Practical Notebook

On

Statistical Data Analysis XIII (Lab XIII)

Course Code: STAT 4109

Course: Time Series Analysis I

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Problem: -1

Random Number Generating.

```
#-GENERATING RANDOM NUMBER FROM NORMAL DIST.
X=RNORM(100,0,1)

#HELP(TS)

#CREATING A TIME SERIES
QUATER_TS=TS(DATA = X,START = 1995,FREQUENCY = 4)

#---CREATING TIME SERIES PLOT FOR QUATERLY  DATA-
PLOT(QUATER_TS,COL=4,YLAB="FREQUENCY",
     XLAB="YEAR",MAIN="QUATERLY TIME SERIES PLOT")
```

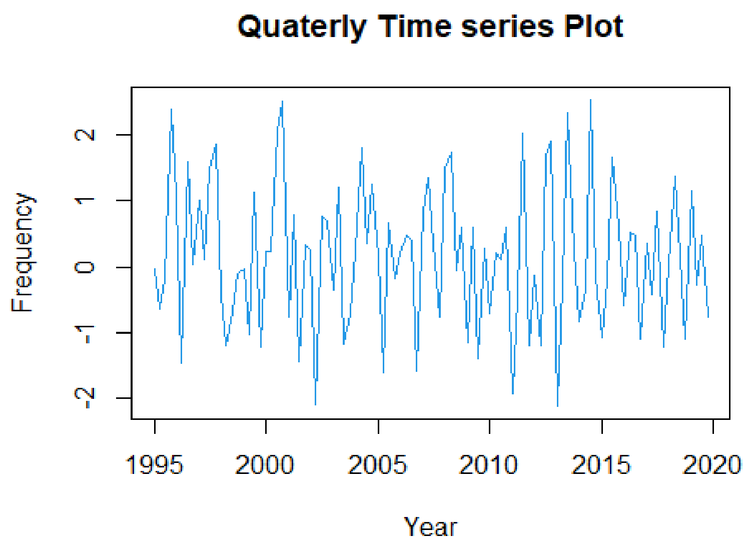


Fig-01: Quarterly Plot Random Number

Comment: *THOSE THE QUARTERLY AND MONTHLY DATA ARE THE STATIONARY CAUSE DATA FORM NORMAL DISTRIBUTION, HAVE EQUAL MEAN AND VARIANCE.*

```
#CREATING TIME SERIES PLOT FOR MONTHLY DATA
MONTHLY_TS=TS(DATA = X,START = 1995,FREQUENCY = 12)

#-------------PLOT--------------------
PLOT(MONTHLY_TS,COL="RED",MAIN="MONTHLY TIME SERIES DATA")

#-DETECTION OF TEND AND GET A STATIONARY TIME SERIES
# INSTALL.PACKAGES("FPP")
LIBRARY(FPP)
```

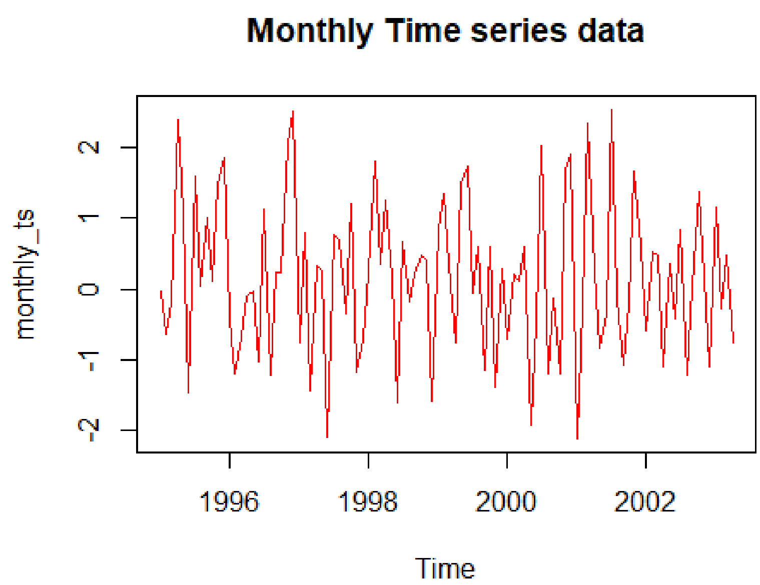


Fig-02: Monthly Time Series

Comment: The plot show data are stationary because sample draw from normal distribution.

Australia beer production Time series analysis.

```
LIBRARY(FORECAST)
DATA(AUSBEER)
VIEW(AUSBEER)
AUSBEER

##      QTR1 QTR2 QTR3 QTR4
## 1956  284  213  227  308
## 1957  262  228  236  320
## 1958  272  233  237  313
## 1959  261  227  250  314
## 1960  286  227  260  311
## 1961  295  233  257  339
## 1962  279  250  270  346
## 1963  294  255  278  363
## 1964  313  273  300  370
## 1965  331  288  306  386
## 1966  335  288  308  402
## 1967  353  316  325  405
## 1968  393  319  327  442
## 1969  383  332  361  446
## 1970  387  357  374  466
```

```
## 1971  410  370  379  487
## 1972  419  378  393  506
## 1973  458  387  427  565
## 1974  465  445  450  556
## 1975  500  452  435  554
## 1976  510  433  453  548
## 1977  486  453  457  566
## 1978  515  464  431  588
## 1979  503  443  448  555
## 1980  513  427  473  526
## 1981  548  440  469  575
## 1982  493  433  480  576
## 1983  475  405  435  535
## 1984  453  430  417  552
## 1985  464  417  423  554
## 1986  459  428  429  534
## 1987  481  416  440  538
## 1988  474  440  447  598
## 1989  467  439  446  567
## 1990  485  441  429  599
## 1991  464  424  436  574
## 1992  443  410  420  532
## 1993  433  421  410  512
## 1994  449  381  423  531
## 1995  426  408  416  520
## 1996  409  398  398  507
## 1997  432  398  406  526
## 1998  428  397  403  517
## 1999  435  383  424  521
## 2000  421  402  414  500
## 2001  451  380  416  492
## 2002  428  408  406  506
## 2003  435  380  421  490
## 2004  435  390  412  454
## 2005  416  403  408  482
## 2006  438  386  405  491
## 2007  427  383  394  473
## 2008  420  390  410
```

```
BEER.TS=WINDOW(AUSBEER,START=1956,END=1975)
PLOT(AS.TS(BEER.TS),COL=5,LWD=2)
```

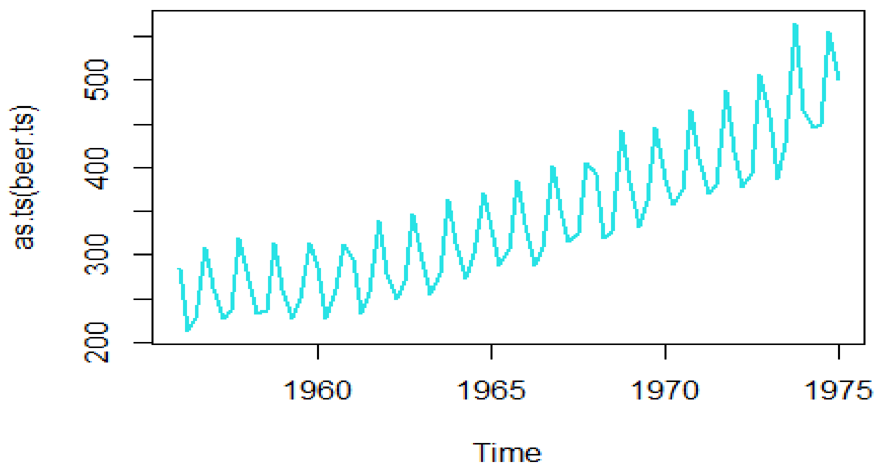


Fig-03: Plotting AusBeer Data

Comment: we can see that clearly an upward trend is presence in the data. So, this is a non-stationary data.

```
# Upper tend data
#Creating a moving average that will be close to trend

beer.trend=ma(beer.ts,order = 4,centre = T)

#Plot trend a MA together
plot(as.ts(beer.ts),col="red",ylab="Value of Beer",main="Beer sells")
lines(beer.trend,col=6,lwd=1.5)
```

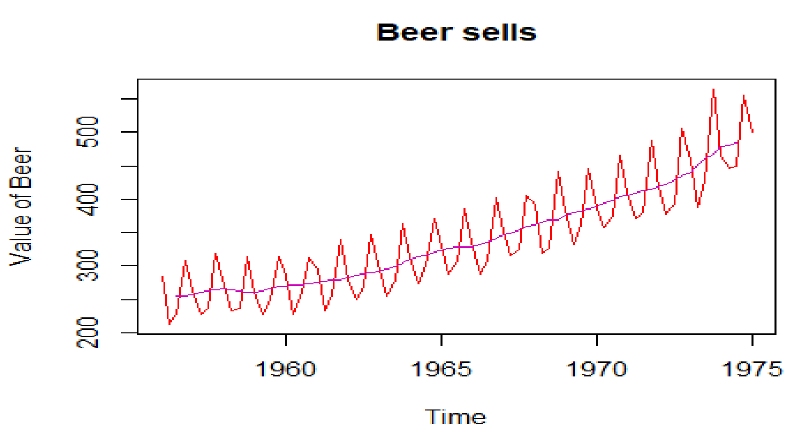


Fig-04: Beer Sells with Moving Average

Comment: A moving average line is also plotted along with the trend which is a proper representative of the trend. And, due to 4th order moving average we will not get first 2 time points and last 2 time points and last 2 time points will not get moving average.

```
#REMOVING THE TREND FROM THE TIME SERIES
BEER.DETREND=BEER.TS-BEER.TREND

#PLOT THE DETREND DATA

PLOT(AS.TS(BEER.DETREND),COL=7,
    MAIN="AUSTRALIA BEER PRODUCTION",YLAB="VALUES",LWD=2)
```

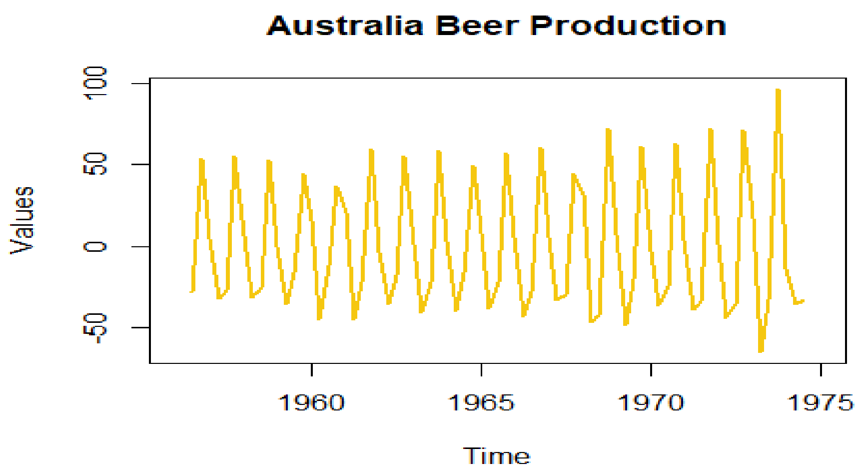


Fig-05: Australia Beer Production After Moving Average

Comment: Now our plot is stationary plot because here over the time mean is same and variance is also same.

```
#BUT IN REAL LIFE PROBLEM ALL DATA SETS ARE NOT STATIONARY
#IN THIS SITUATION WE HAVE TO CONVERT DATA INTO A STATIONARY
#DATA


#-DETECTION OF TEND AND GET A STATIONARY TIME SERIES
# INSTALL.PACKAGES("FPP")
LIBRARY(FPP)
DATA(AUSBEER)
VIEW(AUSBEER)
AUSBEER
```

