Untitled

ERNEST

2024-04-15

Loading of packages

```
library(tseries)

## Registered S3 method overwritten by 'quantmod':

## method from

## as.zoo.data.frame zoo

library(seastests)
library(forecast)
library(ggplot2)
library(readxl)
```

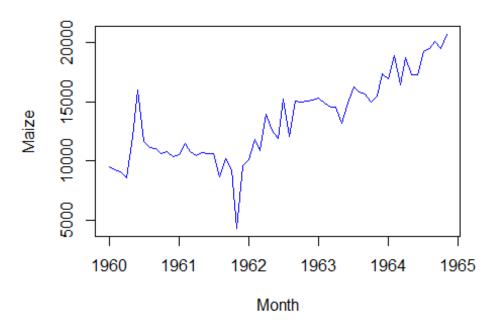
Importing of Data

```
data = read excel("C:/Users/E. K AGYAPONG/Desktop/FINAL YEAR/Sem 1/Applied
Time Series Analysis (STAT 471)/Lecturer/Practicals data.xls")
attach(data)
maize = ts(Maize, start = c(1960,1), frequency = 12)
maize
##
         Jan
               Feb
                     Mar
                                  May
                                        Jun
                                              Jul
                                                          Sep
                                                                0ct
                                                                      Nov
                            Apr
                                                    Aug
Dec
## 1960 9536 9283 9039 8537 12062 16026 11640 11089 11047 10643 10758
10358
## 1961 10525 11431 10741 10438 10703 10634 10615 8682 10161 9276 4300
9613
## 1962 10086 11845 10907 13907 12610 11889 15260 12040 15092 14933 15020
15153
## 1963 15285 14850 14557 14578 13150 14900 16272 15794 15613 14994 15437
17371
## 1964 16969 18874 16458 18712 17240 17291 19218 19500 20112 19474 20697
```

Plotting of Data

```
plot(maize, main = "Time Series Plot Of Maize", ylab="Maize", xlab="Month",
col="blue")
```

Time Series Plot Of Maize



###Test for Stationarity
ADF Test
H₀:The Maize series data is not stationary
H₁:The Maize series data is Stationary
significance level= 0.05

```
##
## Augmented Dickey-Fuller Test
##
## data: maize
## Dickey-Fuller = -1.9609, Lag order = 3, p-value = 0.5905
## alternative hypothesis: stationary
```

Conclusion: Since the p-value(= 0.5905) is greater than the significannce level(=0.05),we fail to reject H₀ and conclude that the maize series data is not stationary.

```
PP Test H_0:The Maize series data is not stationary H_1:The Maize series data is Stationary significance level= 0.05
```

```
pp.test(maize)
```

```
##
## Phillips-Perron Unit Root Test
##
## data: maize
## Dickey-Fuller Z(alpha) = -25.631, Truncation lag parameter = 3, p-value
## = 0.01151
## alternative hypothesis: stationary
```

Conclusion: Since the p-value(= 0.01151) is less than the significance level(=0.05), we reject H₀ and conclude that the maize series data is stationary.

KPSS Test

H₀:The Maize series data is stationary H₁:The Maize series data is not Stationary significance level= 0.05

```
kpss.test(maize)
## Warning in kpss.test(maize): p-value smaller than printed p-value
##
## KPSS Test for Level Stationarity
##
## data: maize
## KPSS Level = 1.3192, Truncation lag parameter = 3, p-value = 0.01
```

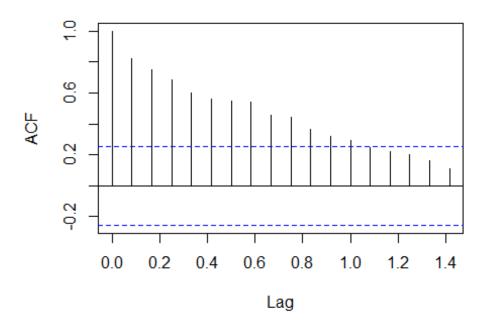
Conclusion: Since the p-value(= 0.01) is less than the significance level(=0.05), we reject H₀ and conclude that the maize series data is not stationary.

Since ADF and KPSS test confirm that the data is not stationary, we conclude that the Maize series data is not Stationary.

Differencing Of Data

```
ndiffs(maize)
## [1] 1
FirstDiff = diff(maize)
/ Ploting of ACF and PACF
acf(maize)
```

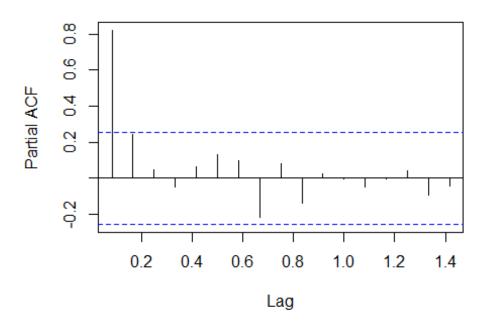
Series maize



The ACF of the Maize series decays exponentially

pacf(maize)

