

ch7_SARIMA

2023-11-11

Summary

General multiplicative Box-Jenkins models:

$$\phi(B) \Phi(B^s) \nabla^d \nabla_S^D y_t = \theta(B) \Theta(B^s) \varepsilon_t$$

SARIMA(p, d, q)(P, D, Q)S

for Seasonal

$$(1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p)(1 - \Phi_1 B^s - \Phi_2 B^{2s} - \dots - \Phi_P B^{Ps})(1 - B)^d (1 - B^s)^D$$
$$= (1 - \theta_1 B - \theta_2 B^2 - \dots - \theta_q B^q)(1 - \Theta_1 B^s - \Theta_2 B^{2s} - \dots - \Theta_Q B^{Qs}) \varepsilon_t$$

Autoregressive operator of order p:

$$\phi(B) = (1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p)$$

seasonal Autoregressive models of order P:

$$\Phi(B^s) = (1 - \Phi_1 B^s - \Phi_2 B^{2s} - \dots - \Phi_P B^{Ps}) ; s: \text{seasonal period length}$$

ϕ : represent the non-*seasonal* autoregressive parameter.

Φ or Φ : represent the *seasonal* autoregressive parameter.

Difference operator of order d:

$$\nabla^d = (1 - B)^d$$

d is the minimum order of the differences that must be taken to render the series stationary.

seasonal differences at the seasonal period S

$$\nabla_S^D = (1 - B^s)^D$$

Moving Average operator of order q:

$$\theta(B) = (1 - \theta_1 B - \theta_2 B^2 - \dots - \theta_q B^q)$$

seasonal Moving Average operator of order Q:


$$\Theta(B^s) = (1 - \Theta_1 B^s - \Theta_2 B^{2s} - \dots - \Theta_Q B^{Qs})$$

Θ : represent the seasonal moving average parameter.

θ : represent the moving average parameter.

Q: Write the mathematical formula for the following models :

1. SARIMA (2,1,2)(1,2,2)₆

SARIMA(2,1,2)(1,2,2)₆

 for Seasonal

S: Seasonal - AR: Autoregressive - I: no. of differences - MA: Moving Average - 6: seasonal periods

$$(1 - \phi_1 B - \phi_2 B^2)(1 - \Phi_1 B^6)(1 - B)(1 - B^6)^2 Y_t = (1 - \theta_1 B - \theta_2 B^2)(1 - \Theta_1 B^6 - \Theta_2 B^{12}) \text{ et}$$

2. SARIMA (2,0,1)(0,1,2)₃

$$(1 - \phi_1 B - \phi_2 B^2)(1 - B^3) Y_t = (1 - \theta_1 B)(1 - \Theta_1 B^3 - \Theta_2 B^6) \text{ et}$$

3. SARIMA (0,2,2)(1,0,1)₅

$$(1 - \Phi_1 B^5)(1 - B)^2 Y_t = (1 - \theta_1 B - \theta_2 B^2)(1 - \Theta_1 B^5) \text{ et}$$

4. SARIMA (1,1,0)(2,3,1)₂

$$(1 - \phi_1 B)(1 - \Phi_1 B^2 - \Phi_2 B^4)(1 - B)(1 - B^2)^3 Y_t = (1 - \Theta_1 B^2) \text{ et}$$

Exercise 1: For the given data (C2 data), do the following:

- 1- Plot the time series and comment.
- 2- Is any transformation/ difference needed for this data to obtain adequate results?
- 3- Plot the ACF and PACF and comment, suggest a preliminary model for the data.
- 4- Obtain a suitable SARIMA or ARIMA model for the time series. Test the significance of the model parameters.
- 5- Check the adequacy of the model? (hint residual plots and tests).
- 6- Write down the model using backshift operator.
- 7- Forecast the next **10** observations of the original series (write the prediction) . Plot the forecast.
- 8- 80% C.I for the next **10** forecast of the original series.

Exercise 1 using R:

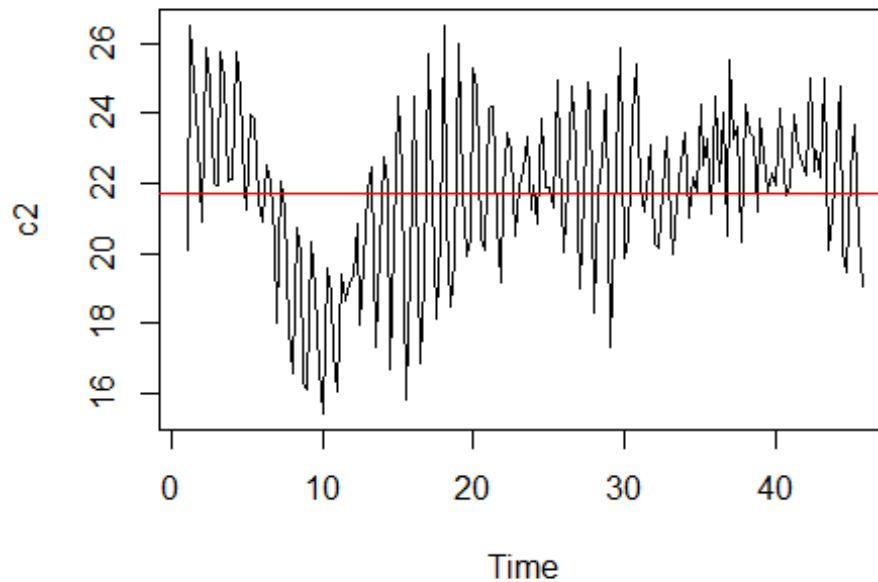
The packages used in time series analysis

```
#install.packages("forecast")
#install.packages("tseries")
#install.packages("randtests")
#install.packages("astsa")
#install.packages("lmttest")
library(forecast)
library(tseries)
library(randtests)
library(astsa)
library(lmttest)
```

Checking stationary of the series:

```
## Checking Stability in the mean and variance .
data<- read.csv(file.choose(),header = T)
d=ts(data,frequency = 4) #time-series objects with seasonal periods 4 .
#figure (1)
plot(d,main="Figure (1)") ; abline(h =mean(d),col="red")
```

Figure (1)



The data is not stationary in the mean and in the variance.

