Final Project

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Change working directory

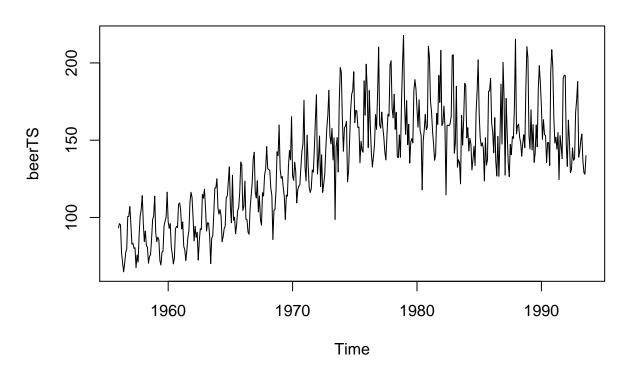
Load data (assumes file is in working directory)

```
#load the data
beerData<-read.csv("monthly-beer-production-in-austr.csv")
#cut off the last row which is NA
beerData<-beerData[-nrow(beerData),]</pre>
colnames(beerData)<-c("Month", "Production")</pre>
#Get a five number summary of the data
summary(beerData$Production)
      Min. 1st Qu. Median Mean 3rd Qu.
                                              Max.
##
      64.8 112.9 139.2 136.4 158.8 217.8
##
#turn into time series also hold back the last two years of data for forecasting
beerTS<-ts(beerData[1:(nrow(beerData)-24),2], frequency=12, start=c(1956,1))
beer_forecast<-ts(beerData[(nrow(beerData)-23):nrow(beerData), 2], start=c(1993,9), frequency=12)
adf.test(beerTS)
## Warning in adf.test(beerTS): p-value smaller than printed p-value
##
   Augmented Dickey-Fuller Test
##
##
## data: beerTS
## Dickey-Fuller = -4.206, Lag order = 7, p-value = 0.01
## alternative hypothesis: stationary
pp.test(beerTS)
## Warning in pp.test(beerTS): p-value smaller than printed p-value
##
##
   Phillips-Perron Unit Root Test
##
## data: beerTS
## Dickey-Fuller Z(alpha) = -167.6, Truncation lag parameter = 5,
## p-value = 0.01
## alternative hypothesis: stationary
```

Plot population data

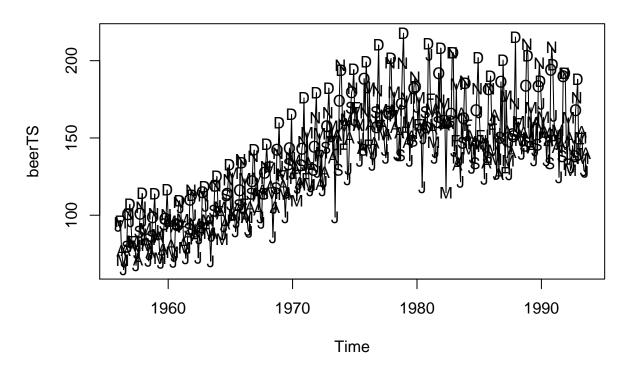
```
library(TSA)
par(mfrow=c(1,1))
plot(beerTS, main="Beer Production in Australia by Month")
```

Beer Production in Australia by Month



plot(beerTS, main="Beer Production in Australia by Month (seasons marked)", type="1")
points(y=beerTS, x=time(beerTS), pch=as.vector(season(beerTS)))

Beer Production in Australia by Month (seasons marked)



require(fpp)

```
## Loading required package: fpp
## Loading required package: forecast
## Loading required package: zoo
##
## Attaching package: 'zoo'
## The following objects are masked from 'package:base':
##
       as.Date, as.Date.numeric
##
## Loading required package: timeDate
##
## Attaching package: 'timeDate'
## The following objects are masked from 'package:TSA':
##
       kurtosis, skewness
## This is forecast 7.0
## Attaching package: 'forecast'
```

```
## The following objects are masked from 'package:TSA':
##
## fitted.Arima, plot.Arima

## The following object is masked from 'package:nlme':
##
## getResponse

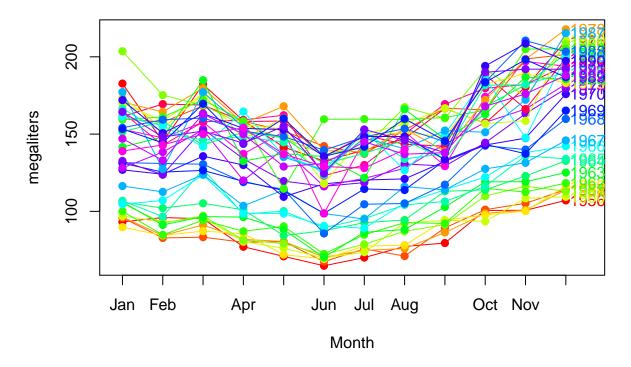
## Loading required package: fma

## Loading required package: expsmooth

## Loading required package: lmtest
```

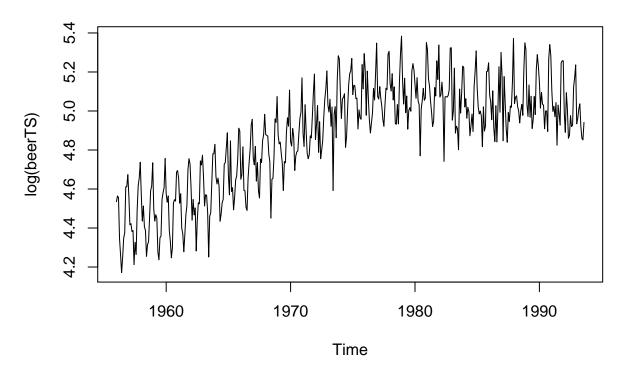
seasonplot(beerTS, year.labels=TRUE, ylab="megaliters", main="Seasonal plot: quarterly beer production", col=rain

Seasonal plot: quarterly beer production



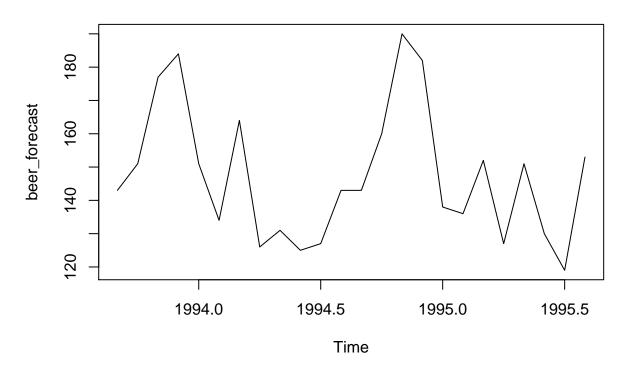
plot(log(beerTS), main="Logged Beer Production in Australia by Month")

Logged Beer Production in Australia by Month



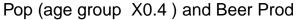
plot(beer_forecast, main="Beer production values to be forecasted")

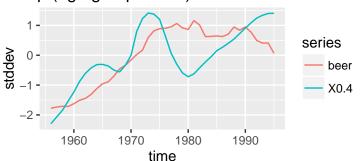
Beer production values to be forecasted



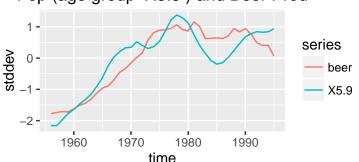
Investigate possible relationship with population data

```
#load population data
library(reshape)
## Warning: package 'reshape' was built under R version 3.2.5
library(ggplot2)
## Warning: package 'ggplot2' was built under R version 3.2.5
#Clean up population data
pop_totalData<-t(read.csv("Pop_total.csv", row.names=1))</pre>
dropCols<-colnames(pop_totalData) %in% c("Unspecified", "Period not indicated")</pre>
rownames(pop_totalData)<-c(1921:2011)</pre>
pop_totalDataLong<-pop_totalData[,!dropCols]</pre>
pop_totalData<-pop_totalData[paste(1956:1995),!dropCols]</pre>
#Aggregate beer data
beerYear <- seq(from = 1956, to = 1996, by = 1)
beerYear <- rep(beerYear, each=12)
beerYear<-beerYear[1:nrow(beerData)]</pre>
beerAg<-aggregate(beerData[,2], FUN=mean, by=list(year=beerYear))</pre>
#Attach to beer data
beerPop<-data.frame(cbind(beer=beerAg[,2],pop_totalData))</pre>
beerPopScale <-scale (beerPop)
beerPopRes<-melt(beerPopScale, variable.name="series")</pre>
colnames(beerPopRes)<-c("time", "series", "stddev")</pre>
allNames<-colnames(beerPop)[2:length(colnames(beerPop))]
#Plot data for each age group and beer data on same plot
par(mfrow=c(2,2))
for (name in allNames) {
  subset_data<-subset(beerPopRes, beerPopRes$series%in%c("beer", name))</pre>
  newPlot<-ggplot(subset_data, aes(time,stddev)) + geom_line(aes(colour = series)) +ggtitle(paste("Pop (age gr
  print(newPlot)
}
```

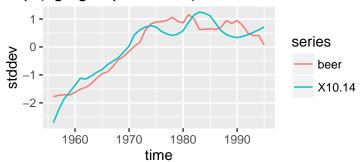




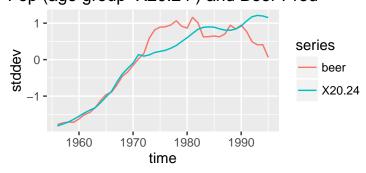
Pop (age group X5.9) and Beer Prod



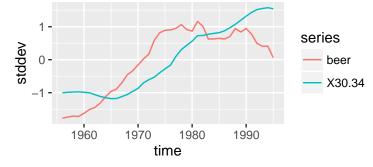
Pop (age group X10.14) and Beer Prod



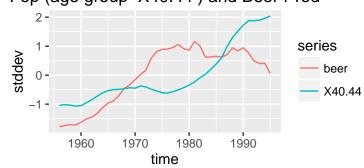
Pop (age group X20.24) and Beer Prod



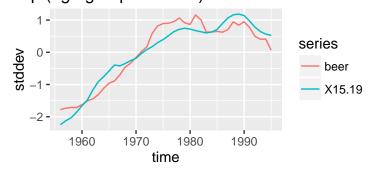
Pop (age group X30.34) and Beer Prod



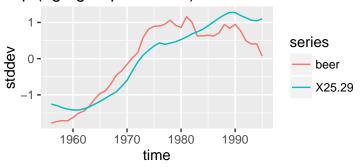
Pop (age group X40.44) and Beer Prod



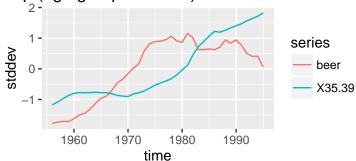
Pop (age group X15.19) and Beer Prod



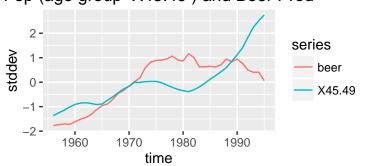
Pop (age group X25.29) and Beer Prod



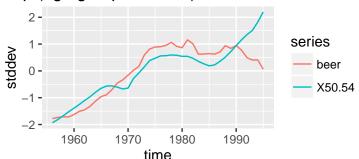
Pop (age group X35.39) and Beer Prod



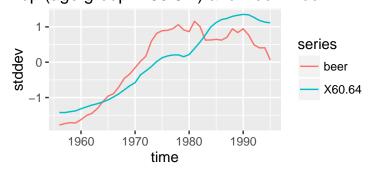
Pop (age group X45.49) and Beer Prod



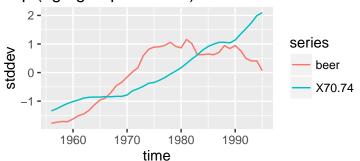
Pop (age group X50.54) and Beer Prod



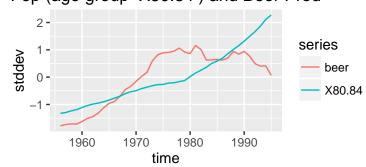
Pop (age group X60.64) and Beer Prod



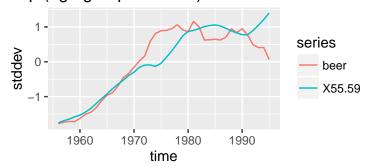
Pop (age group X70.74) and Beer Prod



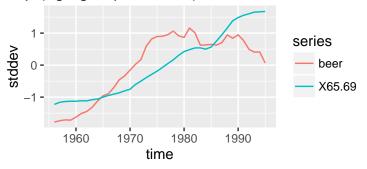
Pop (age group X80.84) and Beer Prod



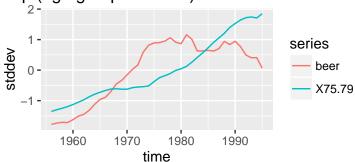
Pop (age group X55.59) and Beer Prod



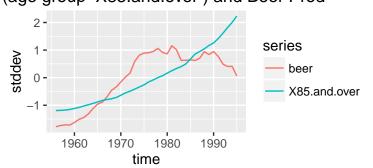
Pop (age group X65.69) and Beer Prod



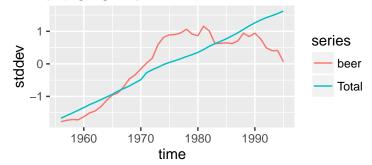
Pop (age group X75.79) and Beer Prod



(age group X85.and.over) and Beer Prod



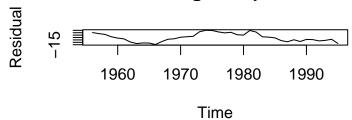
Pop (age group Total) and Beer Prod



```
par(mfrow=c(1,1))
\#Make\ a\ model\ based\ on\ the\ 15-19\ age\ group
yearModel1<-lm(beer ~ X15.19, data=beerPop)</pre>
summary(yearModel1)
##
## Call:
  lm(formula = beer ~ X15.19, data = beerPop)
##
## Residuals:
##
        Min
                  1Q
                       Median
                                             Max
                                     ЗQ
   -14.6061 -6.6167
                      -0.9743
                                6.8537
                                        15.0442
##
##
  Coefficients:
##
                 Estimate Std. Error t value Pr(>|t|)
## (Intercept) -2.713e-01 7.188e+00 -0.038
                                                <2e-16 ***
                1.194e-04 6.163e-06 19.374
## X15.19
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 8.706 on 38 degrees of freedom
## Multiple R-squared: 0.9081, Adjusted R-squared: 0.9057
## F-statistic: 375.4 on 1 and 38 DF, p-value: < 2.2e-16
```

plot(ts(residuals(yearModel1), frequency=1, start=c(1956)), main="Residuals from modeling beer production with

siduals from modeling beer production with

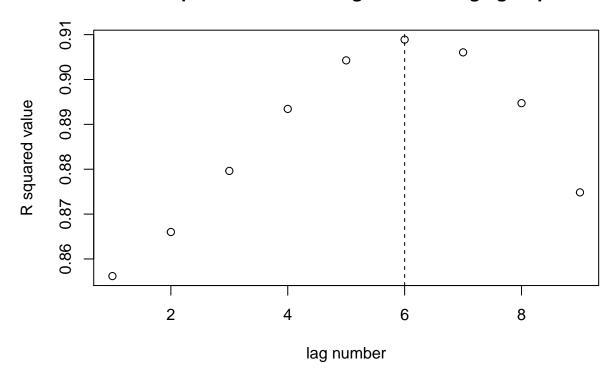


Explore lagged x10.14 data

```
laggedData<-data.frame(beer=beerAg[,2])
models<-list()
modelRsq<-c()
for (lag in 0:8) {
    newColNames<-c(colnames(laggedData), paste("lag", lag, sep=""))
    newLag<-pop_totalDataLong[paste(1956:1995-lag), "10-14"]
    laggedData<-data.frame(laggedData, newLag)
    newModel<-lm(beer ~ newLag, data=laggedData)
    models[[paste("lag", lag, sep="")]]<-newModel
    modelRsq<-c(modelRsq, summary(newModel)$r.squared)
    colnames(laggedData)<-newColNames
}

plot(modelRsq, main="R Squared Values for lags of 10-14 age group", xlab="lag number", ylab="R squared value")
abline(v=6, lty=2)</pre>
```

