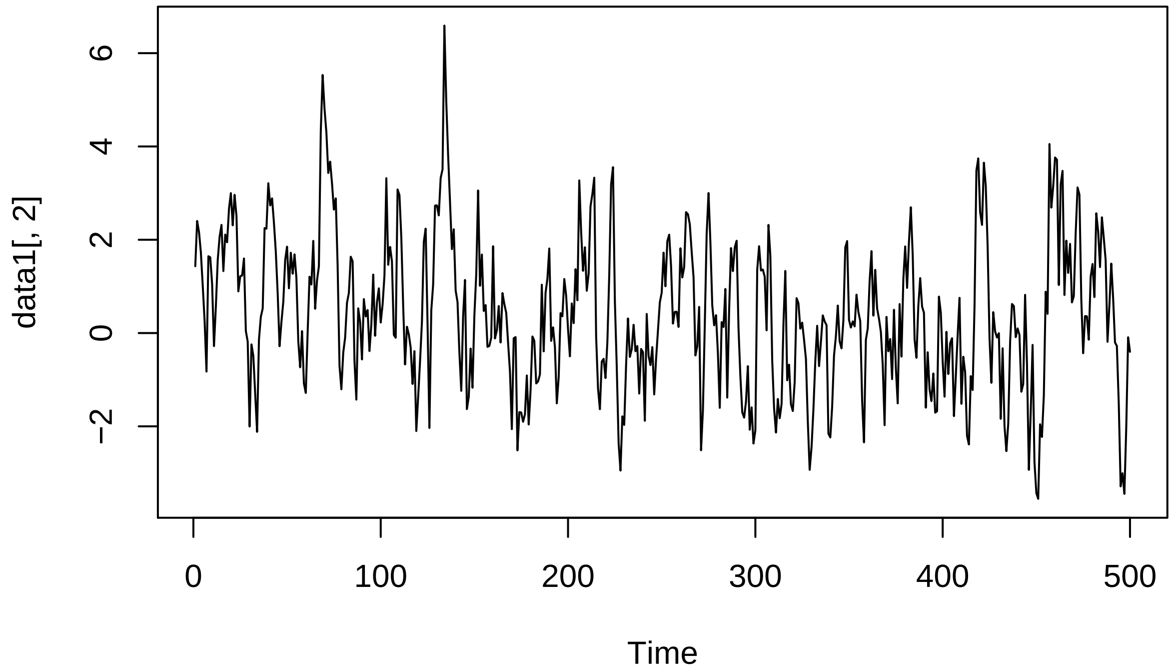
tshw3

```
knitr::opts_chunk$set(echo = TRUE)
```

Problem 1,Problem2

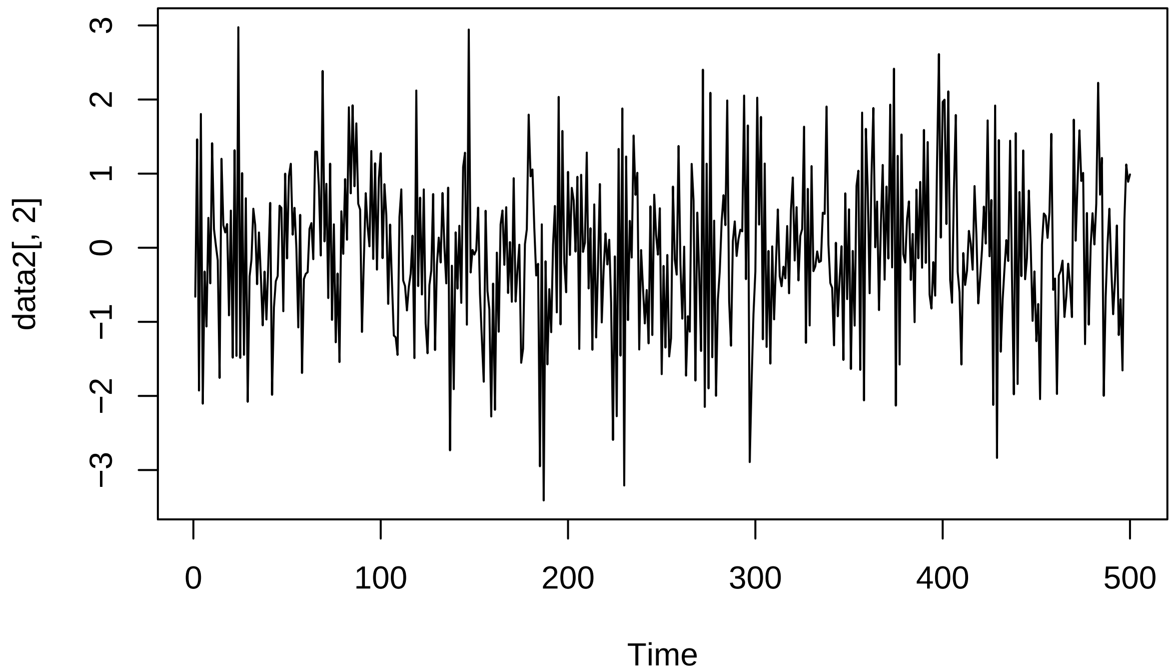
time plot of data1. It seems not stationary ,since the mean level is changing over time.

```
plot.ts(data1[,2])
```



time plot of data2 It seems not stationary ,since the mean level is changing over time.

```
plot.ts(data2[,2])
```