➤ **Normality test**

```
shapiro.test(d)
  Shapiro-Wilk normality test
data:  d
W = 0.98235, p-value = 0.02239
```

The data don't follow Normal distribution based on Shapiro test, which indicate to nonstationary in the variance. Also, we note that from Figure (1).

➤ **Apply Box Cox transformation to stabilize the variance.**

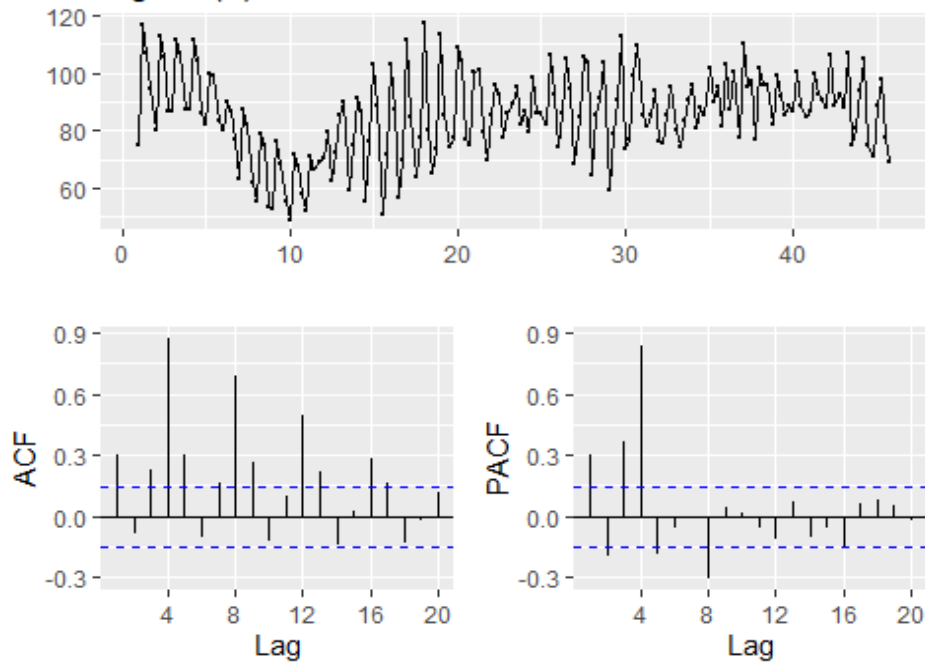
```
(lambda <-BoxCox.lambda( d ))
[1] 1.598283

d.B<-BoxCox( d ,lambda)
shapiro.test(d.B)

  Shapiro-Wilk normality test
data:  d.B
W = 0.98797, p-value = 0.1293

ggtsdisplay(d.B,lag.max=20, main="Figure (2)" )
```

Figure (2)



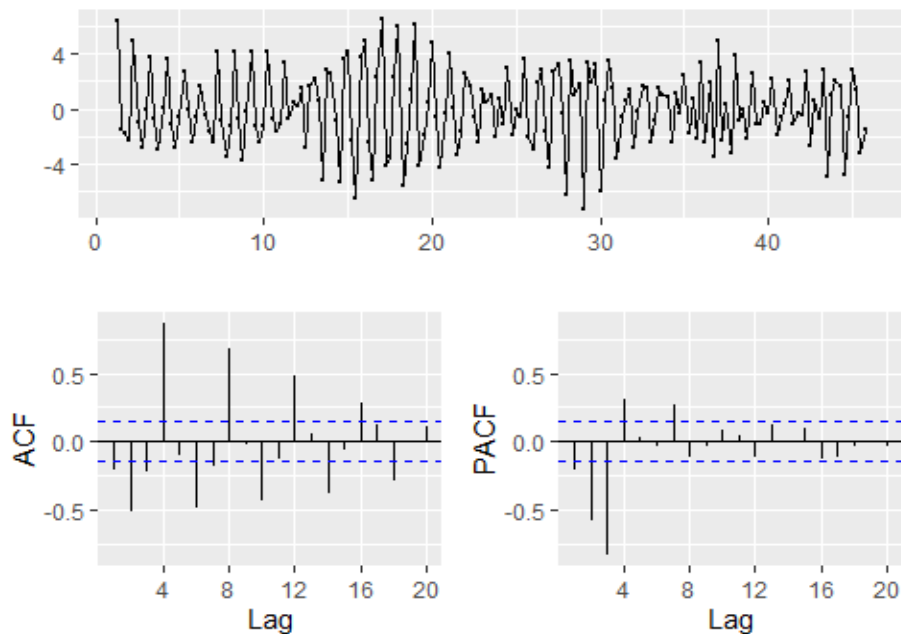
```
#plot(d.B) ; abline(h =mean(d.B),col="red")
```

After taking Box Cox transformation, the data become stationary in the variance but not stationary in the mean.