R Squared Values for lags of 10-14 age group

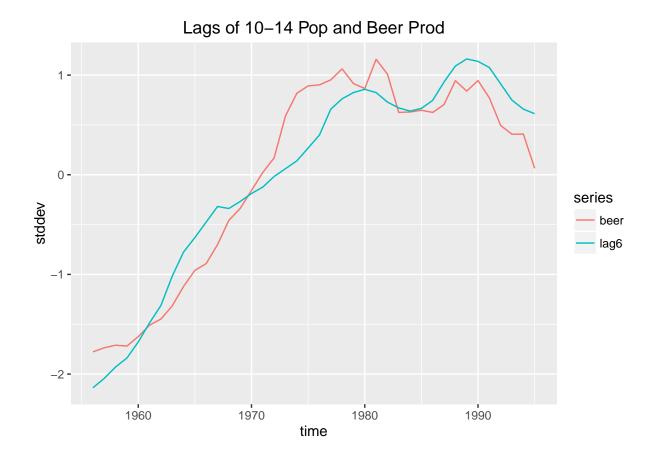


```
max(modelRsq)
```

```
## [1] 0.9088865
```

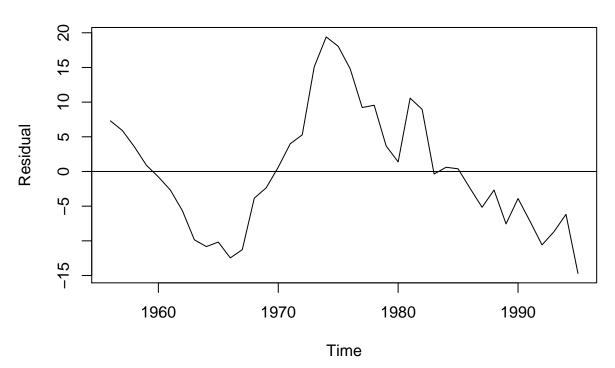
```
lagDataScale<-scale(laggedData)[,c(1,8)]
lagDataMelt<-melt(lagDataScale, variable.name="series")
colnames(lagDataMelt)<-c("time", "series", "stddev")

newPlot<-ggplot(lagDataMelt, aes(time,stddev)) + geom_line(aes(colour = series)) +ggtitle(paste("Lags of 10-14 print(newPlot)))</pre>
```



plot(ts(residuals(models[["lag6"]]), frequency=1, start=c(1956)), main="Residuals from modeling beer production
abline(h=0)

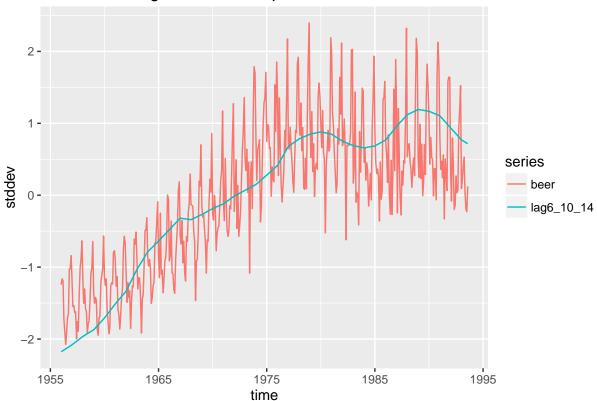
Residuals from modeling beer production with 10-14 lag 6



Interpolate Monthly Numbers

```
library(zoo)
#Create a vector with missing values for zoo to interpolate
for (year in 1:nrow(laggedData)) {
  withNA<-c(withNA, laggedData$lag6[year], rep(NA, 11))
}
#Create a vector with missing values for zoo to interpolate
withNALong<-c()
for (year in 1:nrow(pop_totalDataLong)) {
  withNALong<-c(withNALong, pop_totalDataLong[year, "10-14"], rep(NA, 11))
}
#Interpolate values using zoo library
zooSeries<-zoo(withNA, frequency=12)</pre>
wAppx<-na.approx(zooSeries, na.rm=FALSE)
monthlyLag6<-wAppx
#Interpolate long series for forecasting
zooSeriesLong<-zoo(withNALong, frequency=12)
wAppxLong<-data.frame(na.approx(zooSeriesLong, na.rm=FALSE))
rownames(wAppxLong) <- round(seq(from=(1921+6), length.out=nrow(wAppxLong), by=1/12),2)
monthlyLag6Long<-wAppxLong
#Reattach to beer numbers for plotting
beerPopMonth<-data.frame(beer=beerTS, lag6_10_14=monthlyLag6[1:length(beerTS)])
rownames(beerPopMonth) <- round(seq(from=1956, length.out=length(beerTS), by=1/12),2)
scaleMonth<-scale(beerPopMonth)</pre>
scaleMonthMelt<-melt(scaleMonth, variable.name="series")</pre>
colnames(scaleMonthMelt)<-c("time", "series", "stddev")</pre>
#Make a pretty plot
newPlot<-ggplot(scaleMonthMelt, aes(time,stddev)) + geom_line(aes(colour = series)) +ggtitle(paste("Lag 6 of 1
print(newPlot)
```

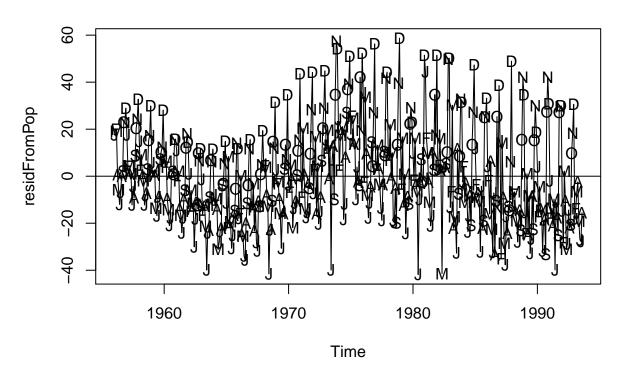
Lag 6 of 10-14 Pop and Beer Prod



```
#Try a model
monthlyPopModel<-lm(beer ~ lag6_10_14, data=beerPopMonth)
summary(monthlyPopModel)</pre>
```

```
##
## Call:
##
  lm(formula = beer ~ lag6_10_14, data = beerPopMonth)
##
  Residuals:
##
##
       Min
                1Q Median
                                3Q
                                       Max
   -41.862 -14.399 -2.561
                           13.099
                                    58.717
##
##
## Coefficients:
##
                Estimate Std. Error t value Pr(>|t|)
                                      1.519
                                                0.129
  (Intercept) 6.919e+00 4.554e+00
  lag6_10_14 1.180e-04 4.076e-06 28.946
                                               <2e-16 ***
##
##
## Signif. codes:
                   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 20.25 on 450 degrees of freedom
## Multiple R-squared: 0.6506, Adjusted R-squared: 0.6498
## F-statistic: 837.9 on 1 and 450 DF, p-value: < 2.2e-16
residFromPop<-ts(residuals(monthlyPopModel), frequency=12, start=c(1956,1))</pre>
plot(residFromPop, type="1", main="Plot of residuals from Pop model")
points(y=residFromPop, x=time(residFromPop), pch=as.vector(season(residFromPop)))
abline(h=0)
```

Plot of residuals from Pop model



Define helper functions

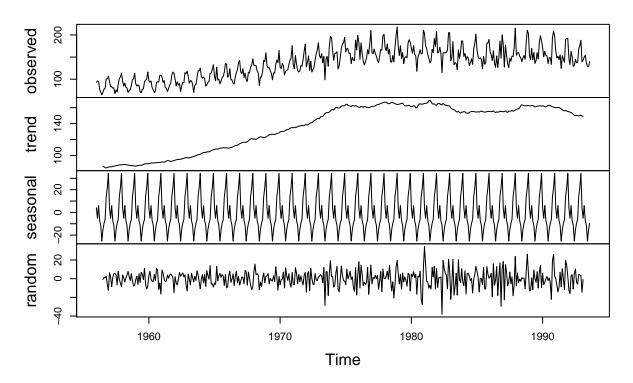
```
getModelString<-function(model) {
  modSpec<-model$arma
  modelString<-paste("SARIMA(", modSpec[1],",", modSpec[6], ",", modSpec[2],")(", modSpec[3], ",", modSpec[7],
  return(modelString)
}

plotResid<-function(model) {
  residuals<-ts(residuals(model), frequency=12, start=c(1956,1))
  modelString<-getModelString(model)
  par(mfrow=c(1,1))
  acf(residuals, main=paste("ACF of", modelString), lag.max=40, cex=.5)
  pacf(residuals, main=paste("PACF of", modelString), lag.max=40, cex=.5)
  par(mfrow=c(1,1))
}</pre>
```

Decompsing the time series to see trends and patterns

```
decompbeer = decompose (beerTS, type="additive")
plot (decompbeer)
```

Decomposition of additive time series



#monthplot(beerTS, main="Decomposition of Series by Month")

-7.721e-04 6.163e-05 -12.53

Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1

Try to figure out deterministic trend

t2

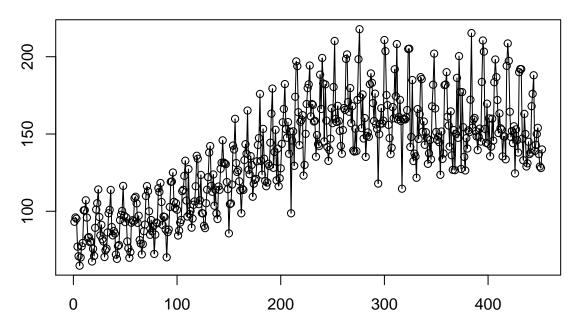
```
t<-1:length(beerTS)
t2<-t^2
t3<-t^3
t4<-t^4
t5<-t<sup>5</sup>
quadFit<-lm(beerTS~t+t2)</pre>
summary(quadFit)
##
## Call:
## lm(formula = beerTS ~ t + t2)
##
## Residuals:
##
       Min
                1Q Median
                                         Max
  -46.861 -14.133 -1.991 11.937 61.174
##
##
## Coefficients:
##
                 Estimate Std. Error t value Pr(>|t|)
## (Intercept) 6.560e+01 2.828e+00
                                         23.20
                                                <2e-16 ***
## t
                5.429e-01 2.883e-02
                                        18.83
                                                 <2e-16 ***
```

<2e-16 ***

```
##
## Residual standard error: 19.95 on 449 degrees of freedom
## Multiple R-squared: 0.6616, Adjusted R-squared: 0.6601
## F-statistic: 439 on 2 and 449 DF, p-value: < 2.2e-16</pre>
```

plot the data and the fitted quadratic trend function
plot(x=1:length(beerTS),y=beerTS,type='o',ylab="",xlab="Time - Number of Months Since Jan 1956",main="Quadrati
curve(expr = coef(quadFit)[1]+coef(quadFit)[2]*x+coef(quadFit)[3]*x^2+coef(quadFit)[4]*x^3,lty=1,add = TRUE, c

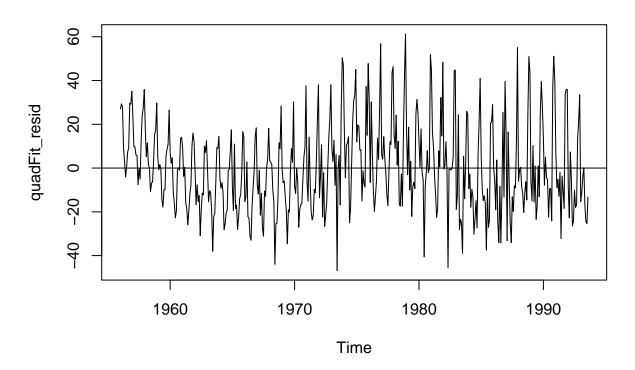
Quadratic Fit on Beer Production Data



Time - Number of Months Since Jan 1956

quadFit_resid<-ts(residuals(quadFit),frequency=12, start=c(1956,1))
plot(quadFit_resid, main="Residuals from a Quadratic Trend Fit")
abline(h=0)</pre>

Residuals from a Quadratic Trend Fit

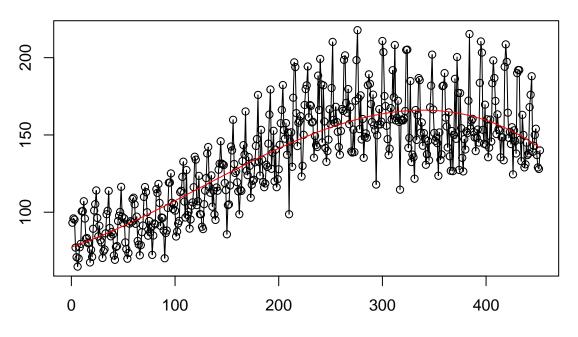


##

```
cubicFit<-lm(beerTS~t+t2+t3)
summary(cubicFit)</pre>
```

```
## Call:
##
   lm(formula = beerTS \sim t + t2 + t3)
##
## Residuals:
##
                10 Median
                                3Q
                                       Max
  -50.660 -13.783 -2.601
##
                           12.434
                                    57.639
##
## Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
##
  (Intercept) 7.745e+01 3.695e+00 20.963 < 2e-16 ***
##
                2.307e-01
                          7.056e-02
                                       3.270 0.00116 **
## t
                9.490e-04
                          3.617e-04
                                       2.624 0.00900 **
## t2
                          5.249e-07
                                     -4.826 1.92e-06 ***
## t3
               -2.533e-06
##
                   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Signif. codes:
##
## Residual standard error: 19.47 on 448 degrees of freedom
## Multiple R-squared: 0.6784, Adjusted R-squared: 0.6762
## F-statistic:
                  315 on 3 and 448 DF, p-value: < 2.2e-16
#### plot the data and the fitted quadratic trend function
plot(x=1:length(beerTS),y=beerTS,type='o',ylab="",xlab="Time - Number of Months Since Jan 1956",main="Cubic Fi
curve(expr = coef(cubicFit)[1]+coef(cubicFit)[2]*x+coef(cubicFit)[3]*x^2+coef(cubicFit)[4]*x^3,lty=1,add = TRU
```

