lab7_fall2017.R

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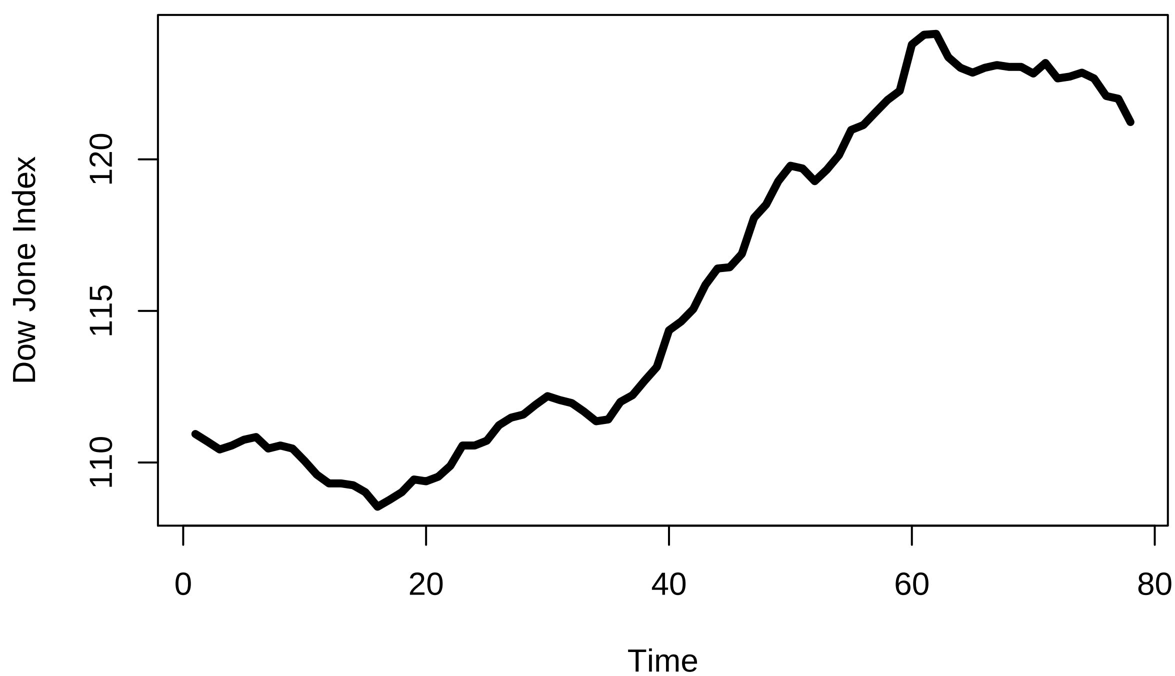
```r
# change working directory to folder that contains the data file
setwd("~/Dropbox/UCSB Classes/274/lab7_fall2017")
list.files()
```

```
## [1] "barley.txt"              "dowj.txt"
## [3] "lab7_fall2017.docx"      "lab7_fall2017.html"
## [5] "lab7_fall2017.R"         "lab7_fall2017.spin.R"
## [7] "lab7_fall2017.spin.Rmd"  "pstat174Lab8.pdf"
## [9] "pstat174Lab8.Rmd"
```

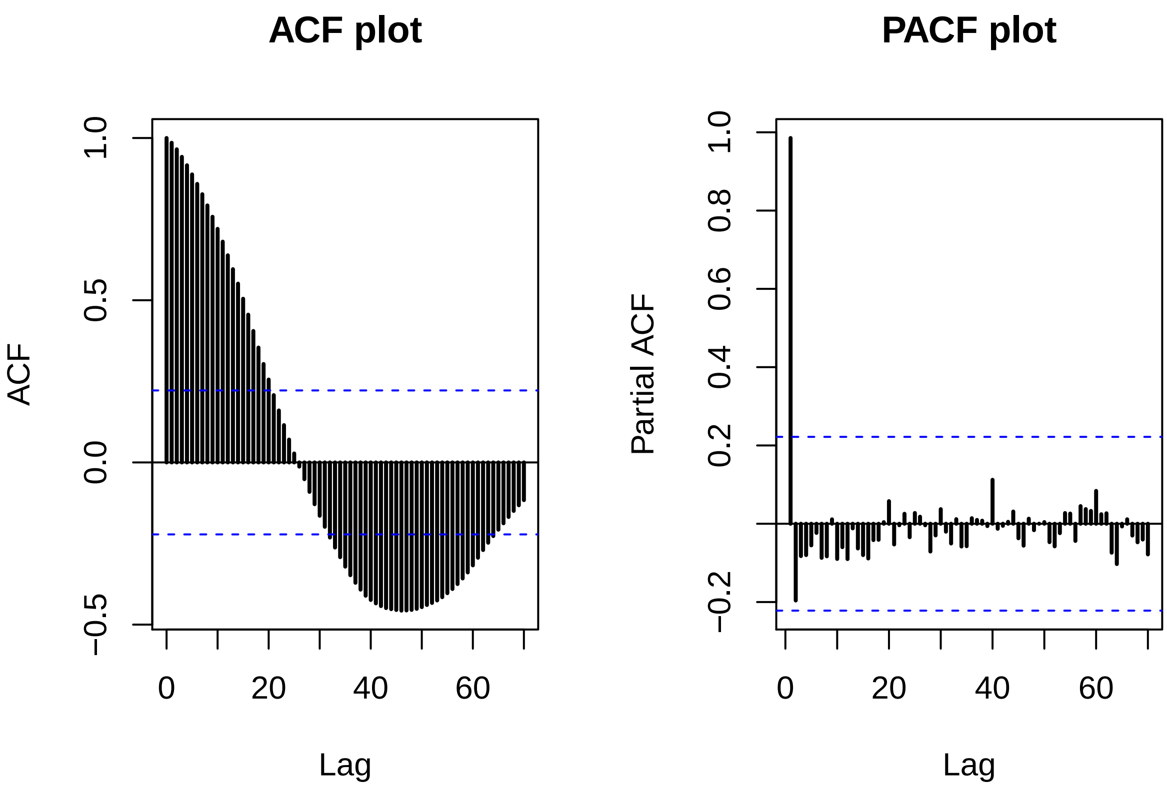
```r
