# W6_1.SARIMA

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Dataset Source https://robjhyndman.com

Seasonal ARIMA autocorrelation-recent lags-seasonal periodic lags Time Series observations-every s observations- -monthly observations(xt)-s=12-depend on annual lags(xt-12,xt-24) -quarterly data-s=4 -e.g.sales of refrigerators:Aug this yr vs.last year-relationship:2 mon-seasonality

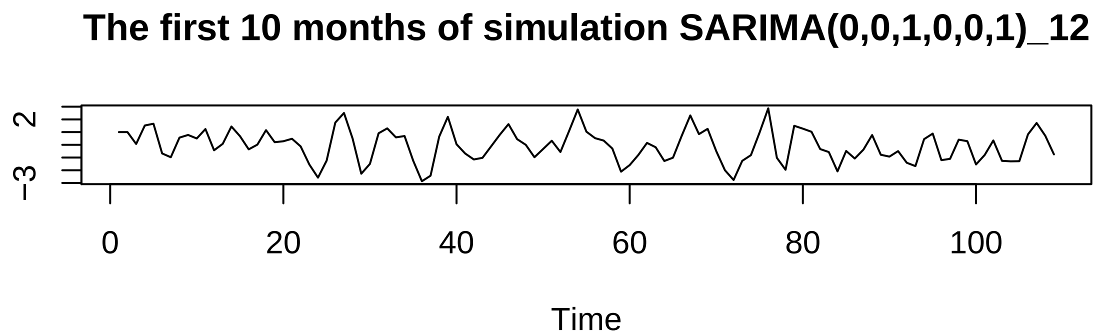
Stationarity, Invertibility-outside of unit circle

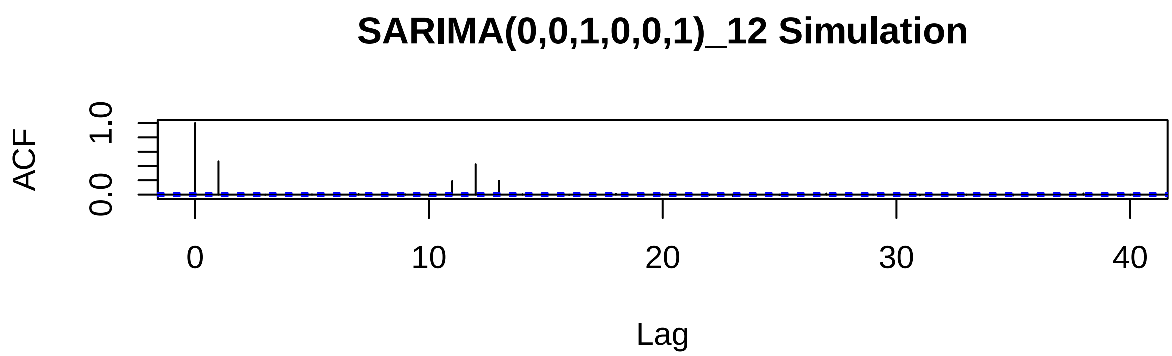
SARMA(P,Q)_S -SARMA(1,0)_12 -SARMA(1,1)_12

SARIMA(p,d,q,P,D,Q)_S -D=1 -D=2 -SARIMA(1,0,0,1,0,1)_12 -SARIMA(0,1,1,0,0,1)_4

SARIMA(0,0,1,0,0,1)_12 simulation xt=zt+0.7*zt-1+0.6*zt-12+0.42*zt-13

```
x=NULL
z=NULL
n=10000

z=rnorm(n)
x[1:13]=1

for (i in 14:n) {
  x[i]=z[i]+0.7*z[i-1]+0.6*z[i-12]+0.42*z[i-13]
}

par(mfrow=c(2,1))
plot.ts(x[12:120],
        main='The first 10 months of simulation SARIMA(0,0,1,0,0,1)_12',ylab='')
acf(x,main='SARIMA(0,0,1,0,0,1)_12 Simulation')
```




```
#lag1:spike-MA(q)
#lag11,12,13:spike-SMA(Q)
```

Modeling -Time plot-stationary:systematic change in trend,variance-outliers -Transformation-variation in variance-log-return-stablize variance -Differencing(seasonal,non-seasonal)-trend-remove trend

-Ljung-Box test-autocorrelation in prevous lags

-ACF -closer spikes-MA order:q -seansonal lags spikes-SMA order:Q -PACF -closer spikes-AR order:p -spikes around seasonal lags-SAR order P

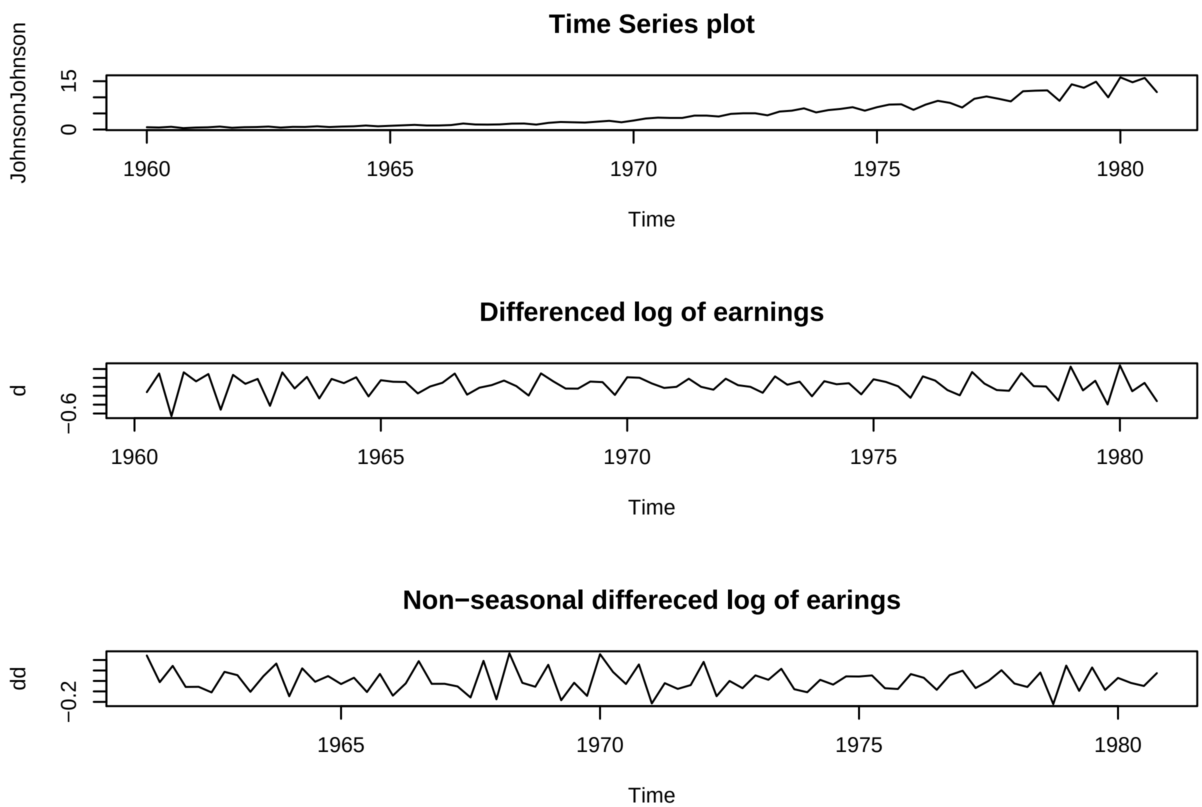
-Fit different models -AIC-compare,choose model with min AIC -The parsimony principle-fit data with simplest model-x overfit t.s. -SARIMA(p,d,q,P,D,Q)_s:p+d+q+P+D+Q<=6