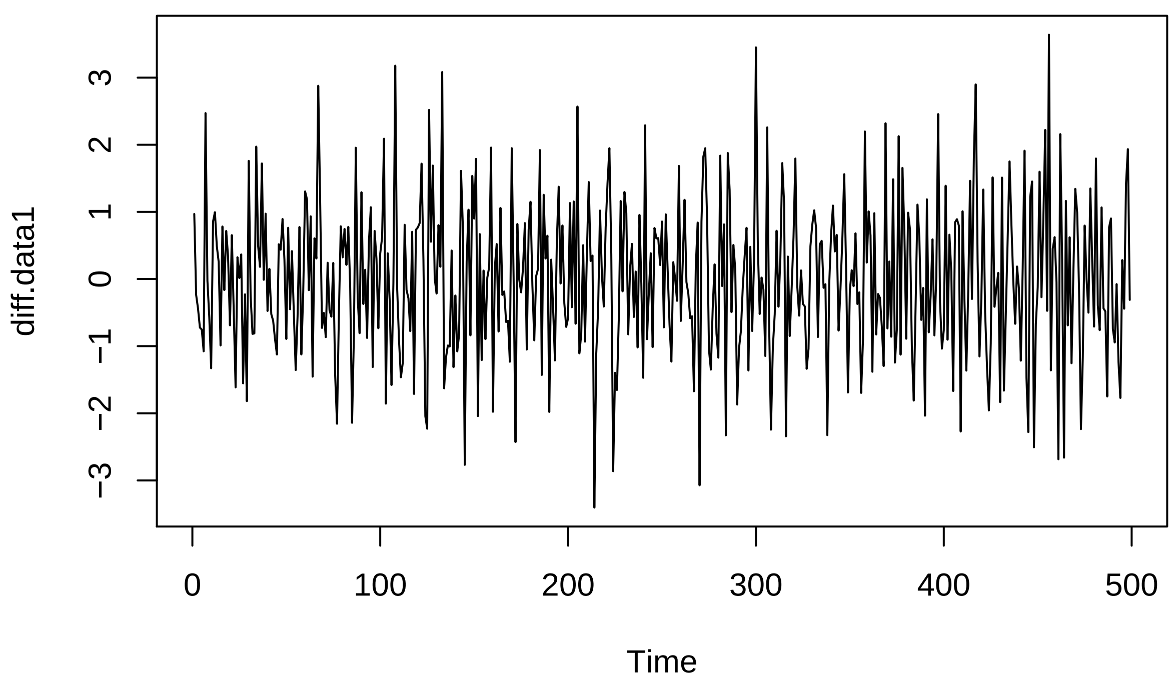


Problem 3

Identify some possible AR(P) Model.

Take difference on data1 and plot it

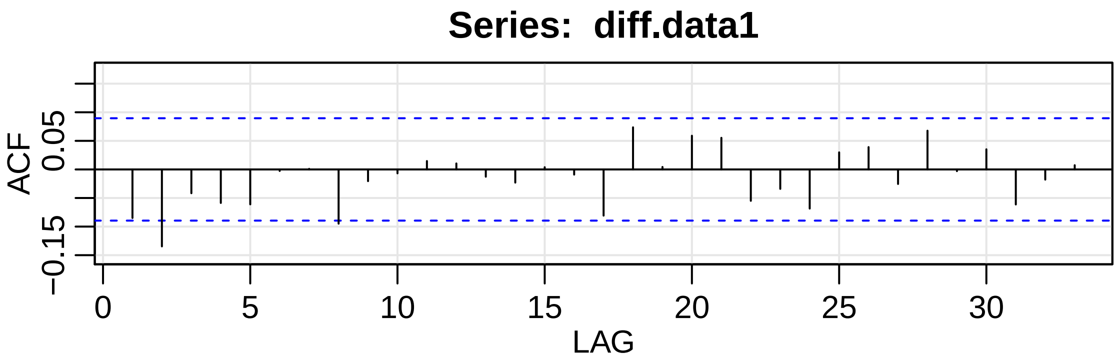
```
diff.data1=diff(data1[,2])
plot.ts(diff.data1)
```



It seems more stationary.

Since pacf plot significant between 2~5,I choose p=4,5 to bulid the model.

```r
acf2(diff.data1)
```

