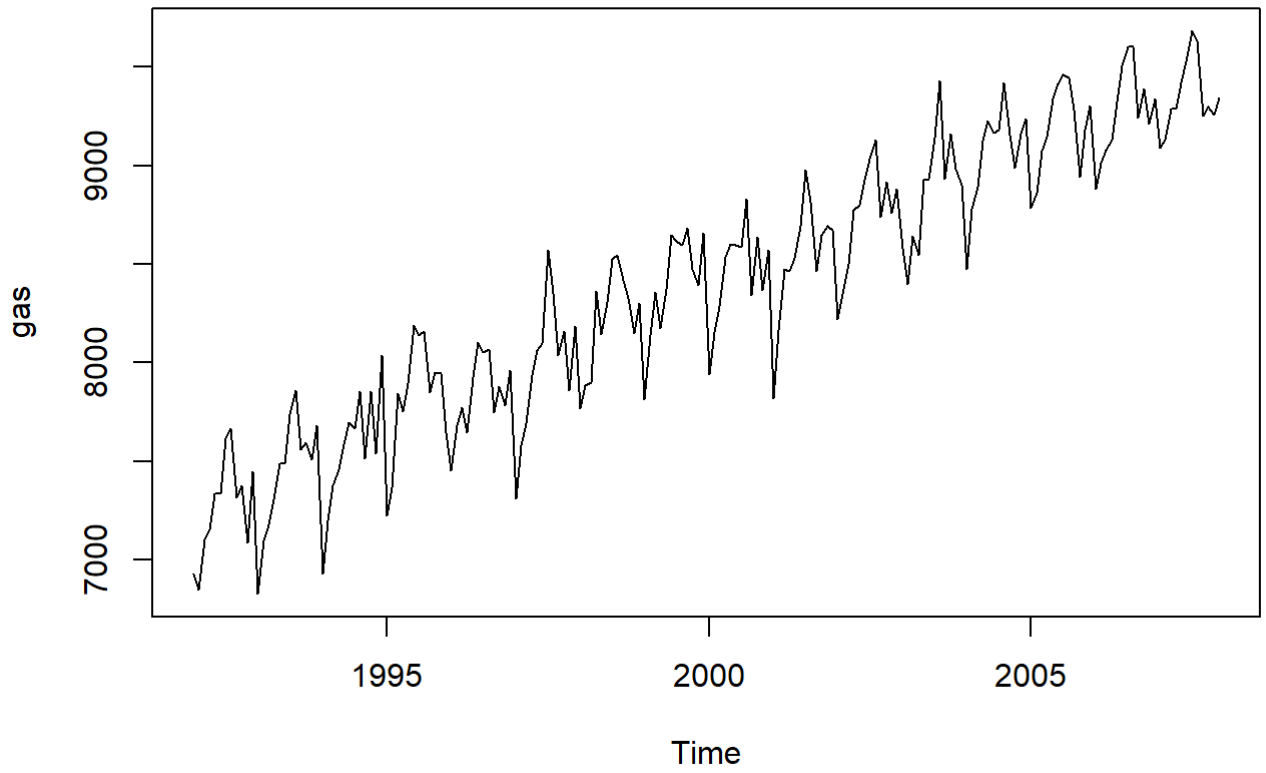
In analyzing my time series data, I have used box-cox transformation for data to be more Gaussian, acf/pacf identification, AICc compare for model identification and checking model unit roots, analysis of residuals, Shapiro-Wilk normality test, Box-Pierce test, Box-Ljung test, for diagnostic checking, h-steps ahead predictions. In my result, my model successfully pass the test and the residuals plot reassembles normal distribution, my prediction of 24 observations are all within 95% confidence interval, positively speaking. Negatively speaking, in my residual plot’s pacf, there is one peak in lag 3 that is a little outside the confidence interval. I tried to add AR(3) to my original AR(3) which ends up with unit roots. Also for Box-Pierce test, though passing, there is only 0.08 > 0.05 which is close to not passing.

Sources:

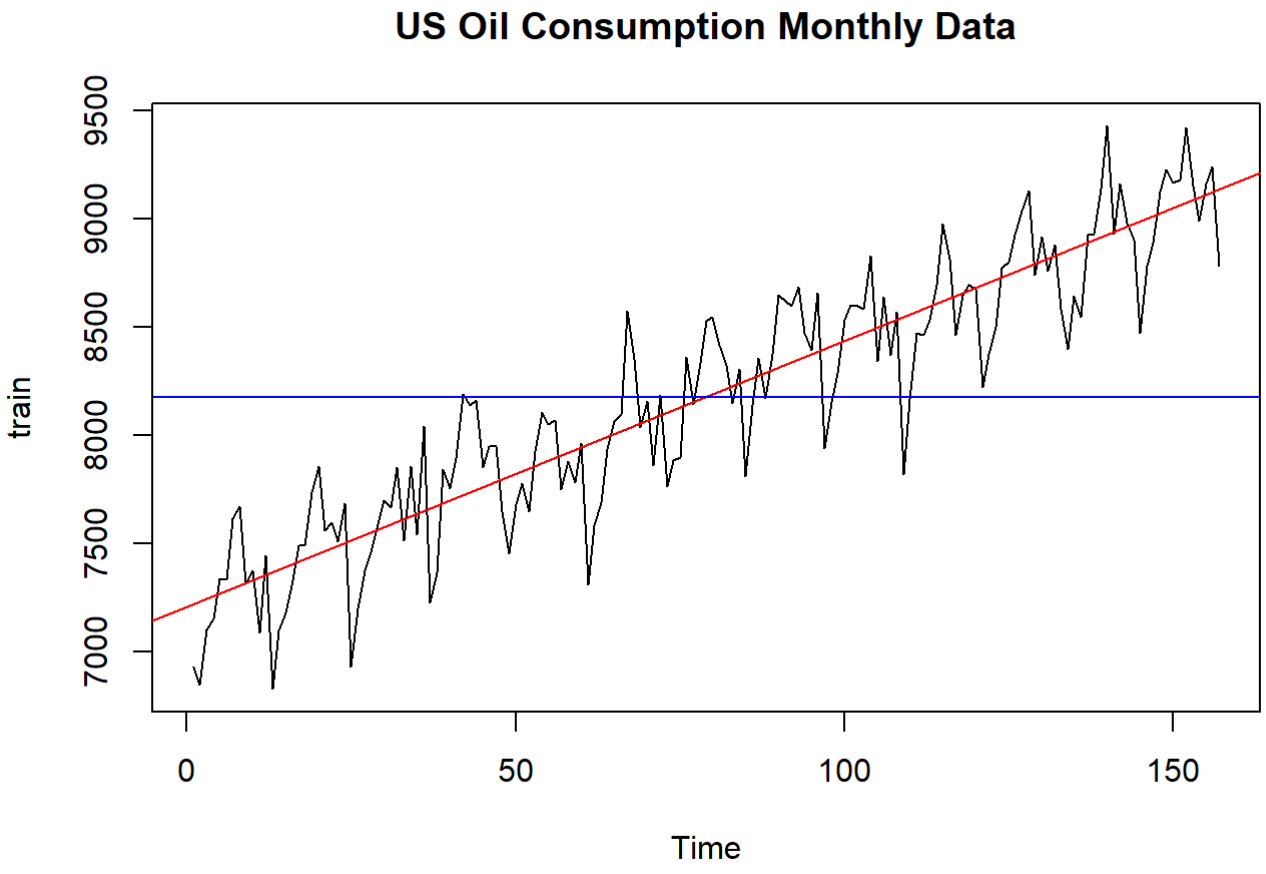
Data collection : https://www.eia.gov/naturalgas/data.php (https://www.eia.gov/naturalgas/data.php) Software: R Studio and R Markdown.

3. Model Building

Data Input:

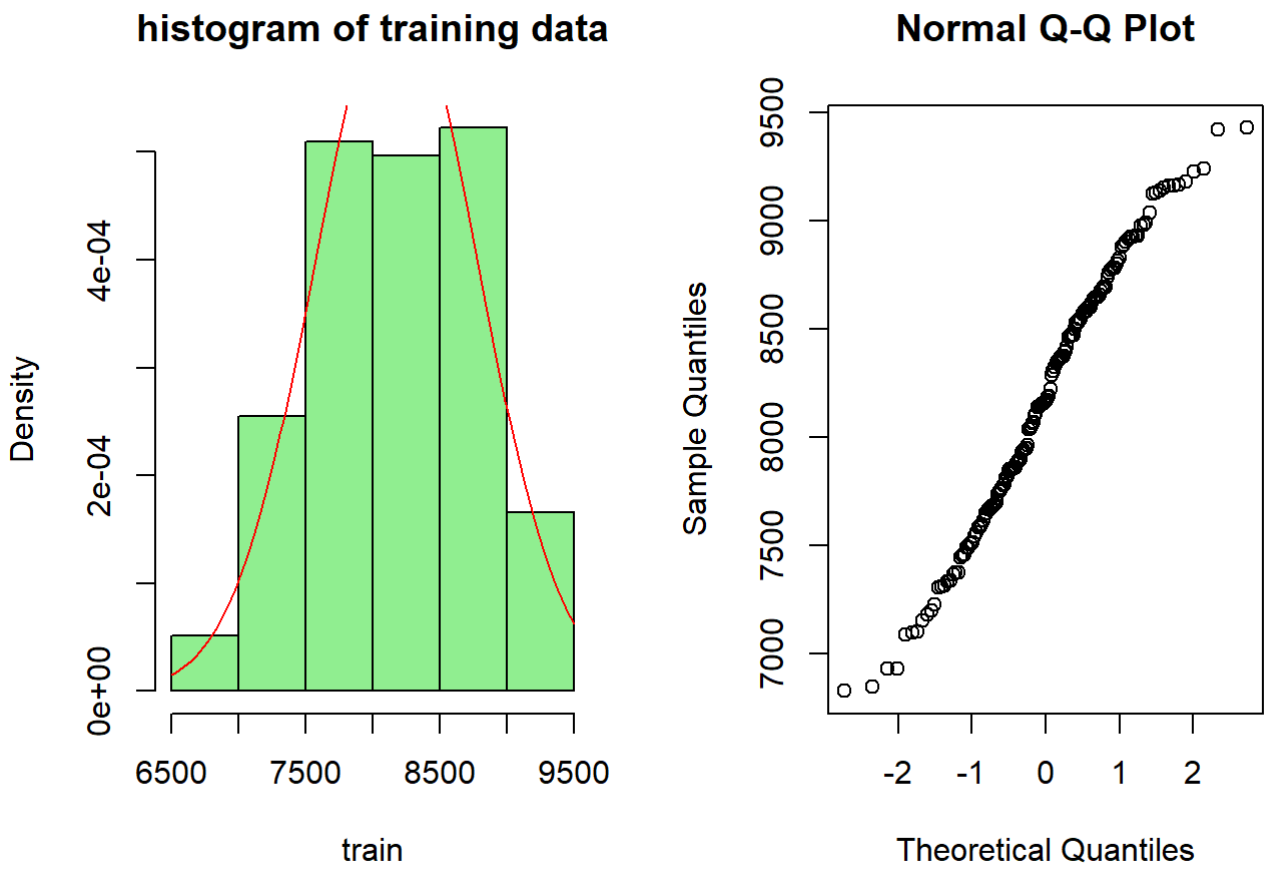


Testing and Training split and added lines for trend and mean:



Normality checking:

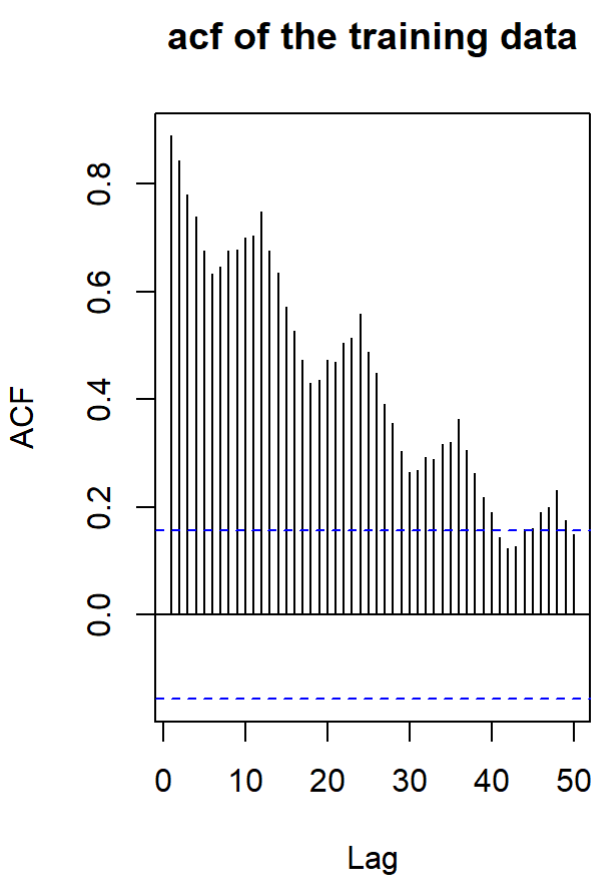
```
par(mfrow = c(1,2))
hist(train, col = "lightgreen", main = "histogram of training data", freq=F)
curve(dnorm(x,mean(train), sqrt(var(train))), col = "red", add = TRUE)
qqnorm(train)
```