-residual analysis -Time plot,ACF,PACF of residulas -Ljung-Box test for residuals

Johnson&Johnson dataset-fit SARIMA model

```
library(astsa)
data("JohnsonJohnson")

#Time plot
par(mfrow=c(3,1))
plot(JohnsonJohnson,main='Time Series plot')
#systematic trend-go up
#-variance increasing
#-quarterly data-see clclic behavior
```

```r
# tranformation-log-return
#-log-stablize variance
#-diff-remove trend
d=diff(log(JohnsonJohnson))
dd=diff(diff(log(JohnsonJohnson)),4)
plot(d,main='Differenced log of earnings')
#seasonal differencing
plot(dd,main='Non-seasonal differeced log of earings')
```




```r
#Ljung-Box test
Box.test(dd,lag = log(length(dd)))
```

```
##
##  Box-Pierce test
##
## data:  dd
## X-squared = 20.95, df = 4.3694, p-value = 0.0004658
```

```r
#p-value is small-reject null hypothesis:there is no autocorrelation between previous lags of

#ACF,PACF
par(mfrow=c(2,1))
acf(dd,main='ACF')
#lag1:spike-die off-MA(1)
```

```r
#lag4:almost significant-maybe exist autocorrelation-SMA(1)
pacf(dd,main='PACF')
#lag1:spike-die off-AR(1)
#lag4:spike-die off-SAR(1)-period 1

#fit different models
D=1
DD=1

per=4

for (p in 1:2) {
  for (q in 1:2) {
    for (i in 1:2) {
      for (j in 1:2) {
        if (p+D+q+i+DD+j <=10) {
          model=arima(x=log(JohnsonJohnson),
                      order = c((p-1),D,(q-1)),
                      seasonal = list(order=c((i-1),DD,(j-1)),period=per))
          pval=Box.test(model$residuals,lag = log(length(model$residuals)))
          sse=sum(model$residuals^2)
          cat(p-1,D,q-1,i-1,DD,j-1,per,
              'AIC=',model$aic,
              'SSE=',sse,
              'p-VALUE',pval$p.value,'\n')
        }

      }

    }

  }

}
```

```
## 0 1 0 0 1 0 4 AIC= -124.0685 SSE= 0.9377872 p-VALUE 0.0002610792
## 0 1 0 0 1 1 4 AIC= -126.3493 SSE= 0.8856995 p-VALUE 0.0001606501
## 0 1 0 1 1 0 4 AIC= -125.9198 SSE= 0.8908546 p-VALUE 0.0001978113
## 0 1 0 1 1 1 4 AIC= -124.3648 SSE= 0.8854555 p-VALUE 0.0001574029
## 0 1 1 0 1 0 4 AIC= -145.5139 SSE= 0.6891989 p-VALUE 0.03543717
## 0 1 1 0 1 1 4 AIC= -150.7528 SSE= 0.6265214 p-VALUE 0.6089542
## 0 1 1 1 1 0 4 AIC= -150.9134 SSE= 0.6251635 p-VALUE 0.7079173
## 0 1 1 1 1 1 4 AIC= -149.1317 SSE= 0.6232876 p-VALUE 0.6780876
## 1 1 0 0 1 0 4 AIC= -139.8248 SSE= 0.7467495 p-VALUE 0.03503386
## 1 1 0 0 1 1 4 AIC= -146.0191 SSE= 0.6692692 p-VALUE 0.5400176
## 1 1 0 1 1 0 4 AIC= -146.0319 SSE= 0.6689661 p-VALUE 0.5612965
## 1 1 0 1 1 1 4 AIC= -144.3766 SSE= 0.6658382 p-VALUE 0.5459446
## 1 1 1 0 1 0 4 AIC= -145.8284 SSE= 0.667109 p-VALUE 0.2200492
## 1 1 1 0 1 1 4 AIC= -148.7706 SSE= 0.6263678 p-VALUE 0.594822
## 1 1 1 1 1 0 4 AIC= -148.9175 SSE= 0.6251104 p-VALUE 0.7195471
## 1 1 1 1 1 1 4 AIC= -144.4483 SSE= 0.6097742 p-VALUE 0.3002703
```

```r
#best fit model
model=arima(x=log(JohnsonJohnson),
            order=c(0,1,1),
            seasonal=list(order=c(1,1,0),period=4))
model
```

```
##
## Call:
## arima(x = log(JohnsonJohnson), order = c(0, 1, 1), seasonal = list(order = c(1,
##     1, 0), period = 4))
##
## Coefficients:
##           ma1     sar1
##       -0.6796  -0.3220
## s.e.   0.0969   0.1124
##
## sigma^2 estimated as 0.007913:  log likelihood = 78.46,  aic = -150.91
```

```r
#time plot-not white noise
#ACF-no significant
#QQplot-normal
#pvalue-not small-no autocorrelation in residuals

#forecast
library(forecast)
```

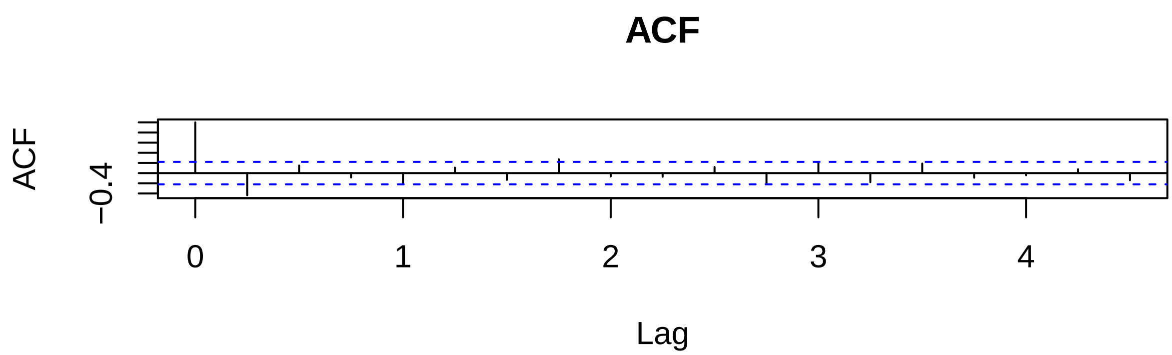
```
## Registered S3 method overwritten by 'xts':
##   method     from
##   as.zoo.xts zoo
```