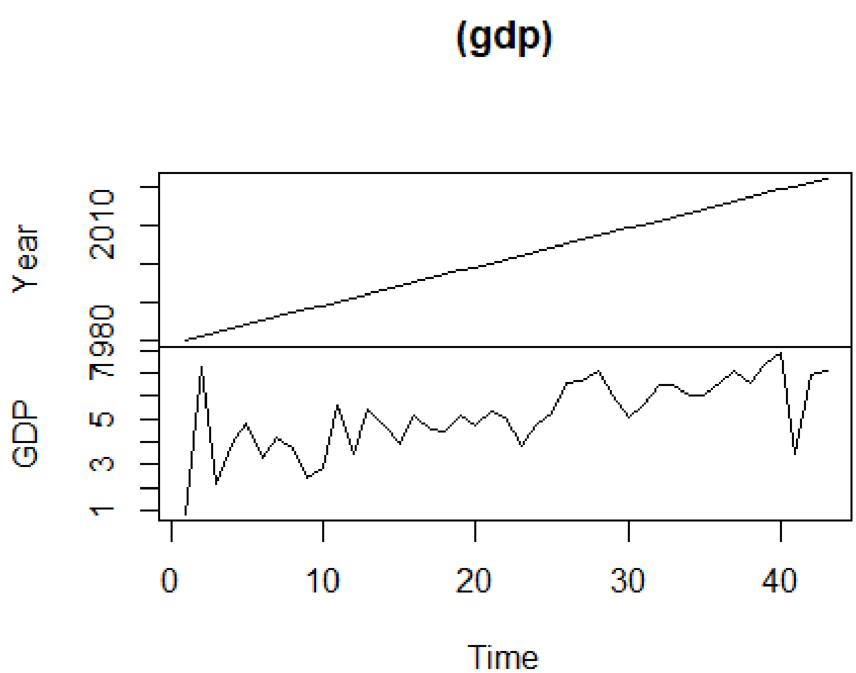
```
##      Qtr1 Qtr2 Qtr3 Qtr4
## 1956  284  213  227  308
## 1957  262  228  236  320
## 1958  272  233  237  313
## 1959  261  227  250  314
## 1960  286  227  260  311
## 1961  295  233  257  339
## 1962  279  250  270  346
## 1963  294  255  278  363
## 1964  313  273  300  370
## 1965  331  288  306  386
## 1966  335  288  308  402
## 1967  353  316  325  405
## 1968  393  319  327  442
## 1969  383  332  361  446
## 1970  387  357  374  466
## 1971  410  370  379  487
## 1972  419  378  393  506
## 1973  458  387  427  565
## 1974  465  445  450  556
## 1975  500  452  435  554
## 1976  510  433  453  548
## 1977  486  453  457  566
## 1978  515  464  431  588
## 1979  503  443  448  555
## 1980  513  427  473  526
## 1981  548  440  469  575
## 1982  493  433  480  576
## 1983  475  405  435  535
## 1984  453  430  417  552
## 1985  464  417  423  554
## 1986  459  428  429  534
## 1987  481  416  440  538
## 1988  474  440  447  598
## 1989  467  439  446  567
## 1990  485  441  429  599
## 1991  464  424  436  574
## 1992  443  410  420  532
## 1993  433  421  410  512
## 1994  449  381  423  531
## 1995  426  408  416  520
## 1996  409  398  398  507
## 1997  432  398  406  526
## 1998  428  397  403  517
## 1999  435  383  424  521
## 2000  421  402  414  500
```

```
## 2001  451  380  416  492
## 2002  428  408  406  506
## 2003  435  380  421  490
## 2004  435  390  412  454
## 2005  416  403  408  482
## 2006  438  386  405  491
## 2007  427  383  394  473
## 2008  420  390  410
```

```
LIBRARY(READXL)
```

```
## WARNING: PACKAGE 'READXL' WAS BUILT UNDER R VERSION 4.3.2
```

```
DF<- READ_EXCEL("GDP OF BANGLADESH.XLSX")
VIEW(DF)
# GDP.TS=WINDOW(DF,START = 1980,END = 2020)
GDP=TS(DF)
PLOT((GDP))
```



Problem: -02

Air Passengers data analysis from 1949-160.

```
DATA("AIRPASSENGER")
```

```
## Warning in data("Airpassenger"): data set 'Airpassenger' not found

AirPassengers

##      Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
## 1949 112 118 132 129 121 135 148 148 136 119 104 118
## 1950 115 126 141 135 125 149 170 170 158 133 114 140
## 1951 145 150 178 163 172 178 199 199 184 162 146 166
## 1952 171 180 193 181 183 218 230 242 209 191 172 194
## 1953 196 196 236 235 229 243 264 272 237 211 180 201
## 1954 204 188 235 227 234 264 302 293 259 229 203 229
## 1955 242 233 267 269 270 315 364 347 312 274 237 278
## 1956 284 277 317 313 318 374 413 405 355 306 271 306
## 1957 315 301 356 348 355 422 465 467 404 347 305 336
## 1958 340 318 362 348 363 435 491 505 404 359 310 337
## 1959 360 342 406 396 420 472 548 559 463 407 362 405
## 1960 417 391 419 461 472 535 622 606 508 461 390 432

#Understanding and Preparing data
boxplot(AirPassengers~cycle(AirPassengers))
```

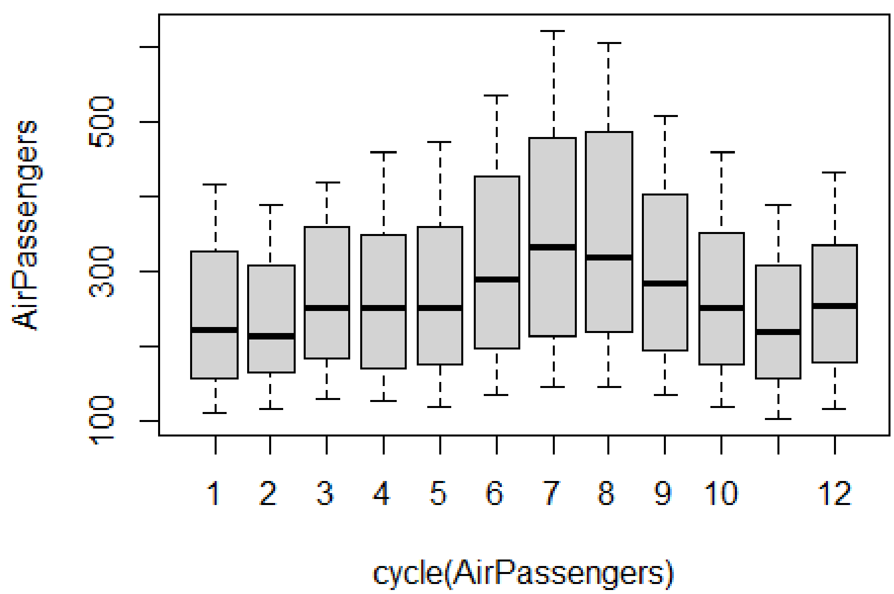


Fig-06: Boxplot of AirPassengers

Comment: Fig-06 shows us how many passengers travels by air in several months. Highest number of passengers travel in August and September and the lowest numbers of passengers travel in November.

```
plot(AirPassengers,main="AirPassengers",ylab="Number of Passengers",
      col="blue",lwd=1.5)

# upward and seasonality  Trend data
abline(lm(AirPassengers~time(AirPassengers)),lwd=1.3,col="red")
```

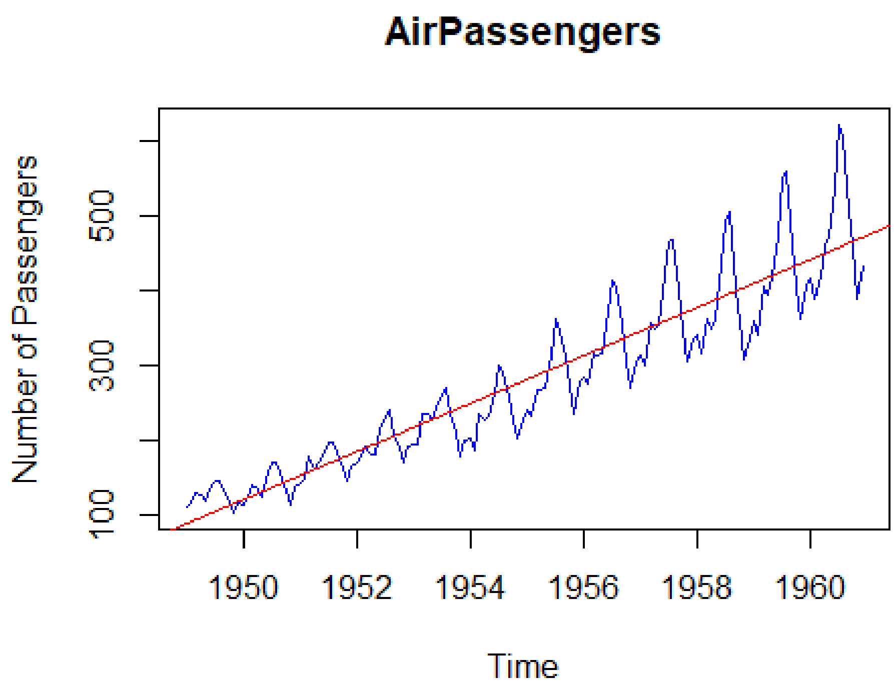


Fig-07: Plotting Airpassengrs with Abline.

Comment:_Show the trend of fig-07 using average method. Here, mean and variance change over time which implies non-stationary.

```
#Make it stationary
# do variance constant
plot(diff(log(AirPassengers)),col="red",lwd=2,ylab="Passengers",main="AirPassengers data"
)
```

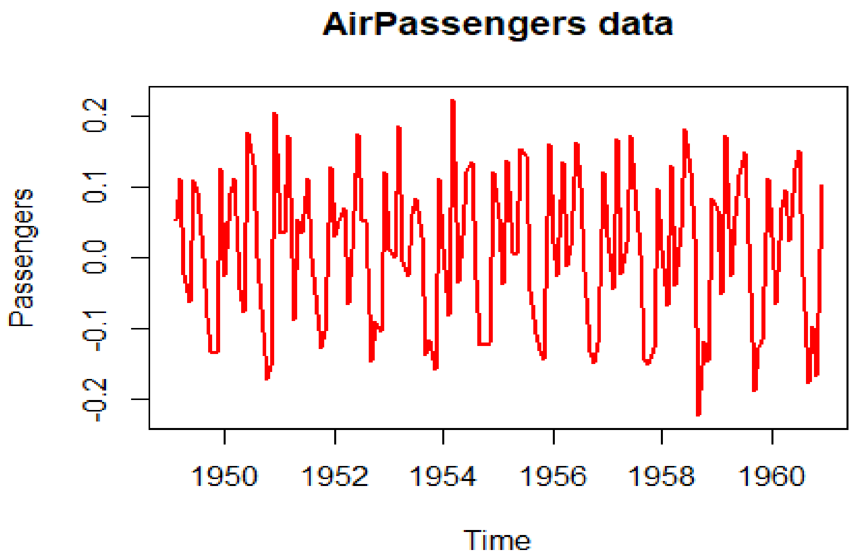


Fig-08: After differention and log transformation of Airpassengers.