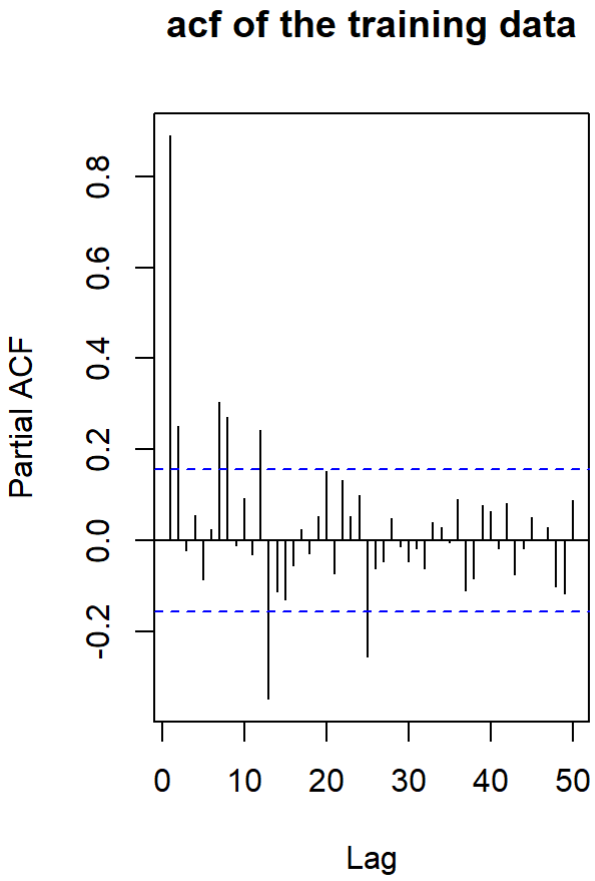


We can see from the graph that is is a little bit skewed to the left.

acf/pacf

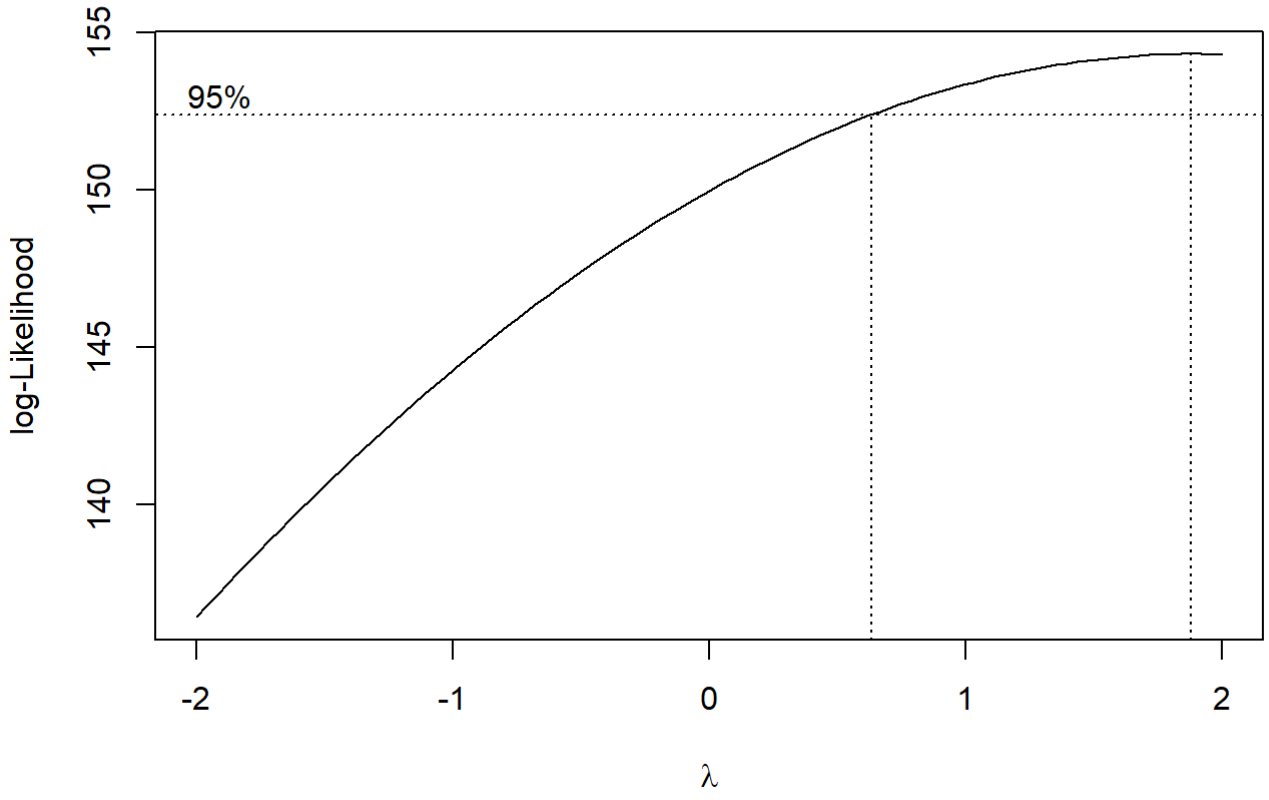
```
par(mfrow=c(1,2))
acf(train, lag.max = 50, main = "acf of the training data")
pacf(train, lag.max = 50, main = "acf of the training data")
```





We can see that there is a seasonal trend for seasonal data

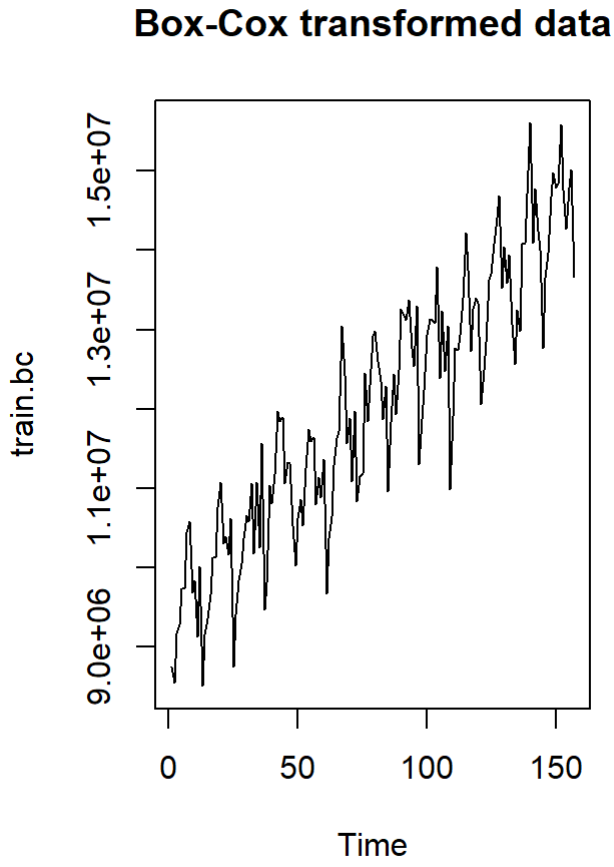
Because there is skewed data, we preform box-cox transformation:

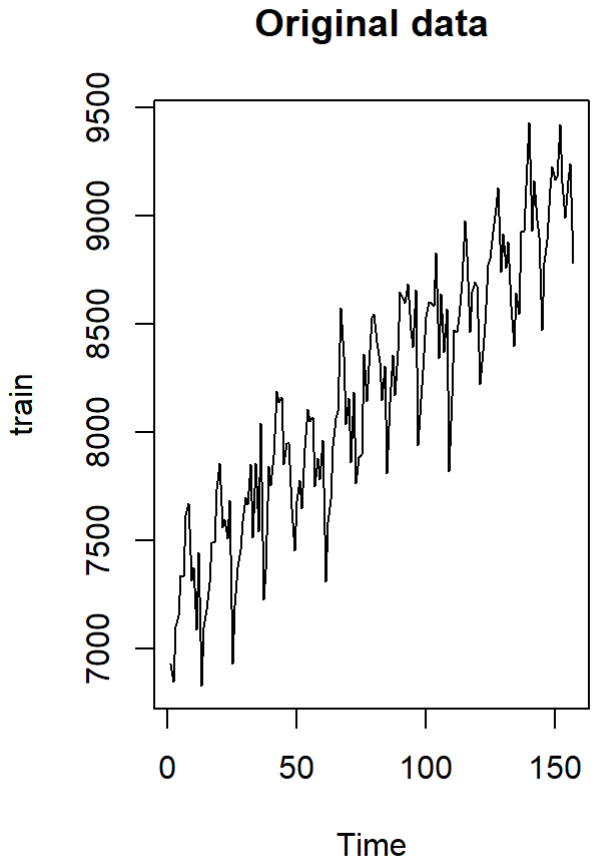


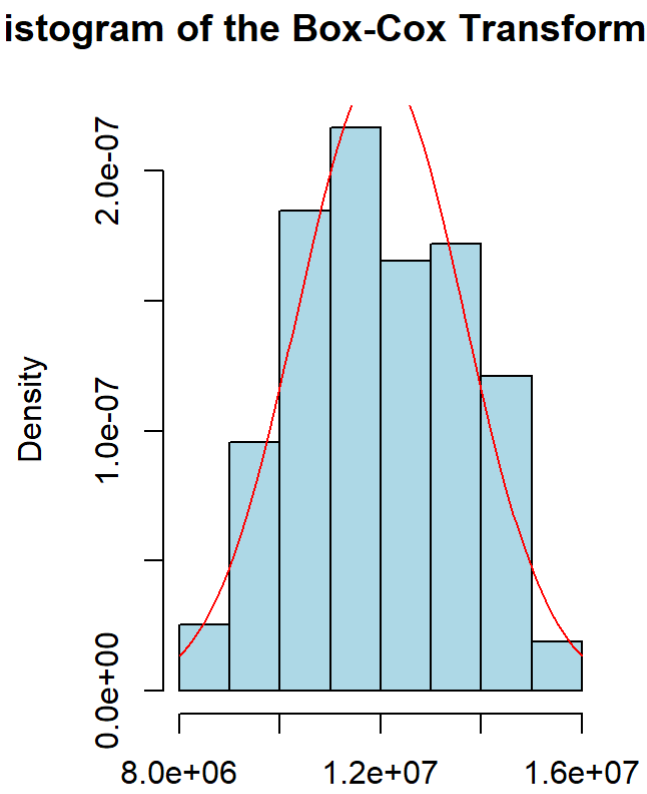
Because 1 is in my confidence interval, I also considered not transforming the data. However, the transformed

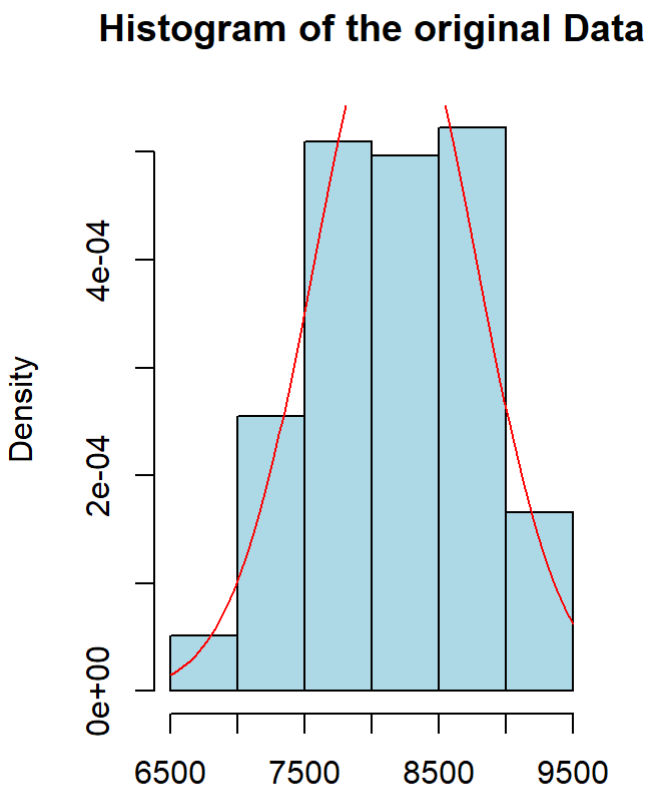
data makes it difficult for me to identify the acf/pacf for appropriate models so I used non-transformed data. The comparison are shown later.