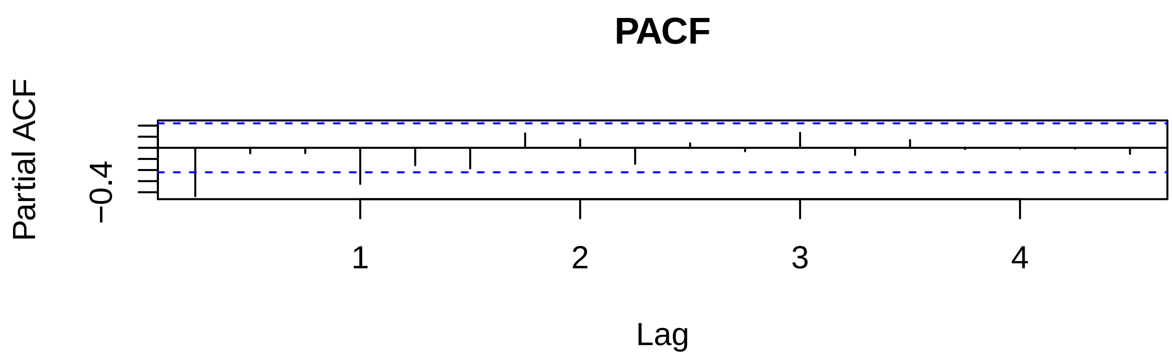
```
## Registered S3 method overwritten by 'quantmod':
##   method            from
##   as.zoo.data.frame zoo
```

```
## Registered S3 methods overwritten by 'forecast':
##   method             from
##   fitted.fracdiff    fracdiff
##   residuals.fracdiff fracdiff
```

```
##
## Attaching package: 'forecast'
```

```
## The following object is masked from 'package:astsa':
##
##     gas
```

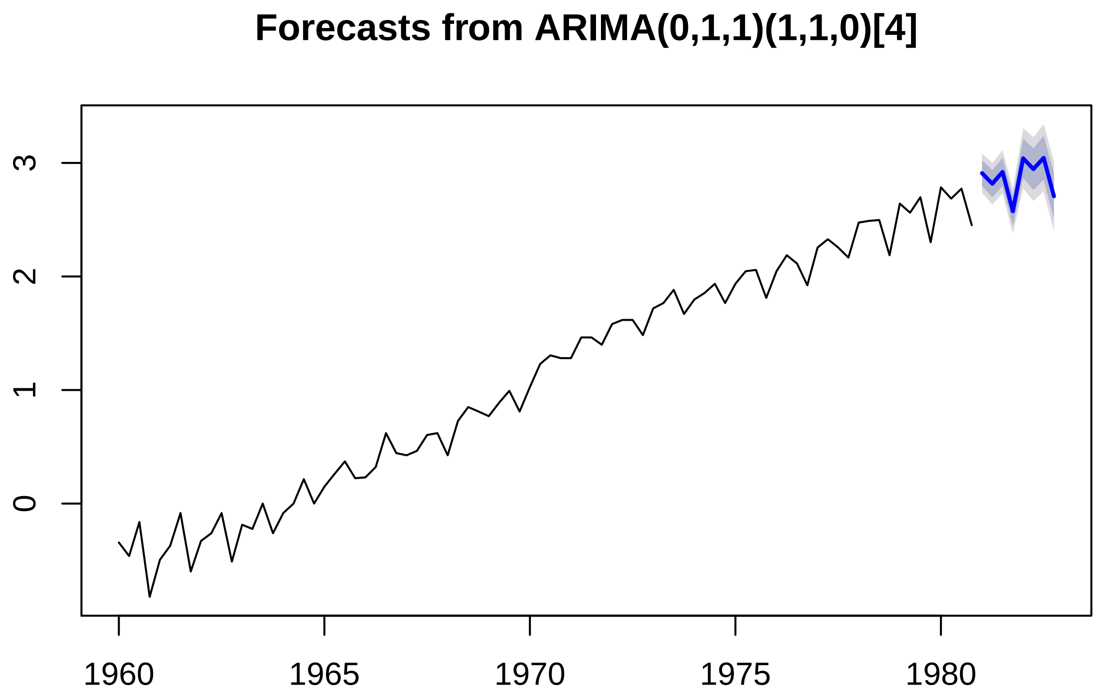



```
forecast(model)
```

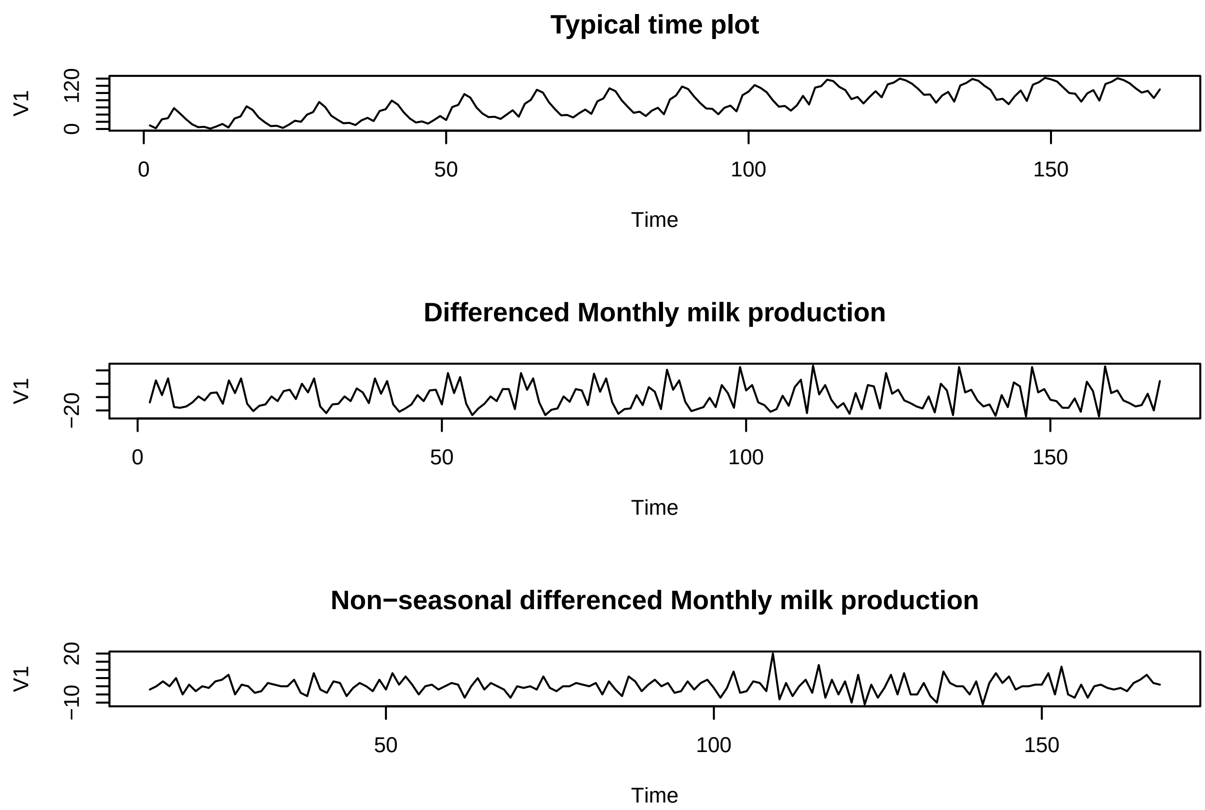
```
##         Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
## 1981 Q1       2.910254 2.796250 3.024258 2.735900 3.084608
## 1981 Q2       2.817218 2.697507 2.936929 2.634135 3.000300
## 1981 Q3       2.920738 2.795580 3.045896 2.729325 3.112151
## 1981 Q4       2.574797 2.444419 2.705175 2.375401 2.774194
## 1982 Q1       3.041247 2.868176 3.214317 2.776559 3.305934
## 1982 Q2       2.946224 2.762623 3.129824 2.665431 3.227016
## 1982 Q3       3.044757 2.851198 3.238316 2.748735 3.340780
## 1982 Q4       2.706534 2.503505 2.909564 2.396028 3.017041
```

```
par(mfrow=c(1,1))
plot(forecast(model))   #plot next 2 cycle-next 2 years
```