Comment: Mean zero and variance constant. Hence, our data now Stationary.

```
#After stationary we can fit ARIMA model
# we need tseries
library(tseries)
# ARIMA(p=Order of AR,d=differencing order,
# order of MA)
#Selecting the value of p(AR)
acf(AirPassengers)
```

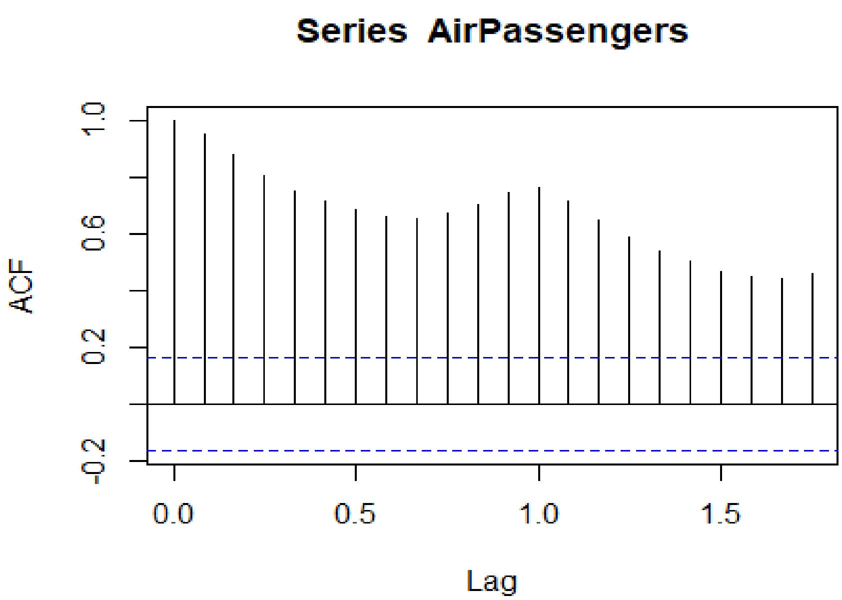


Fig-09: Auto Covariance Function (ACF)

Comment: Here the number of line cross or touch the blue line is no. of AR. we avoid the for zero value and the data is sessional that's why q=1.

```
ACF(DIFF(LOG(AIRPASSENGERS)))
```

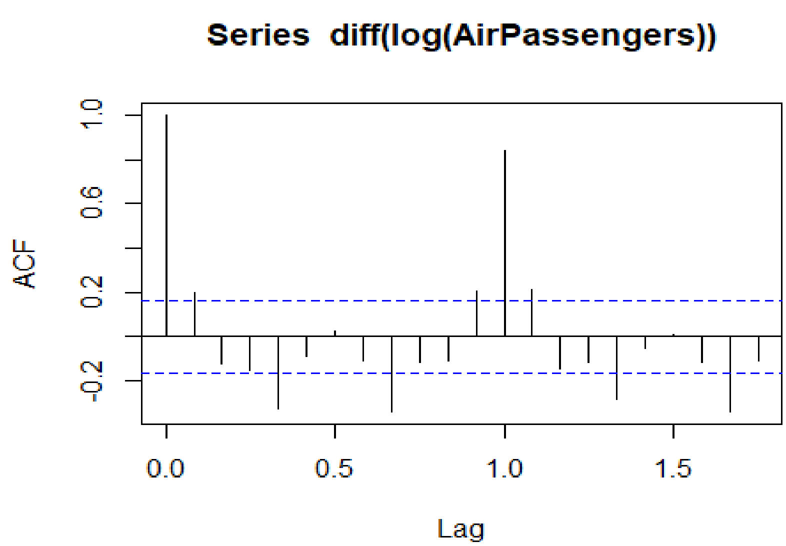


Fig-10: After Transformation of AirPassengers Data.

Comment: Here the number of line cross or touch the blue line is the value of q we ignore the first line for zero value and the next after 1 line because data is seasonal i.e. q=1.

```
#HERE THE NUMBER OF LINE CROSS OR TOUCH THE BLUE LINE IS NO.
# OF AR .WE AVOID THE FOR ZERO VALUE AND THE DATA
# IS SESSIONAL THAT'S WHY Q=1

# SELECTING THE VALUE OF P
PACF(DIFF(LOG(AIRPASSENGERS)))
```

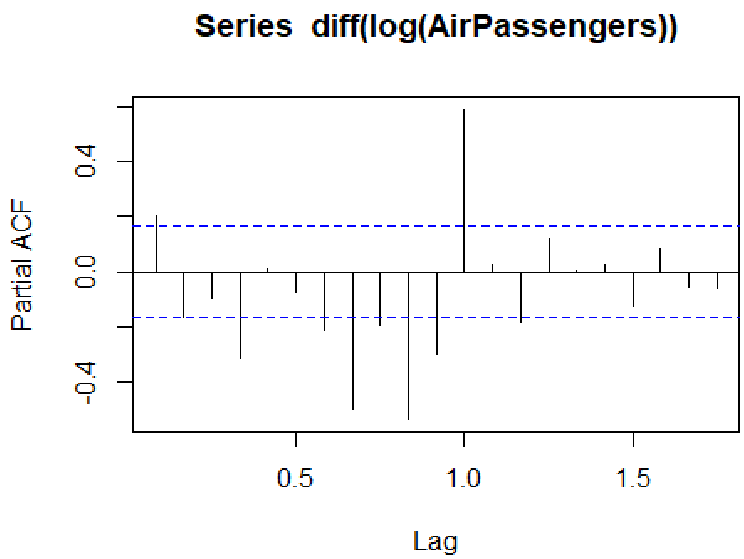


Fig-11: Partial Auto Covariance Function.

Comment: The line only at zero (0) cross the blue line. So, p=0.

```
# FITTING AN ARIMA(0,1,1)
# HELP(ARIMA)

M_FIT=ARIMA(LOG(AIRPASSENGERS),ORDER = C(0,1,1),SEASONAL =LIST(ORDER=C(0,1,1),PERIOD=12
))

M_FIT

##
## CALL:
## ARIMA(X = LOG(AIRPASSENGERS), ORDER = C(0, 1, 1), SEASONAL = LIST(ORDER = C(0,
```

```
##     1, 1), period = 12))
##
## Coefficients:
##           ma1     sma1
##       -0.4018  -0.5569
## s.e.   0.0896   0.0731
##
## sigma^2 estimated as 0.001348:  log likelihood = 244.7,  aic = -483.4
```

```r
#Forecast for next 10 years

pred=predict(m_fit,n.ahead = 10*12)
pred
```

```
## $pred
##           Jan      Feb      Mar      Apr      May      Jun      Jul      Aug
## 1961 6.110186 6.053775 6.171715 6.199300 6.232556 6.368779 6.507294 6.502906
## 1962 6.206435 6.150025 6.267964 6.295550 6.328805 6.465028 6.603543 6.599156
## 1963 6.302684 6.246274 6.364213 6.391799 6.425054 6.561277 6.699792 6.695405
## 1964 6.398933 6.342523 6.460463 6.488048 6.521304 6.657526 6.796042 6.791654
## 1965 6.495183 6.438772 6.556712 6.584297 6.617553 6.753776 6.892291 6.887903
## 1966 6.591432 6.535022 6.652961 6.680547 6.713802 6.850025 6.988540 6.984153
## 1967 6.687681 6.631271 6.749210 6.776796 6.810051 6.946274 7.084789 7.080402
## 1968 6.783930 6.727520 6.845460 6.873045 6.906301 7.042523 7.181039 7.176651
## 1969 6.880180 6.823769 6.941709 6.969294 7.002550 7.138773 7.277288 7.272900
## 1970 6.976429 6.920019 7.037958 7.065544 7.098799 7.235022 7.373537 7.369150
##           Sep      Oct      Nov      Dec
## 1961 6.324698 6.209008 6.063487 6.168025
## 1962 6.420947 6.305257 6.159737 6.264274
## 1963 6.517197 6.401507 6.255986 6.360523
## 1964 6.613446 6.497756 6.352235 6.456773
## 1965 6.709695 6.594005 6.448484 6.553022
## 1966 6.805944 6.690254 6.544734 6.649271
## 1967 6.902194 6.786504 6.640983 6.745520
## 1968 6.998443 6.882753 6.737232 6.841770
## 1969 7.094692 6.979002 6.833481 6.938019
## 1970 7.190941 7.075251 6.929731 7.034268
##
## $se
##             Jan        Feb        Mar        Apr        May        Jun
## 1961 0.03671562 0.04278291 0.04809072 0.05286830 0.05724856 0.06131670
## 1962 0.09008475 0.09549708 0.10061869 0.10549195 0.11014981 0.11461854
## 1963 0.14650643 0.15224985 0.15778435 0.16313118 0.16830825 0.17333075
## 1964 0.20896657 0.21513653 0.22113442 0.22697386 0.23266679 0.23822371
## 1965 0.27748210 0.28408309 0.29053414 0.29684503 0.30302451 0.30908048
## 1966 0.35174476 0.35876289 0.36564634 0.37240257 0.37903840 0.38556004
## 1967 0.43142043 0.43883816 0.44613258 0.45330963 0.46037481 0.46733319
```

```
## 1968 0.51620376 0.52400376 0.53168935 0.53926541 0.54673651 0.55410688
## 1969 0.60582584 0.61399203 0.62205103 0.63000694 0.63786363 0.64562471
## 1970 0.70005133 0.70856907 0.71698563 0.72530453 0.73352910 0.74166246
##             Jul        Aug        Sep        Oct        Nov        Dec
## 1961 0.06513124 0.06873441 0.07215787 0.07542612 0.07855851 0.08157070
## 1962 0.11891946 0.12307018 0.12708540 0.13097758 0.13475740 0.13843405
## 1963 0.17821177 0.18296261 0.18759318 0.19211216 0.19652727 0.20084534
## 1964 0.24365393 0.24896574 0.25416656 0.25926308 0.26426132 0.26916676
## 1965 0.31502004 0.32084967 0.32657525 0.33220217 0.33773535 0.34317933
## 1966 0.39197318 0.39828307 0.40449455 0.41061207 0.41663978 0.42258152
## 1967 0.47418947 0.48094803 0.48761291 0.49418791 0.50067658 0.50708223
## 1968 0.56138049 0.56856106 0.57565206 0.58265678 0.58957827 0.59641945
## 1969 0.65329361 0.66087351 0.66836746 0.67577831 0.68310877 0.69036139
## 1970 0.74970759 0.75766731 0.76554426 0.77334099 0.78105989 0.78870326

#final predicton


finalpred=exp(pred$pred)
ts.plot(AirPassengers,finalpred,log="y",lty=c(1:3),col=c(3,'red'),
       main="Passengers Predicton",ylab="Number of Passengers")
```

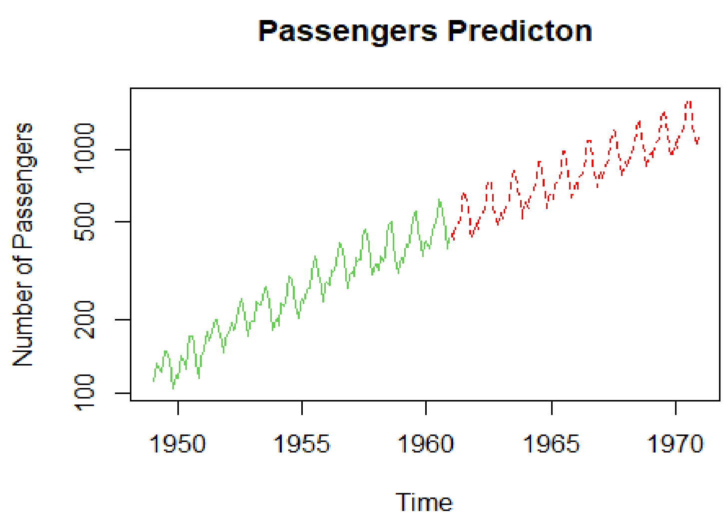


Fig-12: AirPassengers Prediction.