# use read.table() to import txt file into R.
dowj= read.table("dowj.txt",header=FALSE) # Dow Jones Index data
# convert this to time series class:
dowj=ts(dowj)

# I. Description of time series and behavior of ACF and PACF

# display time series:
plot.ts(dowj,lwd=4,ylab="Dow Jone Index")
# Describe this plot:
# (a) There is a significant increasing trend overtime (might or might not linear/ if it is linear tren
# (b) No seasonal trend
# (c) Mean is not constant over time --> Indication of non-stationarity.
library("tseries")
```




```r
adf.test(dowj) # perform augmented dickey-fuller test for stationarity.
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  dowj
## Dickey-Fuller = -1.8053, Lag order = 4, p-value = 0.6552
## alternative hypothesis: stationary
```

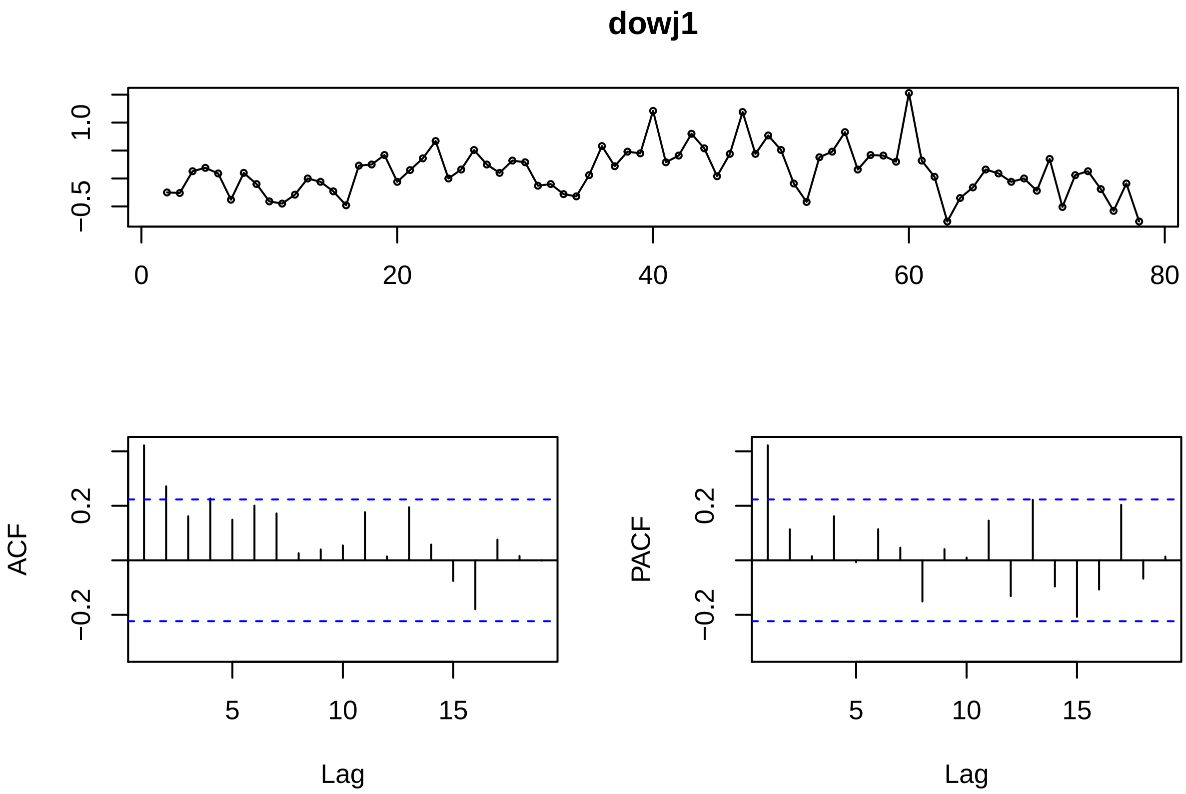
```
# H0: time series is not stationary
# Ha: time series is stationary
# p-value is large --> fail to reject the null. Therefore, time series is not stationary.

# ACF and PACF:
op=par(mfrow=c(1,2))
acf(dowj,lwd=2,lag.max=70,main="ACF plot")
pacf(dowj,lwd=2,lag.max=70,main="PACF plot")
```



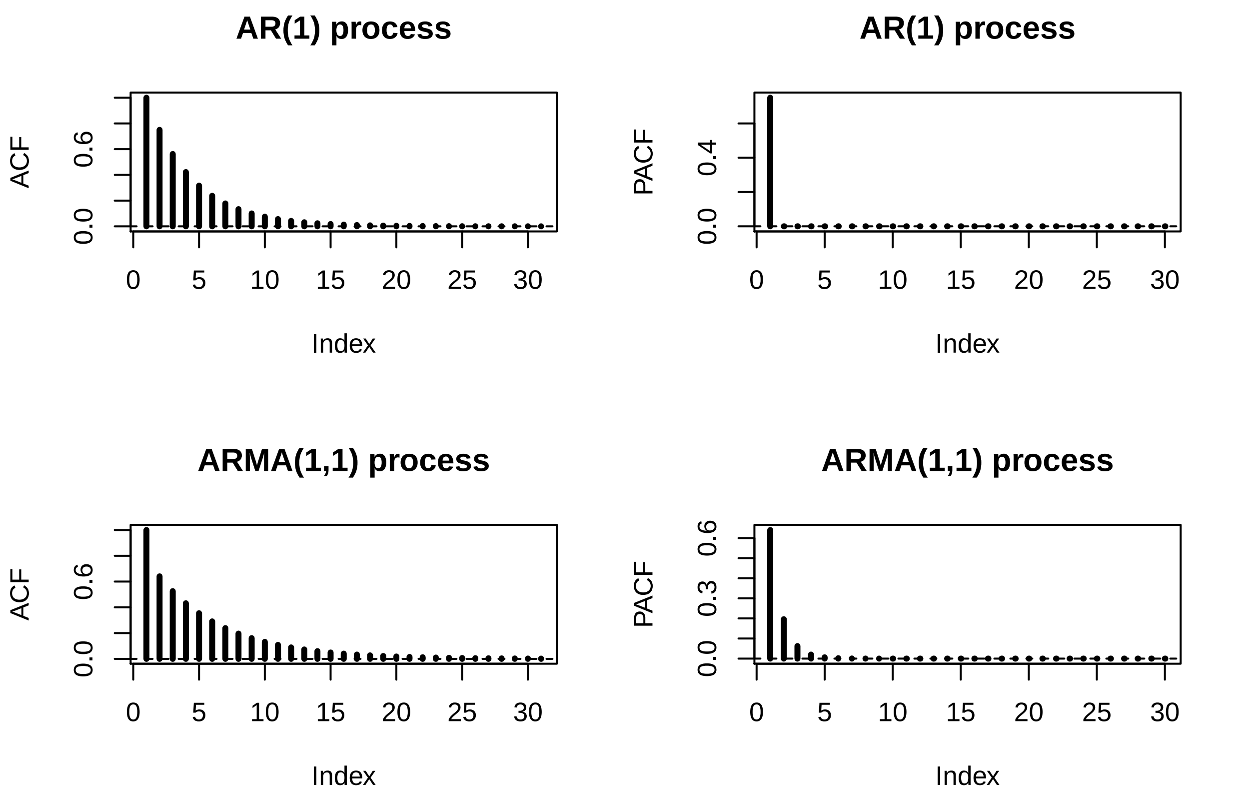

```
par(op)