Compare the transformed data and original data, plot the transformed histogram:



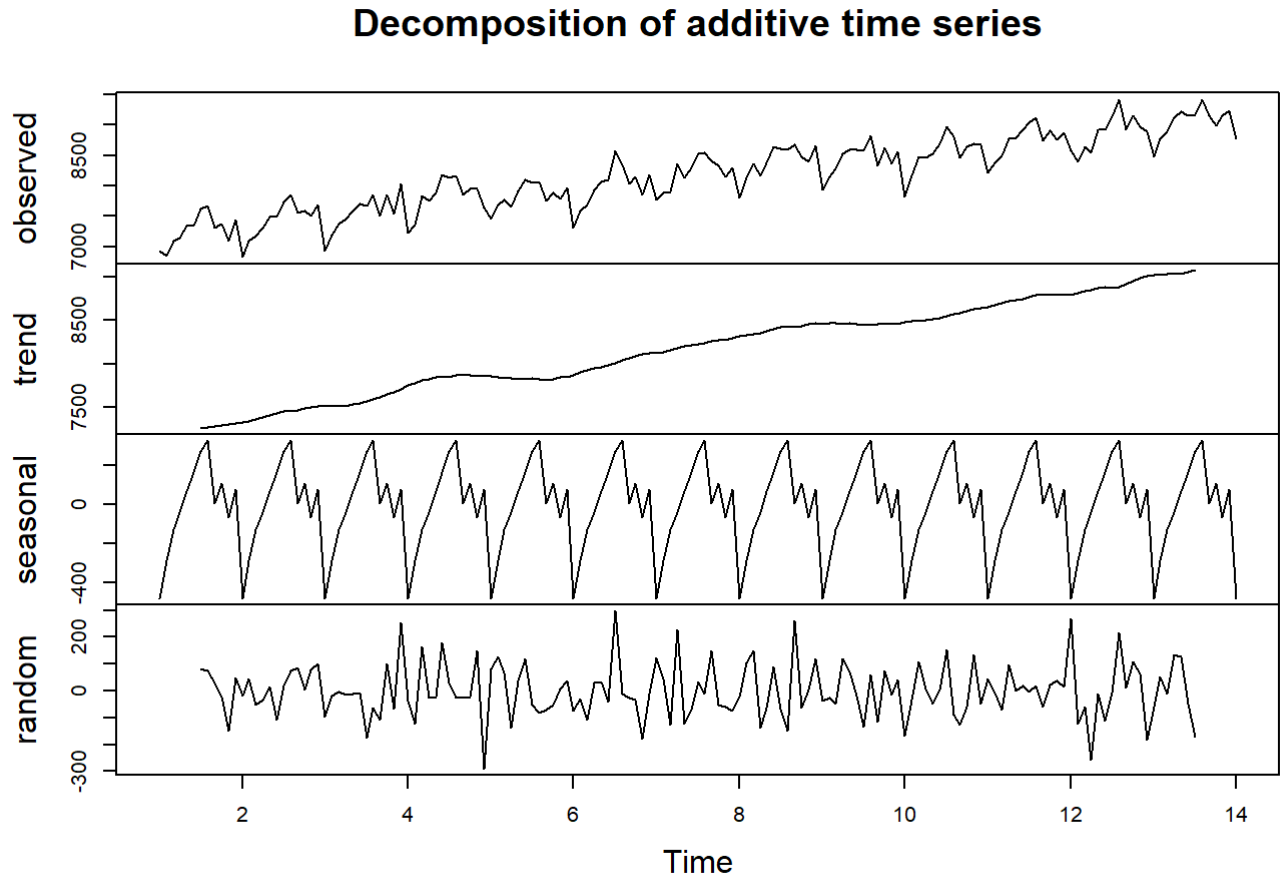






We can see that they both approximately fit normal. So, my final decision is to us the original training data.

Decompose Data:



We can see from the decomposed data that there is a seasonal part and a trend in this data.

Remove trend and seasonality:

```
## [1] 2.782468e+12
```

```
## [1] 32978.84
```

```
## [1] 55798.78
```

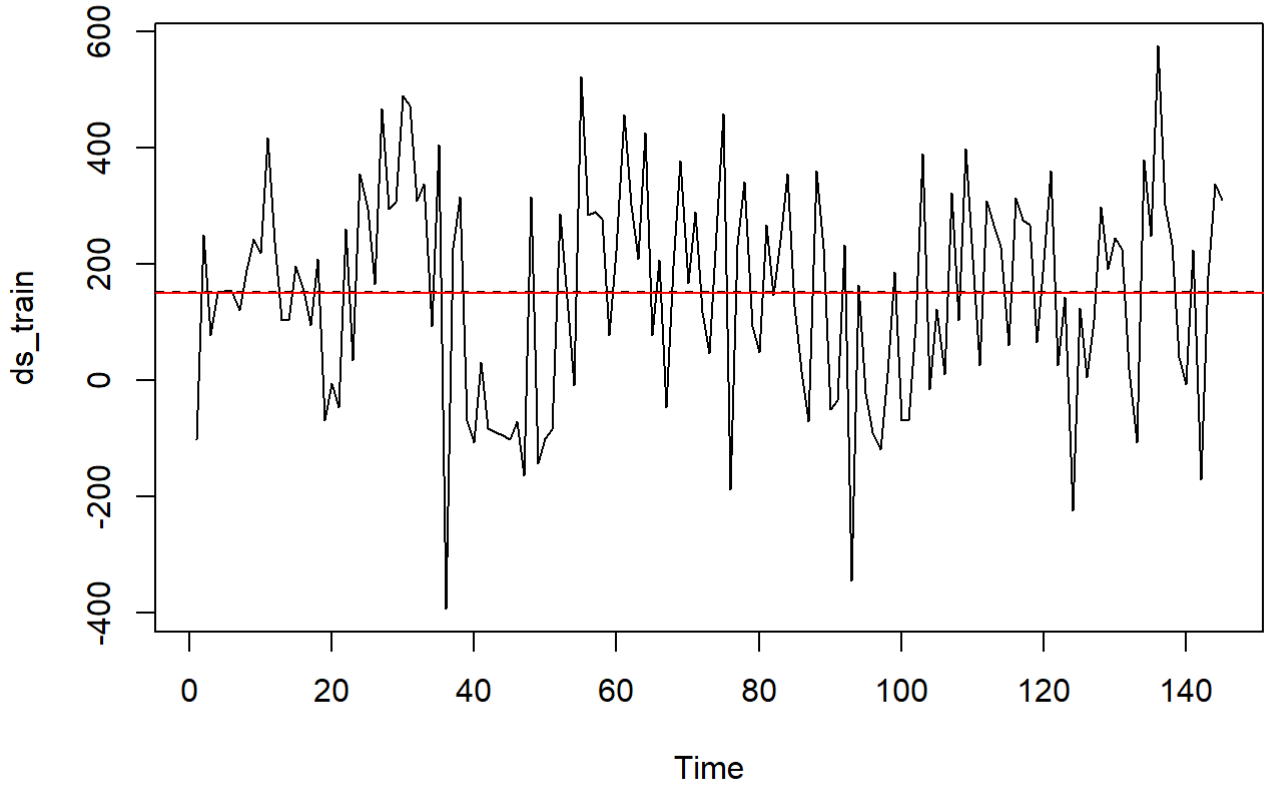
The three are r generated variances. The first is transformed data variance. The second is differenced at

$$\nabla_{12} bc(X[t])$$

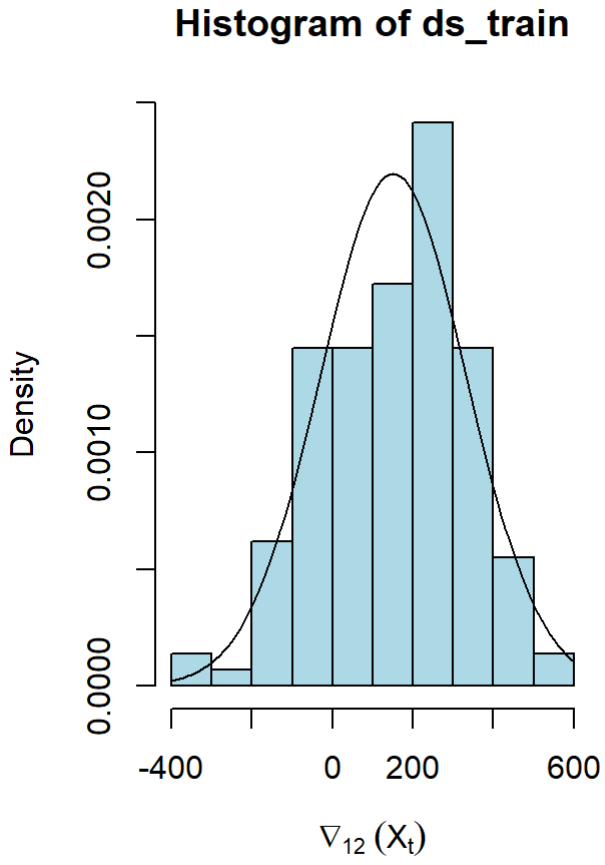
. The third is

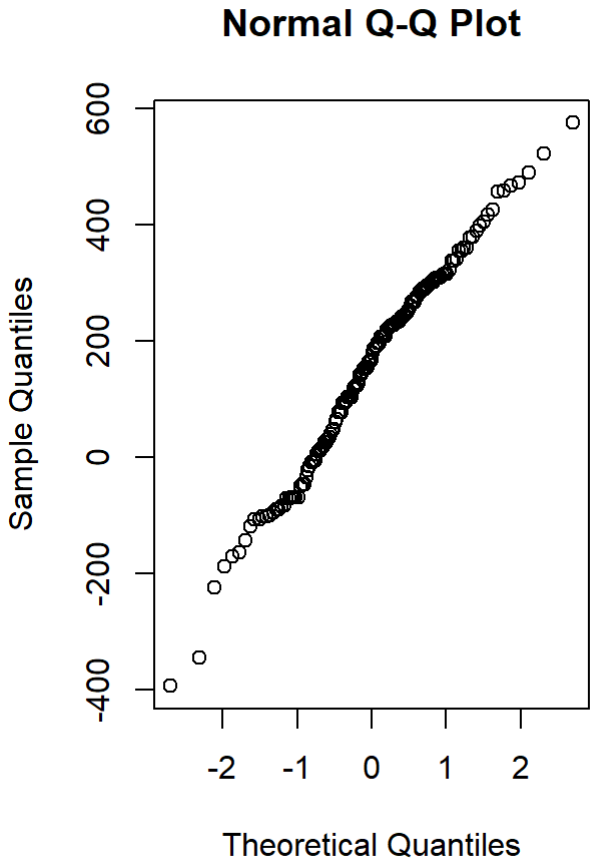
$$\nabla_{12}\nabla_{1} bc(X[t])$$

. We can see that de-seasonalized data have the lowest variance. Observed that after removing trend this model have variance increased, so just remove seasonality.