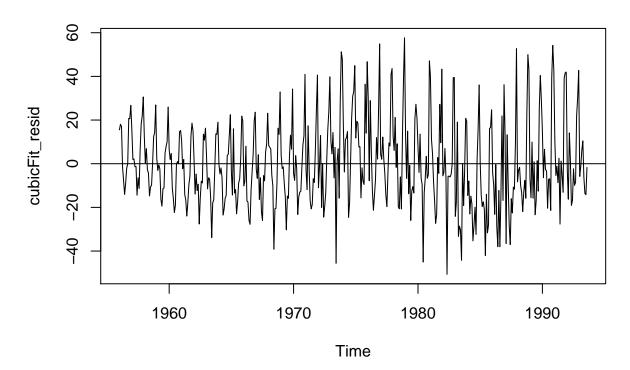
Cubic Fit on Beer Production Data



Time - Number of Months Since Jan 1956

cubicFit_resid<-ts(residuals(cubicFit),frequency=12, start=c(1956,1))
plot(cubicFit_resid, main="Residuals from a Cubic Trend Fit")
abline(h=0)</pre>

Residuals from a Cubic Trend Fit



```
order4polyFit<-lm(beerTS~t+t2+t3+t4)
summary(order4polyFit)</pre>
```

 $lm(formula = beerTS \sim t + t2 + t3 + t4)$

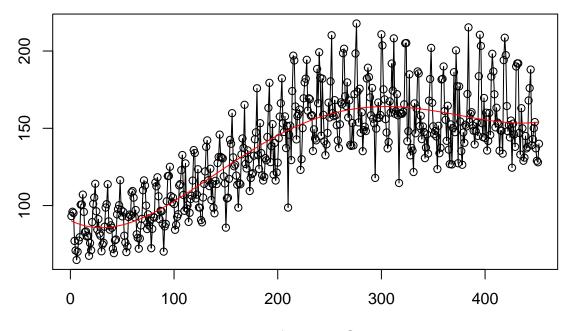
Call:

##

```
## Residuals:
##
       Min
                1Q Median
                                3Q
                                       Max
   -50.079 -12.721 -3.199
                            10.135
                                    57.983
##
##
##
  Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
##
## (Intercept) 9.037e+01 4.536e+00
                                     19.924
                                             < 2e-16 ***
##
               -3.341e-01 1.384e-01
                                     -2.414
                                               0.0162 *
## t.2
                6.545e-03 1.241e-03
                                       5.276 2.07e-07 ***
                                     -5.285 1.97e-07 ***
## t3
               -2.173e-05
                          4.113e-06
                2.119e-08
                          4.504e-09
                                       4.706 3.38e-06 ***
## t4
##
                   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Signif. codes:
##
## Residual standard error: 19.03 on 447 degrees of freedom
## Multiple R-squared: 0.6935, Adjusted R-squared: 0.6908
## F-statistic: 252.9 on 4 and 447 DF, \, p-value: < 2.2e-16
#### plot the data and the fitted 4th order polynomial trend function
plot(x=1:length(beerTS),y=beerTS,type='o',ylab="",xlab="Time - Number of Months Since Jan 1956",main="order4po
```

curve(expr = coef(order4polyFit)[1]+coef(order4polyFit)[2]*x+coef(order4polyFit)[3]*x^2+coef(order4polyFit)[4]

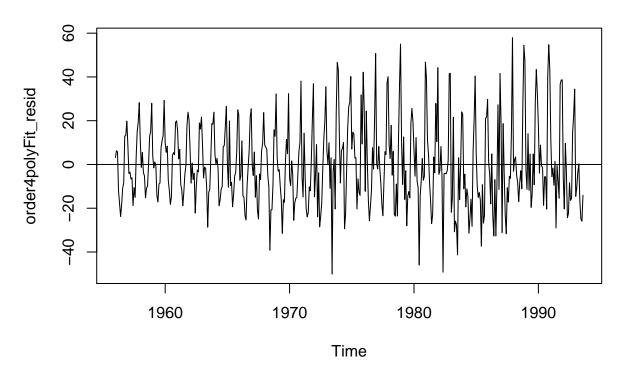
order4poly Fit on Beer Production Data



Time - Number of Months Since Jan 1956

```
order4polyFit_resid<-ts(residuals(order4polyFit),frequency=12, start=c(1956,1))
plot(order4polyFit_resid, main="Residuals from a order4poly Trend Fit")
abline(h=0)
```

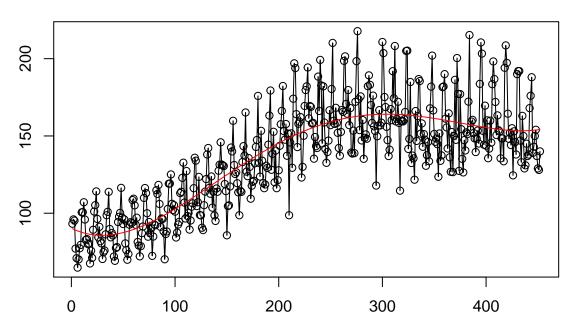
Residuals from a order4poly Trend Fit



```
order5polyFit<-lm(beerTS~t+t2+t3+t4+t5)
summary(order5polyFit)</pre>
```

```
##
## Call:
##
  lm(formula = beerTS \sim t + t2 + t3 + t4 + t5)
##
## Residuals:
##
       Min
                1Q Median
                                3Q
                                       Max
##
   -50.069 -12.729
                   -3.179 10.132
                                    58.012
##
  Coefficients:
##
##
                 Estimate Std. Error t value Pr(>|t|)
  (Intercept) 9.029e+01 5.483e+00
##
                                      16.469
                                                <2e-16 ***
## t
               -3.288e-01
                          2.436e-01
                                      -1.350
                                                0.1778
## t2
                6.463e-03
                          3.323e-03
                                       1.945
                                                0.0524
               -2.126e-05
                           1.858e-05
                                      -1.144
                                                0.2532
## t3
##
  t4
                2.000e-08
                           4.519e-08
                                       0.443
                                                0.6582
                1.049e-12
                                       0.026
                                                0.9789
## t5
                           3.970e-11
##
## Signif. codes:
                   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 19.05 on 446 degrees of freedom
## Multiple R-squared: 0.6935, Adjusted R-squared: 0.6901
## F-statistic: 201.9 on 5 and 446 DF, p-value: < 2.2e-16
```

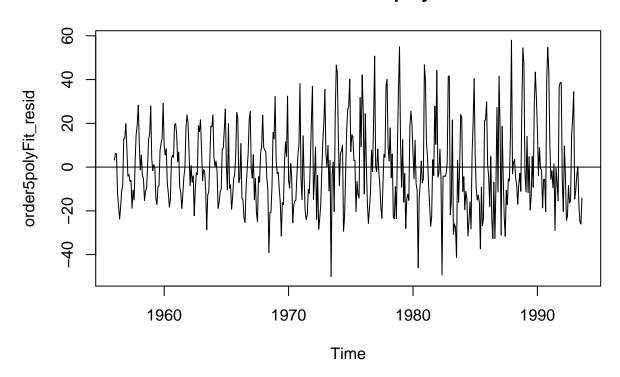
order5poly Fit on Beer Production Data



Time - Number of Months Since Jan 1956

order5polyFit_resid<-ts(residuals(order5polyFit),frequency=12, start=c(1956,1))
plot(order5polyFit_resid, main="Residuals from a order5poly Trend Fit")
abline(h=0)

Residuals from a order5poly Trend Fit



Fit deterministic cosine trend model

Median

-0.261463 -0.039931 0.002551 0.043469 0.183185

1Q

3Q

Estimate Std. Error t value Pr(>|t|)

4.467e+00 1.642e-02 272.071 < 2e-16 ***

1.228e-01 4.572e-03 26.854 < 2e-16 ***

Residuals:

Coefficients:

har.cos(2*pi*t)

(Intercept)

Min

##

##

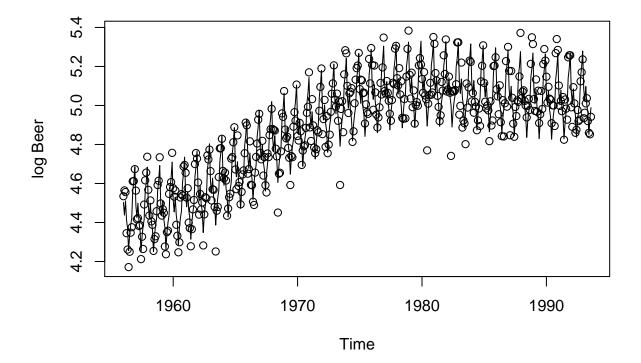
##

```
startDate<-round(start(beer_forecast)[1]+start(beer_forecast)[2]/12,2)</pre>
endDate<-round(end(beer_forecast)[1]+end(beer_forecast)[2]/12,2)</pre>
numToFor<-length(beer_forecast)</pre>
allBeerData<-ts(c(beerTS, beer_forecast), start=c(1956, 1), frequency=12)
tnew<-1:length(allBeerData)</pre>
t2new<-tnew^2
t3new<-tnew<sup>3</sup>
t4new<-tnew<sup>4</sup>
har.=harmonic(logBeer,5)
modelHR=lm(logBeer~har.+t+t2+t3+t4)
summary(modelHR)
##
## Call:
   lm(formula = logBeer \sim har. + t + t2 + t3 + t4)
##
##
```

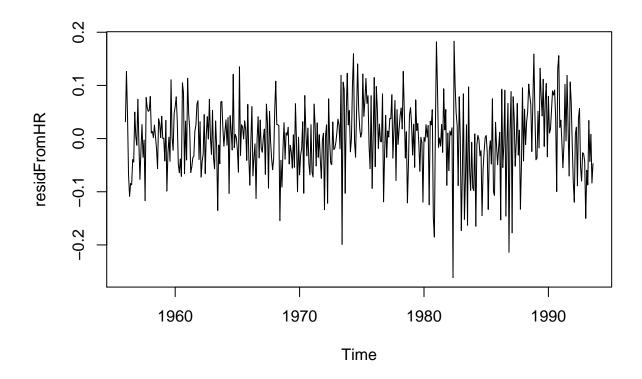
Max

```
## har.cos(4*pi*t) -3.543e-02 4.577e-03 -7.742 6.87e-14 ***
## har.cos(6*pi*t) -2.830e-02 4.579e-03
                                         -6.180 1.47e-09 ***
## har.cos(8*pi*t) -5.185e-03 4.576e-03
                                          -1.133 0.257829
## har.cos(10*pi*t) -1.557e-02 4.571e-03
                                          -3.406 0.000720 ***
## har.sin(2*pi*t) -8.192e-02 4.589e-03 -17.850 < 2e-16 ***
## har.sin(4*pi*t)
                                          -5.605 3.70e-08 ***
                   -2.568e-02 4.581e-03
## har.sin(6*pi*t)
                  -3.967e-02 4.579e-03
                                          -8.663 < 2e-16 ***
                  -1.067e-02 4.581e-03
## har.sin(8*pi*t)
                                          -2.328 0.020366 *
## har.sin(10*pi*t) -3.546e-02 4.586e-03
                                          -7.733 7.30e-14 ***
                   -1.797e-03 5.009e-04
                                          -3.587 0.000372 ***
## t
## t2
                    4.927e-05 4.490e-06
                                         10.973 < 2e-16 ***
## t3
                   -1.745e-07
                               1.488e-08 -11.724
                                                 < 2e-16 ***
## t4
                    1.785e-10 1.630e-11
                                         10.952 < 2e-16 ***
##
                  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Signif. codes:
##
## Residual standard error: 0.06882 on 437 degrees of freedom
## Multiple R-squared: 0.9365, Adjusted R-squared: 0.9345
## F-statistic: 460.5 on 14 and 437 DF, p-value: < 2.2e-16
```

plot(ts(fitted(modelHR),freq=12,start=c(1956,1)),ylab='log Beer',type='l',ylim=range(c(fitted(modelHR),logBeer
points(logBeer)



residFromHR<-ts(residuals(modelHR), frequency=12, start=c(1956,1))
plot(residFromHR)</pre>



```
chosenMod<-modelHR
library(TSA)

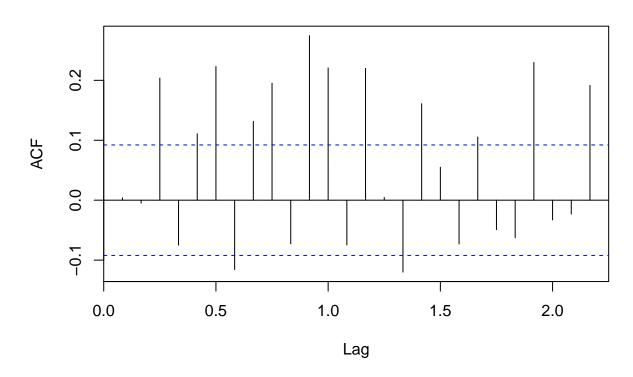
har.=harmonic(log(beer_forecast),5)
newRegData<-data.frame(t=tnew, t2=t2new, t3=t3new, t4=t4new)
newRegData<-newRegData[(nrow(newRegData)-numToFor+1):nrow(newRegData),]
newRegData<-data.frame(har., newRegData)
colnames(newRegData)<-c(colnames(har.),"t","t2","t3","t4")</pre>
```

Diagnostics on Cosine Trend

```
## Phillips-Perron Unit Root Test
##
## data: residFromHR
## Dickey-Fuller Z(alpha) = -490.03, Truncation lag parameter = 5,
## p-value = 0.01
## alternative hypothesis: stationary
```

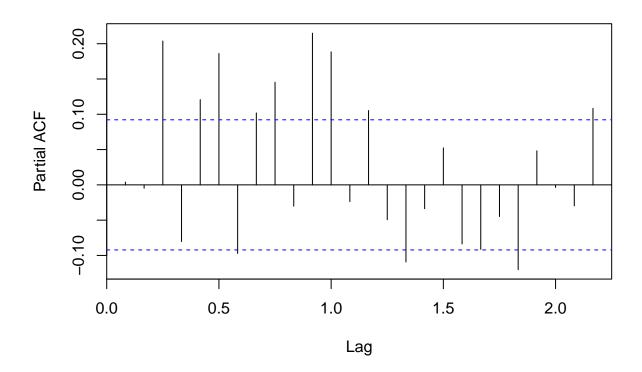
acf(residFromHR)

Series residFromHR

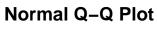


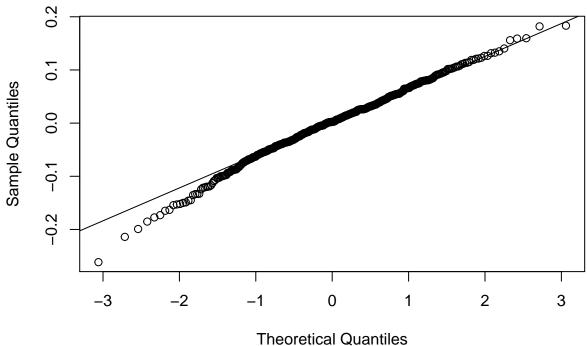
pacf(residFromHR)

Series residFromHR



qqnorm(residFromHR)
qqline(residFromHR)