SARIMA fitting: Milk production-milk dataset

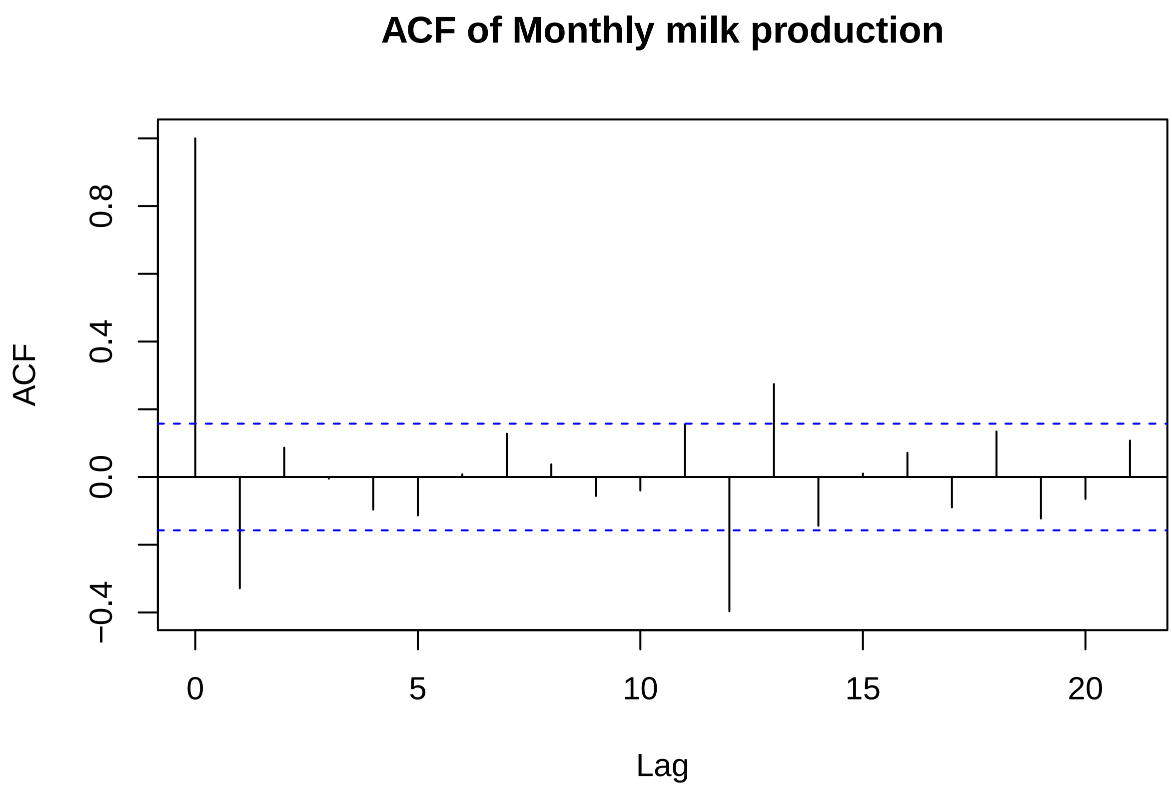
```
# load, preprocess dataset
#milk=read.csv('monthly-milk-production-pounds.csv')
#Milk=milk$Monthly.milk.production..pounds.per.cow.
#Milk
Milk=read.csv('milk.csv',header = FALSE)
Milk=ts(Milk)

par(mfrow=c(3,1))
#time series plot
plot.ts(Milk,main='Typical time plot')
#systematic trend-go up
#cyclic behavior-seasonality

#reduce trend
D=diff(Milk)
plot(D, main='Differenced Monthly milk production')
# reduce seasonality
DD=diff(diff(Milk),12)
plot(DD,main='Non-seasonal differenced Monthly milk production')
```



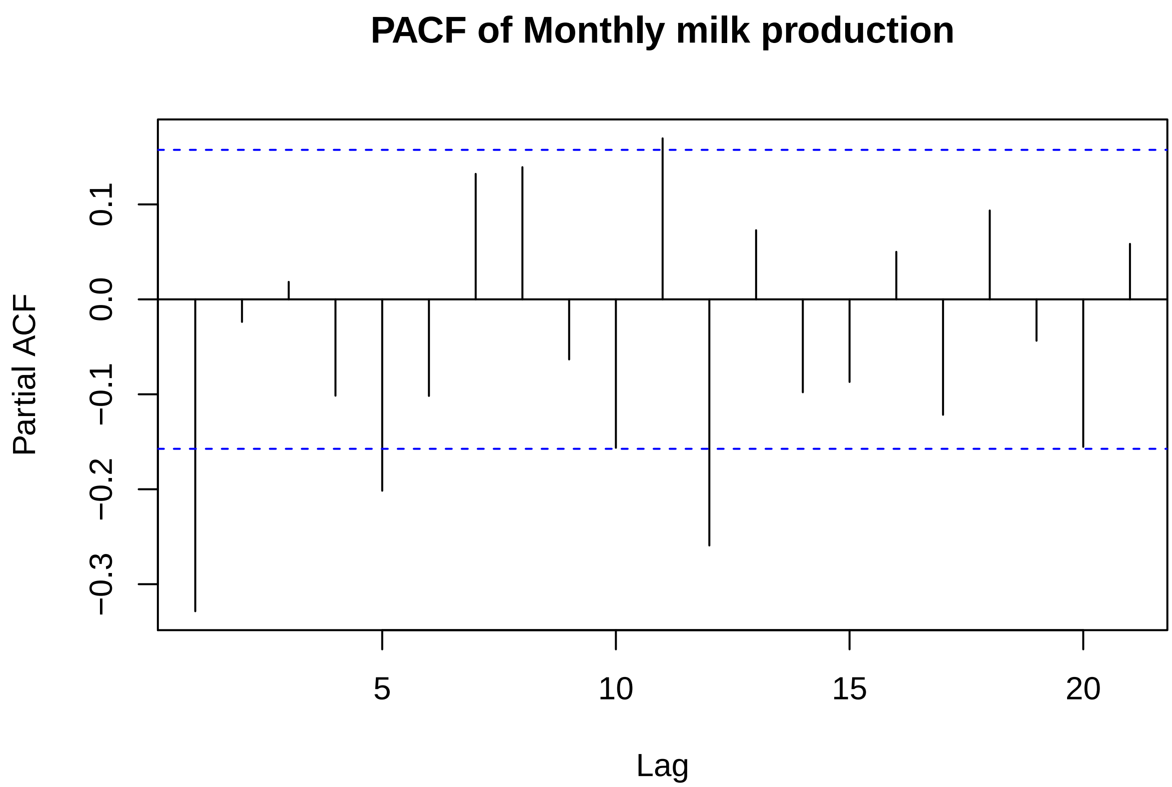

```r
# stationary-no change in trend, variance-spike:outlier

#Ljung-Box test-autocorrelation
Box.test(DD,lag = log(length(DD)))
```

```
##
##  Box-Pierce test
##
## data:  DD
## X-squared = 21.332, df = 5.0434, p-value = 0.0007282
```

```r
#p-value is small-significant evidence to reject null hypothesis:there is no autocorrelation in previou

#ACF, PACF
par(mfrow=c(1,1))
acf(DD,main='ACF of Monthly milk production')
```




```
#closer lags-lag1:spike-MA(q)-q=1
#seasonal lags-lag12,13 spike-SMA(1)-Q=3
pacf(DD,main='PACF of Monthly milk production')
```