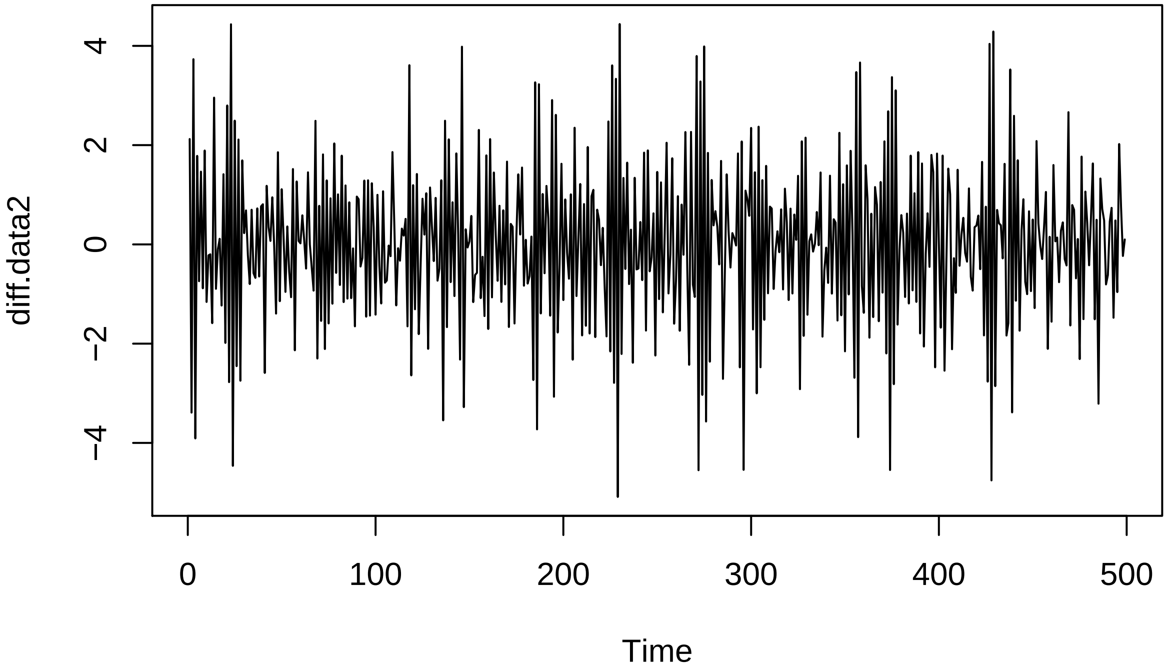



```
##        ACF  PACF
##  [1,] -0.08 -0.08
##  [2,] -0.13 -0.14
##  [3,] -0.04 -0.07
##  [4,] -0.06 -0.09
##  [5,] -0.06 -0.10
##  [6,]  0.00 -0.05
##  [7,]  0.00 -0.04
##  [8,] -0.09 -0.13
##  [9,] -0.02 -0.08
## [10,] -0.01 -0.08
## [11,]  0.01 -0.04
## [12,]  0.01 -0.04
## [13,] -0.01 -0.06
## [14,] -0.02 -0.07
## [15,]  0.00 -0.05
## [16,] -0.01 -0.07
## [17,] -0.08 -0.14
## [18,]  0.07 -0.01
## [19,]  0.00 -0.06
## [20,]  0.06  0.02
## [21,]  0.06  0.03
## [22,] -0.05 -0.06
## [23,] -0.03 -0.05
## [24,] -0.07 -0.12
## [25,]  0.03 -0.04
## [26,]  0.04 -0.01
## [27,] -0.03 -0.07
```

```
## [28,]  0.07  0.05
## [29,]  0.00 -0.01
## [30,]  0.04  0.04
## [31,] -0.06 -0.07
## [32,] -0.02 -0.05
## [33,]  0.01 -0.02
```

Take difference on data2 and plot it

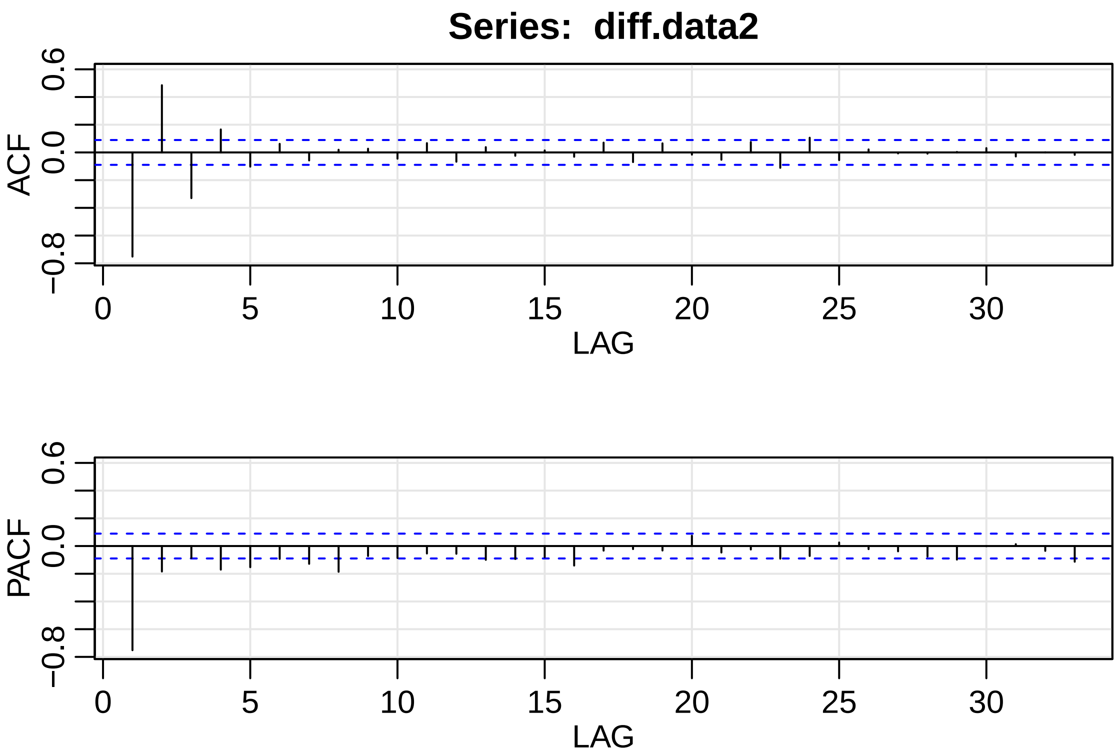
```
diff.data2=diff(data2[,2])
plot.ts(diff.data2)
```



It seems more stationary.