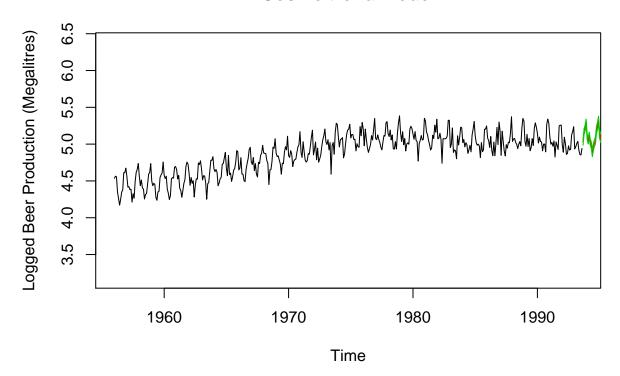




Forecast based on cosine trend model

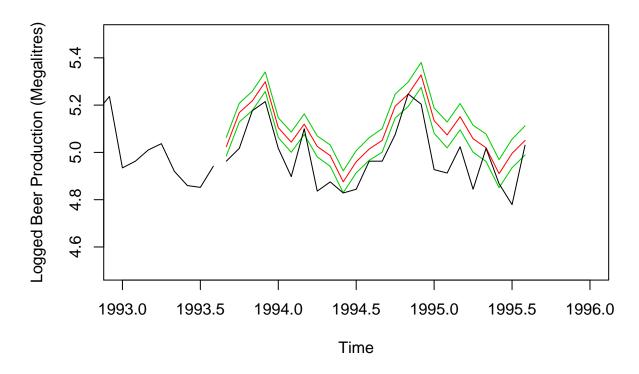
```
modelString<-"Cosine trend model"
predictions<-predict(chosenMod,newdata =newRegData,se.fit = T)
pred<-ts(predictions$fit,start = c(1993,9),frequency = 12)
uci<-ts(pred+2*predictions$se.fit,start = c(1993,9),frequency = 12)
lci<-ts(pred-2*predictions$se.fit,start = c(1993,9),frequency = 12)
ymin=min(c(as.vector(lci),logBeer))-1
ymax=max(c(as.vector(uci),logBeer))+1
plot(logBeer,ylim=c(ymin,ymax),main=modelString, ylab='Logged Beer Production (Megalitres)')
lines(pred,col=2)
lines(uci,col=3)
lines(lci,col=3)</pre>
```

Cosine trend model



```
ymin=min(c(as.vector(lci),logBeer))-1
ymax=max(c(as.vector(uci),logBeer))+1
plot(logBeer,xlim=c(1993, 1996), ylim=c(4.5,5.5),main=modelString, ylab='Logged Beer Production (Megalitres)')
lines(pred,col=2)
lines(uci,col=3)
lines(lci,col=3)
lines(log(beer_forecast), col="black")
```

Cosine trend model

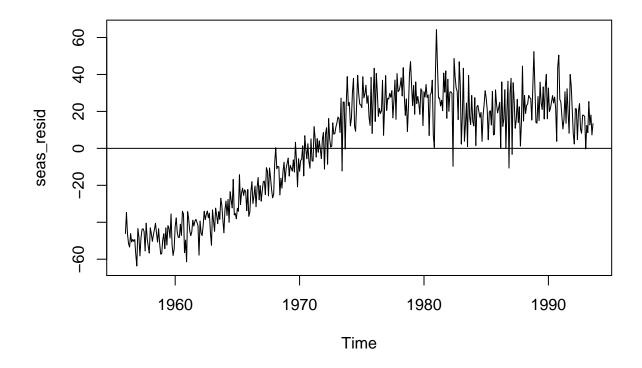


Seasonal means model with ARIMA

```
logBeer<-log(beerTS)</pre>
t<-1:length(logBeer)
t2<-t^2
t3<-t^3
t4<-t^4
month <- season (logBeer)
seasMod<-lm(beerTS~month)</pre>
summary(seasMod)
##
## Call:
## lm(formula = beerTS ~ month)
##
## Residuals:
##
      Min
              1Q Median
                             ЗQ
                                   Max
##
   -63.70 -27.90
                    8.20
                          24.91
                                 64.28
##
## Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
##
## (Intercept)
                    139.316
                                 4.957
                                         28.106
                                                 < 2e-16 ***
## monthFebruary
                     -8.674
                                 7.010
                                        -1.237
                                                 0.21662
## monthMarch
                      2.203
                                 7.010
                                          0.314
                                                 0.75350
                    -10.674
                                 7.010 -1.523
                                                 0.12856
## monthApril
                                        -2.138
## monthMay
                    -14.989
                                 7.010
                                                 0.03304 *
## monthJune
                    -28.361
                                 7.010 -4.046 6.16e-05 ***
## monthJuly
                    -18.571
                                 7.010 -2.649 0.00836 **
```

```
-12.687
                                7.010 -1.810 0.07100 .
## monthAugust
                   -9.516
                                7.057
## monthSeptember
                                       -1.348 0.17822
## monthOctober
                    10.641
                                7.057
                                        1.508 0.13231
## monthNovember
                    18.830
                                7.057
                                        2.668 0.00791 **
## monthDecember
                    31.479
                                7.057
                                        4.461 1.04e-05 ***
##
                   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Signif. codes:
##
## Residual standard error: 30.56 on 440 degrees of freedom
## Multiple R-squared: 0.2224, Adjusted R-squared: 0.2029
## F-statistic: 11.44 on 11 and 440 DF, p-value: < 2.2e-16
seas_resid<-ts(residuals(seasMod),frequency=12, start=c(1956,1))</pre>
plot(seas_resid, main="Residuals from Seasonal Means Model")
abline(h=0)
```

Residuals from Seasonal Means Model



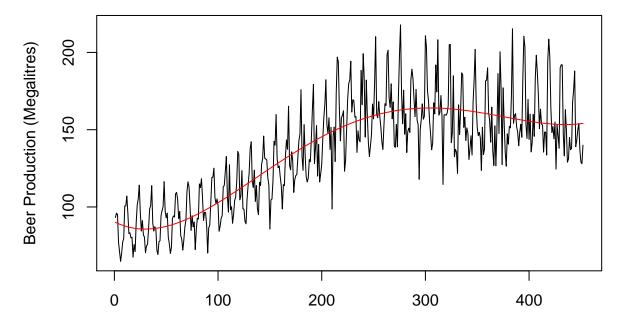
```
order4polyFit<-lm(beerTS~t+t2+t3+t4)
summary(order4polyFit)</pre>
```

```
##
  lm(formula = beerTS \sim t + t2 + t3 + t4)
##
##
##
  Residuals:
##
       Min
                1Q Median
                                3Q
                                       Max
  -50.079 -12.721 -3.199 10.135
                                   57.983
##
##
##
  Coefficients:
##
                 Estimate Std. Error t value Pr(>|t|)
  (Intercept) 9.037e+01 4.536e+00 19.924 < 2e-16 ***
## t
               -3.341e-01 1.384e-01 -2.414
                                               0.0162 *
```

```
## t2
                6.545e-03 1.241e-03
                                       5.276 2.07e-07 ***
               -2.173e-05
                          4.113e-06
                                     -5.285 1.97e-07 ***
## t3
##
  t4
                2.119e-08
                          4.504e-09
                                       4.706 3.38e-06 ***
##
                   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Signif. codes:
##
## Residual standard error: 19.03 on 447 degrees of freedom
## Multiple R-squared: 0.6935, Adjusted R-squared: 0.6908
## F-statistic: 252.9 on 4 and 447 DF, p-value: < 2.2e-16
```

plot the data and the fitted 4th order polynomial trend function
plot(x=1:length(beerTS),y=beerTS,type='l',ylab="Beer Production (Megalitres)",xlab="Time - Number of Months Si
curve(expr = coef(order4polyFit)[1]+coef(order4polyFit)[2]*x+coef(order4polyFit)[3]*x^2+coef(order4polyFit)[4]

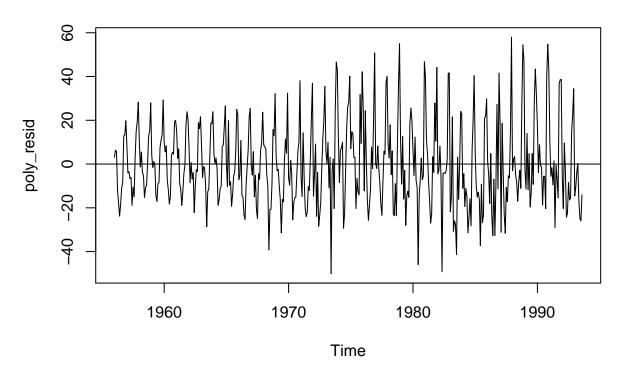
order4poly Fit on Beer Production Data



Time - Number of Months Since Jan 1956

poly_resid<-ts(residuals(order4polyFit),frequency=12, start=c(1956,1))
plot(poly_resid, main="Residuals from 4th order polynomial Model")
abline(h=0)</pre>

Residuals from 4th order polynomial Model



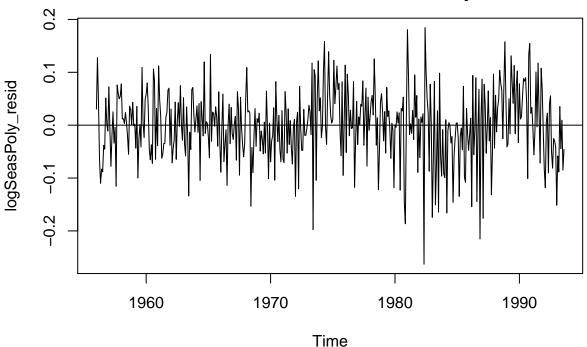
logSeasPoly<-lm(logBeer~t+t2+t3+t4+month)
summary(logSeasPoly)</pre>

```
##
## Call:
   lm(formula = logBeer \sim t + t2 + t3 + t4 + month)
##
##
##
  Residuals:
##
                    10
                           Median
                                         3Q
         Min
                                                  Max
##
   -0.262750 -0.039816
                        0.003297
                                   0.043475
                                             0.184483
##
##
   Coefficients:
##
                    Estimate Std. Error t value Pr(>|t|)
                              1.945e-02 231.675
                                                 < 2e-16 ***
##
  (Intercept)
                   4.506e+00
##
  t
                   -1.796e-03
                               5.014e-04
                                          -3.583 0.000378 ***
                   4.926e-05
                              4.494e-06
                                          10.962
## t2
                                                  < 2e-16
## t3
                  -1.745e-07
                               1.490e-08 -11.713
                                                  < 2e-16 ***
                                         10.941
##
  t4
                   1.785e-10
                              1.631e-11
                                                  < 2e-16 ***
## monthFebruary
                  -6.602e-02
                              1.580e-02
                                          -4.178 3.56e-05 ***
## monthMarch
                   1.069e-02
                               1.580e-02
                                           0.676 0.499268
## monthApril
                  -8.834e-02
                               1.581e-02
                                         -5.590 4.02e-08 ***
## monthMay
                  -1.271e-01
                               1.581e-02
                                         -8.042 8.39e-15 ***
## monthJune
                  -2.427e-01
                               1.581e-02 -15.354
                                                  < 2e-16 ***
  monthJuly
                   -1.578e-01
                               1.581e-02
                                          -9.984
   monthAugust
                  -1.089e-01
                               1.581e-02
                                          -6.890 1.96e-11 ***
  monthSeptember -7.261e-02
                              1.591e-02
                                         -4.563 6.57e-06 ***
  monthOctober
                   6.706e-02
                               1.591e-02
                                           4.213 3.06e-05 ***
  monthNovember
                   1.172e-01
                               1.592e-02
                                           7.363 9.03e-13 ***
##
   monthDecember
##
                   1.936e-01
                               1.592e-02 12.164
                                                  < 2e-16 ***
                   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Signif. codes:
```

```
##
## Residual standard error: 0.06889 on 436 degrees of freedom
## Multiple R-squared: 0.9365, Adjusted R-squared: 0.9344
## F-statistic: 429 on 15 and 436 DF, p-value: < 2.2e-16

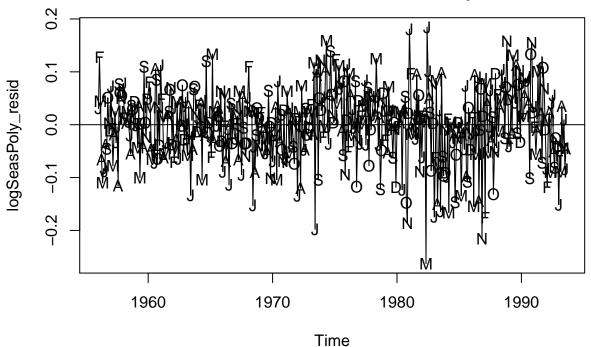
logSeasPoly_resid<-ts(residuals(logSeasPoly),frequency=12, start=c(1956,1))
plot(logSeasPoly_resid, main="Residuals from Logged Beer\nSeasonal Means and 4th Order Poly Fit")
abline(h=0)</pre>
```

Residuals from Logged Beer Seasonal Means and 4th Order Poly Fit



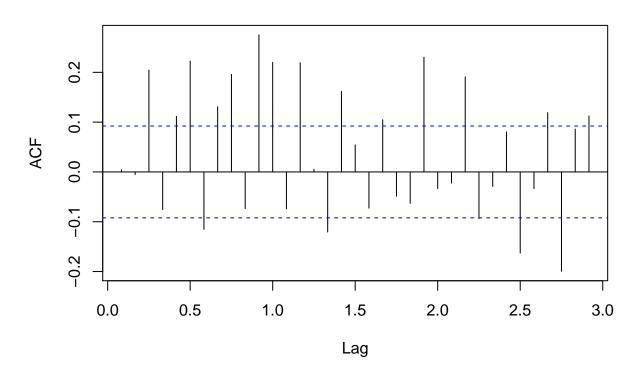
plot(logSeasPoly_resid, main="Residuals from Logged Beer\nSeasonal Means and 4th Order Poly Fit", type="1")
points(y=logSeasPoly_resid, x=time(logSeasPoly_resid), pch=as.vector(season(logSeasPoly_resid)))
abline(h=0)

Residuals from Logged Beer Seasonal Means and 4th Order Poly Fit

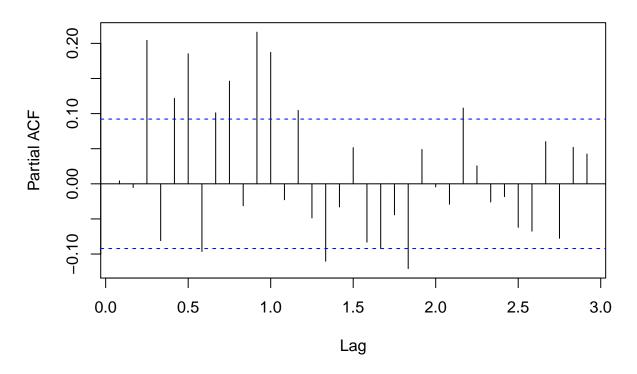


acf(logSeasPoly_resid, main="ACF of Residuals from Logged Beer- Seas Means and Poly Fit", lag=35)