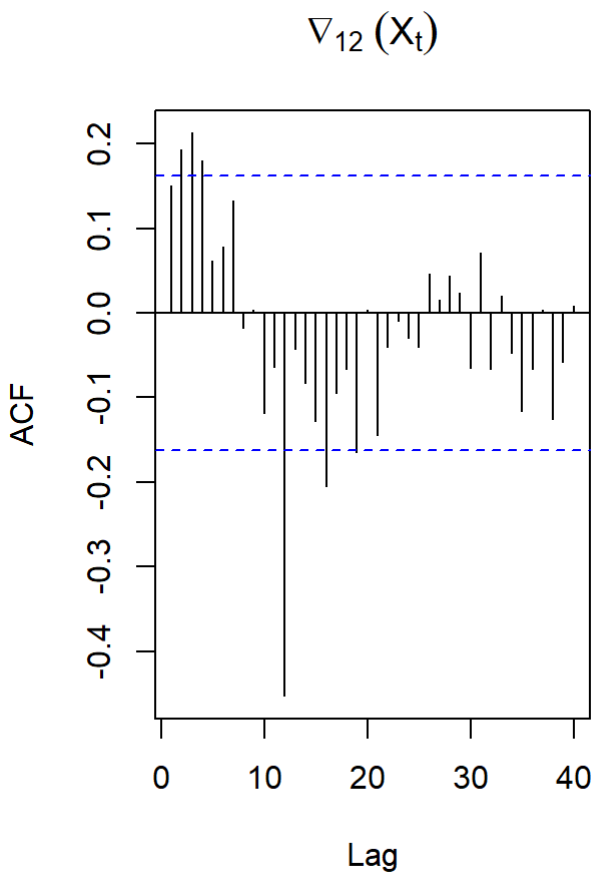


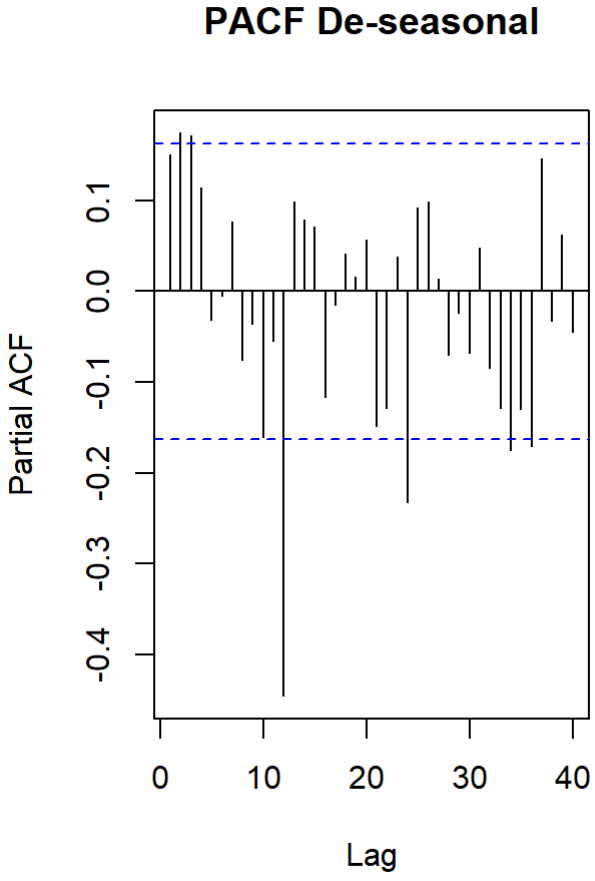
It might seems good Guassian but choose the d_seasonal one because it has lower variance





Plot acf and pacf for the box-cox transformed data:





acf maybe lag 1, lag 2, lag 3, lag 4, lag 12 means s=12,might q = 3 or 2 or 4 need to check different q because

we are considering MA part also. pacf maybe lag 1, lag 2, lag 3, lag 11, lag 12, lag 13 means p = 2 pacf mostly affected by seasonal MA part so we can try out different AICCs s =12
from both plot we can be sure that Q = 1

Model Checking comparing AICc: I tried pure MA but residual acf and pacf shows ar part for non-seasonal Then I also considered the AR(1) but the results having unit roots which brings us here for considering AR(2) and adding MA part.

```
##
## Call:
## arima(x = train, order = c(2, 0, 0), seasonal = list(order = c(0, 1, 1), period = 12),
##     method = "ML")
##
## Coefficients:
##          ar1     ar2     sma1
##       0.4755  0.5244  -0.9872
## s.e.  0.0714  0.0714   0.0550
##
## sigma^2 estimated as 19072:  log likelihood = -935.01,  aic = 1876.02
```

```
## [1] 1878.181
```

```
##
## Call:
## arima(x = train, order = c(2, 0, 1), seasonal = list(order = c(0, 1, 1), period = 12),
##     fixed = c(NA, NA, NA, NA), method = "ML")
##
## Coefficients:
##          ar1     ar2      ma1     sma1
##       0.8803  0.1197  -0.7627  -0.9855
## s.e.  0.1077  0.1077   0.0768   0.0442
##
## sigma^2 estimated as 14777:  log likelihood = -916.94,  aic = 1841.87
```

```
## [1] 1844.137
```

confidance interval suggests that the AR part is not working well because it suggests the

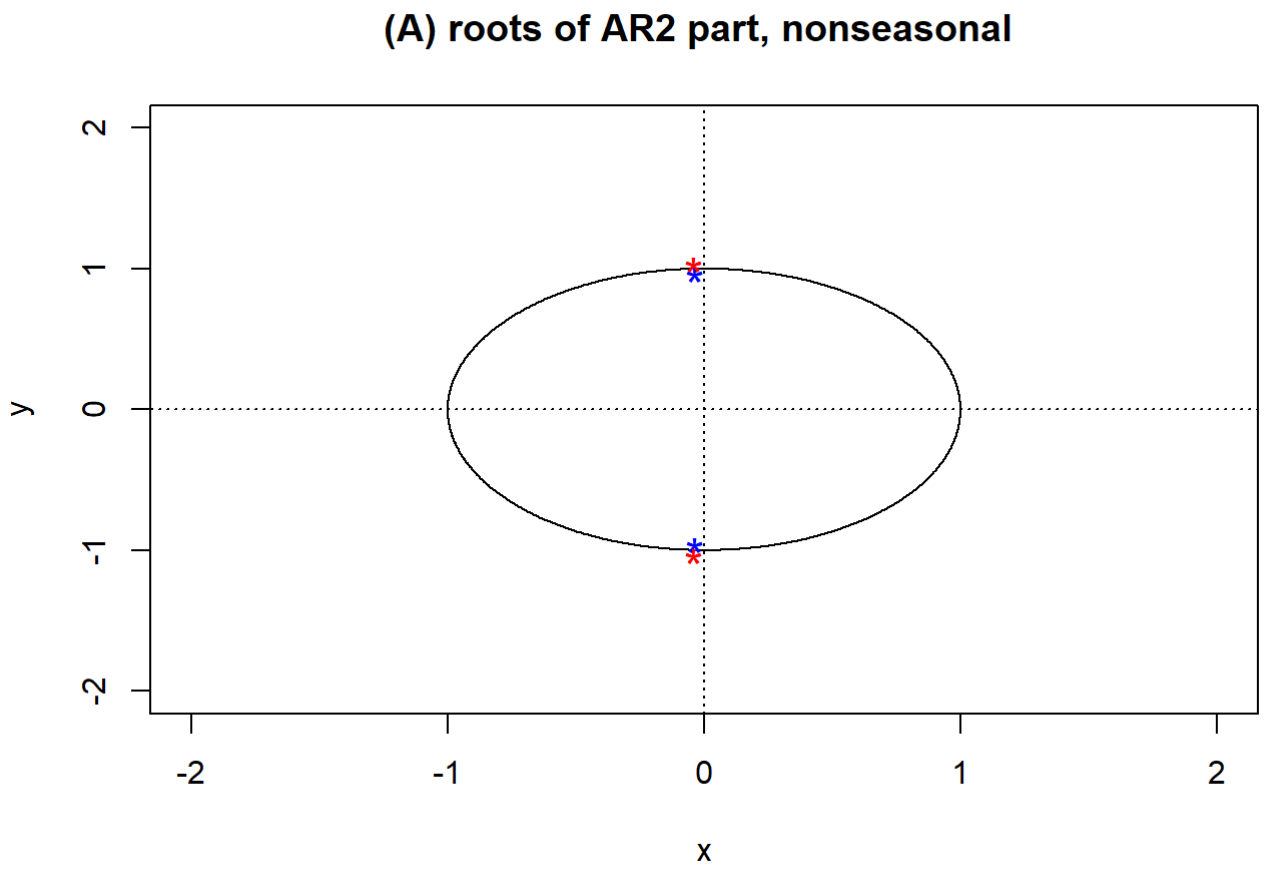
$$\phi_2$$

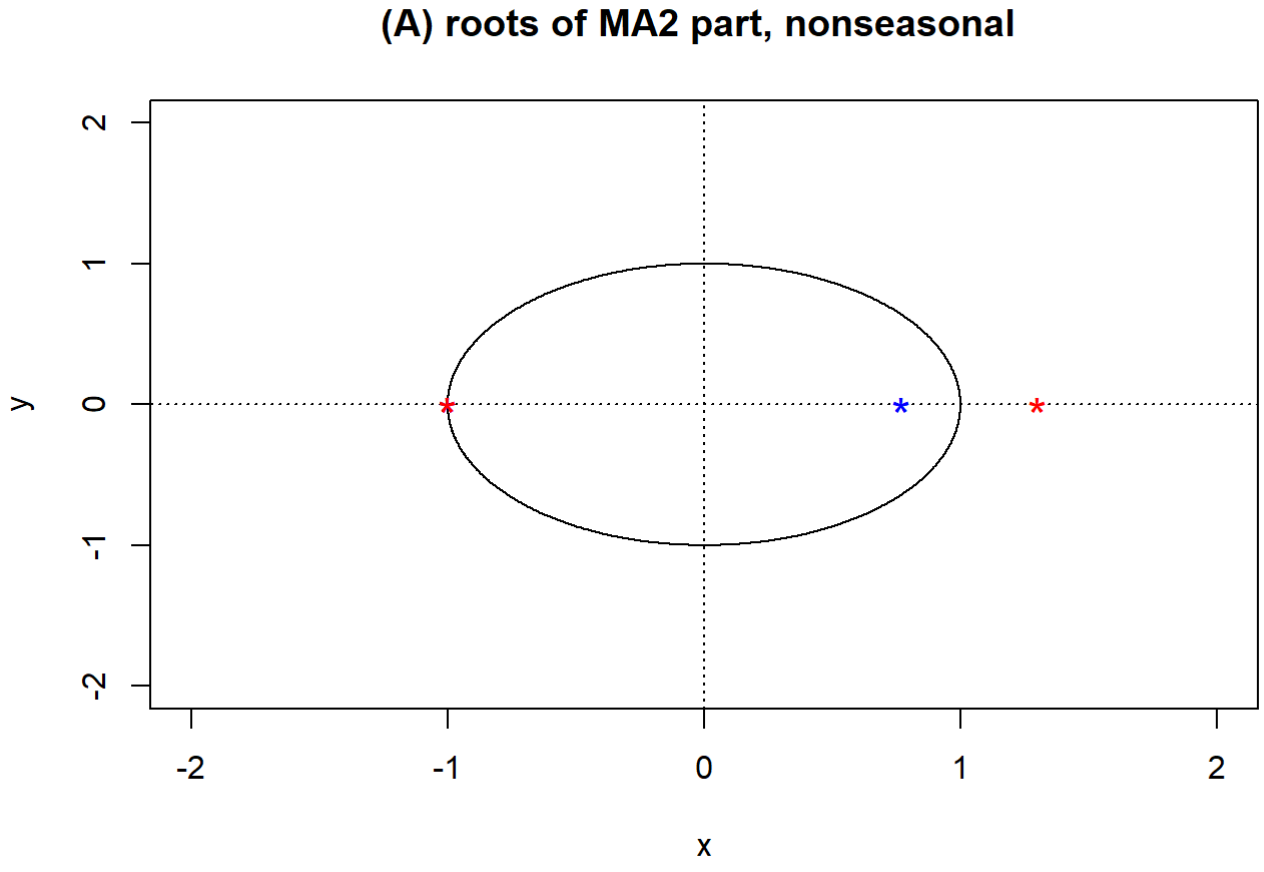
to have 0 in confidence interval

```
##
## Call:
## arima(x = train, order = c(2, 0, 2), seasonal = list(order = c(0, 1, 1), period = 12),
##     fixed = c(NA, NA, NA, NA, NA), method = "ML")
##
## Coefficients:
##          ar1     ar2     ma1      ma2     sma1
##       0.0731  0.9269  0.1777  -0.8172  -0.9794
## s.e.  0.0444  0.0444  0.1152   0.0986   0.0515
##
## sigma^2 estimated as 14433:  log likelihood = -916.67,  aic = 1843.34
```

```
## [1] 1845.742
```