Since pacf plot significant between 2~5,I choose p=4,5,9 to bulid the model.

```
acf2(diff.data2)
```



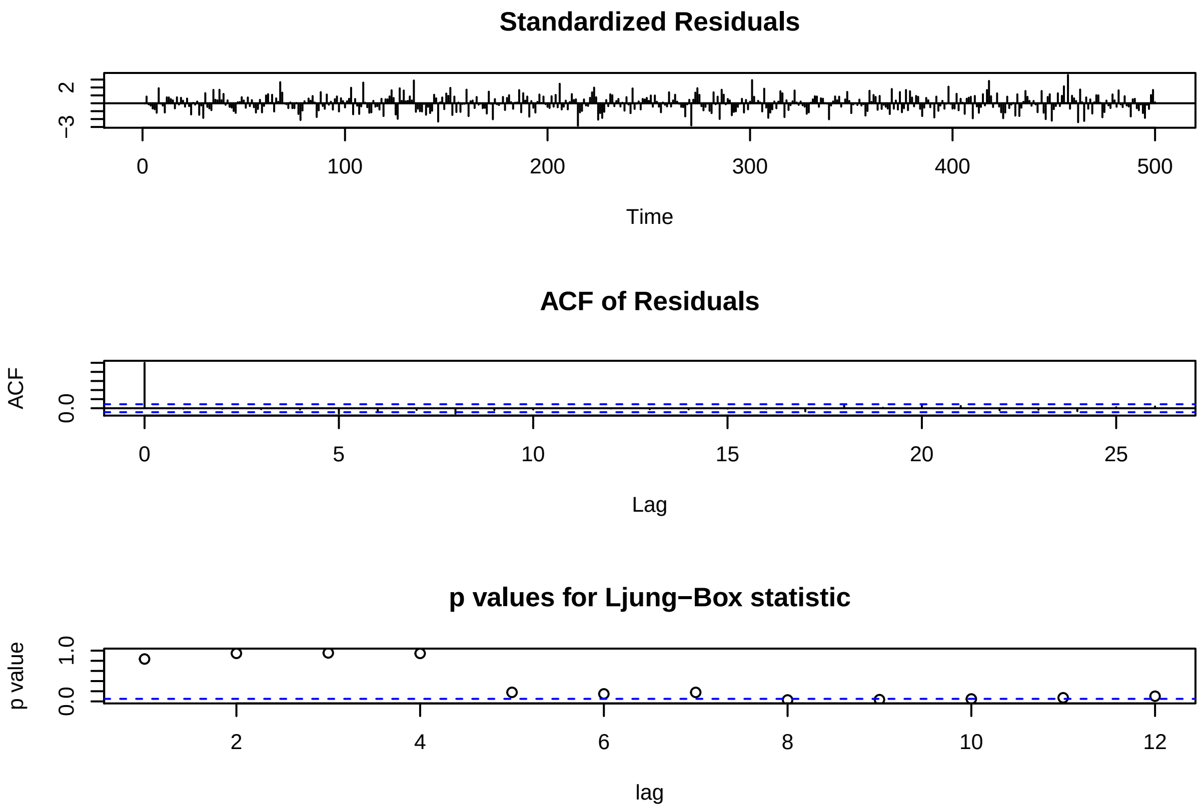

```
##         ACF  PACF
##  [1,] -0.75 -0.75
##  [2,]  0.49 -0.18
##  [3,] -0.33 -0.09
##  [4,]  0.17 -0.17
##  [5,] -0.10 -0.15
##  [6,]  0.06 -0.09
##  [7,] -0.06 -0.13
##  [8,]  0.02 -0.19
##  [9,]  0.03 -0.07
## [10,] -0.05 -0.09
## [11,]  0.07 -0.05
## [12,] -0.07 -0.06
## [13,]  0.04 -0.10
## [14,] -0.02 -0.09
## [15,]  0.01 -0.08
## [16,] -0.03 -0.14
## [17,]  0.07 -0.03
## [18,] -0.07 -0.02
## [19,]  0.07 -0.03
## [20,] -0.02  0.07
## [21,] -0.05 -0.05
## [22,]  0.07 -0.02
## [23,] -0.11 -0.09
## [24,]  0.11 -0.07
## [25,] -0.06  0.03
## [26,]  0.02 -0.02
## [27,] -0.01 -0.04
## [28,] -0.01 -0.08
## [29,]  0.00 -0.10
```

```
## [30,]  0.03  0.00
## [31,] -0.03  0.01
## [32,]  0.00 -0.03
## [33,] -0.02 -0.11
```