ACF of Residuals from Logged Beer- Seas Means and Poly Fit



PACF of Residuals from Logged Beer- Seas Means and Poly Fit



```
adf.test(logSeasPoly_resid)
## Warning in adf.test(logSeasPoly_resid): p-value smaller than printed p-
## value
##
##
    Augmented Dickey-Fuller Test
##
## data: logSeasPoly_resid
## Dickey-Fuller = -5.3999, Lag order = 7, p-value = 0.01
## alternative hypothesis: stationary
pp.test(logSeasPoly_resid)
## Warning in pp.test(logSeasPoly_resid): p-value smaller than printed p-value
##
##
   Phillips-Perron Unit Root Test
##
```

Try an AR 12 model with the seasonal means and polynomial

Dickey-Fuller Z(alpha) = -489.81, Truncation lag parameter = 5,

data: logSeasPoly_resid

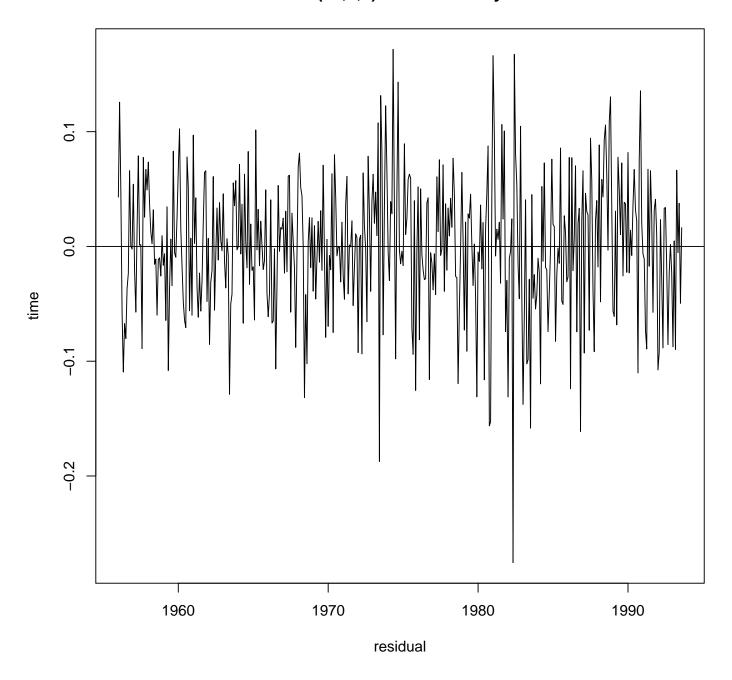
alternative hypothesis: stationary

p-value = 0.01

```
library(forecast)
monthDummies <- seasonaldummy (logBeer)
externReg<-data.frame(t, t2, t3, t4, monthDummies)</pre>
ar12_poly<-arima(logBeer, order=c(12,0,0), xreg=externReg)</pre>
ar12_poly
##
## Call:
## arima(x = logBeer, order = c(12, 0, 0), xreg = externReg)
##
## Coefficients:
##
            ar1
                     ar2
                             ar3
                                     ar4
                                             ar5
                                                     ar6
                                                              ar7
                                                                     ar8
##
        -0.0185 -0.0373 0.0592 -0.0600 0.0852 0.1086 -0.0873 0.0867
## s.e. 0.0460 0.0449 0.0449 0.0441 0.0443 0.0442
                                                           0.0443 0.0438
##
                                  ar12 intercept
           ar9
                   ar10
                           ar11
                                                       t
                                                               t2 t3 t4
        0.1421 -0.0077 0.2301 0.2099
                                           4.6792 -0.0009 0e+00
##
                                                                  0
                                                                       0
## s.e. 0.0440 0.0440 0.0453
                                           0.0781 0.0014 2e-04
##
                     Feb
                                                                 Jul
            Jan
                             Mar
                                               May
                                                        Jun
                                     Apr
        -0.1923 -0.2566 -0.1788 -0.2787 -0.3181 -0.4344 -0.3506
##
## s.e.
        0.0154
                 0.0170
                           0.0156 0.0165
                                           0.0167 0.0156
                                                            0.0167
##
            Aug
                     Sep
                              Oct
                                      Nov
##
        -0.3012 -0.2658 -0.1259 -0.0756
## s.e.
         0.0165
                 0.0157
                           0.0171
                                  0.0155
##
## sigma^2 estimated as 0.003593: log likelihood = 629.73, aic = -1203.47
ar12_poly_resid<-ts(resid(ar12_poly), start=c(1956, 1), frequency=12)
plot(ar12_poly_resid, xlab="residual", ylab="time", main="Residuals from ARIMA(12,0,0) with Seas/Poly Determini
abline(h=0)
```

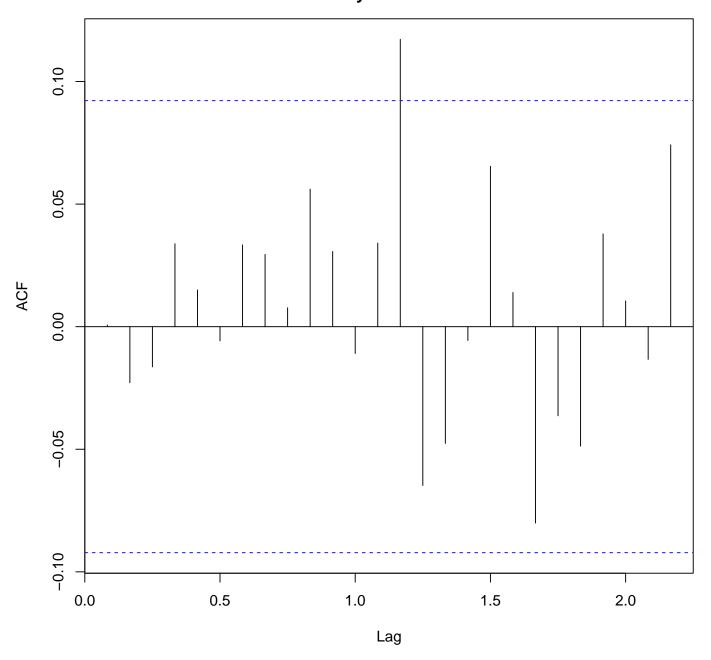
#Set up external regressors and dummy vars

Residuals from ARIMA(12,0,0) with Seas/Poly Deterministic Trend



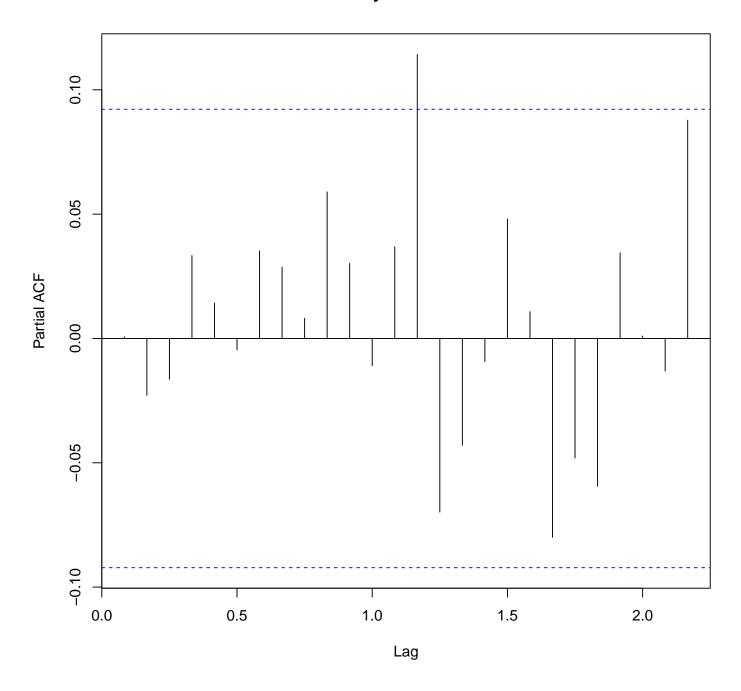
acf(ar12_poly_resid,main="ACF of Residuals from ARIMA(12,0,0)\nwith Seas/Poly Deterministic Trend")

ACF of Residuals from ARIMA(12,0,0) with Seas/Poly Deterministic Trend



pacf(ar12_poly_resid,main="PACF of Residuals from ARIMA(12,0,0)\nwith Seas/Poly Deterministic Trend",mar=c(4,2)

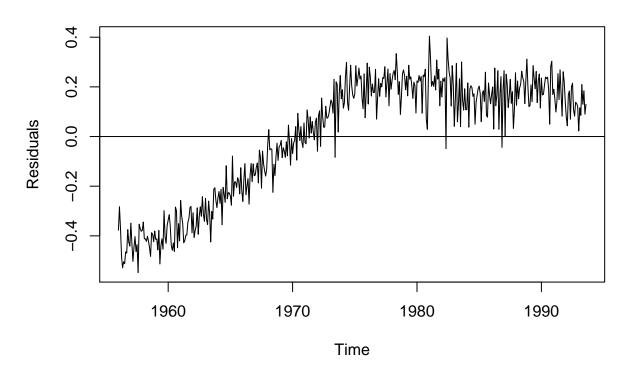
PACF of Residuals from ARIMA(12,0,0) with Seas/Poly Deterministic Trend



Build models based on the seasonal means only

```
seasMeansMod<-lm(logBeer~season(logBeer))
plot(ts(residuals(seasMeansMod), start=c(1956,1),frequency=12), ylab="Residuals", main="Residual from Seasonal
abline(h=0)</pre>
```

Residual from Seasonal Means Fit



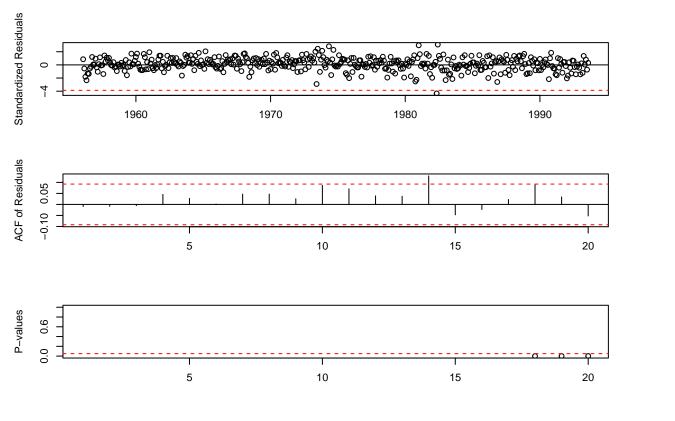
```
ar12<-arima(logBeer, order=c(12,0,0), xreg=monthDummies)
ar12

##
## Call:
## arima(x = logBeer, order = c(12, 0, 0), xreg = monthDummies)
##</pre>
```

```
## Coefficients:
##
            ar1
                    ar2
                            ar3
                                     ar4
                                              ar5
                                                      ar6
                                                               ar7
                                                                        ar8
##
         0.0631
                0.0283
                         0.1255
                                 -0.0127
                                          0.1286
                                                  0.1447
                                                           -0.0733
                                                                    0.0983
         0.0464
                 0.0458
                         0.0458
                                                            0.0461
##
                                  0.0457
                                          0.0458
                                                  0.0460
                                                                    0.0459
  s.e.
##
                    ar10
                            ar11
                                     ar12
                                           intercept
                                                          Jan
##
         0.1446
                 -0.0278 0.2102 0.1670
                                              4.9720
                                                      -0.1925
                                                               -0.2574
##
  s.e.
         0.0461
                  0.0461
                         0.0461 0.0471
                                              0.2644
                                                       0.0152
                                                                0.0169
##
                      Apr
                                         Jun
                                                  Jul
             Mar
                               May
                                                           Aug
                                                                    Sep
##
         -0.1798
                  -0.2797
                                             -0.3507
                                                       -0.3012
                                                                -0.2657
                           -0.3188
                                    -0.4349
## s.e.
         0.0154
                   0.0165
                            0.0167
                                    0.0153
                                               0.0167
                                                        0.0165
                                                                 0.0155
##
            Oct
                     Nov
##
         -0.126
                -0.0757
## s.e.
          0.017
                  0.0153
```

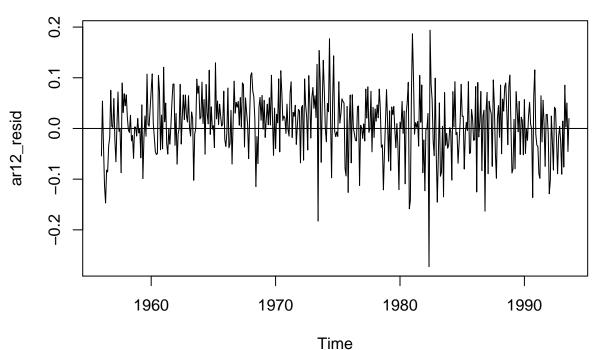
sigma^2 estimated as 0.003946: log likelihood = 606.68, aic = -1165.36

tsdiag(ar12, gof.lag=20)



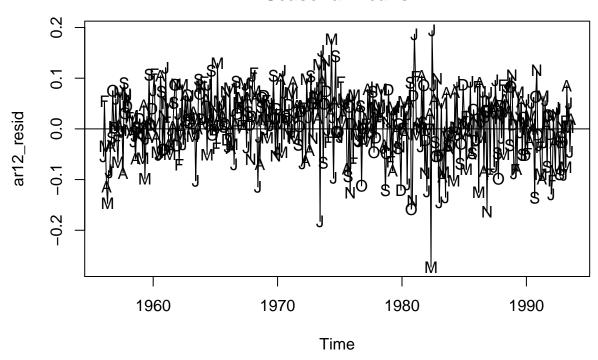
#residuals
ar12_resid<-ts(residuals(ar12), frequency=12, start=c(1956,1))
plot(ar12_resid, main="AR 12 model Residuals from Logged Beer\nSeasonal Means")
abline(h=0)</pre>

AR 12 model Residuals from Logged Beer Seasonal Means



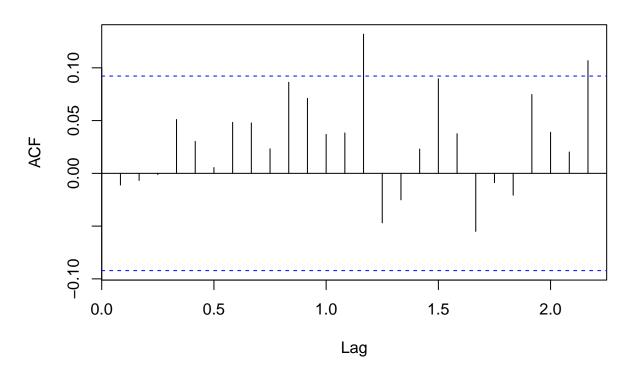
plot(ar12_resid, main="AR 12 model Residuals from Logged Beer\nSeasonal Means", type="1")
points(y=ar12_resid, x=time(ar12_resid), pch=as.vector(season(ar12_resid)))
abline(h=0)

AR 12 model Residuals from Logged Beer Seasonal Means



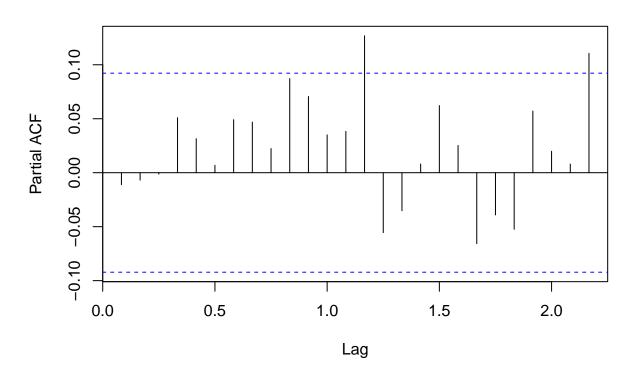
acf(ar12_resid, main="ACF Plot of Residuals from ARIMA(12,0,0)")