Comment: Shows predict for next 10 years Air passengers. We indicate the future in red color.

```
#Checking accuracy of the prediction
train_data=ts(AirPassengers,frequency = 12,start=c(1949,1),end = c(1959,12))

m_fit2=arima(log(train_data),order = c(0,1,1),seasonal =list(order=c(0,1,1),period=12))
```

```
m_fit2

##
## Call:
## arima(x = log(train_data), order = c(0, 1, 1), seasonal = list(order = c(0,
##     1, 1), period = 12))
##
## Coefficients:
##           ma1     sma1
##       -0.3484  -0.5623
## s.e.   0.0943   0.0774
##
## sigma^2 estimated as 0.001313:  log likelihood = 223.63,  aic = -441.26

#Predict for one year
pred2=predict(m_fit2,n.ahead = 1*12)
pred2

## $pred
##           Jan      Feb      Mar      Apr      May      Jun      Jul      Aug
## 1960 6.038647 5.988763 6.145428 6.118993 6.159652 6.304666 6.433288 6.445958
##           Sep      Oct      Nov      Dec
## 1960 6.266719 6.136192 6.007899 6.114338
##
## $se
##             Jan        Feb        Mar        Apr        May        Jun
## 1960 0.03622957 0.04324114 0.04926471 0.05462807 0.05951001 0.06402074
##             Jul        Aug        Sep        Oct        Nov        Dec
## 1960 0.06823394 0.07220170 0.07596249 0.07954568 0.08297427 0.08626671

pred3=exp(pred2$pred)
pred3

##           Jan      Feb      Mar      Apr      May      Jun      Jul      Aug
## 1960 419.3252 398.9209 466.5792 454.4070 473.2633 547.1189 622.2166 630.1501
##           Sep      Oct      Nov      Dec
## 1960 526.7465 462.2898 406.6279 452.2965

pred_1960=round(pred3,0)
true_1960=tail(AirPassengers,12)
df=data.frame(pred_1960,true_1960)
df

##    pred_1960 true_1960
## 1        419       417
## 2        399       391
## 3        467       419
## 4        454       461
```

```
## 5         473       472
## 6         547       535
## 7         622       622
## 8         630       606
## 9         527       508
## 10        462       461
## 11        407       390
## 12        452       432
```

Comment: The difference between the true value and the predicted value is the smallest so the accuracy of the model is large.

Problem: -3

Decomposition and modeling AirPassengers data.

```
#---------------lecture-5.3--------------------------
#Decomposition and modeling
#Data Air Passengers
data("AirPassengers")
View(AirPassengers)
AirPassengers
```

```
##      Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
## 1949 112 118 132 129 121 135 148 148 136 119 104 118
## 1950 115 126 141 135 125 149 170 170 158 133 114 140
## 1951 145 150 178 163 172 178 199 199 184 162 146 166
## 1952 171 180 193 181 183 218 230 242 209 191 172 194
## 1953 196 196 236 235 229 243 264 272 237 211 180 201
## 1954 204 188 235 227 234 264 302 293 259 229 203 229
## 1955 242 233 267 269 270 315 364 347 312 274 237 278
## 1956 284 277 317 313 318 374 413 405 355 306 271 306
## 1957 315 301 356 348 355 422 465 467 404 347 305 336
## 1958 340 318 362 348 363 435 491 505 404 359 310 337
## 1959 360 342 406 396 420 472 548 559 463 407 362 405
## 1960 417 391 419 461 472 535 622 606 508 461 390 432
```

```
#Preparing the time series data
AP=ts(AirPassengers,frequency = 12,start = c(1949,1))

#Understanding data
# Trend(T)
#Seasonal(S)
#Cyclical(C)
```

```
#Irregular(I)
plot(AP,col="green",lwd=1.4,main="Air Passengers",ylab="Numberof Passengers")
```

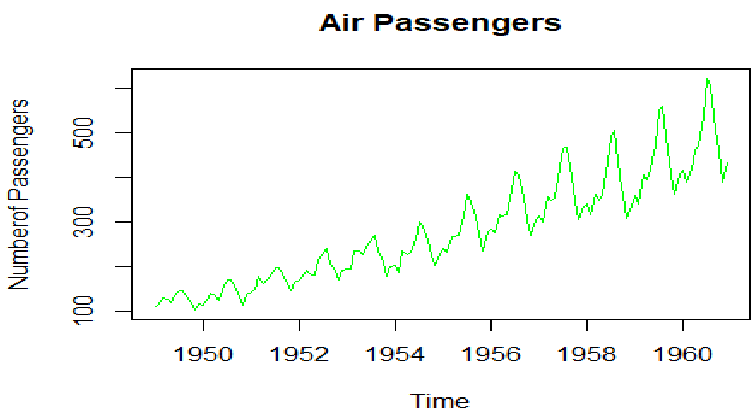


Fig-13: Plotting Airpassengers Data.

Comment: Here, mean and variance both are changed over time also there is a upward trend and follow seasonality. Hence, this plot indicates non-stationary.

```
#Log-transform to fix-up variation
AP2=log(AP)
plot(AP2,lwd=1.2,col="Yellow",
     main="Air Passengers ",ylab="Number of Passengers") #here we see the variance are same
```

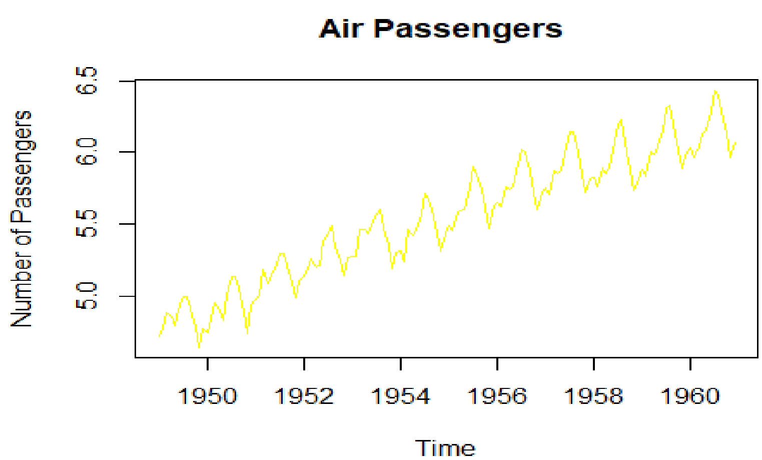


Fig-14: Log Transformation of Air Passengers.

Comment: By log transform we fix up the variance. Here we see the variance is constant. However, still now trend, seasonality and random component are existed in the data.

```
#DECOMPOSE
DAP=DECOMPOSE((AP2))
DAP$FIGURE

##  [1] -0.085815019 -0.114412848  0.018113355 -0.013045611 -0.008966106
##  [6]  0.115392997  0.210816435  0.204512399  0.064836351 -0.075271265
## [11] -0.215845612 -0.100315075

PLOT(DAP$FIGURE,
     TYPE='B',
     XLAB = 'MONTH',
     YLAB = 'SEASONALITY INDEX',
     COL="BLUE",
     LAS=2,
     MAIN = "AIRPASSENGERS",
     LWD=1.3)
```

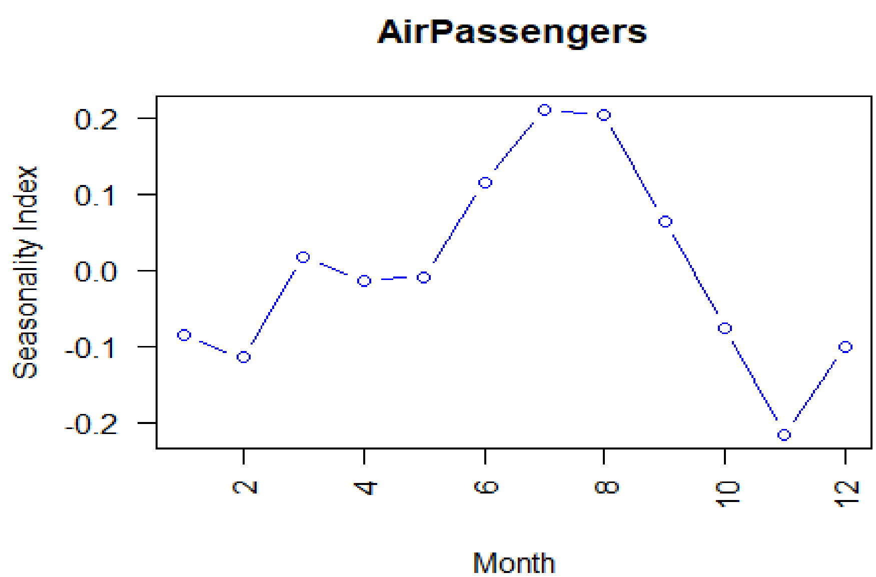


Fig-15: Seasonality Plot

Comment: Decomposed value of the month March, April and May almost close to zero (0). Value of July and August are two times more and value of November two times less.