➤ *Taking First difference to stabilize the mean and variance*

```
d.diff<-diff(d,differences =1 )  
gtsdisplay(d.diff,lag.max=20 , main="Figure (3)")
```

Figure (3)



```
shapiro.test(d.diff)
  Shapiro-Wilk normality test
data:  d.diff
W = 0.99382, p-value = 0.6583

#plot(d.diff) ; abline(h =mean(d.diff),col="red")
```

After taking first difference, the data become stationary in the mean and in the variance.

➤ **Finding the appropriate model using ACF and PACF plot:**

From Figure (3) we suggest the models **SARIMA(1,0,0)(1,1,0)₄**
SARIMA(1,1,1)(2,0,1)₄ , SARIMA(2,0,1)(1,1,1)₄ ...

Or if we consider the data stationary in the mean from Figure (2) , we suggest the models SARIMA(1,0,0)(2,0,1)₄ , SARIMA(0,0,1)(2,0,1)₄ , ...

Model 1: SARIMA(1,0,0)(1,1,0)₄ model

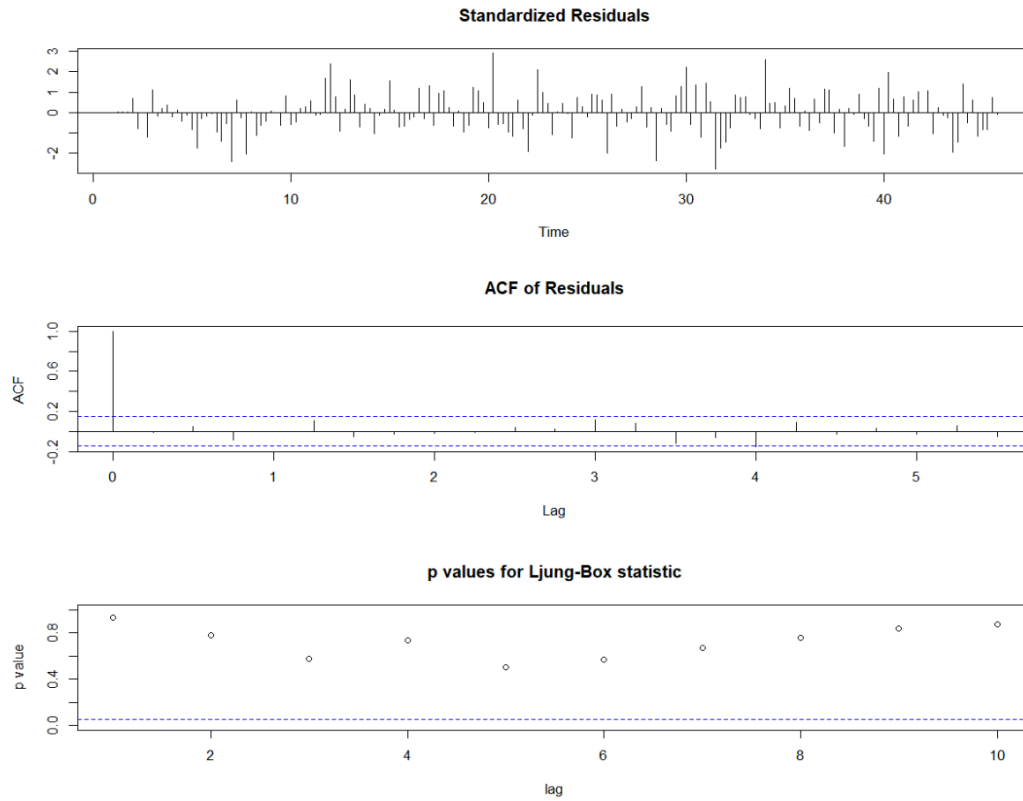
```
model1<-Arima(d,order = c(1,0,0),seasonal = c(1,1,0))
#Testing the coefficients & Diagnosing Residuals
coeftest(model1)
```

z test of coefficients:

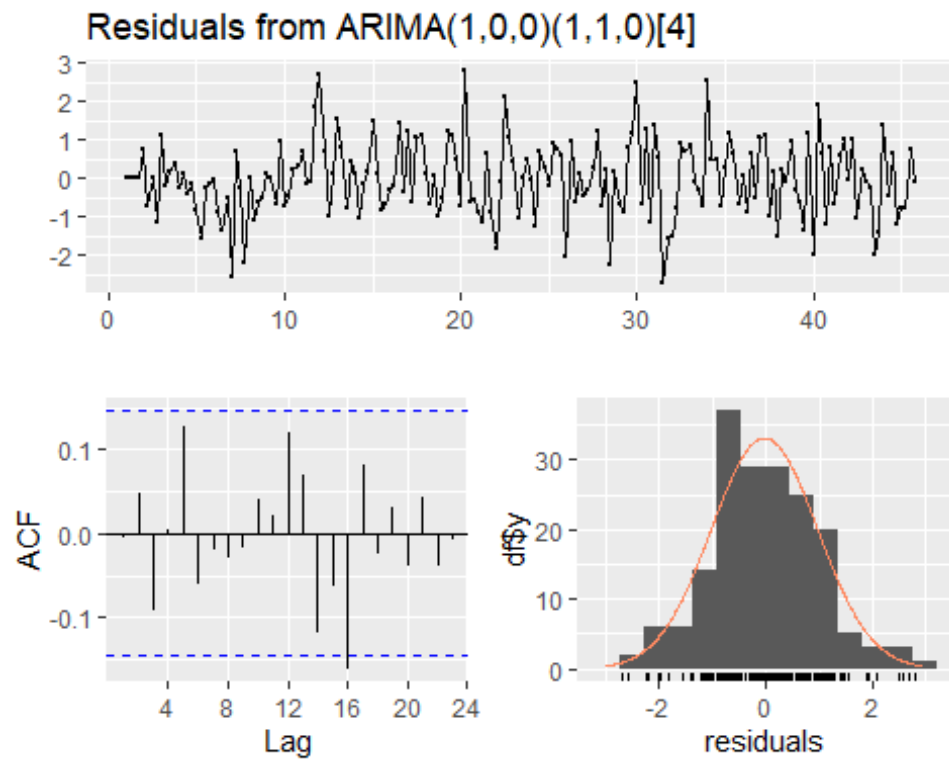
	Estimate	Std. Error	z value	Pr(> z)	
ar1	0.248590	0.072804	3.4145	0.0006389	***
sar1	0.290884	0.072085	4.0353	5.453e-05	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```
tsdiag(model1)
```