Series maize



The PACF of the maize series data cuts off after lag one. From the Acf and the Pacf plot we conclude that the model for the data is ARIMA(1,1,0)

Test for Seasonarity

H₀:There is no seasonarity component

H₁:There is seasonal component

```
welch(maize, freq = 12)
## Test used: Kruskall Wallis
##
## Test statistic: 2
## P-value: 0.09404391
```

Conclusion: Since the p-value (=0.09404391), is greater than the significance level we fail to reject H_0 and conclude that there is no seasonal component in the maize series data.

model

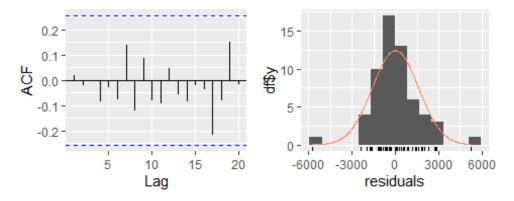
```
model1 = Arima(maize, order = c(1,1,0))
model2 = auto.arima(maize, stepwise = FALSE,approximation = FALSE)
model1
## Series: maize
## ARIMA(1,1,0)
```

```
##
## Coefficients:
## ar1
## -0.3747
## s.e. 0.1207
##
## sigma^2 = 2866400: log likelihood = -513.06
## AIC=1030.12 AICc=1030.33 BIC=1034.24

checkresiduals(model2)
```

Residuals from ARIMA(0,1,1) with drift





```
##
## Ljung-Box test
##
## data: Residuals from ARIMA(0,1,1) with drift
## Q* = 5.123, df = 11, p-value = 0.9251
##
## Model df: 1. Total lags used: 12
```

Splitting data into train and test data

```
traindata = window(maize, start = c(1960,1), end = c(1964,1))
testData = window(maize, start = c(1964,2))
traindata
##
          Jan
                Feb
                      Mar
                             Apr
                                         Jun
                                                Jul
                                                                  0ct
                                                                        Nov
                                   May
                                                      Aug
                                                            Sep
Dec
## 1960 9536 9283
                     9039 8537 12062 16026 11640 11089 11047 10643 10758
```

```
10358
## 1961 10525 11431 10741 10438 10703 10634 10615 8682 10161 9276 4300
## 1962 10086 11845 10907 13907 12610 11889 15260 12040 15092 14933 15020
15153
## 1963 15285 14850 14557 14578 13150 14900 16272 15794 15613 14994 15437
17371
## 1964 16969
testData
          Feb
                Mar
                      Apr
                            May
                                  Jun
                                        Jul
                                              Aug
                                                    Sep
                                                          0ct
                                                                Nov
## 1964 18874 16458 18712 17240 17291 19218 19500 20112 19474 20697
welch(traindata)
## Test used: Kruskall Wallis
## Test statistic: 1.5
## P-value: 0.2339556
m1 = auto.arima(traindata, stepwise = FALSE, approximation = FALSE)
m1
## Series: traindata
## ARIMA(0,1,1)
##
## Coefficients:
##
             ma1
##
         -0.4713
         0.1384
## s.e.
##
## sigma^2 = 2979222: log likelihood = -425.5
## AIC=855
            AICc=855.27
                         BIC=858.75
m2 = Arima(traindata, order = c(1,1,0))
m2
## Series: traindata
## ARIMA(1,1,0)
##
## Coefficients:
##
             ar1
##
         -0.3361
         0.1340
## s.e.
##
## sigma^2 = 3156199: log likelihood = -426.82
## AIC=857.64 AICc=857.91
                             BIC=861.38
f1 = forecast(m1,h = length(testData))
f2 = forecast(m2, h = length(testData))
accuracy(f1,testData)
```

```
ME RMSE MAE MPE MAPE
##
## Training set 278.8484 1690.450 1125.740 -0.1651948 10.61235 0.4401930
## Test set 2044.6850 2417.379 2095.668 10.4641743 10.77395 0.8194595
                      ACF1 Theil's U
## Training set -0.003953328
                                  NA
## Test set
                0.310518088 1.582129
accuracy(f2,testData)
                     ME
                            RMSE
                                      MAE
                                               MPE
                                                        MAPE
                                                                  MASE
## Training set 205.9387 1739.935 1147.436 -0.613419 10.889739 0.4486766
## Test set
               1684.9202 2120.330 1805.062 8.537876 9.267864 0.7058250
                     ACF1 Theil's U
## Training set -0.1002318
                0.3168790 1.390824
## Test set
dat = arima.sim(model = list(oder = c(2,0,2),ar = c(0.25,0.63),ma =
c(0.53,0.43)),n = 60)
auto.arima(dat)
## Series: dat
## ARIMA(2,0,2) with zero mean
## Coefficients:
##
           ar1
                   ar2
                          ma1
                                  ma2
##
        0.1427 0.6011 0.7909 0.5448
## s.e. 0.1342 0.1283 0.1531 0.1166
## sigma^2 = 1.066: log likelihood = -86.38
## AIC=182.76 AICc=183.88 BIC=193.24
```