Problem 4,5

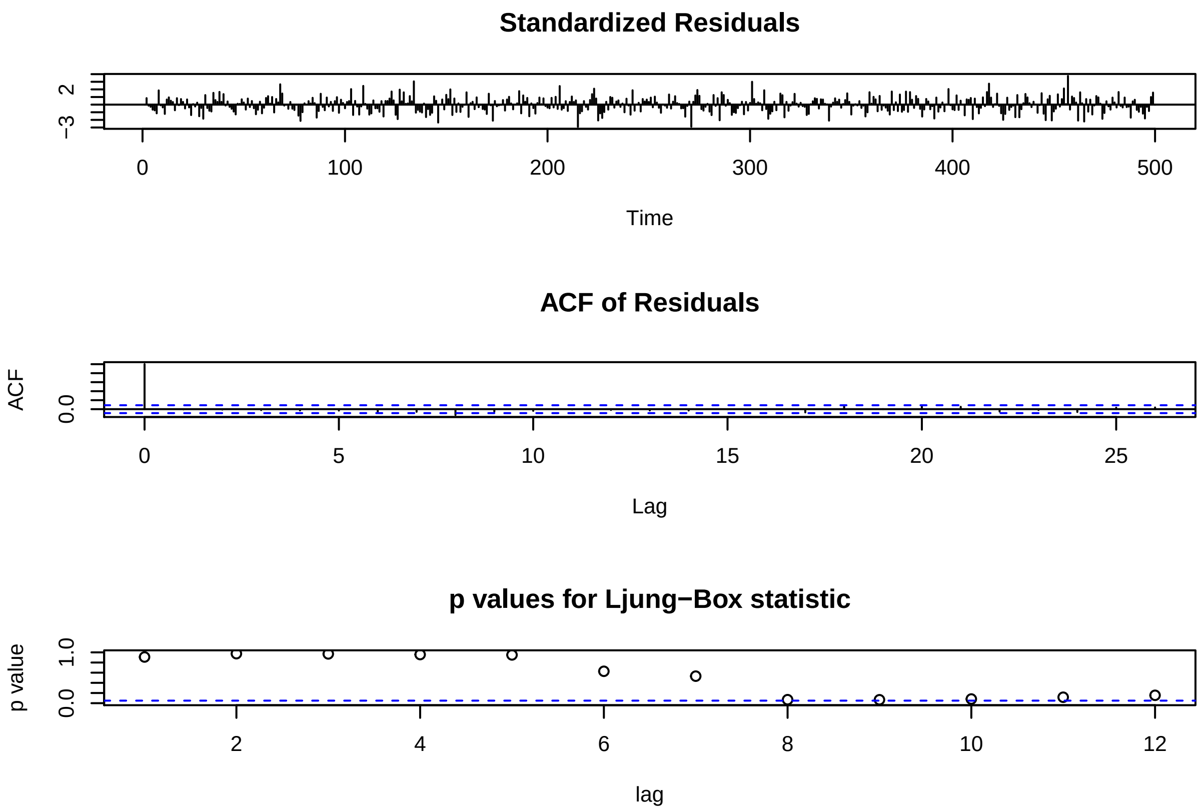
for data1 ARIMA(4,1,0) model The residual plot seems stationary. The acf plot shows the residuals has little serial correlation,but the Ljung Box test shows serial correlations when p=8,9.

```
model_data1_p4=arima(data1[,2],order = c(4,1,0))
tsdiag(model_data1_p4,gof=12)
```



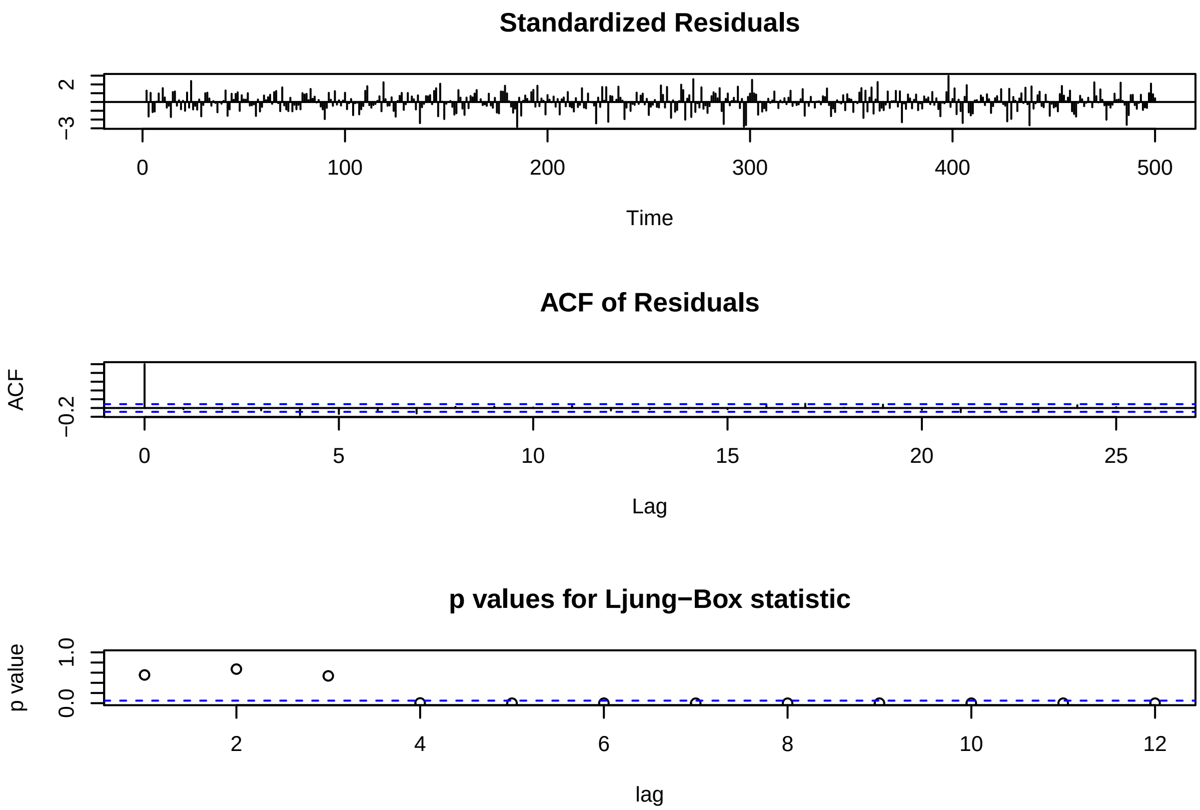
for data1 ARIMA(5,1,0) model The residual plot seems stationary. Both Ljung-Box and acf plot shows the residuals has little serial correlation.

```
model_data1_p5=arima(data1[,2],order = c(5,1,0))
tsdiag(model_data1_p5,gof=12)
```