```
checkresiduals(model11, lag= 12)
```



```
Ljung-Box test
data: Residuals from ARIMA(1,0,0)(1,1,0)[4]
Q* = 9.2283, df = 10, p-value = 0.5106
```

```
Model df: 2. Total lags used: 12
```

```
checkresiduals(modell1, lag= 24,plot=FALSE)
```

```
Ljung-Box test
data: Residuals from ARIMA(1,0,0)(1,1,0)[4]
Q* = 21.669, df = 22, p-value = 0.4798
```

```
Model df: 2. Total lags used: 24
```

```
checkresiduals(modell1, lag= 36,plot=FALSE)
```

```
Ljung-Box test
data: Residuals from ARIMA(1,0,0)(1,1,0)[4]
Q* = 48.15, df = 34, p-value = 0.05464
```

```
Model df: 2. Total lags used: 36
```

```
checkresiduals(modell1, lag= 48,plot=FALSE)
```

```
Ljung-Box test
data: Residuals from ARIMA(1,0,0)(1,1,0)[4]
Q* = 60.148, df = 46, p-value = 0.07865
```

```
Model df: 2. Total lags used: 48
```

```
runs.test(modell1$r)
```

```
Runs Test
data: modell1$r
statistic = 1.9434, runs = 104, n1 = 90, n2 = 90, n = 180, p-value =
0.05197
alternative hypothesis: nonrandomness
```

```
shapiro.test(modell1$residuals)
```

```
Shapiro-Wilk normality test
data: modell1$residuals
W = 0.99169, p-value = 0.3883
```



```
t.test(model1$r)
```

```
One Sample t-test
data: model1$r
t = -0.39531, df = 179, p-value = 0.6931
alternative hypothesis: true mean is not equal to 0
95 percent confidence interval:
 -0.1750647  0.1166304
sample estimates:
 mean of x
-0.02921718
```

- all coefficients of model are significant .
- Plot of residuals with time: The residuals are random around the zero.
- All p-values of the Ljung-Box test > 0.05. The residuals are uncorrelated.
- The ACF of the Residuals are zeros.
- The residuals follow normal dist.
- The residuals are random.

Model 2: SARIMA(1,1,1)(2,0,1)₄ model

```
model2<-Arima(d,order = c(1,1,1),seasonal = c(2,0,1))
#Testing the coefficients & Diagnosing Residuals
coeftest(model2)
```

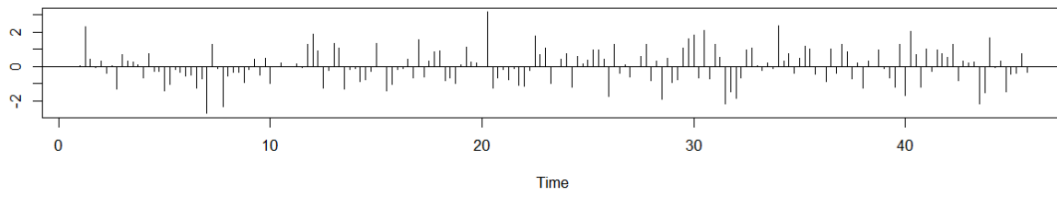
z test of coefficients:

	Estimate	Std. Error	z value	Pr(> z)	
ar1	0.252169	0.072700	3.4686	0.0005231	***
ma1	-1.000000	0.026591	-37.6066	< 2.2e-16	***
sar1	1.680004	0.121438	13.8343	< 2.2e-16	***
sar2	-0.770436	0.104849	-7.3480	2.011e-13	***
sma1	-0.575903	0.179969	-3.2000	0.0013742	**

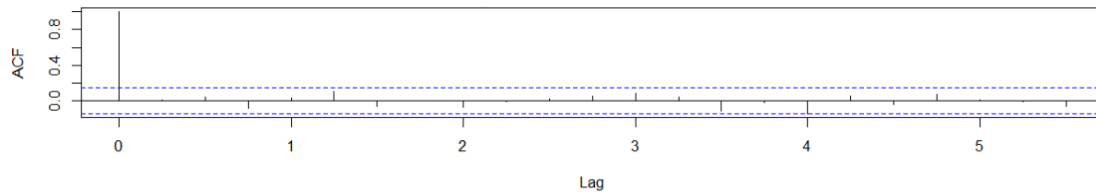
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```
tsdiag(model2)
```