seems fine for confidence interval but having unit roots:





so next I tried to set the

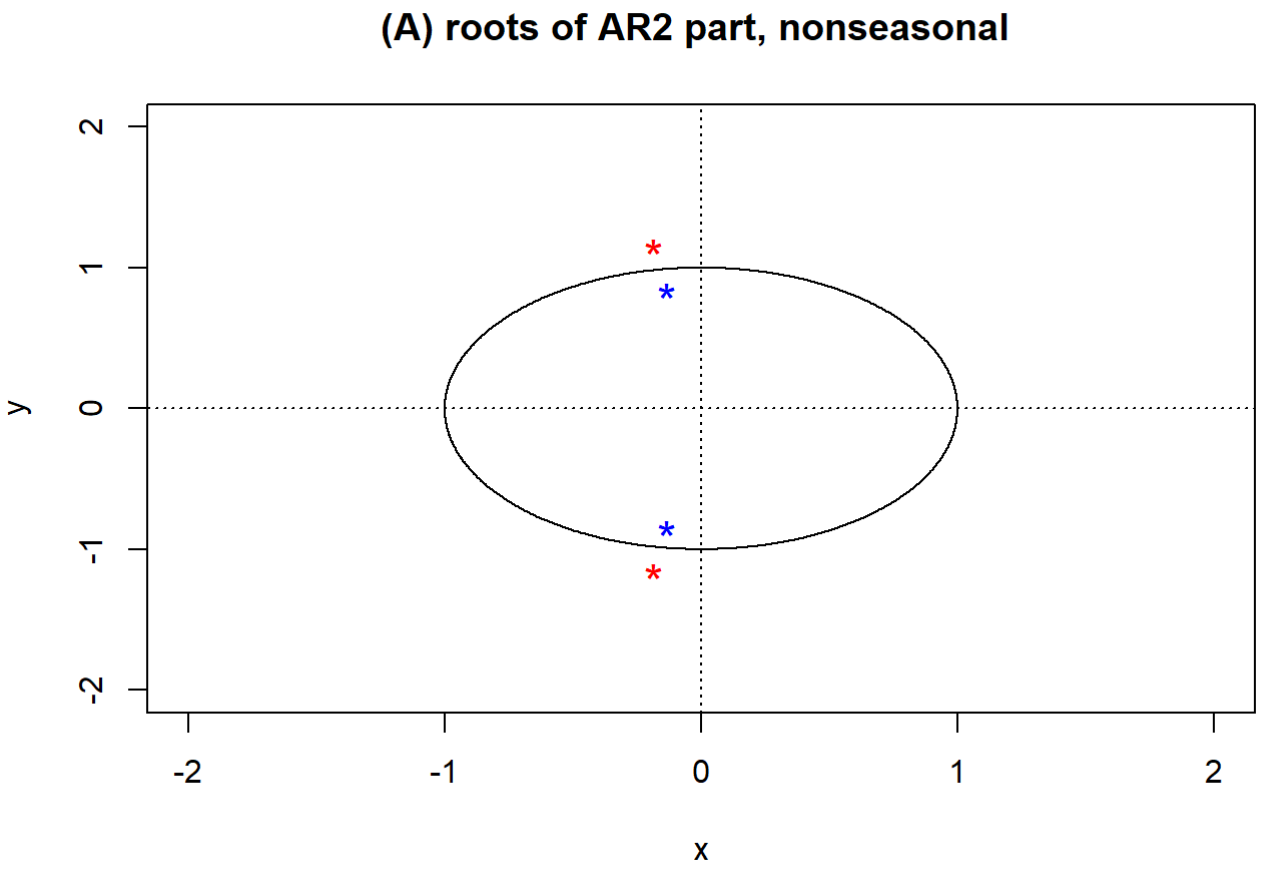
$$\theta_1$$

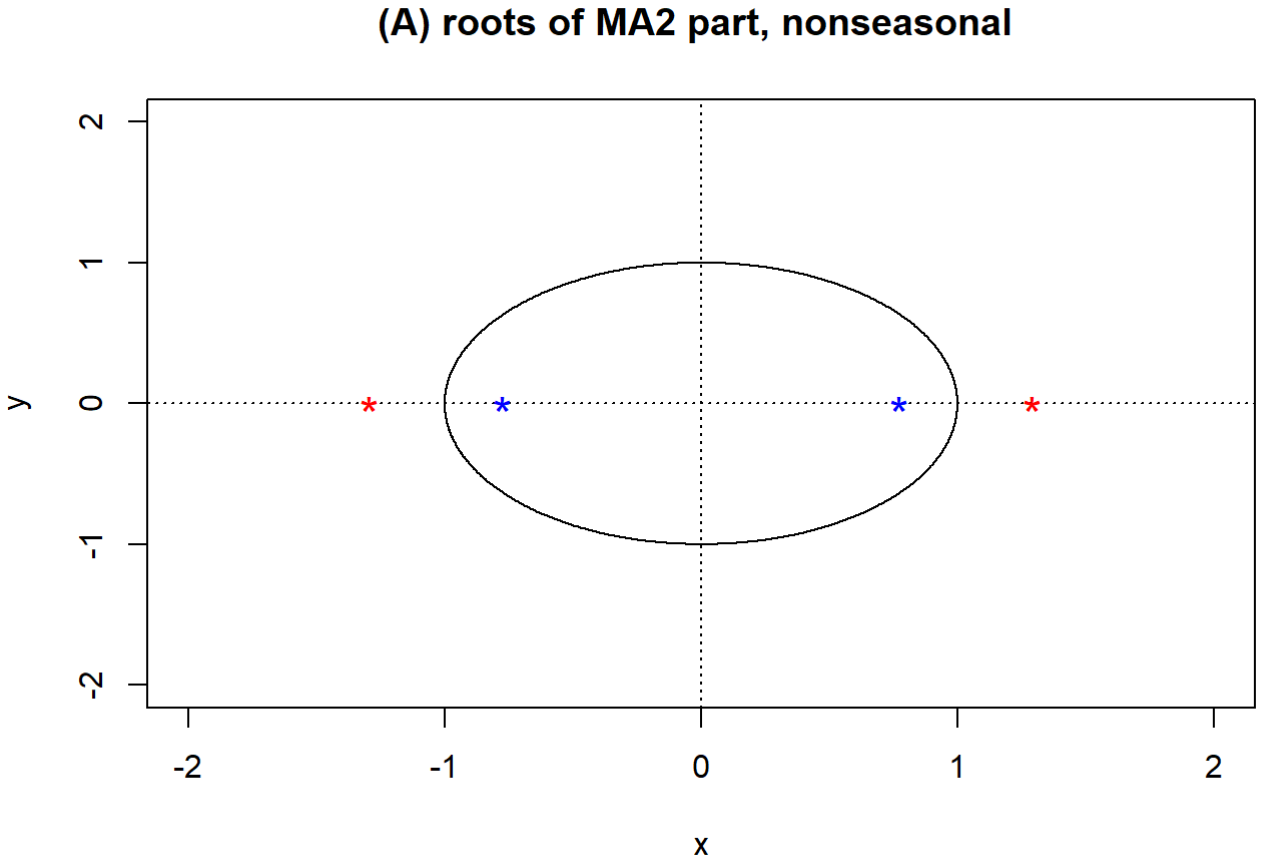
to be zero and I got the following results

```
##
## Call:
## arima(x = train, order = c(2, 0, 2), seasonal = list(order = c(0, 1, 1), period = 12),
##     fixed = c(NA, NA, 0, NA, NA), method = "ML")
##
## Coefficients:
##          ar1     ar2  ma1      ma2     sma1
##       0.1960  0.8040    0  -0.6850  -0.9852
## s.e.  0.0631  0.0631    0   0.1021   0.0449
##
## sigma^2 estimated as 14857:  log likelihood = -917.44,  aic = 1842.87
```

```
## [1] 1845.272
```

Checking for unit roots:





AR and MA outside unit root passed

so far this model seems fine and we can use it for testing later residual plots.

also try to set MA part to 3

```
##
## Call:
## arima(x = train, order = c(2, 0, 3), seasonal = list(order = c(0, 1, 1), period = 12),
##     fixed = c(NA, NA, NA, NA, NA, NA), method = "ML")
##
## Coefficients:
##          ar1     ar2     ma1      ma2     ma3     sma1
##       0.1064  0.8936  0.0586  -0.7666  0.1555  -0.9852
## s.e.  0.1116  0.1116  0.2997   0.2541  0.0974   0.0449
##
## sigma^2 estimated as 14132:  log likelihood = -915.39,  aic = 1842.78
```

```
## [1] 1845.344
```

It is vary close for

$$\theta_3$$

to be zero so I stopped here.

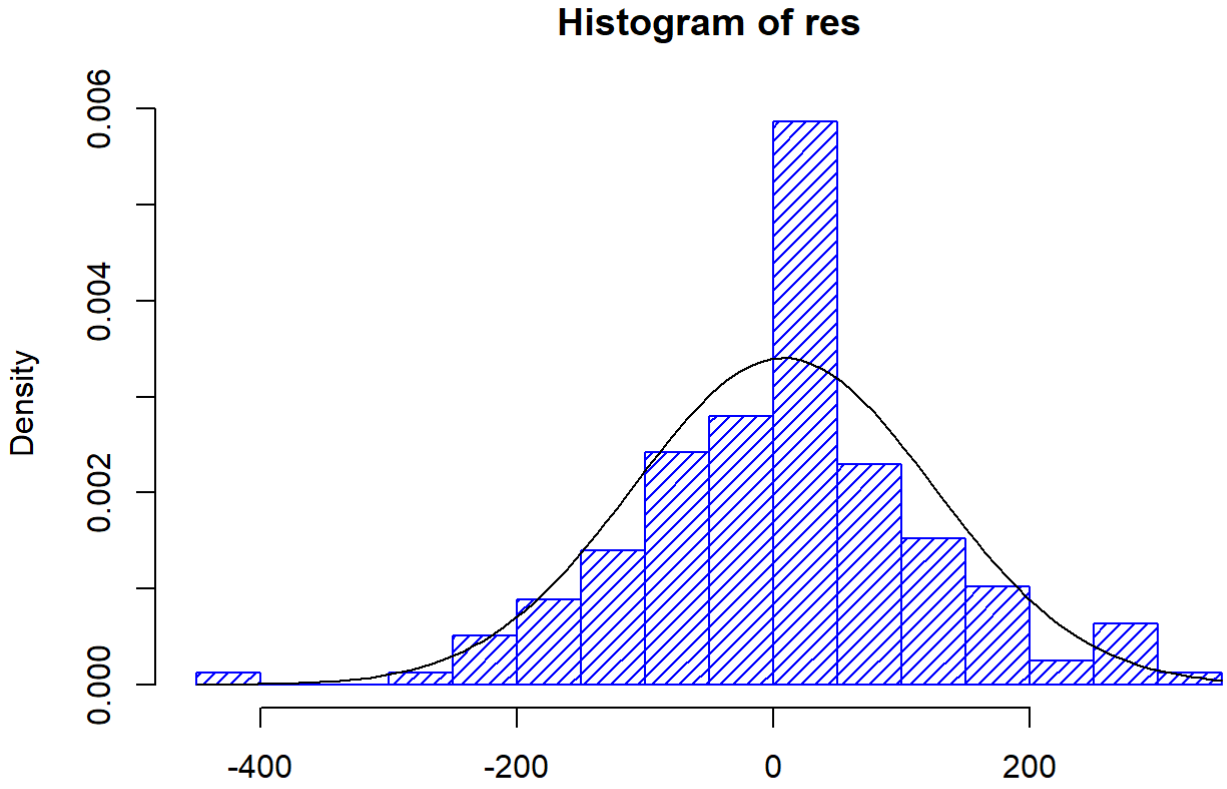
therefore SARIMA(2,0,2)(0,1,1)_12 have the lowest AICcs and do not have unit roots after comparing it to other.