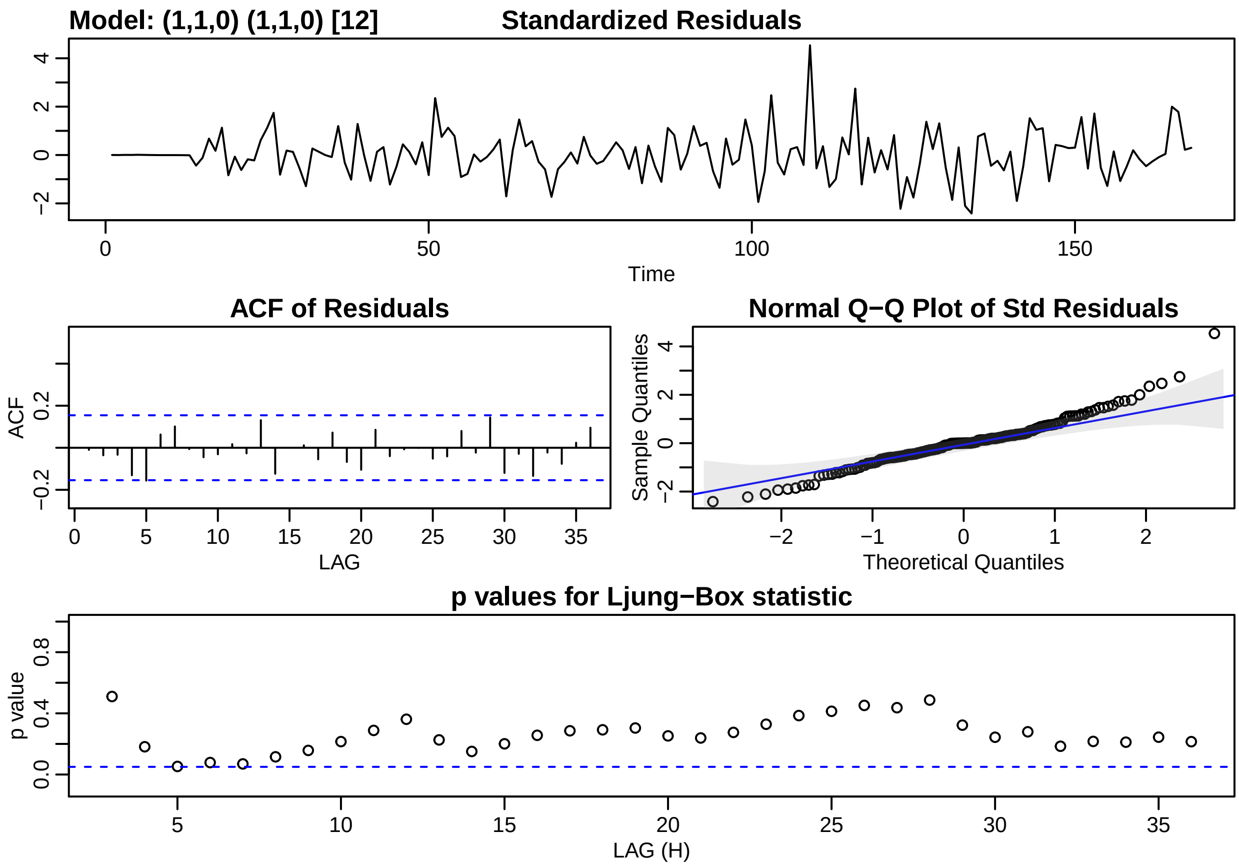

```
#closer lags-lag1 spike-AR(1)-p=1
#seasonal lags-lag12 spike-SAR(1)-P=3

# Fit different models
library(astsa)
D=NULL
DD=NULL
D=1
DD=1
per=12

for (p in 1:2) {
  for (q in 1:2) {
    for (i in 1:3) {
      for (j in 1:2) {
        if (p+D+q+i+DD+j <=10) {
          model=arima(x=Milk, order = c((p-1),D,(q-1)),
                      seasonal=list(order=c((i-1),DD,(j-1)),period=per))
          pval=Box.test(model$residuals,lag = log(length(model$residuals)))
          sse=sum(model$residuals^2)
          cat(p-1,D,q-1,i-1,DD,j-1,per,
              'AIC=',model$aic,
              'SSE=',sse,
              'p-VALUE=',pval$p.value,'\n')

        }
```

```
      }

    }

  }

}
```

```
## 0 1 0 0 1 0 12 AIC= 921.028 SSE= 3411.006 p-VALUE= 0.0003579636
## 0 1 0 0 1 1 12 AIC= 899.5974 SSE= 2902.751 p-VALUE= 0.007398404
## 0 1 0 1 1 0 12 AIC= 896.5571 SSE= 2838.231 p-VALUE= 0.01088766
## 0 1 0 1 1 1 12 AIC= 898.3282 SSE= 2833.236 p-VALUE= 0.01220623
## 0 1 0 2 1 0 12 AIC= 898.2606 SSE= 2831.632 p-VALUE= 0.01246434
## 0 1 0 2 1 1 12 AIC= 900.1889 SSE= 2830.002 p-VALUE= 0.01204409
## 0 1 1 0 1 0 12 AIC= 906.1305 SSE= 3056.502 p-VALUE= 0.1041483
## 0 1 1 0 1 1 12 AIC= 889.6231 SSE= 2689.746 p-VALUE= 0.1954772
## 0 1 1 1 1 0 12 AIC= 887.8059 SSE= 2653.274 p-VALUE= 0.2202284
## 0 1 1 1 1 1 12 AIC= 889.5939 SSE= 2649.069 p-VALUE= 0.2244213
## 0 1 1 2 1 0 12 AIC= 889.505 SSE= 2647.172 p-VALUE= 0.2264251
## 0 1 1 2 1 1 12 AIC= 891.3377 SSE= 2643.603 p-VALUE= 0.2239339
## 1 1 0 0 1 0 12 AIC= 905.4318 SSE= 3042.73 p-VALUE= 0.09257175
## 1 1 0 0 1 1 12 AIC= 890.0441 SSE= 2698.691 p-VALUE= 0.1709162
## 1 1 0 1 1 0 12 AIC= 888.0455 SSE= 2658.504 p-VALUE= 0.203094
## 1 1 0 1 1 1 12 AIC= 889.9198 SSE= 2655.975 p-VALUE= 0.2039101
## 1 1 0 2 1 0 12 AIC= 889.8645 SSE= 2654.777 p-VALUE= 0.2044877
## 1 1 0 2 1 1 12 AIC= 891.7064 SSE= 2651.399 p-VALUE= 0.202264
## 1 1 1 0 1 0 12 AIC= 907.349 SSE= 3041.084 p-VALUE= 0.09337794
## 1 1 1 0 1 1 12 AIC= 891.1486 SSE= 2676.61 p-VALUE= 0.3495219
## 1 1 1 1 1 0 12 AIC= 889.8061 SSE= 2653.402 p-VALUE= 0.2193471

## Warning in log(s2): NaNs produced

## 1 1 1 1 1 1 12 AIC= 891.5906 SSE= 2648.441 p-VALUE= 0.2266909
## 1 1 1 2 1 0 12 AIC= 891.4885 SSE= 2650.522 p-VALUE= 0.2088304
```

```
sarima(Milk,1,1,0,1,1,0,12)
```

```
## initial  value 1.567288
## iter   2 value 1.444154
## iter   3 value 1.438898
## iter   4 value 1.438855
## iter   5 value 1.438855
## iter   5 value 1.438855
## iter   5 value 1.438855
## final  value 1.438855
## converged
## initial  value 1.426483
## iter   2 value 1.426370
## iter   3 value 1.426370
## iter   3 value 1.426370
## iter   3 value 1.426370
## final  value 1.426370
## converged
```