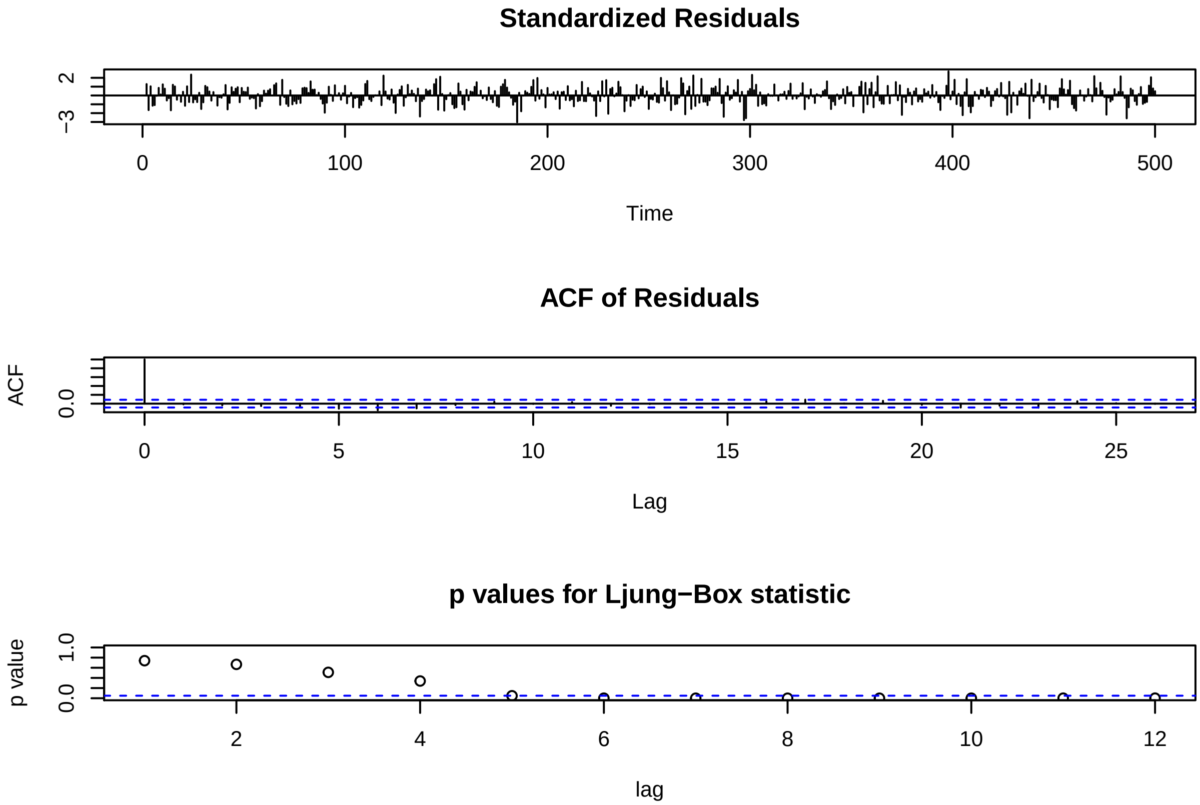
for data2 ARIMA(4,1,0) model The residual plot seems stationary. The acf plot shows the residuals has little serial correlation,but the Ljung Box test shows serial correlations when lag larger than 4

```
model_data2_p4=arima(data2[,2],order = c(4,1,0))
tsdiag(model_data2_p4,gof=12)
```