# Several things we can tell using these two graphs:
# (a). ACF: we observe sinusoidal behavior (wave form) --> typical behavior of AR or ARMA models.
# (b). PACF: the first lag is significant. After the first lag, the remaining lags are insignificant.

## we want to build model on stationary time series to make prediction more reliable. In this case, let
dowj1=diff(dowj,lag=1)
library("forecast")
```

```
## Warning in as.POSIXlt.POSIXct(Sys.time()): unknown timezone 'default/
## America/Los_Angeles'
```

```r
tsdisplay(dowj1)
```




```r
## observation? after taking the difference at lag 1, we remove the linear trend. We improve the origina
# a. ACF: a significant correlation at lag 1. After that, it remains insignificant.
# b. PACF: a significant partial correlation at lag 1. After that, it remains insignificant.
## Some models we can try according to these behaviors:
# 1. AR(1) (using PACF plot) on differenced series. If on the original series, ARIMA(1,1,0)
# 2. MA(1) (using ACF plot) on differenced series. If on the original series, ARIMA(0,1,1)
# 3. ARMA(1,1) (it often has similar behavior in ACF as AR(1) model - See small experiment below) on di

######################## SMALL EXPERIMENT ##########################
# examine theoretical ACF and PACF for AR(1) and ARMA(1,1)
# AR(1) with phi=0.75
acfAR1=ARMAacf(ar=0.75,lag.max=30)
pacfAR1=ARMAacf(ar=0.75,pacf=TRUE,lag.max=30)
# ARMA(1,1) with phi=0.89, and theta=0.54
acfARMA11=ARMAacf(ar=0.821,ma=-.32,lag.max=30)
pacfARMA11=ARMAacf(ar=0.821,ma=-.32,pacf=TRUE,lag.max=30)

# display them altogether:
par(mfrow=c(2,2))
plot(acfAR1,type="h",lwd=3,ylab="ACF",main="AR(1) process")
abline(h=0,lty=2)
plot(pacfAR1,type="h",lwd=3,ylab="PACF",main="AR(1) process")
abline(h=0,lty=2)
plot(acfARMA11,type="h",lwd=3,ylab="ACF",main="ARMA(1,1) process")
abline(h=0,lty=2)
plot(pacfARMA11,type="h",lwd=3,ylab="PACF",main="ARMA(1,1) process")
abline(h=0,lty=2)
```




```r
par(op)
######################################################################

# II. Fitting model:

# 1. Fitting AR model using different methods:
# (a) Yule-Walker equations:
arYW=ar(dowj1,method="yule-walker") # AR(1) using differenced series
arYW
```

```
##
## Call:
## ar(x = dowj1, method = "yule-walker")
##
## Coefficients:
##      1
## 0.4219
##
## Order selected 1  sigma^2 estimated as  0.1518
```

```r
# (b) Maximum likelihood:
arML=arima(dowj,order=c(1,1,0),method="ML") # ARIMA(1,1,0) using orginal data
arML
```

```
##
## Call:
## arima(x = dowj, order = c(1, 1, 0), method = "ML")
##
## Coefficients:
```

```
##          ar1
##       0.4992
## s.e.  0.1001
##
## sigma^2 estimated as 0.1493:  log likelihood = -36.19,  aic = 76.38
```