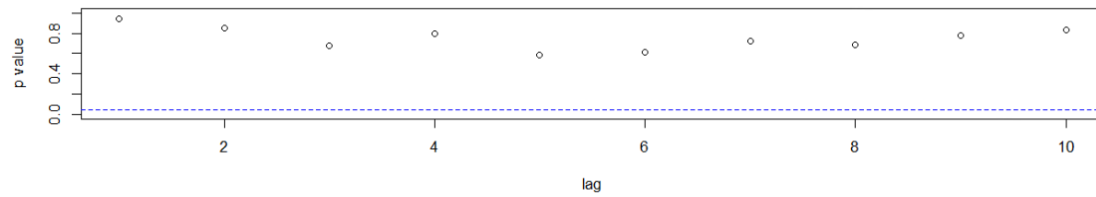
Standardized Residuals



ACF of Residuals

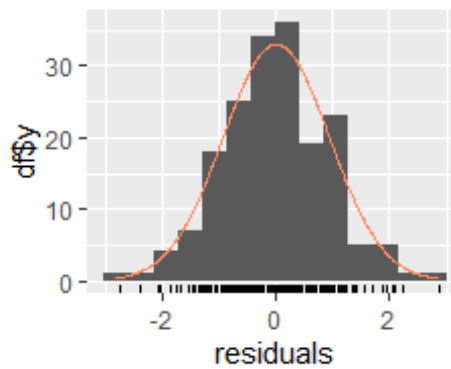
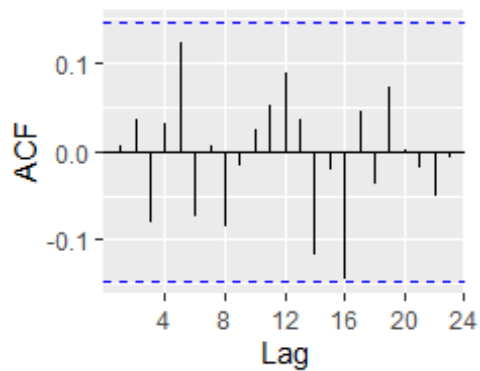
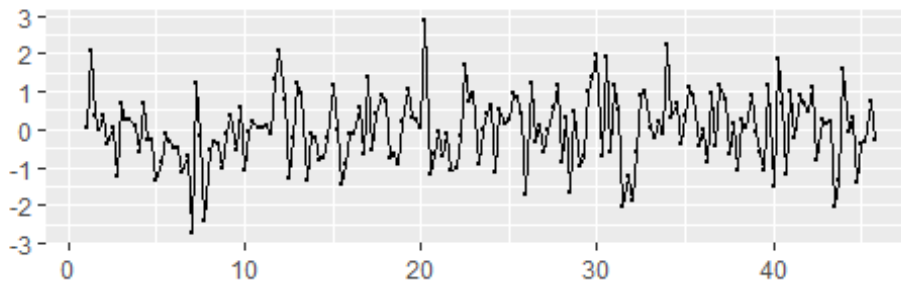


p values for Ljung-Box statistic



```
checkresiduals(model12, lag= 12)
```

Residuals from ARIMA(1,1,1)(2,0,1)[4]



```
Ljung-Box test
data: Residuals from ARIMA(1,1,1)(2,0,1)[4]
Q* = 9.1607, df = 7, p-value = 0.2413
```

```
Model df: 5. Total lags used: 12
```

```
checkresiduals(model2, lag= 24,plot=FALSE)
```

```
Ljung-Box test
data: Residuals from ARIMA(1,1,1)(2,0,1)[4]
Q* = 20.869, df = 19, p-value = 0.3441
```

```
Model df: 5. Total lags used: 24
```

```
checkresiduals(model2, lag= 36,plot=FALSE)
```

```
Ljung-Box test
data: Residuals from ARIMA(1,1,1)(2,0,1)[4]
Q* = 39.107, df = 31, p-value = 0.1505
```

```
Model df: 5. Total lags used: 36
```

```
checkresiduals(model2, lag= 48,plot=FALSE)
```

```
Ljung-Box test
data: Residuals from ARIMA(1,1,1)(2,0,1)[4]
Q* = 51.87, df = 43, p-value = 0.1664
```

```
Model df: 5. Total lags used: 48
```

```
runs.test(model2$r)
```

```
Runs Test
data: model2$r
statistic = -0.44847, runs = 88, n1 = 90, n2 = 90, n = 180, p-value =
0.6538
alternative hypothesis: nonrandomness
```

```
shapiro.test(model2$residuals)
```

```
Shapiro-Wilk normality test
data: model2$residuals
W = 0.99728, p-value = 0.9886
```

```
t.test(model2$r)
  One Sample t-test

data:  model2$r
t = 0.073613, df = 179, p-value = 0.9414
alternative hypothesis: true mean is not equal to 0
95 percent confidence interval:
 -0.1323098  0.1425638
sample estimates:
 mean of x
0.005126972
```

Model 3: SARIMA(1,0,0)(2,0,1)₄ model

```
model3<-Arima(d,order = c(1,0,0),seasonal = c(2,0,1),lambda = lambda, biasadj
=TRUE)
```

```
#biasadj =TRUE: return to raw data, after using BoxCox transformation
#Testing the coefficients & Diagnosing Residuals
```

```
coeftest(model3)
```