Alternatively, we can say the seasonality index of July and August are four times more than November.

```
#Decompose plot
plot(dap)
```

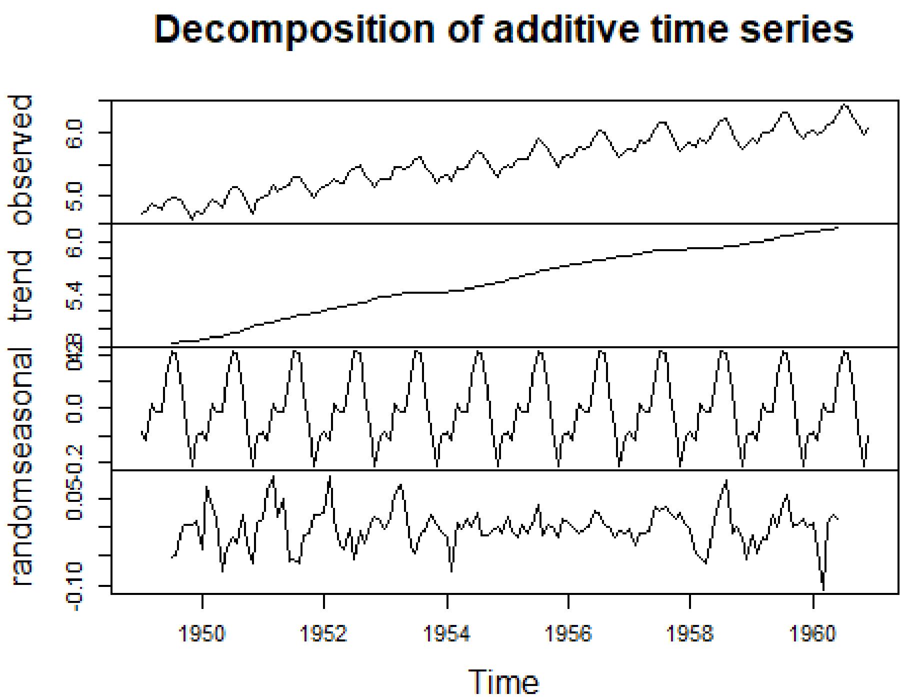


Fig-16: Decomposition of Airpassengers.

Comment: Here we see the nature of the several components exist in the data.

```
#ARIMA(p,d,q) model
library(forecast)
model_fit=auto.arima(ap2)
model_fit

## Series: ap2
## ARIMA(0,1,1)(0,1,1)[12]
##
## Coefficients:
##          ma1     sma1
##      -0.4018  -0.5569
```

```
## s.e.   0.0896   0.0731
##
## sigma^2 = 0.001371:  log likelihood = 244.7
## AIC=-483.4   AICc=-483.21   BIC=-474.77

#Residual plot
hist(model_fit$residuals,
     col='red',
     main = 'Residual plot',
     xlab = 'Error',
     freq=F)
lines(density(model_fit$residuals),
                   col='blue',lw=3)
```

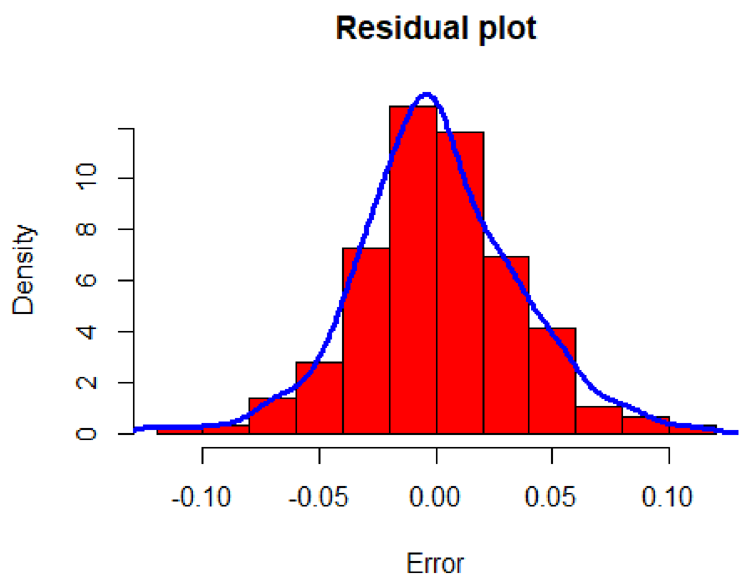


Fig-17: Residual Plot.

Comment: we can see that most of the observations are around 0 and residual are symmetrically distributed. So, we can say that residuals are normally distributed with mean 0.

```
#Forecast for the next 4 years
pred=forecast(model_fit,4*12)
library(ggplot2)

## Warning: package 'ggplot2' was built under R version 4.3.2
```

```
autoplot(pred) #deep blue 80% CI and light blue 95% CI
```

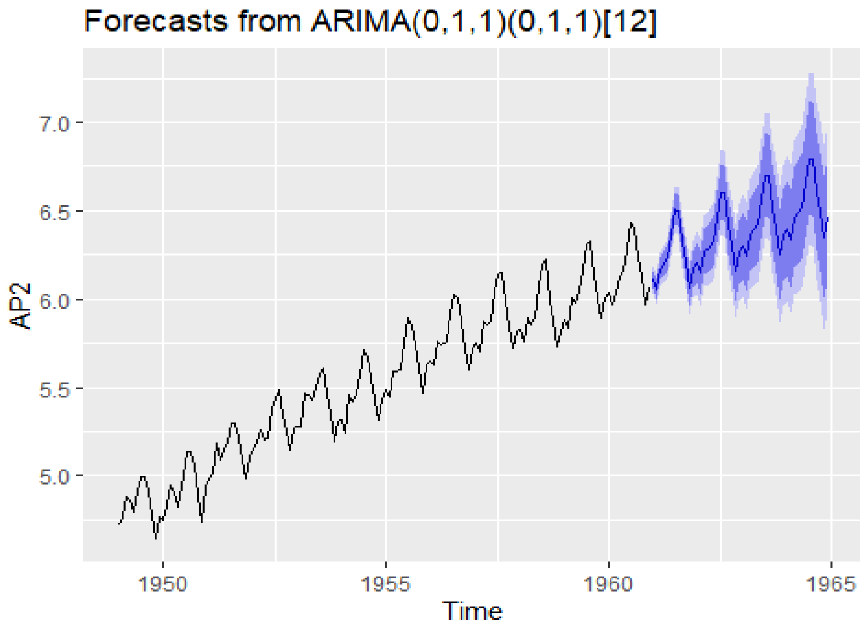


Fig-18: Prediction of Next four year.

Comment: Our data was for 1960, data are forecasted for next 4 years which shown by blue line. 80% confidence interval is shown by deep blue region and 95% CI is shown by shaded blue line.

```
#Checking accuracy
accuracy(pred)

##                        ME       RMSE        MAE        MPE      MAPE      MASE
## Training set 0.0005730622 0.03504883 0.02626034 0.01098898 0.4752815 0.216952
2
##                    ACF1
## Training set 0.01443892
```

Problem: -04

Visualization of data by ggplot2.

Anti diabetic drug subsidy (1991-2009)

The a10 dataset, which is supposed to represent monthly anti-diabetic drug subsidy in Australia from 1991 to 2008

Visualization of data by ggplot2.

```
library(fpp)
library(fpp2)

library(forecast)
library(ggplot2)
# help("autoplot")
data(a10)
a10

##           Jan       Feb       Mar       Apr       May       Jun       Jul
## 1991                                                               3.526591
## 1992  5.088335  2.814520  2.985811  3.204780  3.127578  3.270523  3.737851
## 1993  6.192068  3.450857  3.772307  3.734303  3.905399  4.049687  4.315566
## 1994  6.731473  3.841278  4.394076  4.075341  4.540645  4.645615  4.752607
## 1995  6.749484  4.216067  4.949349  4.823045  5.194754  5.170787  5.256742
## 1996  8.329452  5.069796  5.262557  5.597126  6.110296  5.689161  6.486849
## 1997  8.524471  5.277918  5.714303  6.214529  6.411929  6.667716  7.050831
## 1998  8.798513  5.918261  6.534493  6.675736  7.064201  7.383381  7.813496
## 1999 10.391416  6.421535  8.062619  7.297739  7.936916  8.165323  8.717420
## 2000 12.511462  7.457199  8.591191  8.474000  9.386803  9.560399 10.834295
## 2001 14.497581  8.049275 10.312891  9.753358 10.850382  9.961719 11.443601
## 2002 16.300269  9.053485 10.002449 10.788750 12.106705 10.954101 12.844566
## 2003 16.828350  9.800215 10.816994 10.654223 12.512323 12.161210 12.998046
## 2004 18.003768 11.938030 12.997900 12.882645 13.943447 13.989472 15.339097
## 2005 20.778723 12.154552 13.402392 14.459239 14.795102 15.705248 15.829550
## 2006 23.486694 12.536987 15.467018 14.233539 17.783058 16.291602 16.980282
## 2007 28.038383 16.763869 19.792754 16.427305 21.000742 20.681002 21.834890
## 2008 29.665356 21.654285 18.264945 23.107677 22.912510 19.431740
##           Aug       Sep       Oct       Nov       Dec
## 1991  3.180891  3.252221  3.611003  3.565869  4.306371
## 1992  3.558776  3.777202  3.924490  4.386531  5.810549
## 1993  4.562185  4.608662  4.667851  5.093841  7.179962
## 1994  5.350605  5.204455  5.301651  5.773742  6.204593
## 1995  5.855277  5.490729  6.115293  6.088473  7.416598
## 1996  6.300569  6.467476  6.828629  6.649078  8.606937
## 1997  6.704919  7.250988  7.819733  7.398101 10.096233
## 1998  7.431892  8.275117  8.260441  8.596156 10.558939
## 1999  9.070964  9.177113  9.251887  9.933136 11.532974
## 2000 10.643751  9.908162 11.710041 11.340151 12.079132
## 2001 11.659239 10.647060 12.652134 13.674466 12.965735
## 2002 12.196500 12.854748 13.542004 13.287640 15.134918
## 2003 12.517276 13.268658 14.733622 13.669382 16.503966
```

```
## 2004 15.370764 16.142005 16.685754 17.636728 18.869325
## 2005 17.554701 18.100864 17.496668 19.347265 20.031291
## 2006 18.612189 16.623343 21.430241 23.575517 23.334206
## 2007 23.930204 22.930357 23.263340 25.250030 25.806090
## 2008

#-Plotting the dataset--
autoplot(a10)+
  ggtitle("Antidiabetic drug sales")+
  ylab("$ Million")+
  xlab("Year")
```

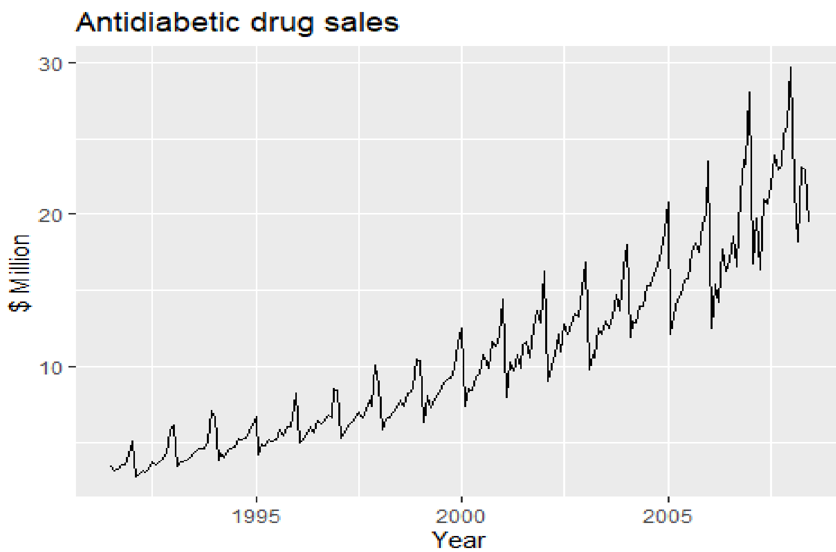


Fig-19: Antidiabetic Drug sales plot

Comment: The plot show that Antidiabetic drug sales in Australia is increase. And This is seasonal upper trend data non stationary data.

```
#Seasonal plot
ggseasonplot(a10,year.labels = T,year.labels.left = T)+
    ggtitle("Seasonal Plot: Antidiabetic drug sales")+
    ylab("$ Million ")+
    xlab("Year")
```