```r
# both methods yield AR(1).

# 2. Fitting MA model using different methods:
# (a) Innovative algorithm method (review lab6_fall2017.R file)
# (b) Maximum likelihood:
maML=arima(dowj,order=c(0,1,2),method="ML")
maML
```

```
##
## Call:
## arima(x = dowj, order = c(0, 1, 2), method = "ML")
##
## Coefficients:
##          ma1     ma2
##       0.4485  0.2343
## s.e.  0.1185  0.0933
##
## sigma^2 estimated as 0.1518:  log likelihood = -36.82,  aic = 79.63
```

```r
# 3. Fitting ARIMA model:
# (a) Write a for loop to pick model with smaller AICc value
library(qpcR,quietly = TRUE)
for (i in 1:3){
  for (j in 1:3){
    current=arima(dowj,order=c(i,1,j),method="ML")
    print(c(i,j,AICc(current)))
  }
}
```

```
## [1]  1.00000  1.00000 75.53827
## [1]  1.00000  2.00000 76.34577
## [1]  1.00000  3.00000 78.12429
## [1]  2.00000  1.00000 79.13451
## [1]  2.00000  2.00000 77.09623
## [1]  2.00000  3.00000 78.98859
## [1]  3.00000  1.00000 78.36411
## [1]  3.00000  2.00000 78.62128
## [1]  3.00000  3.00000 80.02977
```

```r
# a good candiate is ARIMA(1,1,1) with smallest AICc of 75.53827

# (b) Use auto.arima():
autofit=auto.arima(dowj)
autofit
```

```
## Series: dowj
## ARIMA(1,1,1)
##
## Coefficients:
##          ar1      ma1
##       0.8510  -0.5263
```

```
## s.e.  0.1383   0.2548
##
## sigma^2 estimated as 0.1474:  log likelihood=-34.69
## AIC=75.38   AICc=75.71   BIC=82.41
```

```