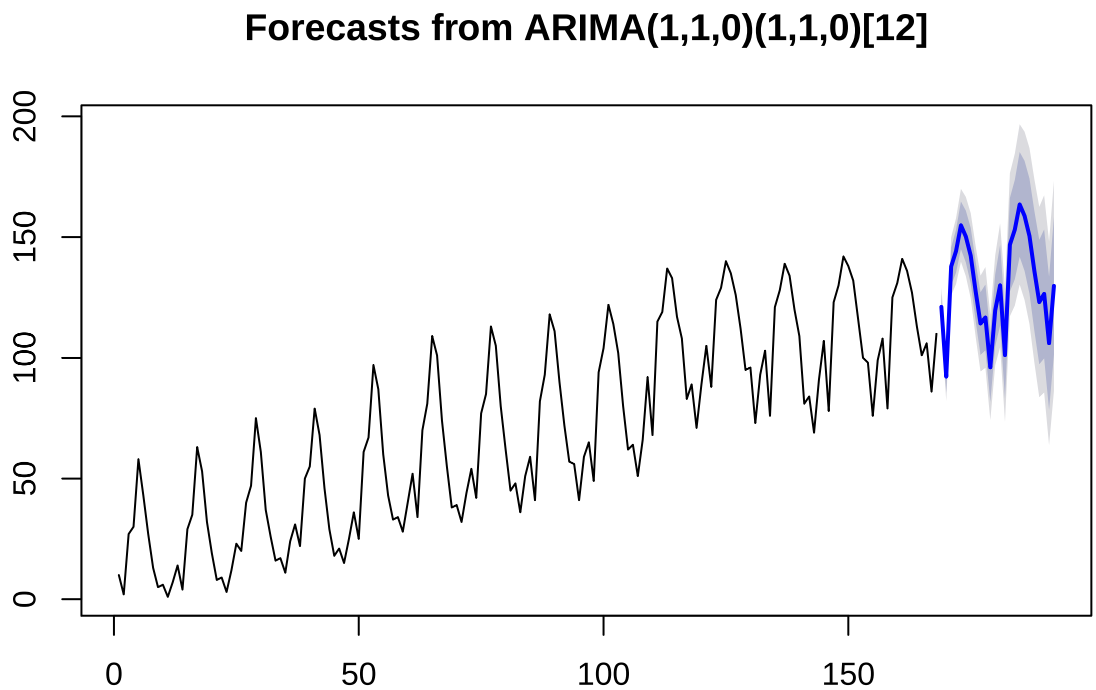

```
## $fit
##
## Call:
## stats::arima(x = xdata, order = c(p, d, q), seasonal = list(order = c(P, D,
##     Q), period = S), include.mean = !no.constant, transform.pars = trans, fixed = fixed,
##     optim.control = list(trace = trc, REPORT = 1, reltol = tol))
##
## Coefficients:
##           ar1     sar1
##       -0.2593  -0.3513
## s.e.   0.0786   0.0760
##
## sigma^2 estimated as 17.15:  log likelihood = -441.02,  aic = 888.05
##
## $degrees_of_freedom
## [1] 153
##
## $ttable
##      Estimate     SE t.value p.value
## ar1   -0.2593 0.0786 -3.2999  0.0012
## sar1  -0.3513 0.0760 -4.6240  0.0000
##
## $AIC
## [1] 5.349672
##
## $AICc
```

```
## [1] 5.350115
##
## $BIC
## [1] 5.404674
```

```r
#residual analysis
model=arima(x=Milk,order = c(1,1,0),seasonal=list(order=c(1,1,0),period=12))
forecast(model)
```

```
##     Point Forecast     Lo 80     Hi 80     Lo 95    Hi 95
## 169      121.10885 115.80137 126.41633 112.99176 129.2259
## 170       92.19972  85.59491  98.80452  82.09854 102.3009
## 171      137.82483 129.95013 145.69953 125.78151 149.8682
## 172      144.18227 135.25963 153.10490 130.53628 157.8283
## 173      154.88333 145.01329 164.75337 139.78841 169.9783
## 174      150.23506 139.50336 160.96677 133.82234 166.6478
## 175      142.28893 130.75919 153.81867 124.65571 159.9221
## 176      127.58631 115.31044 139.86217 108.81199 146.3606
## 177      114.18101 101.20180 127.16021  94.33103 134.0310
## 178      116.72174 103.07541 130.36807  95.85148 137.5920
## 179       96.01909  81.73676 110.30142  74.17615 117.8620
## 180      119.66777 104.77657 134.55896  96.89365 142.4419
## 181      130.03573 113.29107 146.78038 104.42698 155.6445
## 182      101.09467  83.03522 119.15412  73.47512 128.7142
## 183      146.85149 127.48425 166.21873 117.23186 176.4711
## 184      153.08335 132.51154 173.65516 121.62148 184.5452
## 185      163.53811 141.82348 185.25274 130.32845 196.7478
## 186      158.76627 135.96726 181.56529 123.89820 193.6344
## 187      150.44989 126.61548 174.28430 113.99831 186.9015
## 188      135.99412 111.16753 160.82071  98.02513 173.9631
## 189      123.08253  97.30190 148.86316  83.65446 162.5106
## 190      126.48727  99.78666 153.18787  85.65222 167.3223
## 191      106.03147  78.44156 133.62139  63.83634 148.2266
## 192      129.80358 101.35213 158.25502  86.29085 173.3163
```

```r
plot(forecast(model))
```