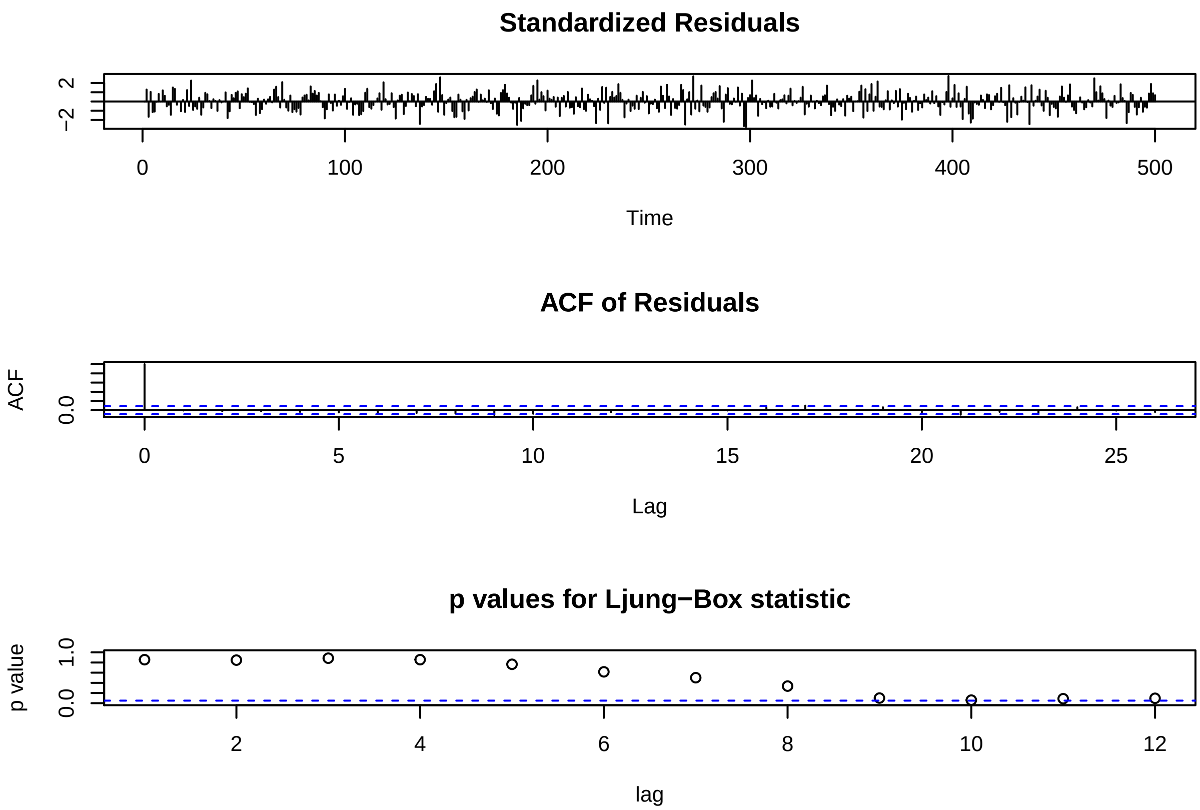
for data2 ARIMA(5,1,0) model The residual plot seems stationary. The acf plot shows the residuals has little serial correlation,but the Ljung Box test shows serial correlations when lag larger than 5

```
model_data2_p5=arima(data2[,2],order = c(5,1,0))
tsdiag(model_data2_p5,gof=12)
```



for data2 ARIMA(9,1,0) model The residual plot seems stationary. Both Ljung-Box and acf plot shows the residuals has little serial correlation.

```
model_data2_p9=arima(data2[,2],order = c(9,1,0))
tsdiag(model_data2_p9,gof=12)
```



For data1 we can use the ARIMA(5,1,0) model ,since the residuals of the model is more likely to satisfy the white noise assumption .

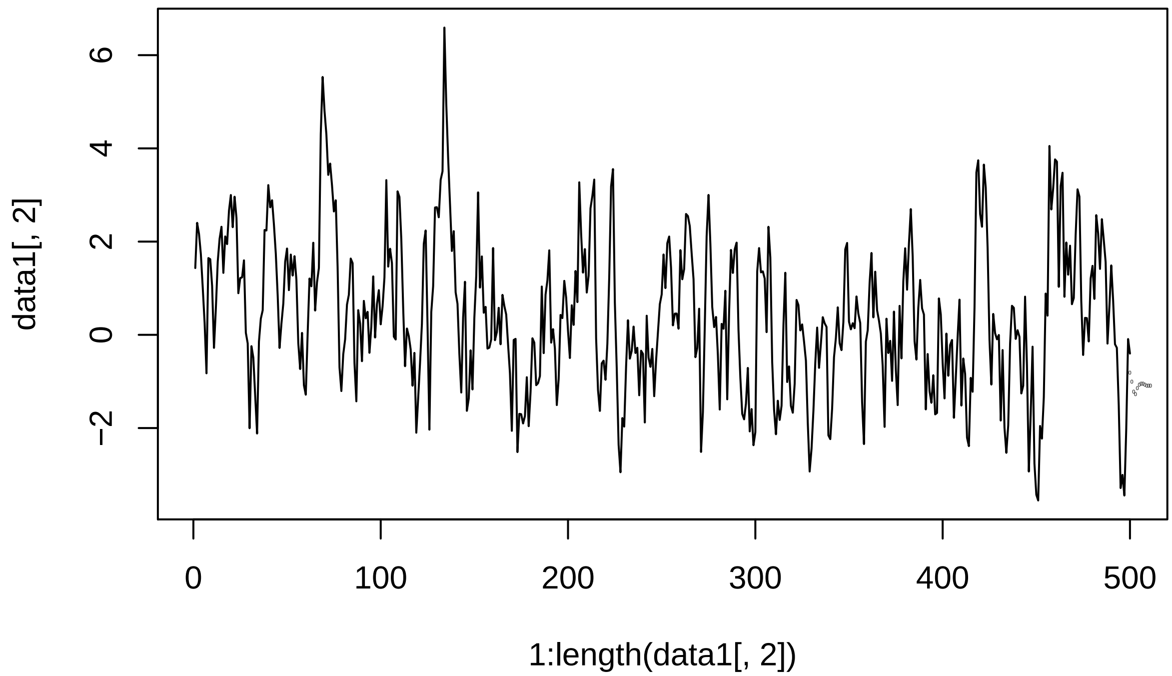
For data2 we can use the ARIMA(9,1,0) model ,since the residuals of the model is more likely to satisfy the white noise assumption .