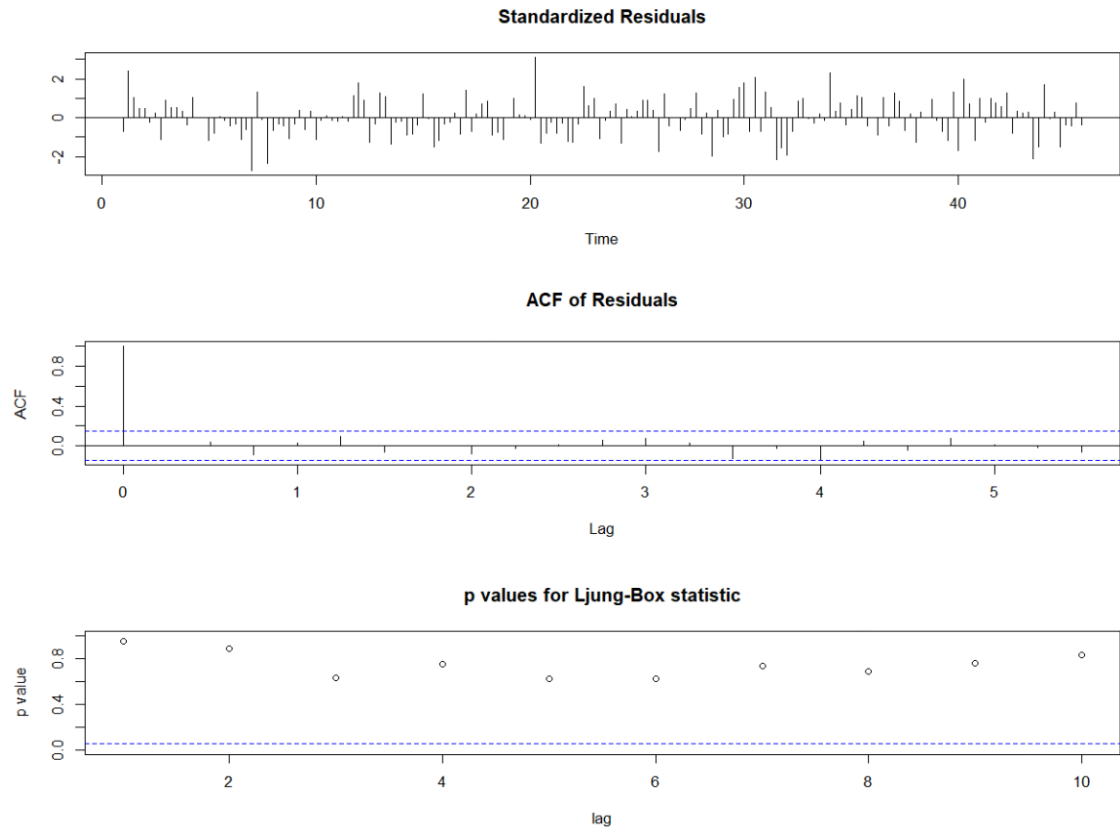
```
z test of coefficients:
```

	Estimate	Std. Error	z value	Pr(> z)	
ar1	0.230383	0.072670	3.1702	0.0015231	**
sar1	1.724466	0.106796	16.1473	< 2.2e-16	***
sar2	-0.809126	0.089803	-9.0100	< 2.2e-16	***
sma1	-0.651400	0.168277	-3.8710	0.0001084	***
intercept	85.332720	2.371989	35.9752	< 2.2e-16	***

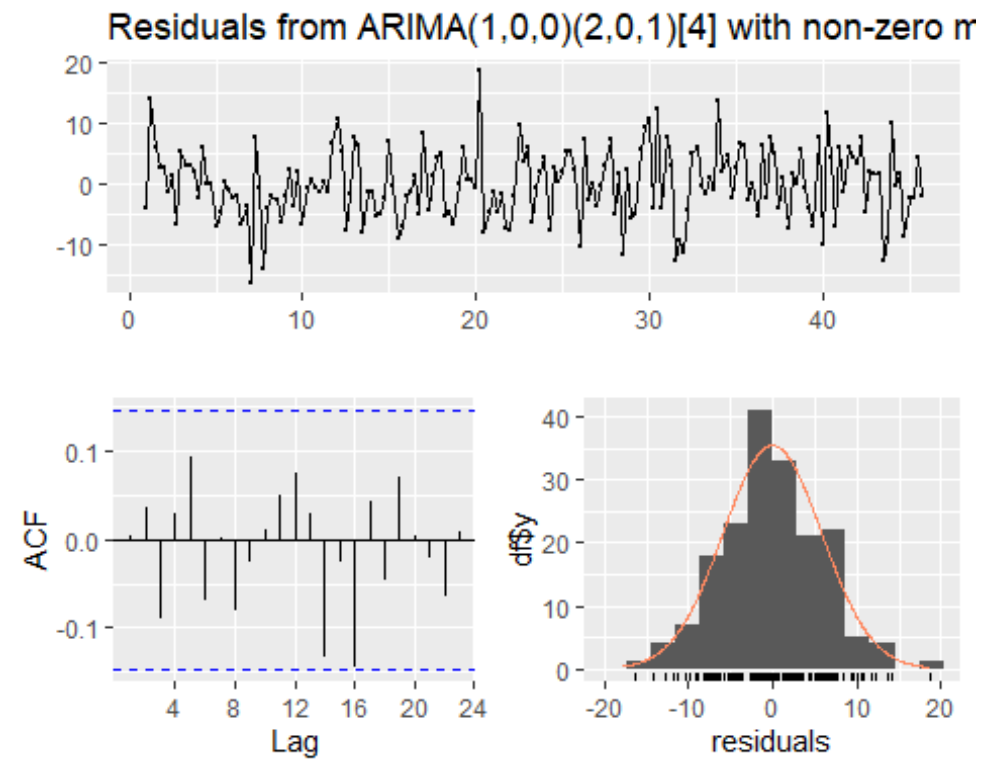
```
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
tsdiag(model3)
```



```
checkresiduals(model13, lag= 12)
```



```
Ljung-Box test
data: Residuals from ARIMA(1,0,0)(2,0,1)[4] with non-zero mean
Q* = 7.3702, df = 8, p-value = 0.4973
```

```
Model df: 4. Total lags used: 12
```

```
checkresiduals(model3, lag= 24,plot=FALSE)
```

```
Ljung-Box test
data: Residuals from ARIMA(1,0,0)(2,0,1)[4] with non-zero mean
Q* = 20.251, df = 20, p-value = 0.4423
```

```
Model df: 4. Total lags used: 24
```

```
checkresiduals(model3, lag= 36,plot=FALSE)
```

```
Ljung-Box test
data: Residuals from ARIMA(1,0,0)(2,0,1)[4] with non-zero mean
Q* = 37.515, df = 32, p-value = 0.231
```

```
Model df: 4. Total lags used: 36
```

```
checkresiduals(model3, lag= 48,plot=FALSE)
```

```
Ljung-Box test
data: Residuals from ARIMA(1,0,0)(2,0,1)[4] with non-zero mean
Q* = 48.92, df = 44, p-value = 0.2821
```

```
Model df: 4. Total lags used: 48
```

```
runs.test(model3$r)
```

```
Runs Test
data: model3$r
statistic = 0, runs = 91, n1 = 90, n2 = 90, n = 180, p-value = 1
alternative hypothesis: nonrandomness
```

```
shapiro.test(model3$residuals)
```

```
Shapiro-Wilk normality test
data: model3$residuals
W = 0.99657, p-value = 0.9593
```

```

t.test(model3$r)
  One Sample t-test

data:  model3$r
t = -0.1511, df = 179, p-value = 0.8801
alternative hypothesis: true mean is not equal to 0
95 percent confidence interval:
 -0.9292902  0.7970975
sample estimates:
mean of x
-0.0660963