ACF Plot of Residuals from ARIMA(12,0,0)



pacf(ar12_resid, main="PACF Plot of Residuals from ARIMA(12,0,0)")

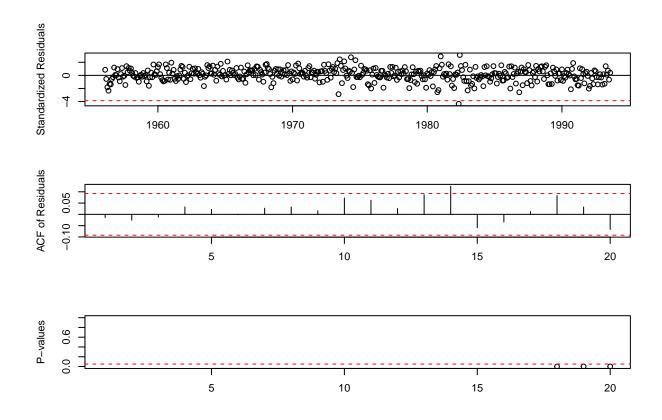
PACF Plot of Residuals from ARIMA(12,0,0)



```
ar13<-arima(logBeer, order=c(13,0,0), xreg=monthDummies)
ar13</pre>
```

```
##
## Call:
  arima(x = logBeer, order = c(13, 0, 0), xreg = monthDummies)
##
##
  Coefficients:
##
                    ar2
                             ar3
                                      ar4
                                              ar5
                                                      ar6
                                                                ar7
                                                                        ar8
            ar1
##
         0.0731
                0.0406
                         0.1232
                                 -0.0038
                                           0.1344
                                                   0.1406
                                                           -0.0638
                                                                     0.1074
                                                   0.0460
         0.0470
                 0.0467
                         0.0458
                                   0.0461
                                           0.0459
                                                             0.0466
                                                                     0.0464
##
            ar9
                    ar10
                             ar11
                                     ar12
                                              ar13 intercept
                                                                    Jan
##
                 -0.0190
                         0.2112 0.1696
                                           -0.0614
                                                       4.9746
         0.1442
                                                               -0.1925
                  0.0465
                         0.0460 0.0470
                                                       0.2625
##
         0.0460
                                            0.0477
                                                                 0.0152
  s.e.
##
             Feb
                      Mar
                                Apr
                                         May
                                                  Jun
                                                            Jul
                                                                     Aug
##
         -0.2571
                  -0.1795
                           -0.2793
                                    -0.3185 -0.4344
                                                       -0.3504
                                                                -0.3009
                                                                  0.0159
                                      0.0162
                                               0.0152
                                                        0.0162
##
          0.0164
                   0.0152
                            0.0159
##
             Sep
                      Oct
                                Nov
                  -0.1258
                           -0.0755
##
         -0.2656
          0.0153
                   0.0165
                             0.0153
## s.e.
##
## sigma^2 estimated as 0.003931: log likelihood = 607.51, aic = -1165.02
```

tsdiag(ar13, gof.lag=20)

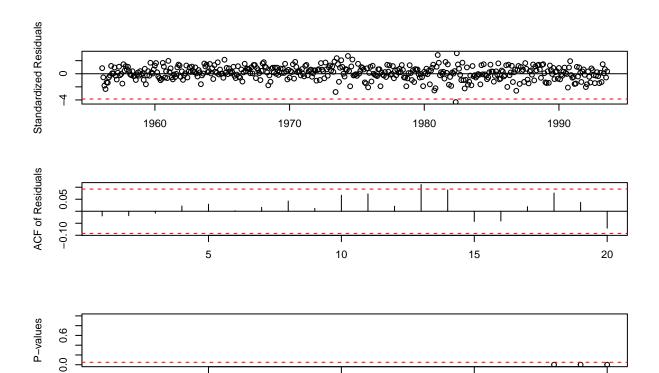


```
ar12ma1<-arima(logBeer, order=c(12,0,1), xreg=monthDummies)
ar12ma1</pre>
```

Call:

```
## arima(x = logBeer, order = c(12, 0, 1), xreg = monthDummies)
##
##
  Coefficients:
##
                      ar2
                                                ar5
                                                       ar6
                                                               ar7
                                                                        ar8
##
         -0.4282
                  0.0770
                           0.1375
                                   0.0634
                                            0.1301
                                                     0.205
                                                            0.0136
                                                                     0.0737
          0.1845
                                    0.0576
                                            0.0494
                                                                     0.0504
##
                   0.0522
                           0.0501
                                                     0.056
                                                           0.0609
##
            ar9
                    ar10
                            ar11
                                                                    Jan
                                     ar12
                                              ma1
                                                    intercept
                                                                             Feb
##
         0.1947
                  0.0575
                          0.1979
                                   0.2726
                                           0.5101
                                                       4.9738
                                                               -0.1927
                                                                         -0.2573
         0.0542
                  0.0593
                          0.0499
                                  0.0503
                                           0.1902
                                                       0.2632
                                                                 0.0151
                                                                          0.0160
##
                                                                       Sep
##
                                          Jun
                                                    Jul
             Mar
                       Apr
                                 May
                                                             Aug
                   -0.2794
##
         -0.1799
                            -0.3189
                                      -0.4344
                                                -0.3507
                                                         -0.3009
                                                                   -0.2659
##
  s.e.
          0.0152
                    0.0157
                             0.0160
                                       0.0150
                                                0.0160
                                                          0.0157
                                                                    0.0153
##
             Oct
                       Nov
##
         -0.1260
                   -0.0757
                    0.0152
          0.0161
##
   s.e.
##
## sigma^2 estimated as 0.003916: log likelihood = 608.36, aic = -1166.72
```

tsdiag(ar12ma1, gof.lag=20)



5

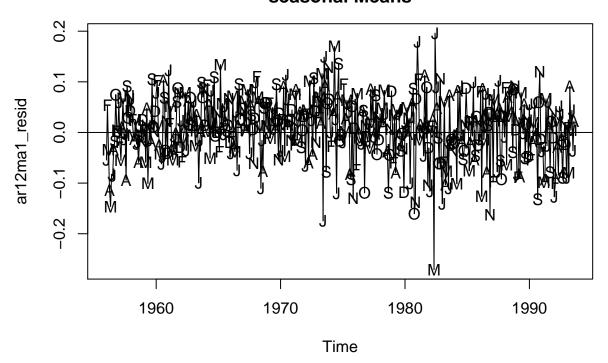
ar12ma1_resid<-ts(residuals(ar12ma1), frequency=12, start=c(1956,1))
plot(ar12ma1_resid, main="AR 12 MA 1 model Residuals from Logged Beer\nseasonal Means", type="l")
points(y=ar12ma1_resid, x=time(ar12ma1_resid), pch=as.vector(season(ar12ma1_resid)))
abline(h=0)</pre>

15

20

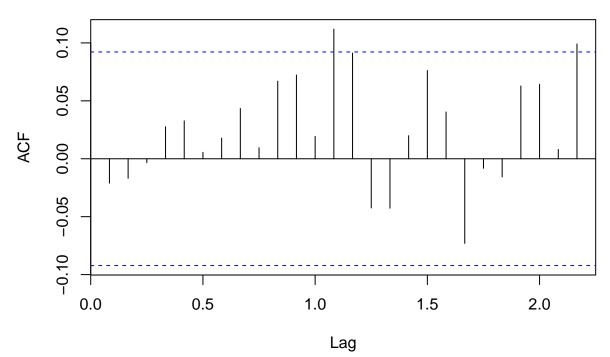
10

AR 12 MA 1 model Residuals from Logged Beer seasonal Means

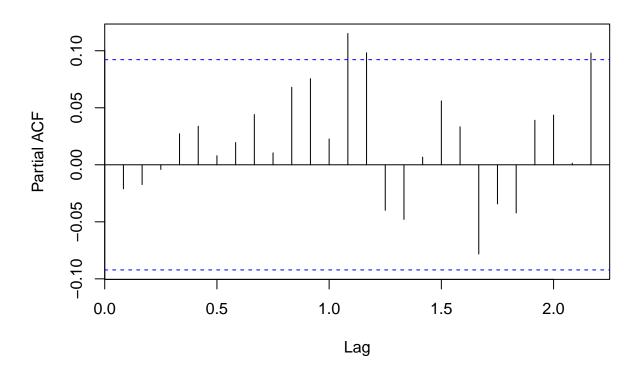


acf(ar12ma1_resid,main="ACF of Residuals from ARIMA(12,0,1)\nwith Seas Trend")

ACF of Residuals from ARIMA(12,0,1) with Seas Trend



PACF of Residuals from ARIMA(12,0,1) with Seas Trend



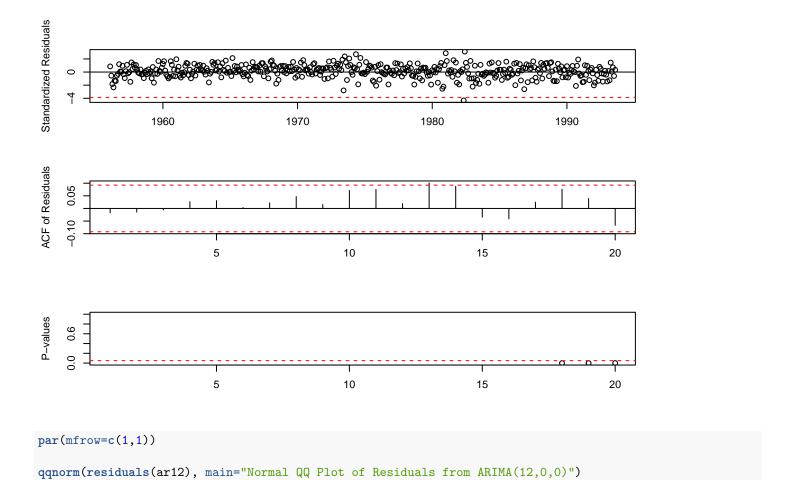
```
ar13ma1<-arima(logBeer, order=c(13,0,1), xreg=monthDummies)
ar13ma1</pre>
```

```
##
## Call:
## arima(x = logBeer, order = c(13, 0, 1), xreg = monthDummies)
##
##
   Coefficients:
##
                                               ar5
                                                                ar7
             ar1
                      ar2
                              ar3
                                       ar4
                                                        ar6
                                            0.1281
                                                             0.0217
                                                                     0.0664
##
         -0.5046
                  0.0793 0.1393
                                   0.0704
                                                    0.2144
                  0.0532
                          0.0517
                                   0.0608
                                            0.0512
                                                    0.0633
                                                             0.0647 0.0565
## s.e.
          0.2870
##
            ar9
                    ar10
                            ar11
                                     ar12
                                             ar13
                                                       ma1
                                                            intercept
##
         0.2012
                  0.0663
                          0.1953
                                  0.2919
                                           0.0248
                                                   0.5841
                                                               4.9734
                                                                       -0.1927
         0.0581
                  0.0642
                          0.0520 0.0780 0.0804
                                                   0.2826
                                                               0.2635
                                                                         0.0152
##
                                          May
##
             Feb
                       Mar
                                Apr
                                                   Jun
                                                             Jul
                                                                      Aug
                   -0.1799
         -0.2573
                            -0.2794
                                      -0.3190
                                               -0.4345
                                                         -0.3507
##
                                                                  -0.3009
##
          0.0161
                    0.0153
                             0.0158
                                      0.0162
                                                0.0151
                                                          0.0162
                                                                   0.0158
   s.e.
##
             Sep
                       Oct
                                 Nov
##
         -0.2660
                   -0.1260
                            -0.0757
## s.e.
          0.0155
                    0.0162
                             0.0153
##
## sigma^2 estimated as 0.003915: log likelihood = 608.41, aic = -1164.82
```

tsdiag(ar13ma1, gof.lag=20)

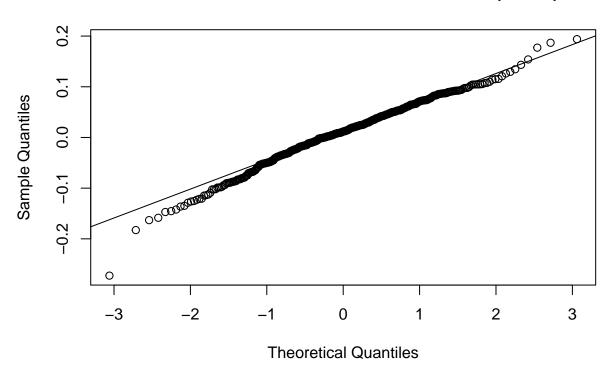
```
Standardized Residuals
                  1960
                                        1970
                                                                                   1990
                                                              1980
ACF of Residuals
    0.05
    -0.10
                            5
                                                 10
                                                                       15
                                                                                            20
P-values
    9.0
    0.0
                            5
                                                 10
                                                                                            20
                                                                       15
ar12ma2<-arima(logBeer, order=c(12,0,2), xreg=monthDummies)
ar12ma2
##
## Call:
## arima(x = logBeer, order = c(12, 0, 2), xreg = monthDummies)
##
## Coefficients:
##
              ar1
                       ar2
                                ar3
                                         ar4
                                                  ar5
                                                           ar6
                                                                   ar7
                                                                            ar8
##
                                                        0.2020
                                                                 0.000
          -0.4094
                    0.1303
                            0.1308
                                      0.0563
                                               0.1201
                                                                         0.0627
                                                        0.0553
                    0.1517
                            0.0528
                                      0.0592
                                               0.0559
                                                                 0.069 0.0581
##
           0.1777
   s.e.
##
                     ar10
                              ar11
                                       ar12
             ar9
                                                 ma1
                                                            ma2
                                                                 intercept
                                    0.2742
                                             0.4882
##
          0.1944
                   0.0460
                            0.1877
                                                       -0.0600
                                                                    4.9731
                                                                             -0.1928
##
          0.0534
                   0.0652
                            0.0571 0.0496 0.1843
                                                        0.1602
                                                                    0.2638
                                                                               0.0152
##
              Feb
                        Mar
                                             May
                                                       Jun
                                                                 Jul
                                                                           Aug
                                   Apr
##
          -0.2573
                    -0.1800
                                        -0.3190
                                                            -0.3508
                                                                      -0.3009
                              -0.2795
                                                  -0.4345
           0.0162
                                         0.0162
                                                              0.0162
## s.e.
                     0.0154
                               0.0159
                                                   0.0151
                                                                        0.0159
##
              Sep
                        Oct
                                   Nov
##
          -0.2660
                    -0.1260
                              -0.0757
## s.e.
           0.0155
                     0.0163
                               0.0153
##
## sigma^2 estimated as 0.003915: log likelihood = 608.43, aic = -1164.85
```

tsdiag(ar12ma2, gof.lag=20)