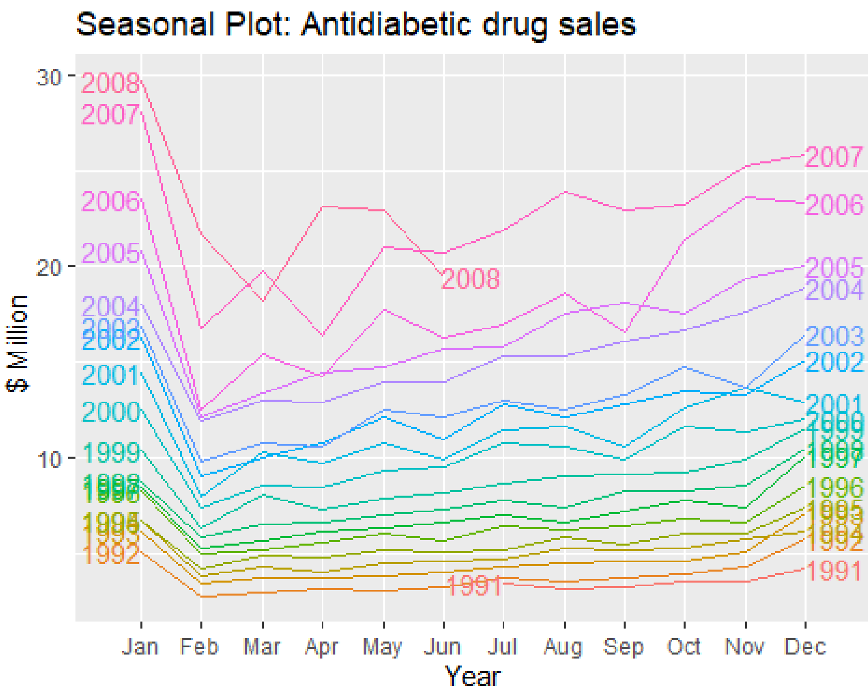


Fig-20: Antidiabetic Drug sales Seasonal Plot.

Comment: Visualization of year wise monthly anti diabetic drug sells and comparative picture of several year. This is seasonal plot.

```
#Polar seasonal plot
ggseasonplot(a10,polar =T)+
  ggtitle("Polar Plot: Antidiabetic drug sales")+
  ylab("$ Million ")+
  xlab("Year")
```

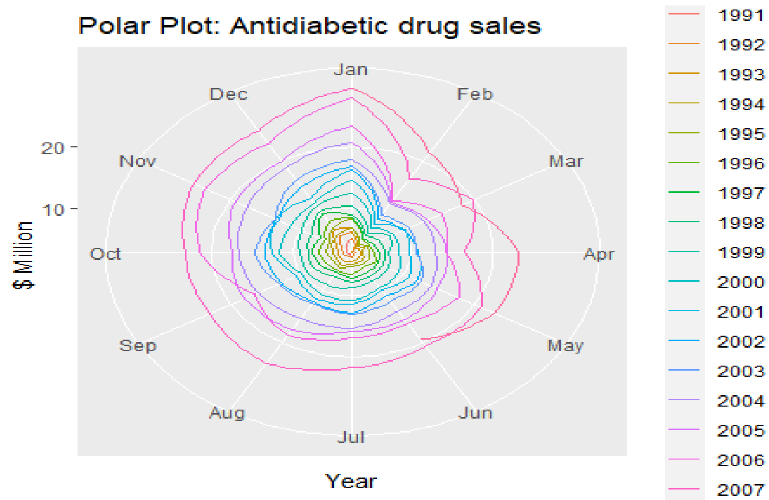


Fig-21: Polar Plot of Antidiabetic Drug sales.

Comment: This is year wise monthly anti diabetic drug sells and comparative picture of several year. This is polar plot.

```
#SEASONAL SUB-SERIES PLOT

GGSUBSERIESPLOT(A10)+
    GGTITLE("SUB-SERIES PLOT:ANTIDIABETIC DRUG SALES")+
    YLAB('$ MILLION')
```

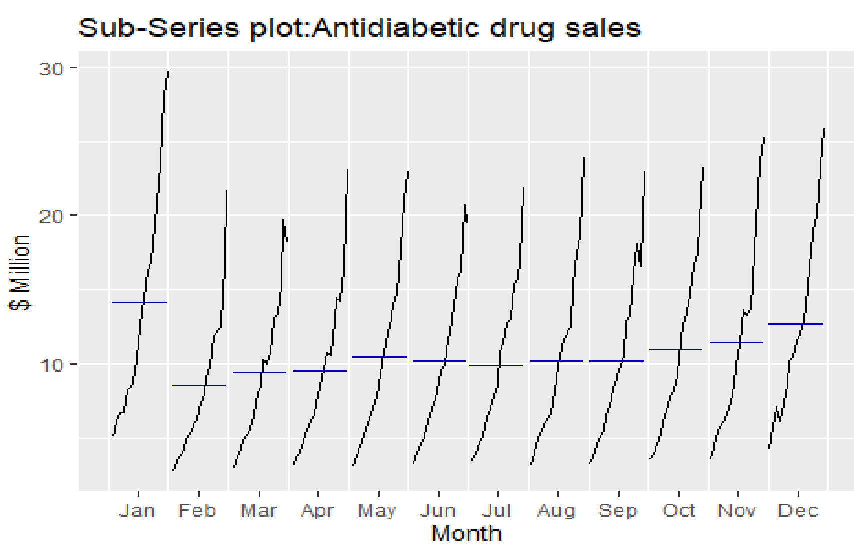


Fig-22: Sub-plot Of Antidiabetic drug sales.

Comment: The plot represents the average sells of drug of several month.

```
#Visualizing ausbeer data
```

```
Total quarterly beer production in Australia (in megalitres) from 1956:Q1 to 2010:Q2.
```

```
ausbeer
```

```
##      Qtr1 Qtr2 Qtr3 Qtr4
## 1956  284  213  227  308
## 1957  262  228  236  320
## 1958  272  233  237  313
## 1959  261  227  250  314
## 1960  286  227  260  311
## 1961  295  233  257  339
## 1962  279  250  270  346
## 1963  294  255  278  363
## 1964  313  273  300  370
## 1965  331  288  306  386
## 1966  335  288  308  402
## 1967  353  316  325  405
## 1968  393  319  327  442
## 1969  383  332  361  446
## 1970  387  357  374  466
## 1971  410  370  379  487
## 1972  419  378  393  506
## 1973  458  387  427  565
## 1974  465  445  450  556
## 1975  500  452  435  554
## 1976  510  433  453  548
## 1977  486  453  457  566
## 1978  515  464  431  588
## 1979  503  443  448  555
## 1980  513  427  473  526
## 1981  548  440  469  575
## 1982  493  433  480  576
## 1983  475  405  435  535
## 1984  453  430  417  552
## 1985  464  417  423  554
## 1986  459  428  429  534
## 1987  481  416  440  538
## 1988  474  440  447  598
## 1989  467  439  446  567
## 1990  485  441  429  599
## 1991  464  424  436  574
## 1992  443  410  420  532
## 1993  433  421  410  512
```

```
## 1994  449  381  423  531
## 1995  426  408  416  520
## 1996  409  398  398  507
## 1997  432  398  406  526
## 1998  428  397  403  517
## 1999  435  383  424  521
## 2000  421  402  414  500
## 2001  451  380  416  492
## 2002  428  408  406  506
## 2003  435  380  421  490
## 2004  435  390  412  454
## 2005  416  403  408  482
## 2006  438  386  405  491
## 2007  427  383  394  473
## 2008  420  390  410  488
## 2009  415  398  419  488
## 2010  414  374

BEER2=WINDOW(AUSBEER,START=1993,END=C(2006,4))
AUTOPLOT(BEER2)
```

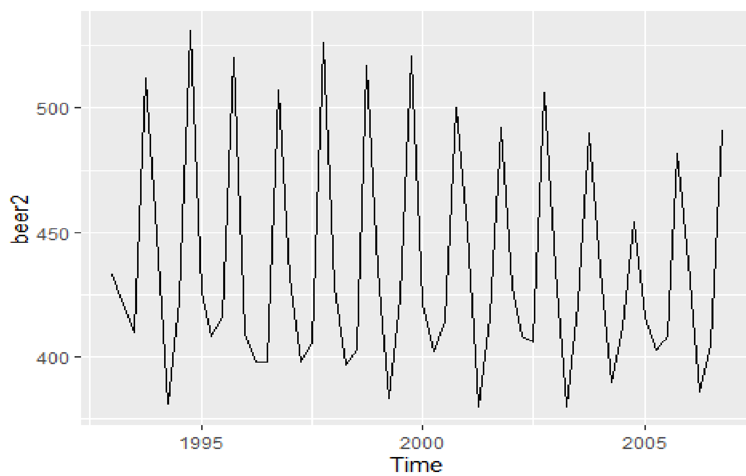


Fig-23: Potting Australia Beer Production.

Comment: Time series plot of Australia beer production.

```
#--SIMPLE FORECASTING METHODS
# AVERAGE
# NAIVE(WORK WITH MOST RECENT VALUES)
# SEASONAL NAIVE
# DRIFT
```

```
BEERFIT1=MEANF(BEER2,H=12)
BEERFIT2=RWF(BEER2,H=12)
BEERFIT3=SNAIVE(BEER2,H=12)

#WE PLOT FULL DATA SET
AUTOPLOT(WINDOW(AUSBEER,START=1993))+
    AUTOLAYER(BEERFIT1,SERIES="MEAN",PI=F)+
    AUTOLAYER(BEERFIT2,SERIES="NAIVE",PI=F)+
    AUTOLAYER(BEERFIT3,SERIES="SEASONAL NAIVE",PI=F)+
    XLAB("YEAR")+YLAB("MEGALITRES")+
    GGTITLE("FORECASTED QUATERLY BEER PRODUCTION ")+
    GUIDES(COLOUR=GUIDE_LEGEND(TITLE = "FORECAST"))
```

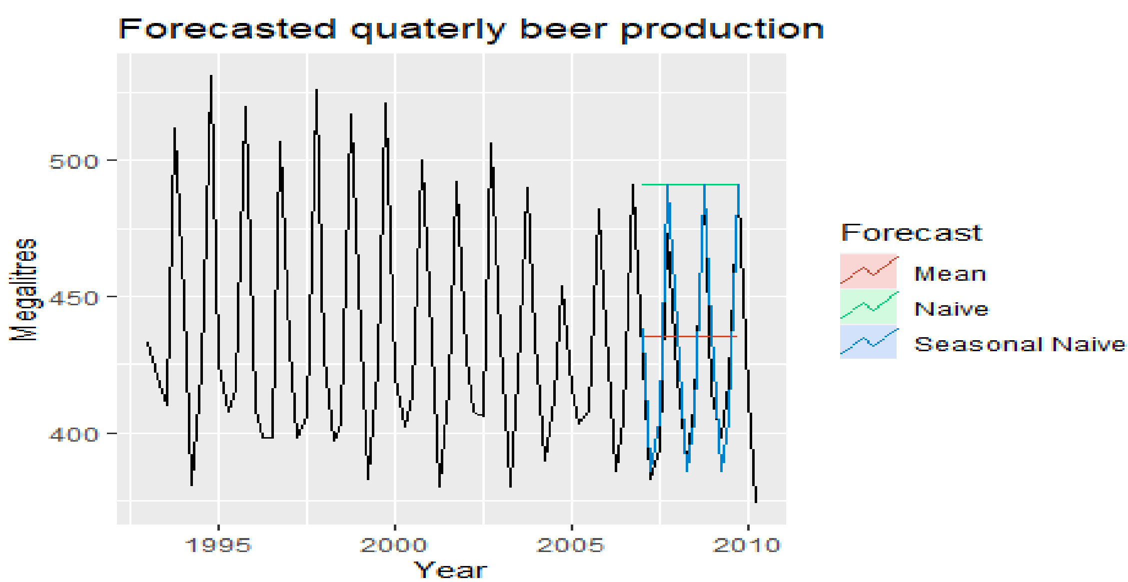


Fig-24: Forecasted Quarterly Beer Production.