## now it is a good time to turn our head back and compare all models we have been building so far:
# ARIMA(1,1,0) (using MLE method) has AICc:
AICc(arML)
```

```
## [1] 76.43379
```

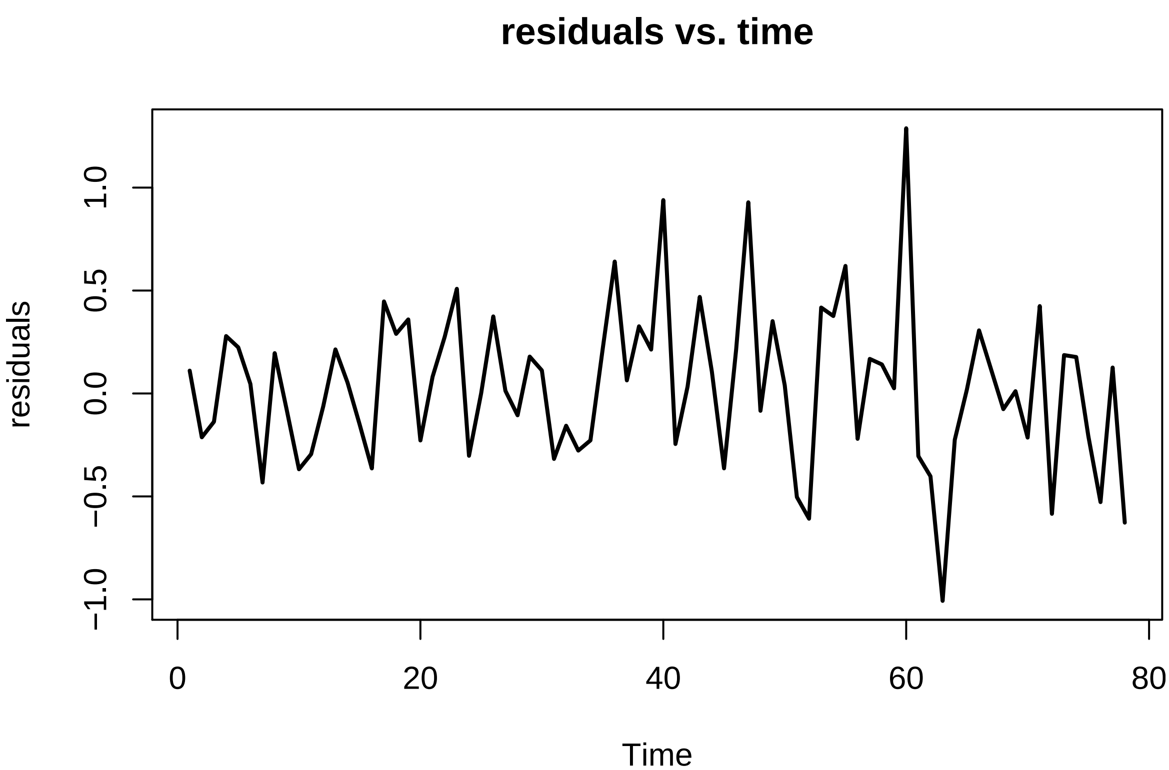
```
# ARIMA(0,1,2) (using MLE method) has AICc:
AICc(maML)
```

```
## [1] 79.79421
```

```
# ARIMA(1,1,1) has AICc:
AICc(autofit)
```

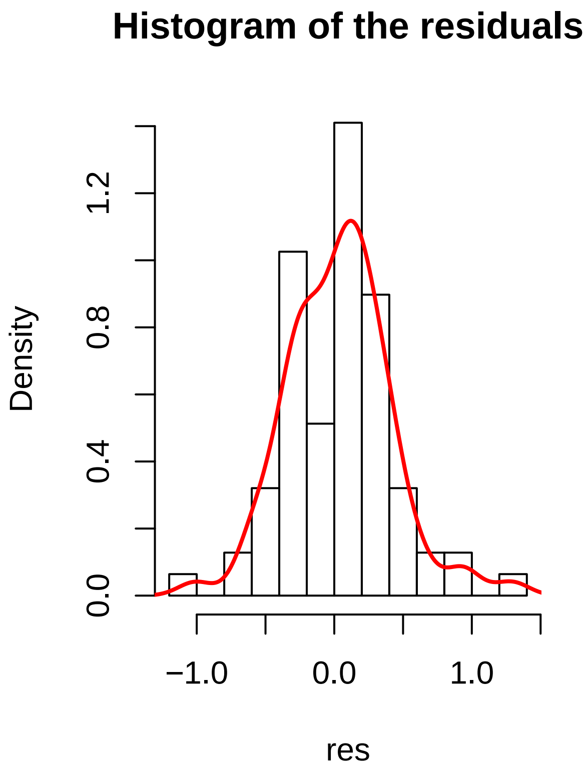
```
## [1] 75.53826
```

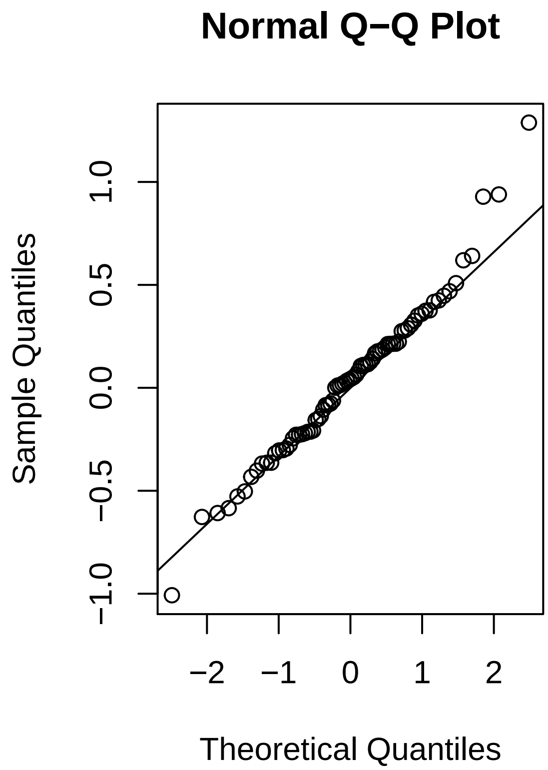
```
# Best candidate is ARIMA(1,1,1)

#### III. Model diagnostic ######
# Check for 2 important things: normality and independence using the residuals:
res=residuals(autofit)
plot(res,lwd=2,type="l",ylab="residuals",main="residuals vs. time")
```




```
# (a) Check normality:
op=par(mfrow=c(1,2))
hist(res,breaks=10,probability = TRUE,main="Histogram of the residuals")
lines(density(res),col="red",lwd=2)
qqnorm(res)
```

```
qqline(res)
```





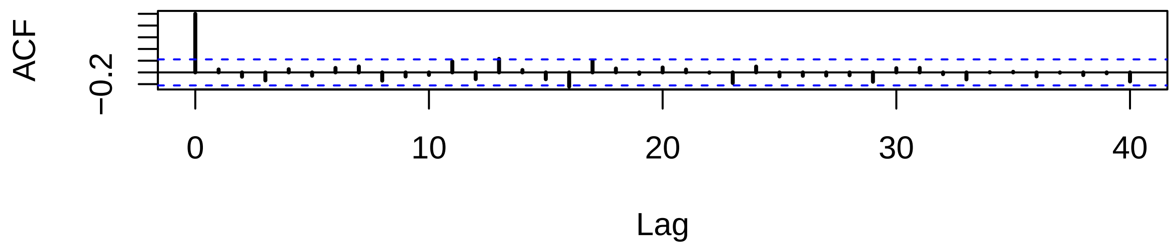

```
par(op)
# Some potential outliers but most of the points are lying near qqline
# Using hypothesis test such as Shapiro-Wilk test for normality assumption. Keep in mind that these hyp
shapiro.test(res)
```

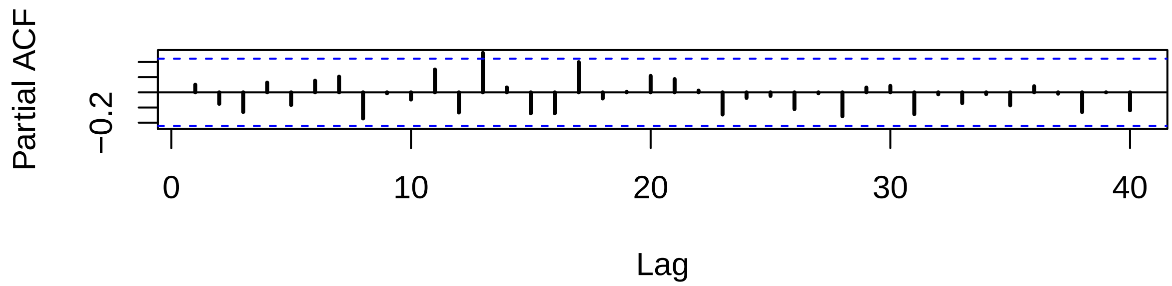
```
##
##  Shapiro-Wilk normality test
##
## data:  res
## W = 0.97899, p-value = 0.2248
```

```