```

Model 4: SARIMA(0,0,1)(2,0,1)[4]

```

model4<-Arima(d,order = c(0,0,1),seasonal = c(2,0,1),lambda = lambda, biasadj
=TRUE)

```

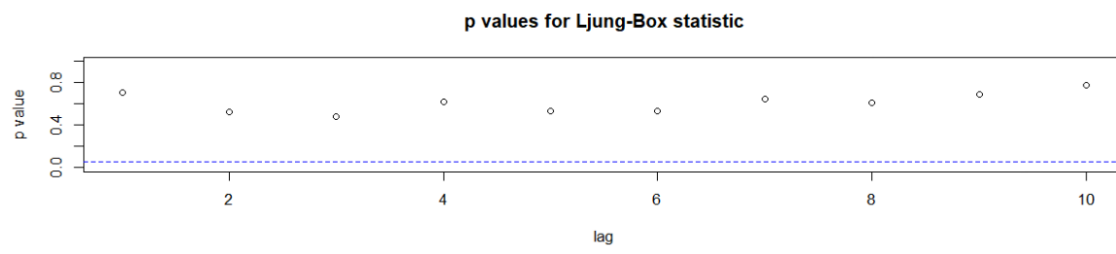
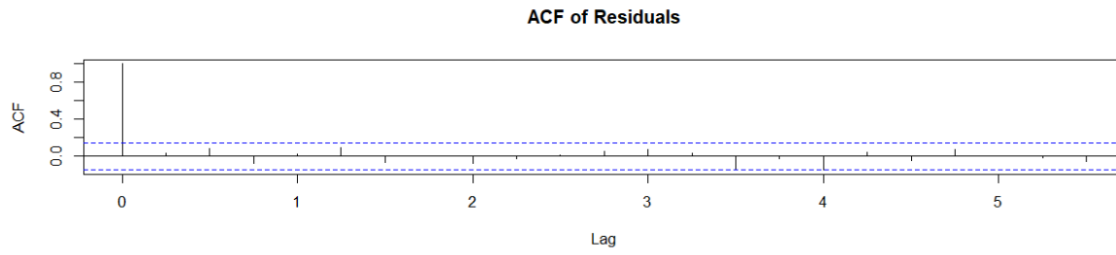
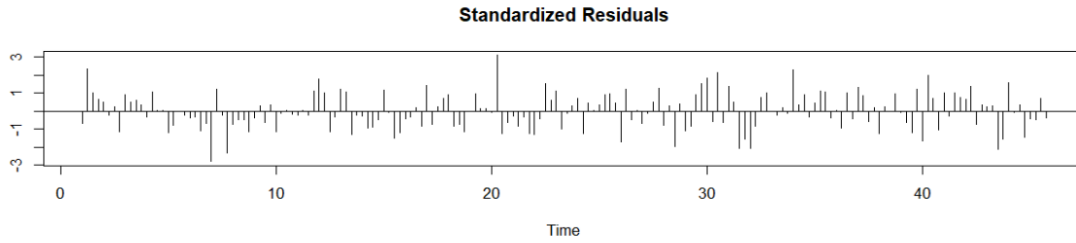
#Testing the coefficients & Diagnosing Residuals

```

coeftest(model4)
z test of coefficients:
      Estimate Std. Error z value Pr(>|z|)
ma1      0.206488  0.067637  3.0529 0.0022665 **
sar1      1.715405  0.109710 15.6358 < 2.2e-16 ***
sar2     -0.803230  0.091820 -8.7479 < 2.2e-16 ***
sma1     -0.639457  0.170578 -3.7488 0.0001777 ***
intercept 85.340044  2.201998 38.7557 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

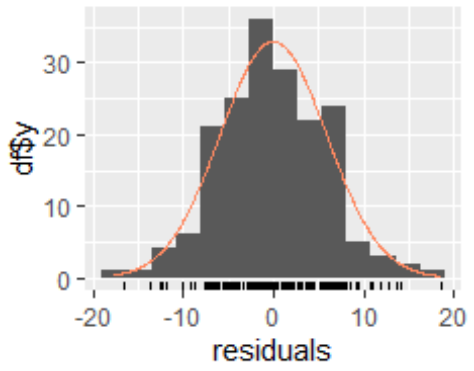
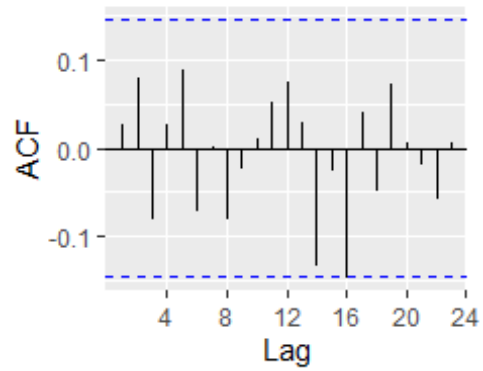
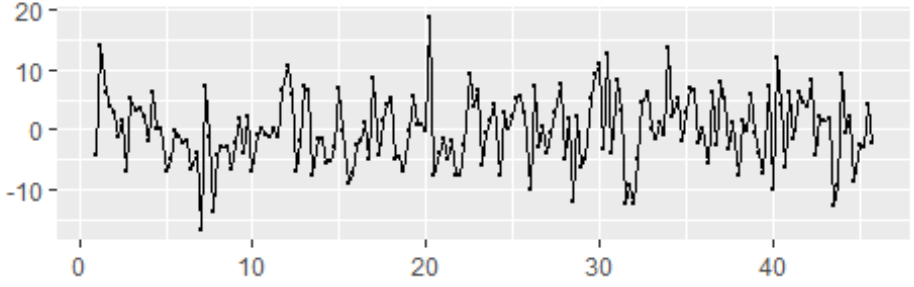
tsdiag(model4)