Normal QQ Plot of Residuals from ARIMA(12,0,0)

qqline(ar12_resid)



```
shapiro.test(ar12_resid)
##
##
    Shapiro-Wilk normality test
##
## data: ar12_resid
## W = 0.98657, p-value = 0.000348
LB.test(ar12, lag=35)
##
##
   Box-Ljung test
##
## data: residuals from ar12
## X-squared = 49.126, df = 23, p-value = 0.001198
pacf_acf<-data.frame(acfVal=acf(ar12_resid, plot=FALSE)$acf, pacfVal=pacf(ar12_resid, plot=FALSE)$acf)
#print(pacf_acf)
```

Make the forecasts- set up external regressor data frame

```
newMonthDummy<-seasonaldummy(beer_forecast)
```

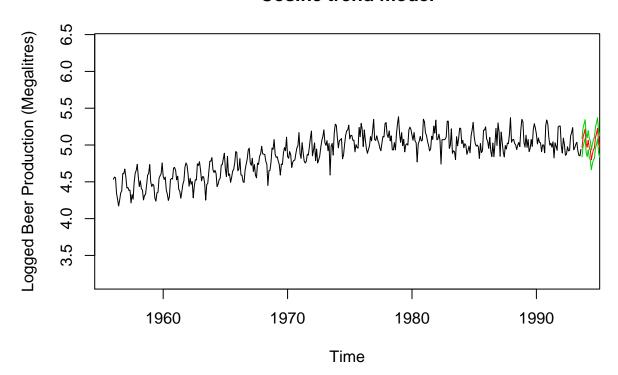
Plot the model forecasts

```
chosenMod<-ar12
predictions<-predict(chosenMod, n.ahead=24,newxreg=newMonthDummy)
pred<-predictions$pred
uci<-pred+2*predictions$se
lci<-pred-2*predictions$se

sumSqErrSeasMean<-sum((log(beer_forecast)-pred)^2)

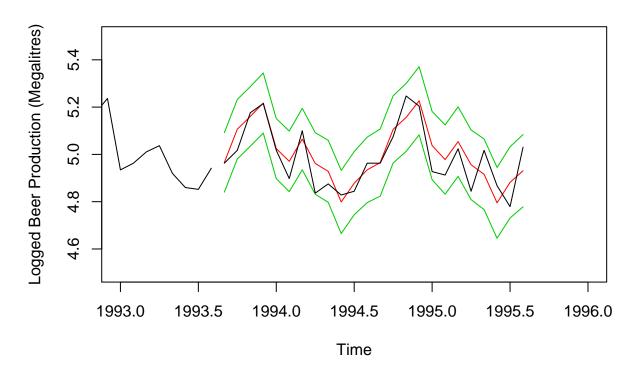
ymin=min(c(as.vector(lci),logBeer))-1
ymax=max(c(as.vector(uci),logBeer))+1
plot(logBeer,ylim=c(ymin,ymax),main=modelString, ylab='Logged Beer Production (Megalitres)')
lines(pred,col=2)
lines(uci,col=3)
lines(lci,col=3)</pre>
```

Cosine trend model



```
ymin=min(c(as.vector(lci),logBeer))-1
ymax=max(c(as.vector(uci),logBeer))+1
plot(logBeer,xlim=c(1993, 1996), ylim=c(4.5,5.5),main=modelString, ylab='Logged Beer Production (Megalitres)')
lines(pred,col=2)
lines(uci,col=3)
lines(lci,col=3)
lines(log(beer_forecast), col="black")
```

Cosine trend model



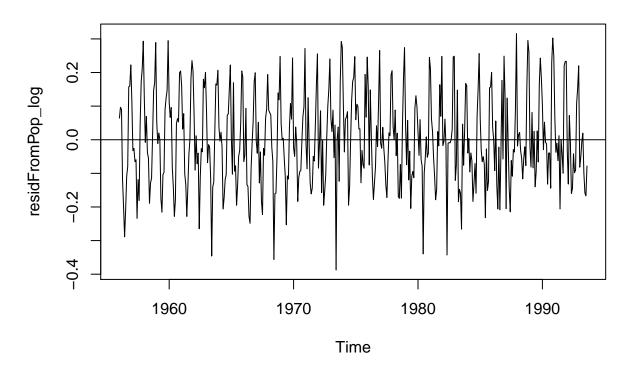
SARIMA model with population data

```
logBeer<-log(beerPopMonth$beer)</pre>
lag6_10_14<-beerPopMonth$lag6_10_14
t<-1:length(beerTS)
t2<-t^2
t3<-t^3
t4<-t^4
externalReg<-data.frame(lag6_10_14, t, t2, t3, t4)
\verb|monthlyPopModel_log<-lm(logBeer ~ lag6_10_14+t+t2+t3+t4)|
monthlyPopOnly_log<-lm(logBeer ~ lag6_10_14)</pre>
summary(monthlyPopModel_log)
##
## Call:
## lm(formula = logBeer ~ lag6_10_14 + t + t2 + t3 + t4)
##
## Residuals:
##
                  1Q
                        Median
                                     3Q
                                             Max
   -0.38742 -0.09499 -0.01169
                               0.08863
##
                                        0.31604
##
## Coefficients:
##
                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)
                4.233e+00
                           1.167e-01
                                      36.286
                                               < 2e-16 ***
                4.122e-07
                           2.091e-07
                                        1.971
                                                0.0493 *
## lag6_10_14
                                      -2.356
## t
               -3.114e-03
                           1.322e-03
                                                0.0189 *
                4.855e-05 8.989e-06
                                        5.401 1.08e-07 ***
## t2
               -1.647e-07 2.938e-08 -5.604 3.67e-08 ***
## t3
## t4
                1.668e-10 3.217e-11
                                       5.185 3.28e-07 ***
```

```
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1357 on 446 degrees of freedom
## Multiple R-squared: 0.748, Adjusted R-squared: 0.7452
## F-statistic: 264.8 on 5 and 446 DF, p-value: < 2.2e-16

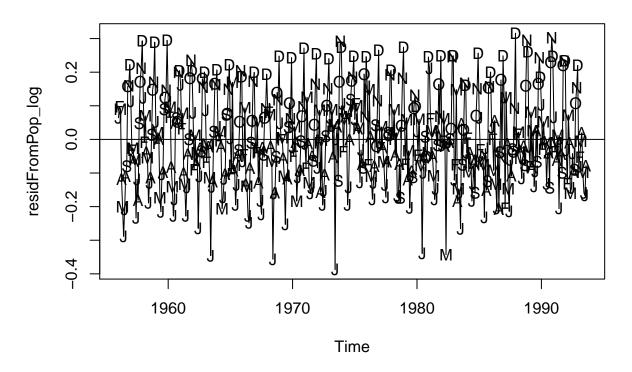
residFromPop_log<-ts(residuals(monthlyPopModel_log), frequency=12, start=c(1956,1))
plot(residFromPop_log, main="Plot of residuals from Pop/Poly Trend logged model")
abline(h=0)</pre>
```

Plot of residuals from Pop/Poly Trend logged model



plot(residFromPop_log, type="1", main="Plot of residuals from Pop/Poly Trend logged model")
points(y=residFromPop_log, x=time(residFromPop_log), pch=as.vector(season(residFromPop_log)))
abline(h=0)

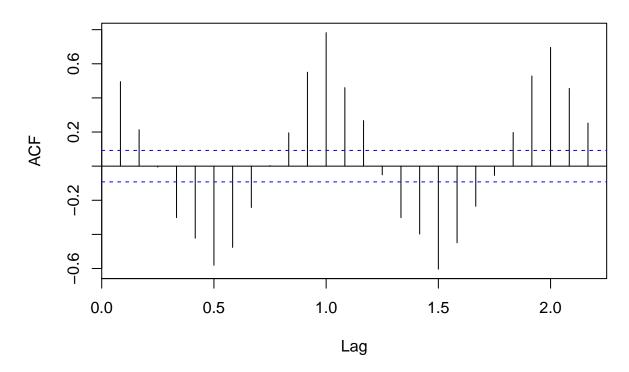
Plot of residuals from Pop/Poly Trend logged model



```
adf.test(residFromPop_log)
## Warning in adf.test(residFromPop_log): p-value smaller than printed p-value
##
   Augmented Dickey-Fuller Test
##
##
## data: residFromPop_log
## Dickey-Fuller = -14.166, Lag order = 7, p-value = 0.01
## alternative hypothesis: stationary
pp.test(residFromPop_log)
## Warning in pp.test(residFromPop_log): p-value smaller than printed p-value
   Phillips-Perron Unit Root Test
##
##
## data: residFromPop_log
## Dickey-Fuller Z(alpha) = -217.82, Truncation lag parameter = 5,
## p-value = 0.01
## alternative hypothesis: stationary
nsdiffs(residFromPop_log, m=frequency(residFromPop_log), test=c("ocsb","ch"), max.D=1)
```

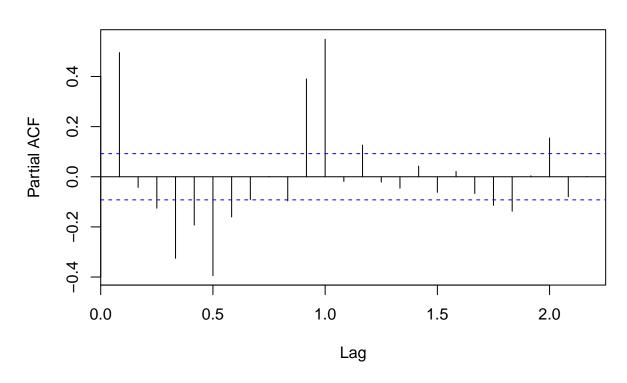
[1] 0

Series residFromPop_log



pacf(residFromPop_log)

Series residFromPop_log

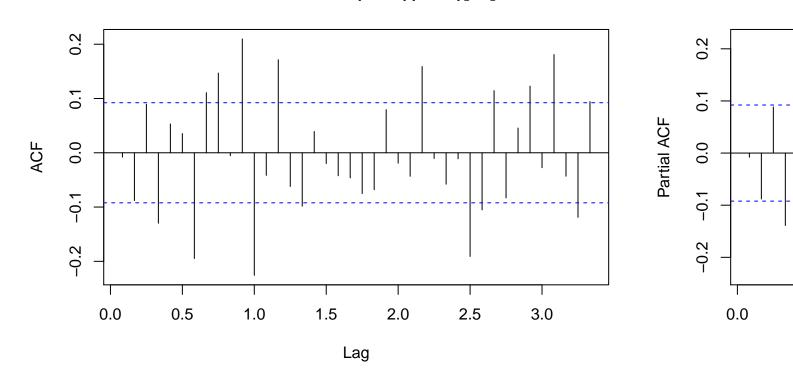


eacf(residFromPop_log)

Build initial model

```
popModel1<-arima(residFromPop_log, order=c(1,0,0), seasonal=list(order=c(1,0,0), period=12))
plotResid(popModel1)</pre>
```

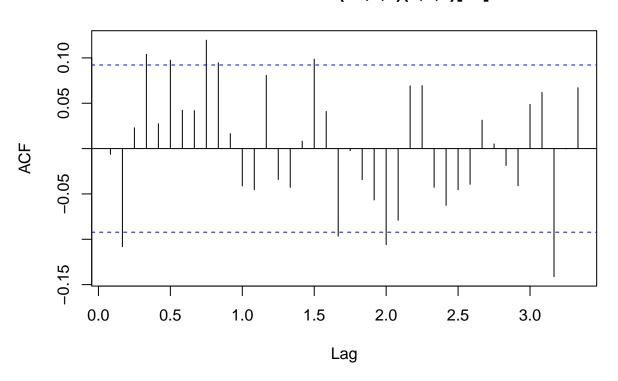
ACF of SARIMA(1,0,0)(1,0,0)[12]

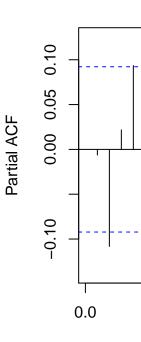


Try p=12 and q=12

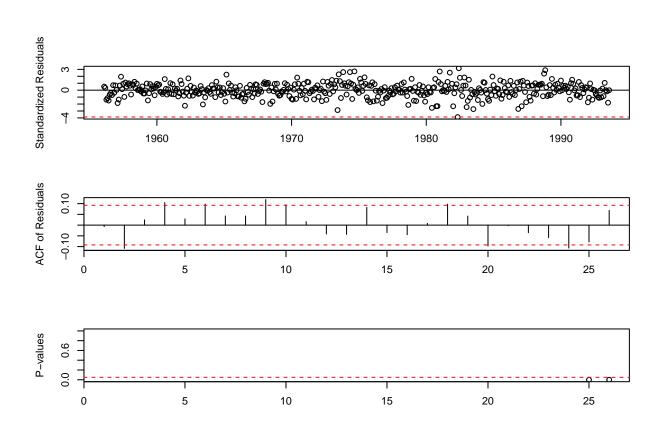
```
popModel2<-arima(residFromPop_log, order=c(12,0,0), seasonal=list(order=c(1,0,0), period=12))
plotResid(popModel2)</pre>
```

ACF of SARIMA(12,0,0)(1,0,0)[12]

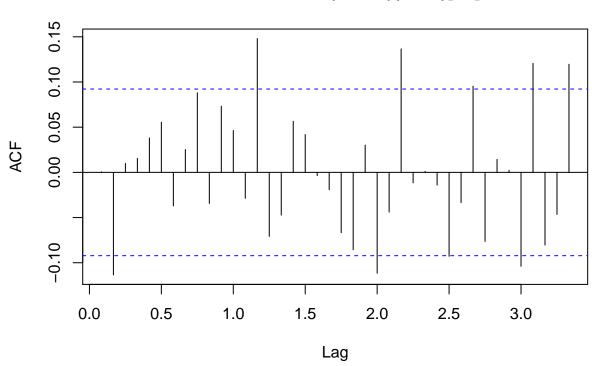


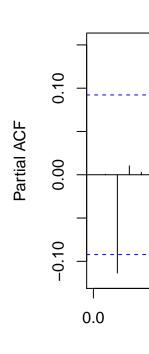


tsdiag(popModel2)

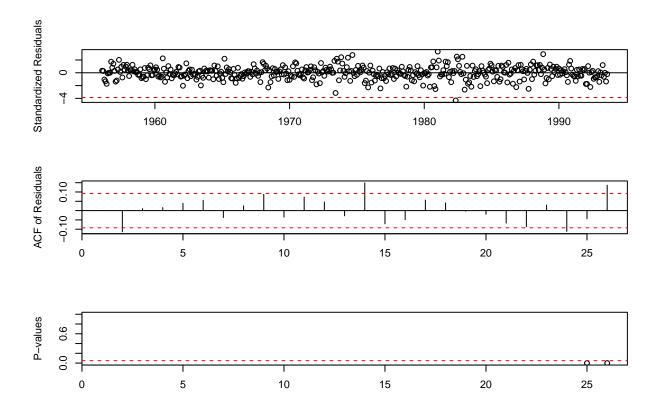


ACF of SARIMA(1,0,12)(1,0,0)[12]





tsdiag(popModel3)



Try overfitting the SARIMA(12,0,0)(1,0,0)[12]