# H0: the distribution follows normal distribution
# Ha: not H0
# using p-value from ouput --> normality assumption is ok.

# (b) Test for independence
# If model does a good job at fitting the data, model should explain most of systematic part, what is l
Box.test(res)
```

```
##
##  Box-Pierce test
##
## data:  res
## X-squared = 0.19685, df = 1, p-value = 0.6573
```

```
# p-value suggests that residuals are uncorrelated. If we want to visualize the result, we can construc
op=par(mfrow=c(2,1))
acf(res,lag.max = 40,lwd=2,main=" ")
pacf(res,lag.max = 40,lwd=2,main=" ")
```






```
par(op)

##### IV. Forecast #####
### Forecast the next 5 observations using the model:
pred = predict(autofit,n.ahead=5)

# 95% lower CI of the prediction:
lower= pred$pred-1.96*pred$se
lower
```

```
## Time Series:
## Start = 79
## End = 83
## Frequency = 1
## [1] 120.1524 119.3793 118.6575 117.9743 117.3261
```

```
# 95% upper CI of the prediction:
upper=pred$pred+1.96*pred$se
upper
```

```
## Time Series:
## Start = 79
## End = 83
## Frequency = 1
## [1] 121.6572 121.8768 122.1276 122.4100 122.7171
```

```
par(mfrow=c(1,1))
ts.plot(dowj,lwd=4,xlim=c(0,85))
polygon(c(79:83, rev(79:83)),c(lower,rev(upper)),
        col = "thistle", border = NA) # shaded the CI region first
points(79:83,pred$pred,pch=19) # add predicted points onto the plot
# the next 10 predicted steps show decreasing pattern in the future
```

```r
lines(79:83,lower,col="red",lwd=2) # add 95% confidence interval for each predicted points
lines(79:83,upper,col="red",lwd=2)
```