Comment: The figure shows the forecasted value using three descriptive methods.

```
#ACCURACY
BEER3=WINDOW(AUSBEER,START=2008)
ACCURACY(BEERFIT1,BEER3)

##                         ME     RMSE      MAE       MPE     MAPE     MASE
## TRAINING SET -2.436072E-14 43.42591 35.19005 -0.928920 7.875648 2.395134
## TEST SET     -6.892857E+00 36.33196 33.19643 -2.269843 7.659919 2.259443
```

```
##                   ACF1 Theil's U
## Training set -0.11704504       NA
## Test set     -0.07153733 0.7810277
```

```
accuracy(beerfit2,beer3)
```

```
##                      ME     RMSE      MAE         MPE     MAPE     MASE
## Training set   1.054545 65.06416 54.47273  -0.7865823 12.10955 3.707568
## Test set     -62.500000 71.96353 62.50000 -15.3314577 15.33146 4.253927
##                   ACF1 Theil's U
## Training set -0.22916007       NA
## Test set     -0.07153733   1.45868
```

```
accuracy(beerfit3,beer3)
```

```
##                     ME     RMSE      MAE        MPE     MAPE     MASE
## Training set -1.076923 17.32162 14.69231 -0.3312997 3.415323 1.000000
## Test set     -1.500000 12.51000 10.25000 -0.3069842 2.457364 0.697644
##                  ACF1 Theil's U
## Training set -0.2880890       NA
## Test set     -0.1108185 0.2180679
```

```
#Another data
# Closing stock prices of GOOG from the NASDAQ exchange, for 1000 consecutive trading days
# between 25 February 2013 and 13 February 2017. Adjusted for splits. goog200 contains
the first
# 200 observations from goog
```

Google Stock (2013-2017)

```
## Time Series:
## Start = 1
## End = 200
## Frequency = 1
##   [1] 392.8300 392.5121 397.3059 398.0113 400.4902 408.0957 416.5905 413.003
8
##   [9] 413.6099 413.0734 414.7127 411.1310 409.9884 408.1156 404.5190 401.285
0
##  [17] 403.0386 404.7227 403.0088 402.5369 402.2040 403.5851 398.7366 394.529
0
##  [25] 398.0063 403.8931 400.4952 394.9661 388.9950 384.9214 386.3124 392.536
9
##  [33] 392.6412 392.4724 388.4386 394.1216 388.7516 380.4803 397.3506 397.469
8
##  [41] 401.3397 404.0967 401.9358 398.1206 406.8836 409.6208 407.5642 412.124
5
##  [49] 420.1275 427.9913 425.8453 433.9923 432.9243 437.2710 435.9297 440.683
```

```
8
##  [57] 454.9857 449.0146 451.6524 451.3295 450.5546 441.8363 438.5427 433.838
3
##  [65] 437.7876 431.3495 432.5666 432.7951 431.0117 426.7742 427.0723 429.526
3
##  [73] 437.0226 442.2337 437.0623 433.1726 435.6664 434.6927 440.2615 447.400
1
##  [81] 447.4299 439.5114 437.6187 432.0847 430.3013 434.0022 435.7012 437.340
5
##  [89] 441.0713 438.3043 440.3510 443.8581 449.6206 449.6952 450.0677 457.146
7
##  [97] 458.5178 459.3573 456.8337 456.3072 452.3976 445.4031 452.4075 448.979
8
## [105] 448.5327 440.9818 439.8144 438.2844 442.5814 441.0067 449.1885 450.355
9
## [113] 449.5759 445.3882 442.4473 443.4458 442.3281 439.8939 437.7777 432.094
6
## [121] 427.0524 425.6863 430.0281 429.9138 431.8562 434.0320 432.2933 430.395
7
## [129] 422.3282 421.5333 424.9511 420.7137 427.4101 432.9987 436.9381 436.948
1
## [137] 441.1557 441.4637 445.1994 443.6445 441.6624 441.0117 440.1920 448.741
4
## [145] 446.2923 448.6371 440.3857 440.5546 435.7807 436.2476 435.3634 435.124
9
## [153] 440.6341 441.1259 435.2144 433.3564 430.0728 424.0768 425.1647 431.314
7
## [161] 433.1776 435.2243 438.1552 446.1135 441.5233 502.4371 498.4083 500.246
4
## [169] 512.3725 509.4615 504.3199 504.2205 514.7719 511.8807 511.9602 510.201
6
## [177] 509.7396 507.4595 508.0705 500.7183 504.7322 502.0298 502.6209 512.899
1
## [185] 514.2701 513.4406 512.4421 509.2876 507.8519 513.6939 512.6110 519.585
6
## [193] 525.7853 528.1201 526.3715 523.8329 523.2269 525.6710 525.2537 531.478
3

AUTOPLOT(GOOG200)
```

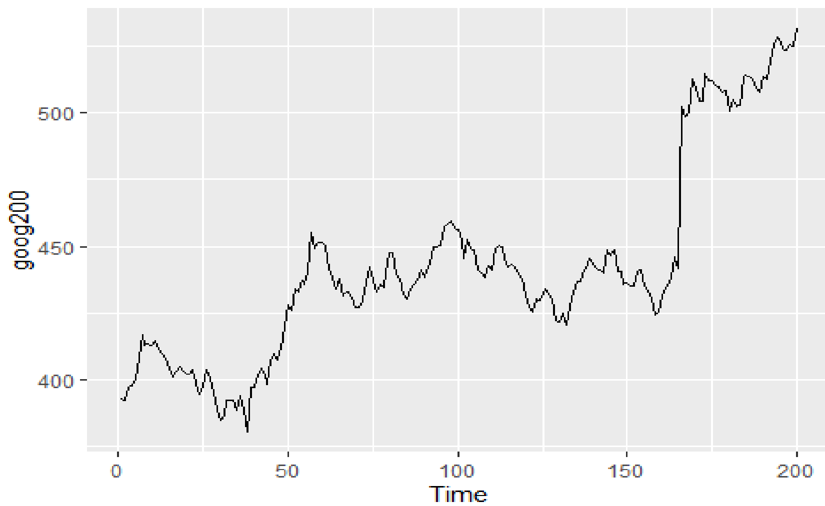


Fig-25: Auto Plot Google data.

Comment: This figure shows time series plot of **STOCK PRICES OF GOOG FROM THE NASDAQ EXCHANGE, FOR 1000 CONSECUTIVE TRADING DAY**

```
#FORECAST FOR NEXT 40


GOOGF1=MEANF(GOOG200,H=40)
GOOGF2=RWF(GOOG200,H=40)
GOOGF3=RWF(GOOG200,DRIFT=T,H=40)

AUTOPLOT(SUBSET(GOOG200,END = 240))+
  AUTOLAYER(GOOGF1,SERIES="MEAN",PI=F)+
  AUTOLAYER(GOOGF2,SERIES="NAIVE",PI=F)+
  AUTOLAYER(GOOGF3,SERIES="DRIFT",PI=F)+
  XLAB("DAY")+YLAB("CLOSING PRICE(US$")+
  GGTITLE("GOOGLE STOCK PRICE")+
  GUIDES(COLOUR=GUIDE_LEGEND(TITLE = "FORECAST"))
```

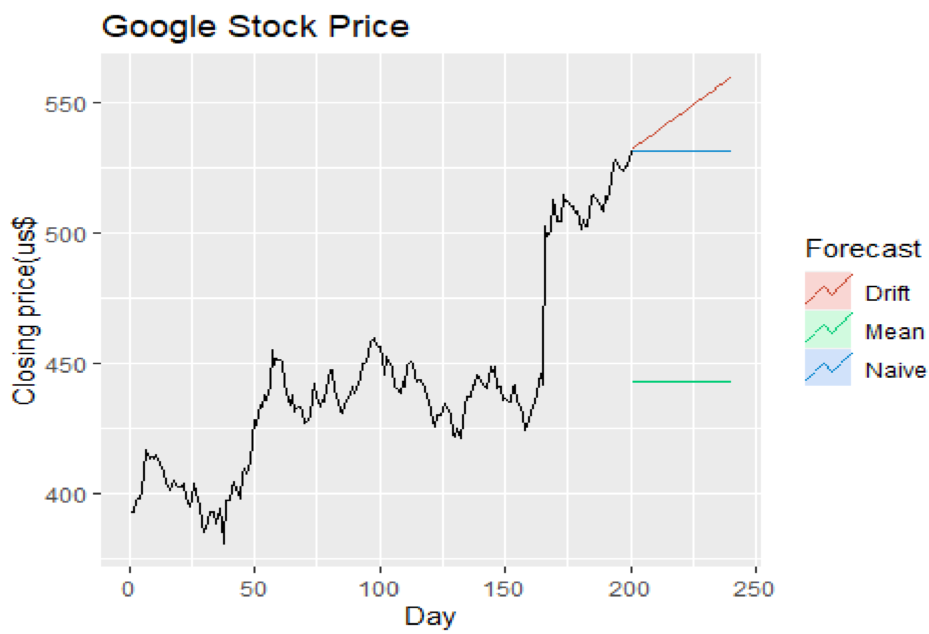


Fig-26: Forecast Google Stock Price.

Comment: Forecasted value of Mean, Naïve and Drift method. Here we see that Drift method provide best forecast.

```
AUTOPLOT(GOOGF3)
```

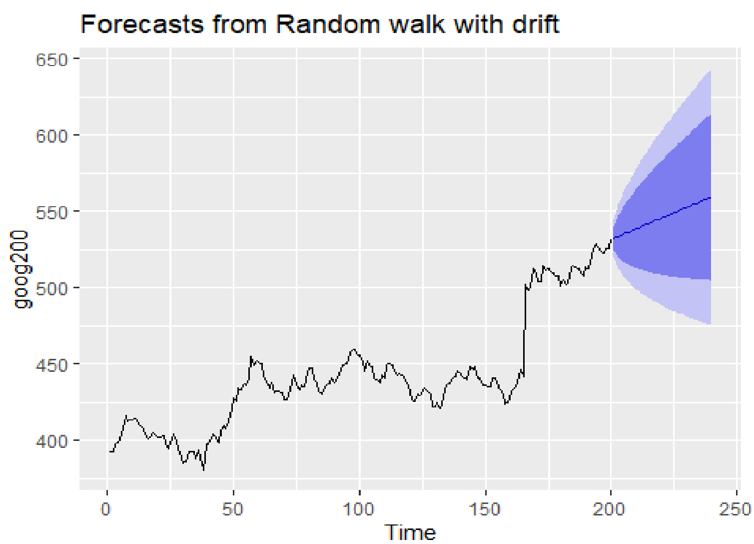


Fig-27: Forecast From Random Walk.