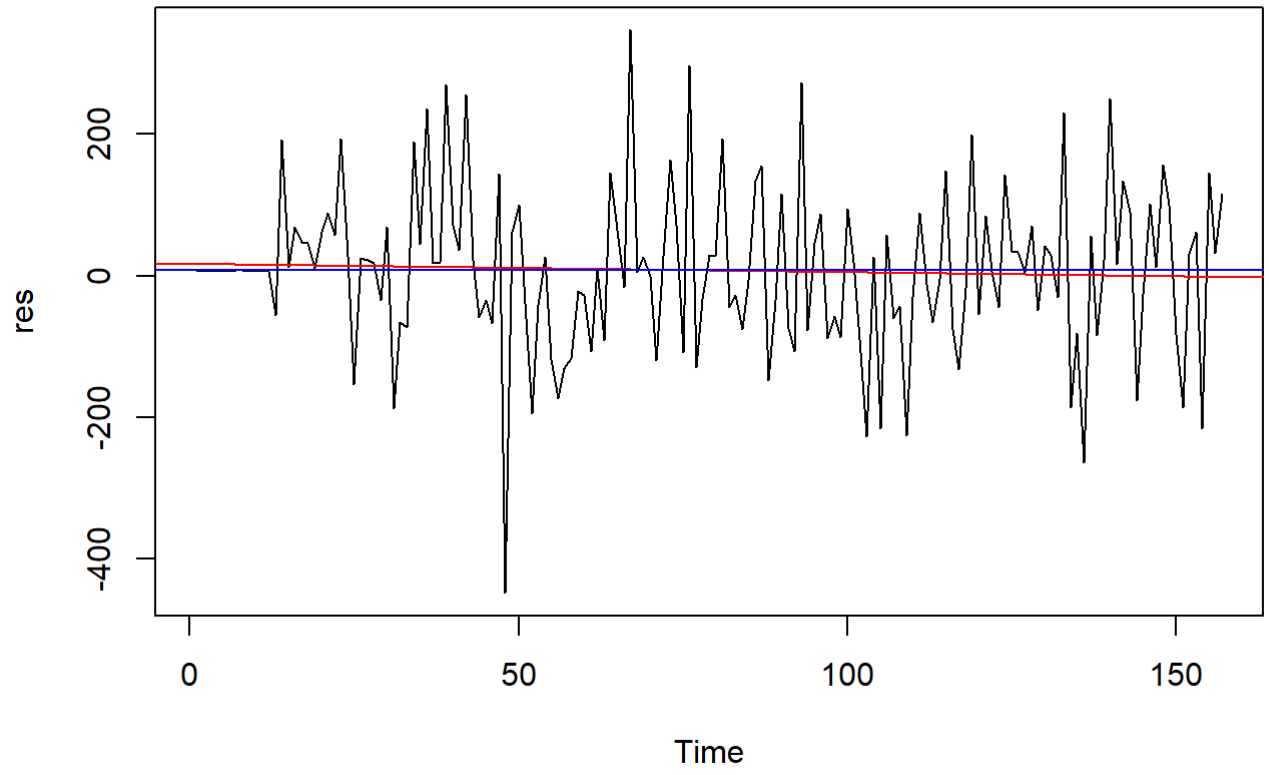
Diagnostic Checking: Fitting the model and checking the residual plots.

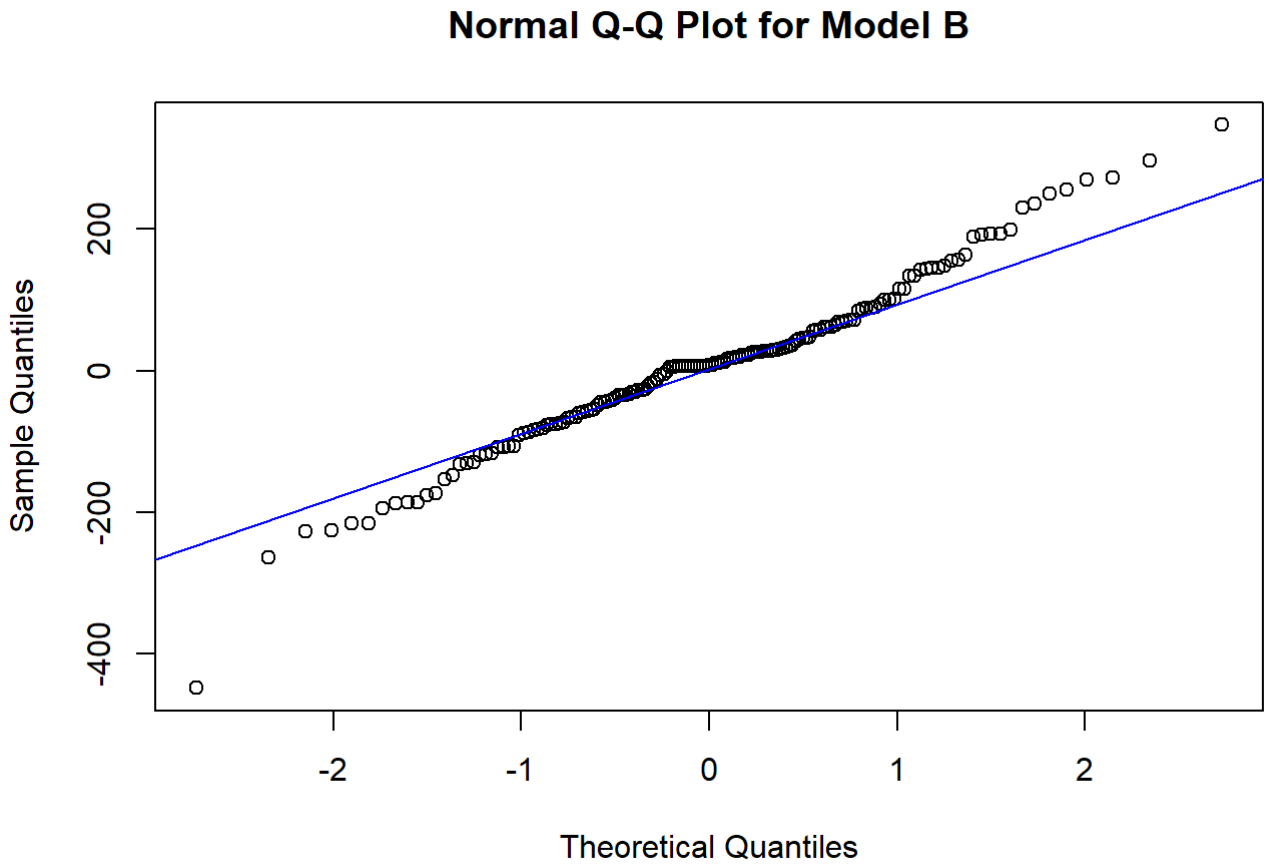
```
## [1] 7.925046
```

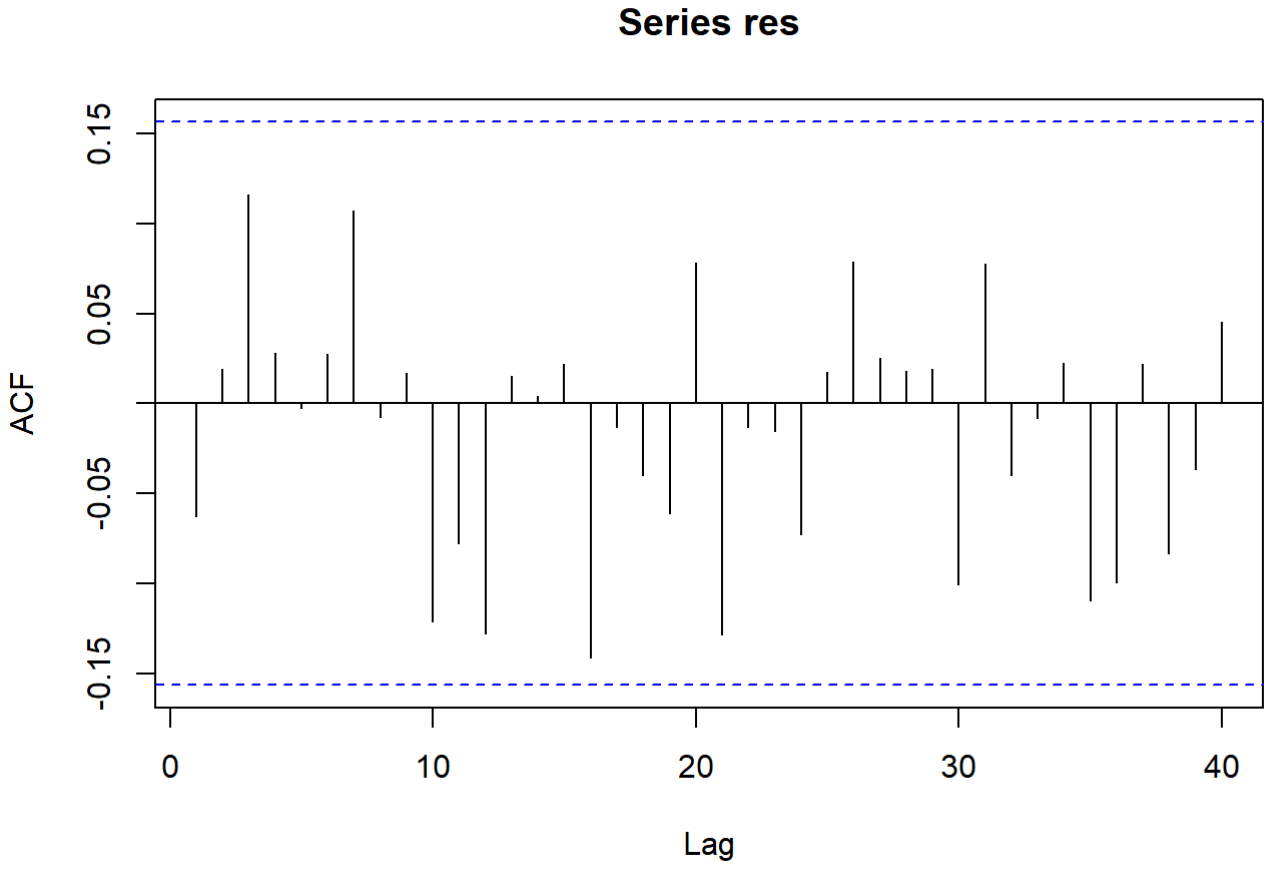
```
## [1] 13750.44
```

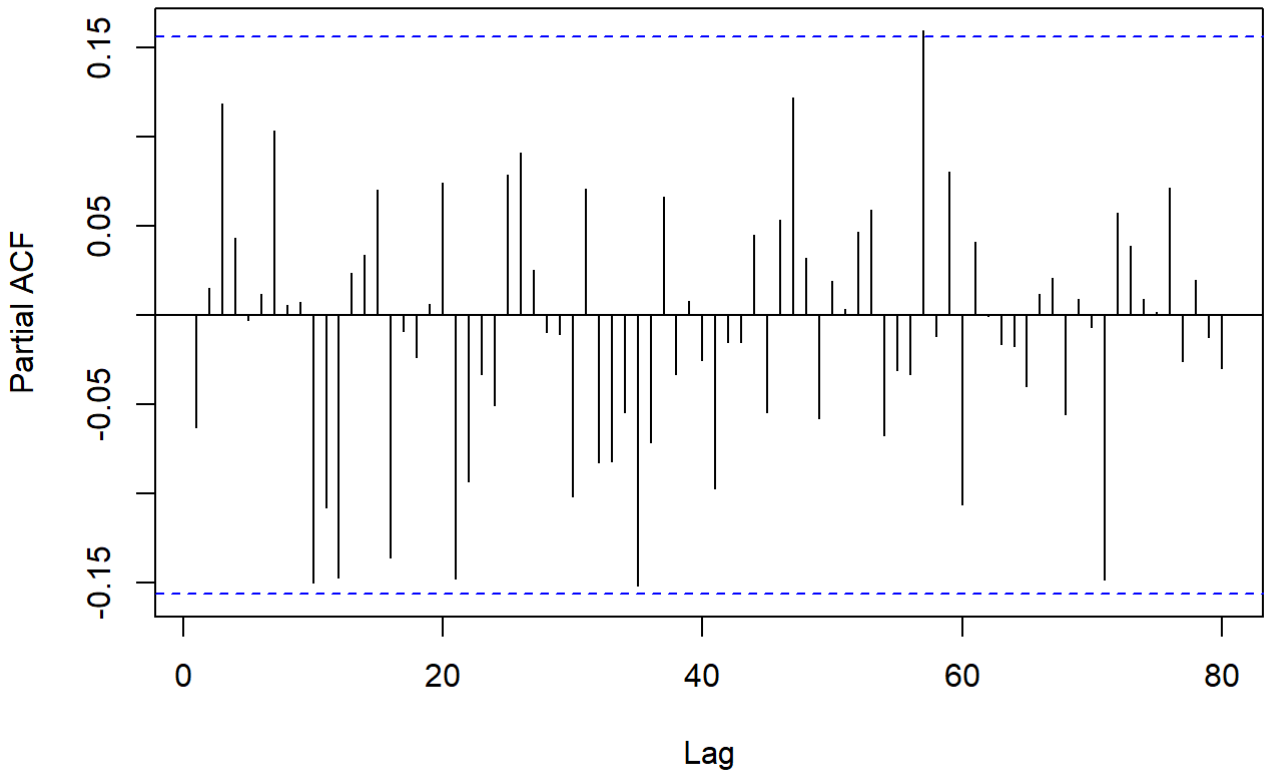
residual behaves like normal and mean is small relatively speaking






Normal Q-Q Plot for Model B
Sample Quantiles
200
0
-200
-400
-2
-1
0
1
2
Theoretical Quantiles


Series res
ACF
0.15
0.05
-0.05
-0.15
0
10
20
30
40
Lag



The plots shows no trend no visible change of variance, no seasonality. Histogram and Q-Q plot look OK All acf and pacf of residuals are within confidence intervals and can be counted as zeros because it passed the tests as shown later.