```



```
checkresiduals(model14, lag= 12)
```

Residuals from ARIMA(0,0,1)(2,0,1)[4] with non-zero π




```
Ljung-Box test
data: Residuals from ARIMA(0,0,1)(2,0,1)[4] with non-zero mean
Q* = 8.1499, df = 8, p-value = 0.419
```

```
Model df: 4. Total lags used: 12
```

```
checkresiduals(model4, lag= 24,plot=FALSE)
```

```
Ljung-Box test
data: Residuals from ARIMA(0,0,1)(2,0,1)[4] with non-zero mean
Q* = 21.055, df = 20, p-value = 0.3939
```

```
Model df: 4. Total lags used: 24
```

```
checkresiduals(model4, lag= 36,plot=FALSE)
```

```
Ljung-Box test
data: Residuals from ARIMA(0,0,1)(2,0,1)[4] with non-zero mean
Q* = 38.555, df = 32, p-value = 0.1973
```

```
Model df: 4. Total lags used: 36
```

```
checkresiduals(model4, lag= 48,plot=FALSE)
```

```
Ljung-Box test
data: Residuals from ARIMA(0,0,1)(2,0,1)[4] with non-zero mean
Q* = 49.806, df = 44, p-value = 0.2534
```

```
Model df: 4. Total lags used: 48
```

```
runs.test(model4$r)
```

```
Runs Test
data: model4$r
statistic = 0.29898, runs = 93, n1 = 90, n2 = 90, n = 180, p-value =
0.765
alternative hypothesis: nonrandomness
```

```
shapiro.test(model4$residuals)
```

```
Shapiro-Wilk normality test
data: model4$residuals
W = 0.99615, p-value = 0.9304
```

```
t.test(model4$r)
  One Sample t-test
data:  model4$r
t = -0.16351, df = 179, p-value = 0.8703
alternative hypothesis: true mean is not equal to 0
95 percent confidence interval:
 -0.9375985  0.7941074
sample estimates:
 mean of x
-0.07174551
```

Using AIC or BIC to choose best model

```
model1$aic
[1] 506.0465

model2$aic
[1] 505.3966

model3$aic
[1] 1167.146

model4$aic
[1] 1168.165
```

The best model has the lowest AIC value , which is model 2.

$$(1 - 0.2522B)(1 - 1.68B^4 - (-0.7704)B^8)(1 - B)^1 y_t = (1 - (-1)B)(1 - (-0.5759)B^4) \varepsilon_t$$

$$(1 - 0.2522B)(1 - 1.68B^4 + 0.7704B^8)(1 - B) y_t = (1 + B)(1 + 0.5759B^4) \varepsilon_t$$

Forecasting using SARIMA(1,1,1)(2,0,1)4:

```
best.model<-Arima(d,order = c(1,1,1),seasonal = c(2,0,1))
(f=forecast(best.model, h=10,level = c(80, 95)))
```

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
46 Q1	22.04153	20.82358	23.25947	20.17884	23.90421
46 Q2	22.95799	21.70029	24.21569	21.03450	24.88147
46 Q3	20.66510	19.40450	21.92569	18.73719	22.59301
46 Q4	19.03367	17.77279	20.29455	17.10532	20.96202
47 Q1	21.81451	19.96105	23.66797	18.97988	24.64913
47 Q2	22.28156	20.39419	24.16894	19.39507	25.16806
47 Q3	20.86137	18.97122	22.75153	17.97064	23.75211
47 Q4	19.27213	17.38165	21.16262	16.38088	22.16338
48 Q1	21.62871	19.30870	23.94873	18.08056	25.17687
48 Q2	21.70723	19.35954	24.05492	18.11675	25.29772

`autoplot(f)`