Problem 6

```
result1= predict(model_data1_p5,n.ahead = 12)
result1
```

```
## $pred
## Time Series:
## Start = 501
## End = 512
## Frequency = 1
##  [1] -0.814278 -1.000660 -1.217267 -1.275915 -1.140296 -1.066277 -1.052267
##  [8] -1.052451 -1.070314 -1.090396 -1.093544 -1.089343
##
## $se
## Time Series:
## Start = 501
## End = 512
## Frequency = 1
##  [1] 1.111312 1.478797 1.681840 1.837084 1.956865 2.051225 2.158104
##  [8] 2.269977 2.378034 2.481638 2.579952 2.672295
```

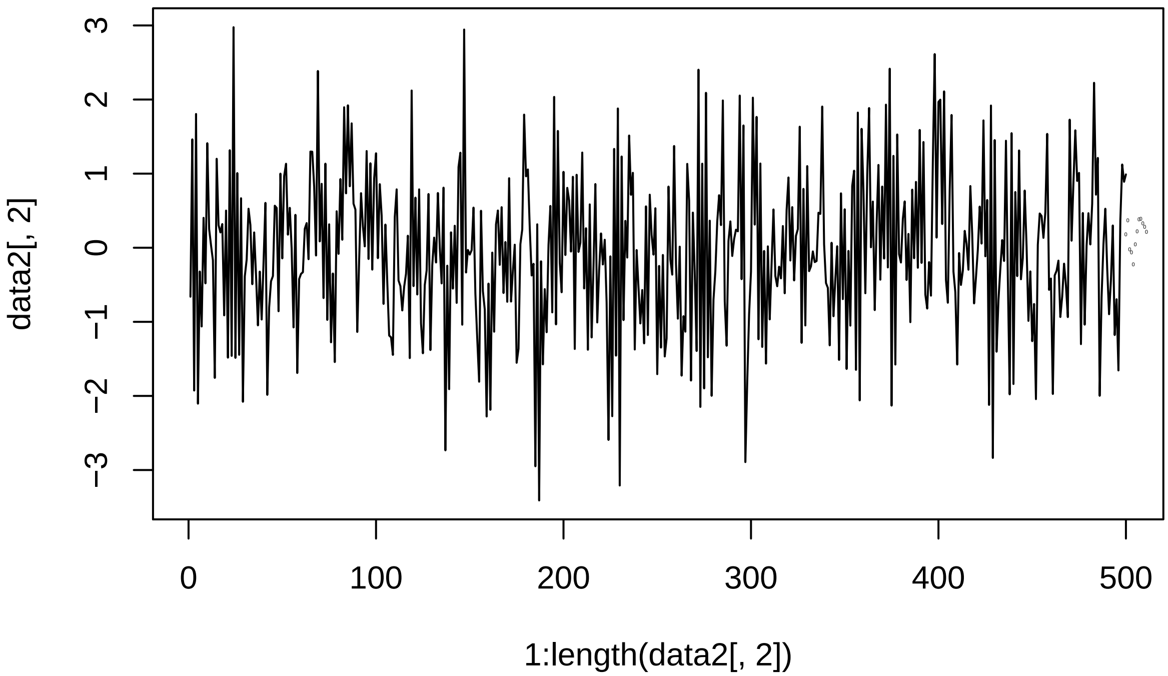
```
plot(1:length(data1[,2]),data1[,2],type='l')
points(length(data1[,2]):(length(data1[,2])+11),result1$pred,pch='0',cex=0.2)
```




```
result2= predict(model_data2_p9,n.ahead = 12)
result2
```

```
## $pred
## Time Series:
## Start = 501
## End = 512
## Frequency = 1
##  [1]  0.18215758  0.36792893 -0.02325047 -0.06342056 -0.22526831
##  [6]  0.04661845  0.22103058  0.38058057  0.38746717  0.32612318
## [11]  0.27944136  0.21272797
##
## $se
## Time Series:
## Start = 501
## End = 512
## Frequency = 1
##  [1] 0.9980345 0.9981222 1.1357577 1.1358290 1.1622206 1.1673546 1.1796683
##  [8] 1.1832384 1.2006221 1.2259941 1.2512870 1.2766976
```

```
plot(1:length(data2[,2]),data2[,2],type='l')
points(length(data2[,2]):(length(data2[,2])+11),result2$pred,pch='0',cex=0.2)
```


3
2
1
0
−1
−2
−3
data2[, 2]
0
100
200
300
400
500
1:length(data2[, 2])