Run tests:

```
##
##  Shapiro-Wilk normality test
##
## data:  res
## W = 0.97835, p-value = 0.0143
```

```
##
##  Box-Pierce test
##
## data:  res
## X-squared = 10.761, df = 9, p-value = 0.2924
```

```
##
##  Box-Ljung test
##
## data:  res
## X-squared = 11.491, df = 9, p-value = 0.2435
```

```
##
##  Box-Ljung test
##
## data:  res^2
## X-squared = 15.685, df = 13, p-value = 0.2666
```

```
##
## Call:
## ar(x = res, aic = TRUE, order.max = NULL, method = c("yule-walker"))
##
##
## Order selected 0  sigma^2 estimated as  13750
```

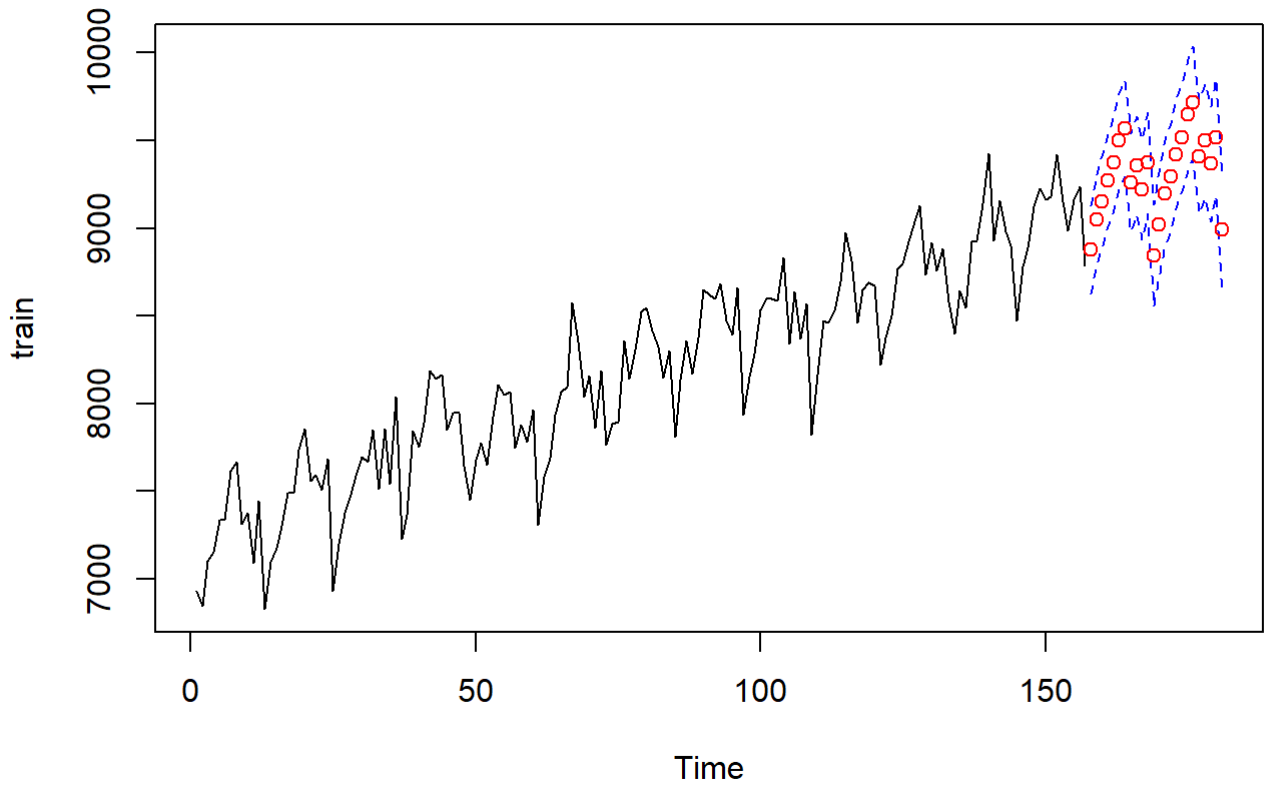
all tests p-value is larger than 0.05 passed This is great! We can move on to prediction.

4. Prediction and Forecasting:

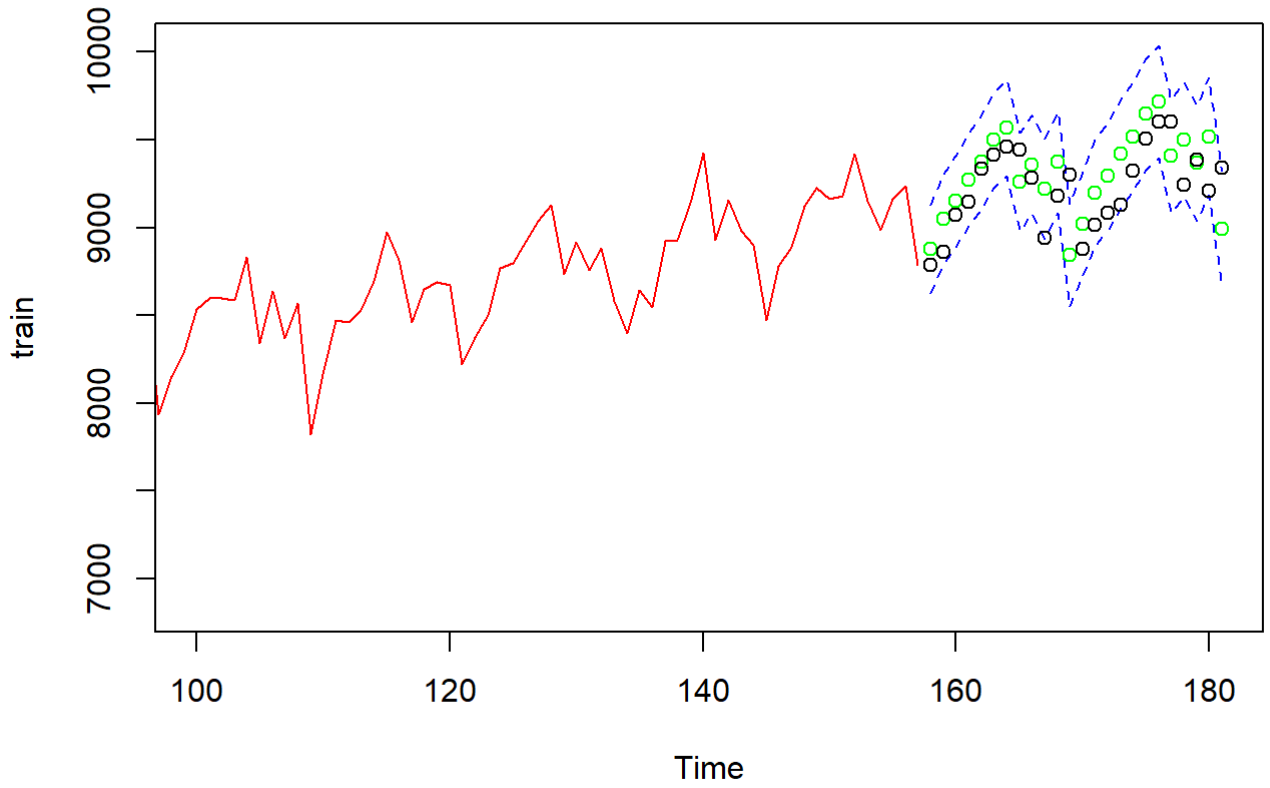
We have picked the model

$$\nabla_{12}(1-0.2677_{(0.0733)}B-0.7323B^2_{(0.0733)})X_t=(1-0.5979B^2_{(0.1005)})(1-0.9749B^{12}_{(0.0738)})Z_t$$

Draw the prediction interval for 2 year in the future:



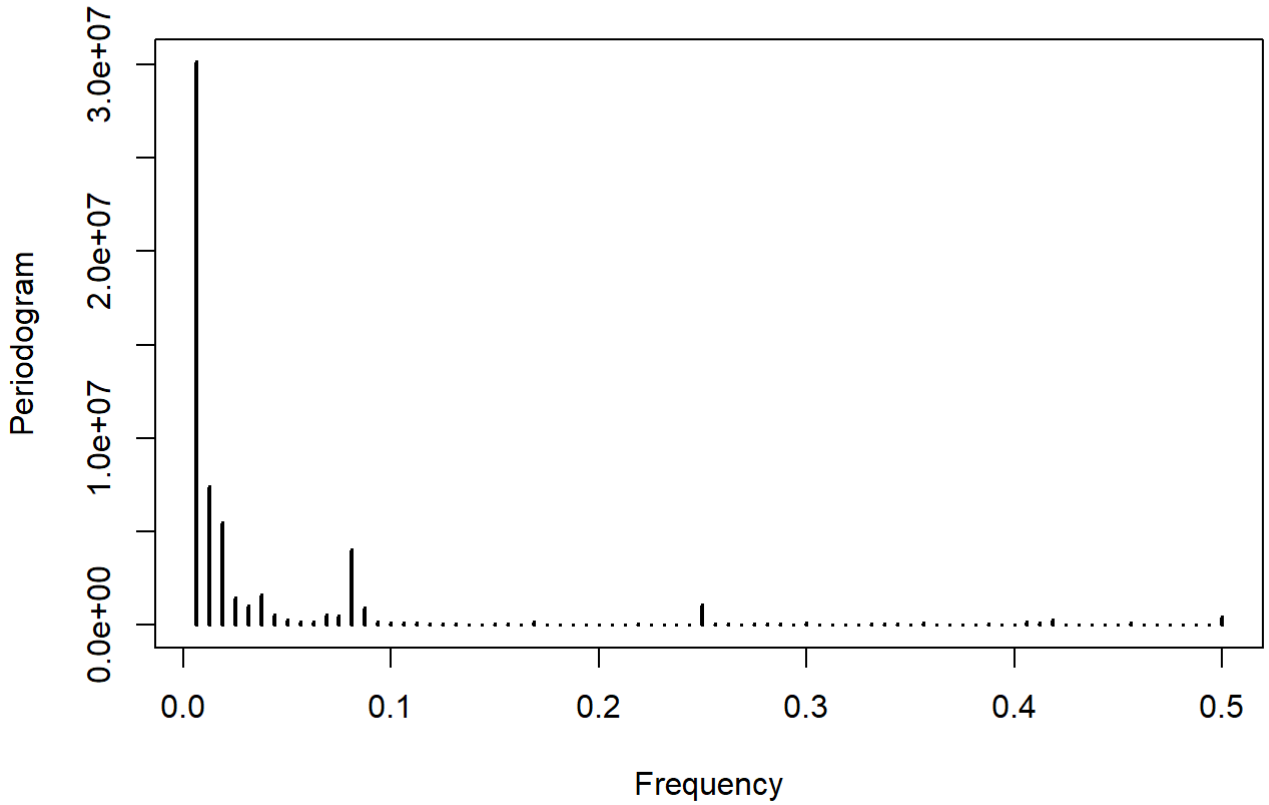
Then I zoom in on 100 and later and added the testing set, our model seems to preform well



This is great! We can see that for two years prediction that all observations are in side confidence interval and follows the approximate pattern.