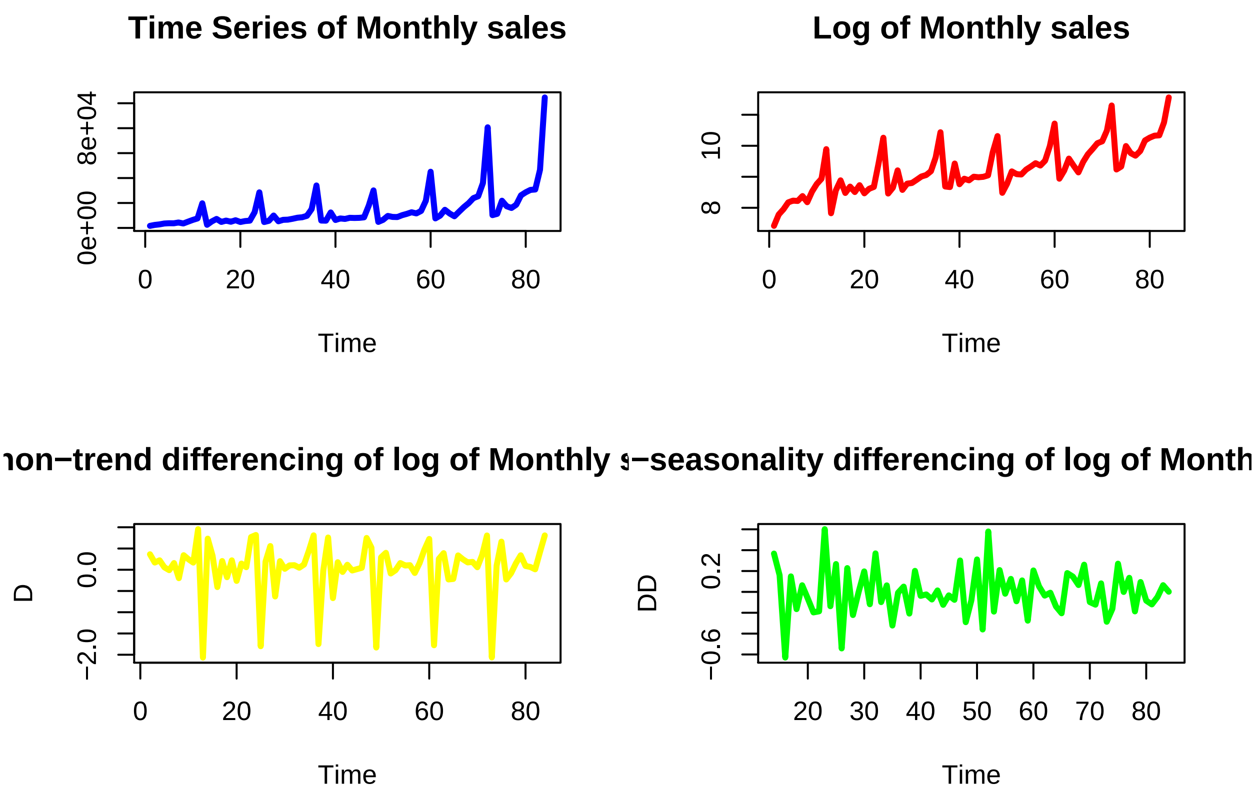

SARIMA fitting Sales at a souvenir shop-fancy datatset

```r
SUV=scan('https://robjhyndman.com/tsdldata/data/fancy.dat')
suv=ts(SUV)
suv
```

```
## Time Series:
## Start = 1
## End = 84
## Frequency = 1
##  [1]   1664.81   2397.53   2840.71   3547.29   3752.96   3714.74   4349.61
##  [8]   3566.34   5021.82   6423.48   7600.60  19756.21   2499.81   5198.24
## [15]   7225.14   4806.03   5900.88   4951.34   6179.12   4752.15   5496.43
## [22]   5835.10  12600.08  28541.72   4717.02   5702.63   9957.58   5304.78
## [29]   6492.43   6630.80   7349.62   8176.62   8573.17   9690.50  15151.84
## [36]  34061.01   5921.10   5814.58  12421.25   6369.77   7609.12   7224.75
## [43]   8121.22   7979.25   8093.06   8476.70  17914.66  30114.41   4826.64
## [50]   6470.23   9638.77   8821.17   8722.37  10209.48  11276.55  12552.22
## [57]  11637.39  13606.89  21822.11  45060.69   7615.03   9849.69  14558.40
## [64]  11587.33   9332.56  13082.09  16732.78  19888.61  23933.38  25391.35
## [71]  36024.80  80721.71  10243.24  11266.88  21826.84  17357.33  15997.79
## [78]  18601.53  26155.15  28586.52  30505.41  30821.33  46634.38 104660.67
```

```r
#load-preprocess dataset
#SUV=read.csv('monthly-sales-for-a-souvenir-sho.csv')
#suv=ts(SUV$Monthly.sales.for.a.souvenir.shop.on.the.wharf.at.a.beach.resort.town.in.Queensland..Austra
```