Comment: This is forecasted value for Drift method where deep blue region shows 80% CI and light blue shaded shows 95% CI.

Problem: -05

ANALYZING AND FORECASTING MONTHLY RAINFALL OF BANGLADESH.

```
DF=READ.CSV(FILE.CHOOSE(),HEADER = T,SEP = ",")
DF

HEAD(DF)

##   YEAR STATION MONTH RAINFALL STATIONINDEX
## 1 1970 BARISAL     1        0            2
## 2 1970 BARISAL     2       24            2
## 3 1970 BARISAL     3        5            2
## 4 1970 BARISAL     4       91            2
## 5 1970 BARISAL     5      124            2
## 6 1970 BARISAL     6      408            2

VIEW(DF)
#PACKAGES
LIBRARY(GGPLOT2)
LIBRARY(DPLYR)

LIBRARY(FORECAST)

#PREPARING DATA FOR ANALYSIS
DF1<-FILTER(DF,DF$YEAR>="2007")
DF1=FILTER(DF1,STATION=="RAJSHAHI")
VIEW(DF1)

DF2=SELECT(DF1,RAINFALL)
DF2

##     RAINFALL
## 1          0
## 2         27
## 3         59
## 4         13
## 5        260
## 6        313
## 7        364
## 8        236
```

```
## 9        309
## 10        76
## 11         1
## 12         0
## 13        26
## 14         0
## 15         0
## 16        30
## 17       144
## 18       247
## 19       373
## 20       245
## 21       129
## 22       121
## 23         0
## 24         0
## 25         1
## 26         7
## 27        28
## 28         0
## 29       131
## 30       126
## 31       183
## 32       240
## 33       282
## 34        45
## 35         0
## 36         0
## 37         0
## 38         2
## 39         2
## 40        37
## 41        75
## 42       211
## 43        94
## 44       101
## 45       101
## 46       127
## 47         3
## 48        39
## 49         6
## 50         0
## 51        10
## 52        94
## 53       187
## 54       341
```

```
## 55       144
## 56       454
## 57       203
## 58        35
## 59         1
## 60         0
## 61         6
## 62         0
## 63         6
## 64       123
## 65        17
## 66       137
## 67       314
## 68       179
## 69       178
## 70       102
## 71       101
## 72         1
## 73         0
## 74        22
## 75        12
## 76        51
## 77       188
## 78       178
## 79       101
## 80       254
## 81       238
## 82       204
## 83         0
## 84         0
## 85         0
## 86        27
## 87        12
## 88        51
## 89       151
## 90       188
## 91       242
## 92       359
## 93       153
## 94         5
## 95         0
## 96         0
## 97        14
## 98        14
## 99        39
## 100      144
```

```
## 101      177
## 102      285
## 103      353
## 104      127
## 105      254
## 106        7
## 107        6
## 108        1
## 109       42
## 110        3
## 111       25
## 112      175
## 113      212
## 114      109
## 115      376
## 116      168
## 117      170
## 118       95
## 119        0
## 120        0

#Convert the value in continuous formate

df2$Rainfall=as.numeric(df2$Rainfall)
#Convert into a time series data

RD=ts(df2$Rainfall,start = 2007,frequency = 12)
RD

##      Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
## 2007   0  27  59  13 260 313 364 236 309  76   1   0
## 2008  26   0   0  30 144 247 373 245 129 121   0   0
## 2009   1   7  28   0 131 126 183 240 282  45   0   0
## 2010   0   2   2  37  75 211  94 101 101 127   3  39
## 2011   6   0  10  94 187 341 144 454 203  35   1   0
## 2012   6   0   6 123  17 137 314 179 178 102 101   1
## 2013   0  22  12  51 188 178 101 254 238 204   0   0
## 2014   0  27  12  51 151 188 242 359 153   5   0   0
## 2015  14  14  39 144 177 285 353 127 254   7   6   1
## 2016  42   3  25 175 212 109 376 168 170  95   0   0

#Time series Plot
plot(RD,lwd=1.2,col="green",main="Rainfall in Rajshahi
     ")
```

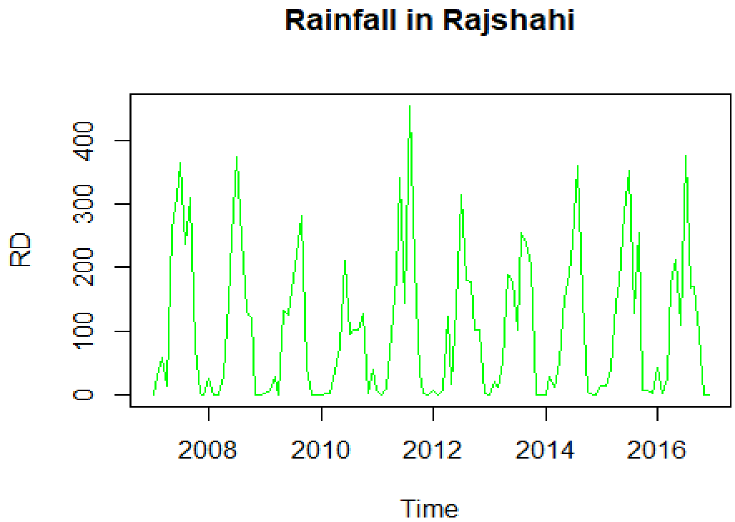


Fig-28: Plotting Rainfall Time Series Data.

Comment: Here mean and variance more or less constant, seasonal component exists.

```
#DECOMPOSE
RDR=DECOMPOSE(RD)
PLOT(RDR)
```

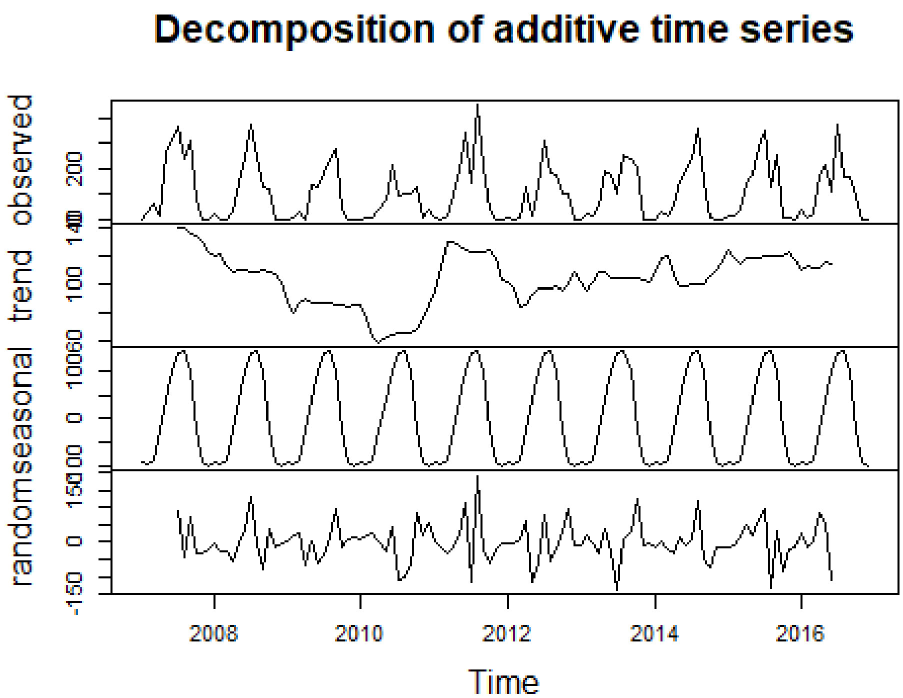


Fig-29: Decomposition of Rainfall Data.

Comment: The figure shows visualization of several time series components**.**

```
#FITTING AN ARIMA MODEL
FIT_MODEL=AUTO.ARIMA(RD)
FIT_MODEL

## SERIES: RD
## ARIMA(0,0,0)(2,1,0)[12]
##
## COEFFICIENTS:
##          SAR1     SAR2
##       -0.7061  -0.3468
## S.E.   0.0922   0.0936
##
## SIGMA^2 = 5435:  LOG LIKELIHOOD = -620.14
## AIC=1246.28   AICC=1246.51   BIC=1254.33

#FORECAST
PRED=FORECAST(FIT_MODEL,4*12)
AUTOPLOT(PRED,PI=T)+
  YLIM(0,550)
```

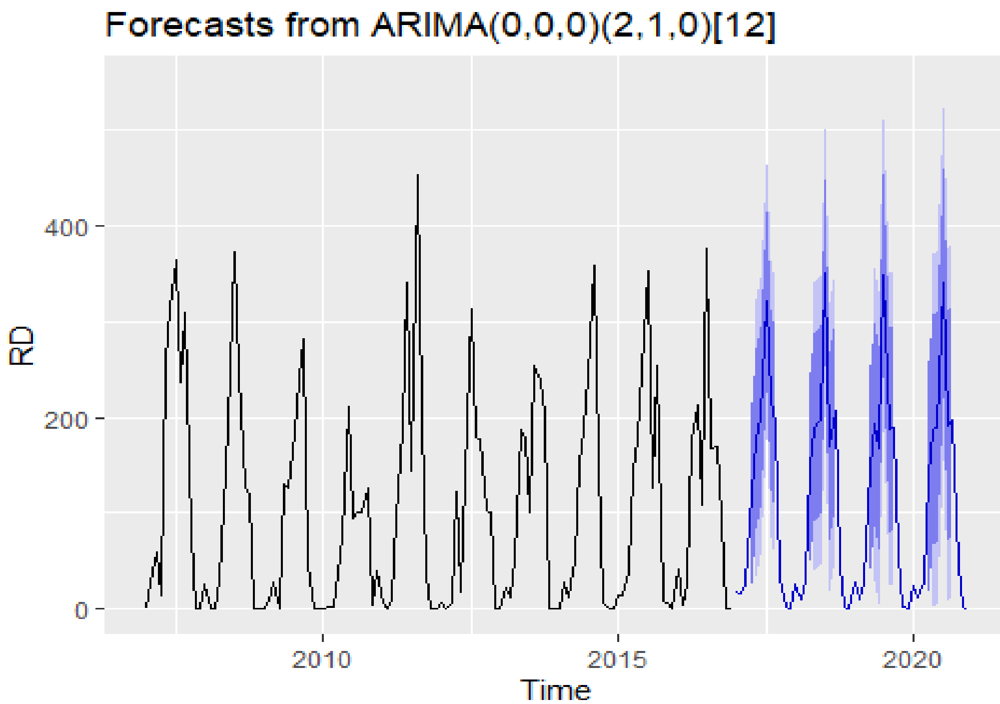


Fig-30: Forecast Next Four Year.

Comment: Here, deep blue region shows 80% CI and light blue shaded region shows 95% CI and now forecasted value with 80% and 95% CI show only positive value.