5. Spectral Analysis:

plot the periodogram:

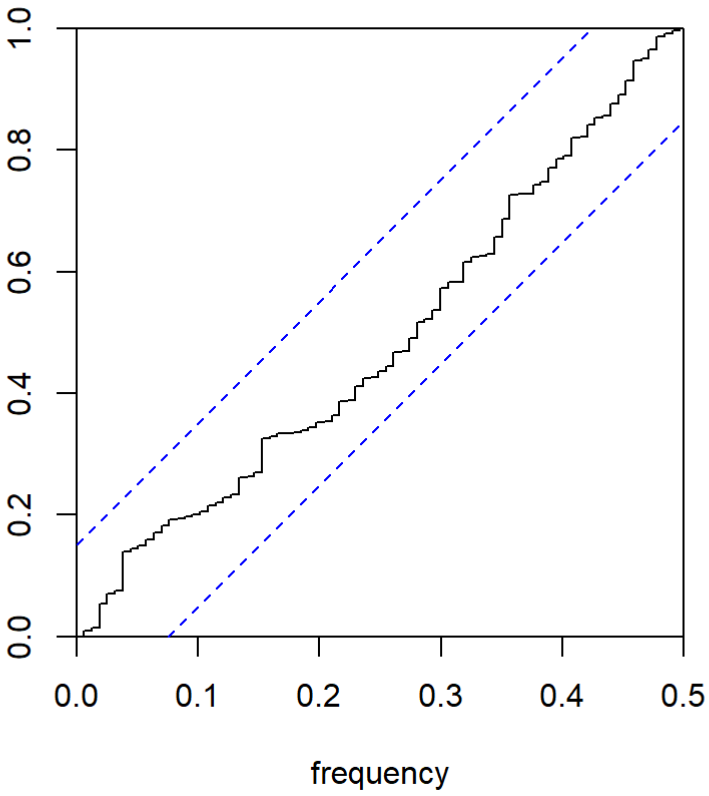


We can see a period here from the graph

Preform Fisher and Kolmogorov-Smirnov Test:

```
## [1] 0.6562926
```

From the fisher's p-value we can conclude that the residuals is a white noise



Also, from the Kolmogorov-Smirnov test we can see that the lines are all withing confidence interval that can be counted as passing this test.

5. Conclusion:

The goal of the project is to predict US gas supply with data presented and time series analysis. I managed to achieve good predicting with solid time series analysis that models the US monthly gas supply in two years. The model I used is

$$\nabla_{12}(1-0.2677_{(0.0733)}B-0.7323B^2_{(0.0733)})X_t=(1-0.5979B^2_{(0.1005)})(1-0.9749B^{12}_{(0.0738)})Z_t$$

this model work fine by the validation of diagnostic checking and spectral analysis. I examined the acf and pacf for further validating the residuals that it resembles white noise process. Thanks to professor Feldman's great course contents and instruction, I finally achieved using time series analysis to build model.

6. Reference:

People Helped: Prof. Raya Fledman and Lecture slides & notes

Data collection : https://www.eia.gov/naturalgas/data.php (https://www.eia.gov/naturalgas/data.php)

Software: R Studio and R Markdown.

Package and Functions Reference: https://cran.r-project.org/web/packages/forecast/forecast.pdf (https://cran.r-project.org/web/packages/forecast/forecast.pdf) https://cran.r-project.org/web/packages/TSA/TSA.pdf (https://cran.r-project.org/web/packages/TSA/TSA.pdf)
https://github.com/nickpoison/astsa/blob/master/fun_with_astsa/fun_with_astsa.md#arima simulation

(https://github.com/nickpoison/astsa/blob/master/fun_with_astsa/fun_with_astsa.md#arima simulation)
https://cran.r-project.org/web/packages/astsa/astsa.pdf (https://cran.r-project.org/web/packages/astsa/astsa.pdf)

7. Appendix:

```
#input data
library(tsdl)
gas.csv <- read.csv("US_Gas_Supply.csv")
rusage <- gas.csv$Usage
usage = rev(rusage)
gas = ts(usage, start= c(1992,1), frequency = 12)
plot.ts(gas)

#test train split and draw test
train <- gas[c(1:157)]
test <- gas[c(157:180)]
plot.ts(train, main = "US Oil Consumption Monthly Data")
fit <- lm(train ~ as.numeric(1:length(train)))
abline(fit, col = "red")
abline(h = mean(train), col = "blue")

#histogram and qqplots for normality checking
par(mfrow = c(1,2))
hist(train, col = "lightgreen", main = "histogram of training data", freq=F)
curve(dnorm(x,mean(train), sqrt(var(train))), col = "red", add = TRUE)
qqnorm(train)

#acf/pacf checking
par(mfrow=c(1,2))
acf(train, lag.max = 50, main = "acf of the training data")
pacf(train, lag.max = 50, main = "acf of the training data")

#box-cox transform and compare it to original
library(MASS)
t <- 1:length(train)
bcTransform <- boxcox(train ~ t)
lambda <- bcTransform$x[which.max(bcTransform$y)]
train.bc = (1/lambda)*((train)^lambda - 1)
par(mfrow=c(1,2))
plot.ts(train.bc,main = "Box-Cox transformed data")
plot.ts(train,main = "Original data")
par(mfrow=c(1,2))
hist(train.bc, col="light blue", xlab="", main="Histogram of the Box-Cox Transformed Data",freq
= F)
m1 <- mean(train.bc)
std1 <- sqrt(var(train.bc))
curve(dnorm(x, m1, std1), col="red", add=TRUE)
hist(train, col="light blue", xlab="", main="Histogram of the original Data",freq = F)
m2 <- mean(train)
std2 <- sqrt(var(train))
curve(dnorm(x, m2, std2), col="red", add=TRUE)

#decompose data
y <- ts(as.ts(train), frequency = 12)
decomp <- decompose(y)
plot(decomp)
#difference data
ds_train <- diff(train, 12)
dst_train <- diff(ds_train, 1)
var(train.bc)
```

```
var(ds_train)
var(dst_train)

#plot data
plot.ts(ds_train)
abline(h=mean(ds_train), lty=2)
fitdiff1 <- lm(ds_train ~ as.numeric(1:length(ds_train)))
abline(fitdiff1, col="red")
par(mfrow=c(1,2))
hist(ds_train, col="light blue", xlab=expression(nabla[12]~(X[t])), prob=TRUE)
m <- mean(ds_train)
std <- sqrt(var(ds_train))
curve(dnorm(x,m,std), add=TRUE)
qqnorm(ds_train)

#plotted acf and pacf for the data
par(mfrow=c(1,2))
acf(ds_train, lag.max=40, main=expression(nabla[12]~(X[t])))
pacf(ds_train, lag.max=40, main="PACF De-seasonal")

#plot the roots for unit root checking
plot.roots <- function(ar.roots=NULL, ma.roots=NULL, size=2, angles=FALSE, special=NULL, sqeci
al=NULL,my.pch=1,first.col="blue",second.col="red",main=NULL)
{xylims <- c(-size,size)
      omegas <- seq(0,2*pi,pi/500)
      temp <- exp(complex(real=rep(0,length(omegas)),imag=omegas))
      plot(Re(temp),Im(temp),typ="l",xlab="x",ylab="y",xlim=xylims,ylim=xylims,main=main)
      abline(v=0,lty="dotted")
      abline(h=0,lty="dotted")
      if(!is.null(ar.roots))
        {
          points(Re(1/ar.roots),Im(1/ar.roots),col=first.col,pch=my.pch)
          points(Re(ar.roots),Im(ar.roots),col=second.col,pch=my.pch)
        }
      if(!is.null(ma.roots))
        {
          points(Re(1/ma.roots),Im(1/ma.roots),pch="*",cex=1.5,col=first.col)
          points(Re(ma.roots),Im(ma.roots),pch="*",cex=1.5,col=second.col)
        }
      if(angles)
        {
          if(!is.null(ar.roots))
            {
              abline(a=0,b=Im(ar.roots[1])/Re(ar.roots[1]),lty="dotted")
              abline(a=0,b=Im(ar.roots[2])/Re(ar.roots[2]),lty="dotted")
            }
          if(!is.null(ma.roots))
            {
              sapply(1:length(ma.roots), function(j) abline(a=0,b=Im(ma.roots[j])/Re(ma.roots
[j]),lty="dotted"))
            }
        }
      if(!is.null(special))
        {
          lines(Re(special),Im(special),lwd=2)
        }
```

```
      if(!is.null(sqecial))
        {
          lines(Re(sqecial),Im(sqecial),lwd=2)
        }
        }

#parameter estimation and AICc chenkings
arima(train, order=c(2,0,3), seasonal = list(order = c(0,1,1), period = 12),  fixed = c( NA,
NA,NA, NA, NA, NA), method="ML")
AICc(arima(train, order=c(2,0,3), seasonal = list(order = c(0,1,1), period = 12),  fixed = c( N
A,
NA,NA, NA, NA,NA), method="ML"))

arima(train, order=c(2,0,2), seasonal = list(order = c(0,1,1), period = 12),  fixed = c( NA,
NA,0, NA, NA), method="ML")
AICc(arima(train, order=c(2,0,2), seasonal = list(order = c(0,1,1), period = 12),  fixed = c( N
A,
NA,0, NA, NA), method="ML"))

arima(train, order=c(2,0,1), seasonal = list(order = c(0,1,1), period = 12),fixed = c(
NA,NA,NA,NA) ,
      method="ML")
AICc(arima(train, order=c(2,0,1), seasonal = list(order = c(0,1,1), period = 12),fixed = c(
NA,NA,NA,NA) ,
      method="ML"))

#Checking for unit roots:

#source("plot.roots.R")
library(qpcR)
plot.roots(NULL,polyroot(c(1, 0.2677,0.7323)), main="(A) roots of AR2 part, nonseasonal ")
plot.roots(NULL,polyroot(c(1,0,-0.5979)), main="(A) roots of MA2 part, nonseasonal ")

#Diagonistic Checking
library(astsa)
fit<- arima(train, order=c(2,0,2), seasonal = list(order = c(0,1,1), period = 12),  fixed = c(
NA,
NA,0, NA, NA), method="ML")
res <- fit$residuals
mean(res)
var(res)
hist(res,density=20,breaks=20, col="blue", xlab="", prob=TRUE)
m1 <- mean(res)
std1 <- sqrt(var(res))
curve( dnorm(x,m1,std1), add=TRUE )
plot.ts(res)
fitt <- lm(res ~ as.numeric(1:length(res))); abline(fitt, col="red")
abline(h=mean(res), col="blue")
qqnorm(res,main= "Normal Q-Q Plot for Model B")
qqline(res,col="blue")
acf(res, lag.max=40)
pacf(res, lag.max=80)

#run tests
shapiro.test(res)
Box.test(res, lag = 13, type = c("Box-Pierce"), fitdf = 4)
```

```
Box.test(res, lag = 13, type = c("Ljung-Box"), fitdf = 4)
Box.test(res^2, lag = 13, type = c("Ljung-Box"), fitdf = 0)
#acf(res^2, lag.max=40)
ar(res, aic = TRUE, order.max = NULL, method = c("yule-walker"))

#predictions:
library(forecast)
fit.A <- arima(train, order=c(2,0,2), seasonal = list(order = c(0,1,1), period = 12),  fixed =
 c( NA,
NA,0, NA, NA), method="ML")

#plot it
pred.tr <- predict(fit.A, n.ahead = 24)
pred.orig <- pred.tr$pred
U= pred.tr$pred + 2*pred.tr$se #upper bound of prediction interval
L= pred.tr$pred - 2*pred.tr$se #lower bound
ts.plot(train, xlim=c(1,length(train)+24), ylim = c(min(train),max(U)))
lines(U, col="blue", lty="dashed")
lines(L, col="blue", lty="dashed")
points((length(train)+1):(length(train)+24), pred.orig, col="red")

ts.plot(train, xlim = c(100,length(train)+24),ylim = c(min(train),max(U)), col="red")
lines(U,col="blue", lty="dashed")
lines(L, col="blue", lty="dashed")
points((length(train)+1):(length(train)+24), pred.orig, col="green")
points((length(train)+1):(length(train)+24), test, col="black")

#Spectral Analysis
#install.packages("TSA")
#require(TSA)
#library("TSA")
TSA::periodogram(train, plot = T) #abline(h=0);
#axis(1,at=c(0.01, 0.02, 0.03,0.083, 0.1))
library("GeneCycle")
fisher.g.test(res)
cpgram(res,main="")
```