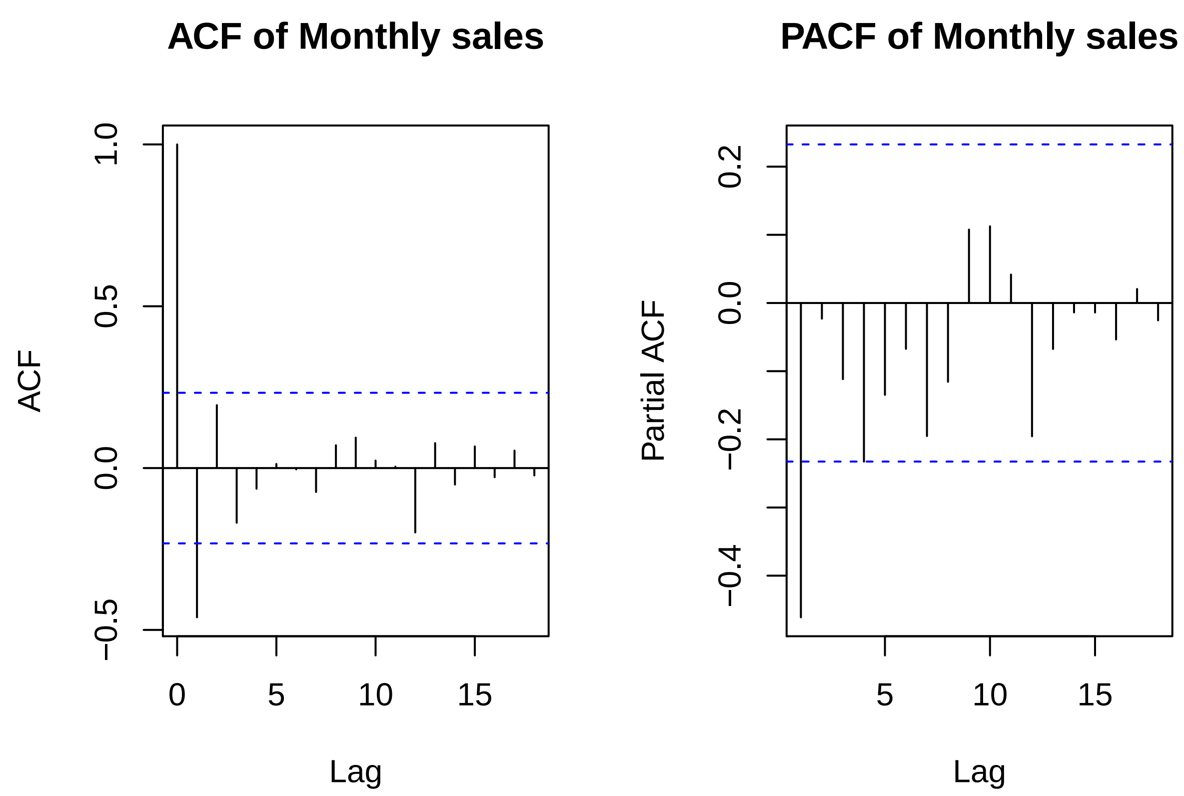
```r
#suv

#time series plot
par(mfrow=c(2,2))
plot(suv,main='Time Series of Monthly sales',ylab=' ',col='blue',lwd=3)
#stablize variance
L=log(suv)
plot(L,main='Log of Monthly sales',ylab=' ',col='red',lwd=3)
#reduce trend
D=diff(L)
plot(D,main='non-trend differencing of log of Monthly sales', col='yellow',lwd=3)
#reduce seasonality
DD=diff(D,12)
plot(DD,main='non-seasonality differencing of log of Monthly sales', col='green',lwd=3)
```




```r
Box.test(DD,lag = log(length(DD)))
```

```
##
##  Box-Pierce test
##
## data:  DD
## X-squared = 20.097, df = 4.2627, p-value = 0.0006166
```

```
par(mfrow=c(1,2))
acf(DD,main='ACF of Monthly sales')
#lag=1-q=1
#lag=10,12-Q=1
pacf(DD, main='PACF of Monthly sales')
```




```
#lag=1-p=1
#lag=12-P=1

#fit differenct models
D=1
DD=1
per=12

for (p in 1:5) {
  for (q in 1:4) {
    for (i in 1:2) {
      for (j in 1:2) {
        if (p+D+q+i+DD+j<=10) {
          model=arima(x=log(suv),
                      order = c((p-1),D,(q-1)),
                      seasonal = list(order=c((i-1),DD,(j-1)),period=per))
          pval=Box.test(model$residuals,lag=log(length(model$residuals)))
          sse=sum(model$residuals^2)
          cat(p-1,D,q-1,i-1,DD,q-1,per,
```

```r
              'AIC=',model$aic,
              'SSE=',sse,
              'p-VALUE=',pval$p.value,'\n')

        }

      }

    }

  }

}
```

```
## 0 1 0 0 1 0 12 AIC= -11.60664 SSE= 3.432906 p-VALUE= 0.0001365568
## 0 1 0 0 1 0 12 AIC= -16.09179 SSE= 2.977559 p-VALUE= 3.149961e-05
## 0 1 0 1 1 0 12 AIC= -13.43083 SSE= 3.214065 p-VALUE= 4.083829e-05
## 0 1 0 1 1 0 12 AIC= -17.76362 SSE= 2.399748 p-VALUE= 0.0001916571
## 0 1 1 0 1 1 12 AIC= -27.78538 SSE= 2.643277 p-VALUE= 0.1742485
## 0 1 1 0 1 1 12 AIC= -34.54538 SSE= 2.233424 p-VALUE= 0.2730773
## 0 1 1 1 1 1 12 AIC= -32.33191 SSE= 2.360508 p-VALUE= 0.2584528
## 0 1 1 1 1 1 12 AIC= -34.0881 SSE= 1.842013 p-VALUE= 0.2843227
## 0 1 2 0 1 2 12 AIC= -25.86905 SSE= 2.638868 p-VALUE= 0.1984322
## 0 1 2 0 1 2 12 AIC= -32.60285 SSE= 2.231016 p-VALUE= 0.2827513
## 0 1 2 1 1 2 12 AIC= -30.40452 SSE= 2.356141 p-VALUE= 0.2583268
## 0 1 2 1 1 2 12 AIC= -32.20925 SSE= 1.839125 p-VALUE= 0.2898996
## 0 1 3 0 1 3 12 AIC= -30.74478 SSE= 2.377591 p-VALUE= 0.9791776
## 0 1 3 0 1 3 12 AIC= -37.55951 SSE= 1.993621 p-VALUE= 0.9413639
## 0 1 3 1 1 3 12 AIC= -34.77145 SSE= 2.140723 p-VALUE= 0.9563346
## 1 1 0 0 1 0 12 AIC= -27.07825 SSE= 2.6747 p-VALUE= 0.2297854
## 1 1 0 0 1 0 12 AIC= -34.98918 SSE= 2.209442 p-VALUE= 0.4633807
## 1 1 0 1 1 0 12 AIC= -32.64858 SSE= 2.340077 p-VALUE= 0.4022225
## 1 1 0 1 1 0 12 AIC= -33.48894 SSE= 2.125764 p-VALUE= 0.4442667
## 1 1 1 0 1 1 12 AIC= -26.17089 SSE= 2.624282 p-VALUE= 0.2507444
## 1 1 1 0 1 1 12 AIC= -33.30647 SSE= 2.201798 p-VALUE= 0.4110141
## 1 1 1 1 1 1 12 AIC= -31.10127 SSE= 2.323818 p-VALUE= 0.3492748
## 1 1 1 1 1 1 12 AIC= -32.69913 SSE= 1.823507 p-VALUE= 0.3092289
## 1 1 2 0 1 2 12 AIC= -24.2842 SSE= 2.626063 p-VALUE= 0.176575
## 1 1 2 0 1 2 12 AIC= -31.62158 SSE= 2.196289 p-VALUE= 0.3746215
## 1 1 2 1 1 2 12 AIC= -29.45743 SSE= 2.316214 p-VALUE= 0.3276389
## 1 1 3 0 1 3 12 AIC= -28.92233 SSE= 2.369393 p-VALUE= 0.9865122
## 2 1 0 0 1 0 12 AIC= -25.22251 SSE= 2.669048 p-VALUE= 0.1902755
## 2 1 0 0 1 0 12 AIC= -33.23683 SSE= 2.202801 p-VALUE= 0.4316609
## 2 1 0 1 1 0 12 AIC= -31.00943 SSE= 2.325851 p-VALUE= 0.3705584
## 2 1 0 1 1 0 12 AIC= -31.69207 SSE= 2.122952 p-VALUE= 0.4063853
## 2 1 1 0 1 1 12 AIC= -24.62028 SSE= 2.567613 p-VALUE= 0.2073684
## 2 1 1 0 1 1 12 AIC= -31.47211 SSE= 2.191357 p-VALUE= 0.4652086
## 2 1 1 1 1 1 12 AIC= -29.2209 SSE= 2.315034 p-VALUE= 0.4155682
## 2 1 2 0 1 2 12 AIC= -27.22133 SSE= 2.3698 p-VALUE= 0.8687555
## 3 1 0 0 1 0 12 AIC= -23.70688 SSE= 2.650316 p-VALUE= 0.2141522
## 3 1 0 0 1 0 12 AIC= -31.28024 SSE= 2.203071 p-VALUE= 0.4193469
## 3 1 0 1 1 0 12 AIC= -29.03325 SSE= 2.326852 p-VALUE= 0.3620668
## 3 1 1 0 1 1 12 AIC= -27.05935 SSE= 2.440423 p-VALUE= 0.936714
```

```
## 4 1 0 0 1 0 12 AIC= -26.03727 SSE= 2.48338 p-VALUE= 0.96216
```