Call:

```
\#popModel4 < -arima(residFromPop_log, order=c(13,0,0), seasonal=list(order=c(1,0,0), period=12))
#Produces error
popModel5<-arima(residFromPop_log, order=c(12,0,1), seasonal=list(order=c(1,0,0), period=12))
popModel5
##
##
   arima(x = residFromPop_log, order = c(12, 0, 1), seasonal = list(order = c(1, 0, 1), seasonal)
##
       0, 0), period = 12))
##
   Coefficients:
##
                                       ar4
                                                ar5
                                                                            ar8
                     ar2
                              ar3
                                                         ar6
                                                                   ar7
##
         0.0083
                  0.0269
                          0.0119
                                   -0.1320
                                            0.1293
                                                     -0.1074
                                                               -0.0709
                                                                        0.0316
         0.0493
                  0.0327
                          0.0295
                                    0.0291
                                            0.0311
                                                      0.0307
                                                                0.0336 0.0299
##
                     ar10
##
                              ar11
                                      ar12
                                                 ma1
                                                         sar1
                                                                intercept
                           0.2063
                                    0.7417
                                             -0.0301
                                                                  -0.0008
##
         0.0174
                  -0.1302
                                                      -0.3180
## s.e.
                   0.0292
                          0.0318
                                    0.0405
                                              0.0825
         0.0296
                                                       0.0528
                                                                   0.0082
##
## sigma^2 estimated as 0.00456: log likelihood = 571, aic = -1112
popModel6<-arima(residFromPop_log, order=c(12,0,0), seasonal=list(order=c(2,0,0), period=12))
popModel6
```

```
## arima(x = residFromPop_log, order = c(12, 0, 0), seasonal = list(order = c(2,
##
       0, 0), period = 12)
##
##
   Coefficients:
##
                                       ar4
                                                ar5
             ar1
                      ar2
                              ar3
                                                        ar6
                                                                 ar7
                                                                         ar8
                  -0.1008
                                                                      0.0549
##
         -0.0548
                           0.0923
                                   -0.0492
                                            0.0658
                                                     0.0729
                                                             -0.0987
                                    0.0460
## s.e.
          0.0500
                   0.0483
                           0.0465
                                            0.0473
                                                     0.0515
                                                              0.0506
                                                                      0.0481
##
            ar9
                    ar10
                            ar11
                                     ar12
                                              sar1
                                                      sar2
                                                            intercept
                                  -0.0683
##
         0.2046
                 -0.0134 0.2072
                                           0.5945
                                                   0.3155
                                                              -0.0092
         0.0470
                  0.0490 0.0491
                                   0.0707
                                           0.0723
                                                  0.0650
## s.e.
                                                               0.0401
##
## sigma^2 estimated as 0.004827: log likelihood = 554.21, aic = -1078.41
popModel7<-arima(residFromPop_log, order=c(12,0,0), seasonal=list(order=c(1,0,1), period=12))
popModel7
##
## Call:
## arima(x = residFromPop_log, order = c(12, 0, 0), seasonal = list(order = c(1,
##
       0, 1), period = 12)
##
## Coefficients:
##
             ar1
                     ar2
                              ar3
                                       ar4
                                                ar5
                                                         ar6
                                                                  ar7
                                                                          ar8
                                                                       0.0234
##
         -0.0127
                  0.0180
                          -0.0031
                                   -0.0785
                                            0.0743
                                                    -0.0670
                                                              -0.0219
## s.e.
          0.0197
                  0.0219
                           0.0183
                                    0.0284
                                            0.0339
                                                      0.0244
                                                               0.0232
                                                                       0.0226
##
             ar9
                     ar10
                             ar11
                                     ar12
                                              sar1
                                                       sma1
                                                             intercept
##
         -0.0127
                  -0.0726
                           0.0907
                                   0.9079
                                           0.1563
                                                    -0.7465
                                                                0.0008
## s.e.
          0.0183
                   0.0273 0.0418
                                  0.0390
                                           0.0779
                                                     0.1105
                                                                0.0056
##
## sigma^2 estimated as 0.004344: log likelihood = 580.28,
                                                              aic = -1130.57
Overfit model 7 (SARIMA(12,0,0)(1,0,1)[12])
popModel8<-arima(residFromPop_log, order=c(13,0,0), seasonal=list(order=c(1,0,1), period=12))
```

```
popModel8
##
## Call:
## arima(x = residFromPop_log, order = c(13, 0, 0), seasonal = list(order = c(1,
##
       0, 1), period = 12))
##
## Coefficients:
## Warning in sqrt(diag(x$var.coef)): NaNs produced
##
                                                                             ar8
              ar1
                     ar2
                              ar3
                                        ar4
                                                ar5
                                                          ar6
                                                                    ar7
         -0.0600
                          0.0068
                                   -0.0947
##
                   0.016
                                             0.0988
                                                      -0.0754
                                                                -0.0276
                                                                         0.0322
          0.0056
                          0.0037
                                             0.0047
                                                                 0.0033
##
   s.e.
                     NaN
                                        {\tt NaN}
                                                          NaN
                                                                            NaN
##
              ar9
                      ar10
                               ar11
                                        ar12
                                                ar13
                                                         sar1
                                                                   sma1
                                                                         intercept
                                                       0.0909
                                                               -0.6295
##
         -0.0027
                   -0.0964 0.1196
                                     0.8842
                                              0.0480
                                                                            -0.0015
                    0.0013 0.0071
                                                                            0.0076
## s.e.
          0.0040
                                         NaN
                                              0.0038
                                                          \mathtt{NaN}
                                                                 0.0345
##
## sigma^2 estimated as 0.004419: log likelihood = 577.49, aic = -1122.98
```

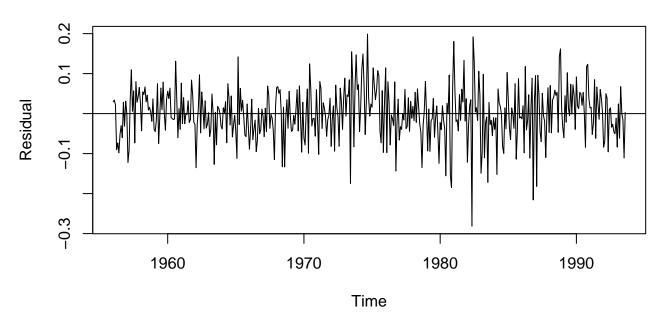
```
popModel9<-arima(residFromPop_log, order=c(12,0,1), seasonal=list(order=c(1,0,1), period=12))
popModel9
##
## Call:
## arima(x = residFromPop_log, order = c(12, 0, 1), seasonal = list(order = c(1,
##
       0, 1), period = 12)
##
   Coefficients:
##
##
             ar1
                      ar2
                              ar3
                                       ar4
                                               ar5
                                                         ar6
                                                                  ar7
                                                                          ar8
##
         -0.0005 0.0087 0.0001
                                  -0.0702 0.0667
                                                    -0.0649
                                                              -0.0088
                                                                       0.0146
## s.e.
                                    0.0292
          0.0208
                  0.0219
                          0.0179
                                            0.0380
                                                      0.0268
                                                               0.0226
                                                                       0.0234
##
             ar9
                     ar10
                              ar11
                                      ar12
                                                ma1
                                                        sar1
                                                                 sma1
##
         -0.0089
                  -0.0649 0.0790 0.9158
                                            -0.0730
                                                     0.1851
                                                              -0.7909
## s.e.
          0.0180
                   0.0279 0.0451 0.0412
                                             0.0561
                                                     0.0748
                                                               0.1079
##
         intercept
##
            0.0009
            0.0051
## s.e.
##
## sigma^2 estimated as 0.004323: log likelihood = 581.08, aic = -1130.15
popModel10<-arima(residFromPop_log, order=c(12,0,0), seasonal=list(order=c(2,0,1), period=12))
popModel10
##
## Call:
  arima(x = residFromPop_log, order = c(12, 0, 0), seasonal = list(order = c(2,
##
       0, 1), period = 12)
##
## Coefficients:
##
             ar1
                      ar2
                               ar3
                                        ar4
                                                ar5
                                                         ar6
                                                                  ar7
                                                                          ar8
##
         -0.0246
                  -0.0221
                           0.0663
                                   -0.0715
                                             0.0796
                                                     0.0831
                                                              -0.1084
                                                                       0.0583
## s.e.
          0.0482
                   0.0505
                           0.0453
                                     0.0447
                                             0.0451
                                                      0.0482
                                                               0.0472
                                                                       0.0457
##
            ar9
                    ar10
                             ar11
                                     ar12
                                             sar1
                                                      sar2
                                                               sma1
                                                                     intercept
##
         0.1370
                 -0.0217
                          0.2249
                                   0.2416
                                           0.9178
                                                   0.0803
                                                            -0.9069
                                                                       -0.0014
## s.e. 0.0492
                  0.0478 0.0462 0.1065 0.1056
                                                   0.1054
                                                             0.0335
                                                                        0.0711
##
## sigma^2 estimated as 0.003779: log likelihood = 602.36, aic = -1172.72
popModel11<-arima(residFromPop_log, order=c(12,0,0), seasonal=list(order=c(1,0,2), period=12))
popModel11
##
## Call:
## arima(x = residFromPop_log, order = c(12, 0, 0), seasonal = list(order = c(1,
##
       0, 2), period = 12)
##
## Coefficients:
##
             ar1
                     ar2
                               ar3
                                        ar4
                                                ar5
                                                          ar6
                                                                   ar7
                                                                            ar8
##
                  0.0179
                          -0.0020
                                             0.0729
                                                               -0.0217
         -0.0124
                                    -0.0773
                                                     -0.0658
                                                                        0.0232
## s.e.
          0.0196
                  0.0227
                            0.0183
                                     0.0296
                                             0.0363
                                                       0.0253
                                                                0.0236
                                                                        0.0236
##
             ar9
                     ar10
                              ar11
                                      ar12
                                               sar1
                                                         sma1
                                                                  sma2
##
         -0.0118
                  -0.0710 0.0892
                                    0.9091
                                            -0.0100
                                                     -0.5788
                                                               -0.1180
##
          0.0183
                   0.0283 0.0448 0.0413
                                             0.3515
                                                       0.3665
                                                                0.2292
##
         intercept
            0.0010
##
## s.e.
            0.0057
##
## sigma^2 estimated as 0.004342: log likelihood = 580.41, aic = -1128.83
```

Run diagnostics on model 7

```
chosenMod<-popModel7
modelString<-paste(getModelString(chosenMod), "with Population Data")

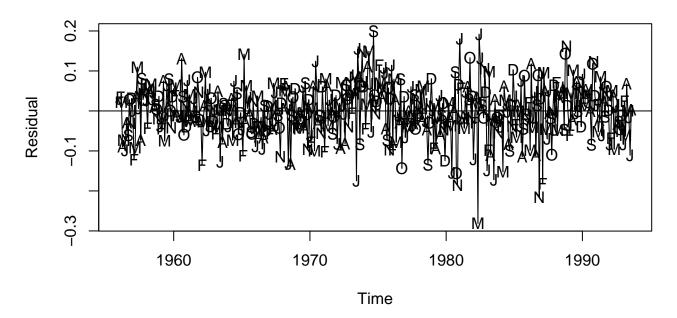
par(mfrow=c(1,1))
plot(residuals(chosenMod), main=paste("Residuals of Model", modelString), ylab="Residual")
abline(h=0)</pre>
```

Residuals of Model SARIMA(12,0,0)(1,0,1)[12] with Population Data



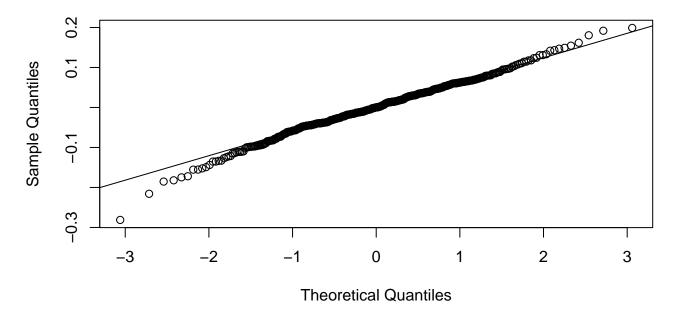
par(mfrow=c(1,1))
plot(residuals(chosenMod), main=paste("Residuals of Model", modelString), ylab="Residual", type="l")
points(y=residuals(chosenMod), x=time(residuals(chosenMod)), pch=as.vector(season(residuals(chosenMod))))
abline(h=0)

Residuals of Model SARIMA(12,0,0)(1,0,1)[12] with Population Data



```
par(mfrow=c(1,1))
qqnorm(residuals(chosenMod), main=paste("Normal QQ Plot of Residuals from", modelString))
qqline(residuals(chosenMod))
```

Normal QQ Plot of Residuals from SARIMA(12,0,0)(1,0,1)[12] with Population



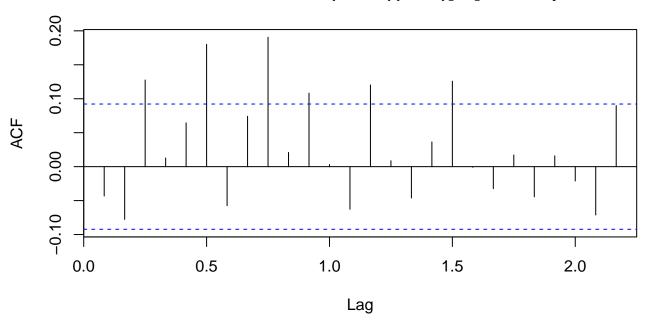
```
shapiro.test(residuals(chosenMod))
```

```
##
## Shapiro-Wilk normality test
##
```

```
## data: residuals(chosenMod)
## W = 0.9911, p-value = 0.008028

par(mfrow=c(1,1))
acf(residuals(chosenMod), main=paste("ACF of Residuals from", modelString))
```

ACF of Residuals from SARIMA(12,0,0)(1,0,1)[12] with Population Data



LB.test(chosenMod, lag=35)

```
##
## Box-Ljung test
##
## data: residuals from chosenMod
## X-squared = 87.347, df = 21, p-value = 4.611e-10
```

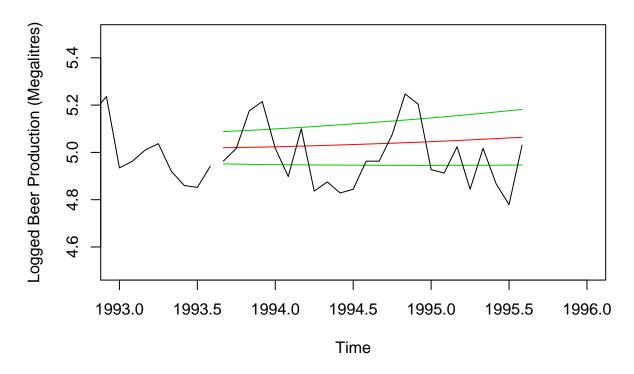
runs(residuals(chosenMod))

```
## $pvalue
## [1] 0.963
##
## $observed.runs
##
   [1] 227
##
## $expected.runs
  [1] 226.9956
##
##
## $n1
##
  [1] 225
##
## $n2
##
   [1] 227
##
## $k
## [1] 0
```

Set up for forecast of population model

```
startDate<-round(start(beer_forecast)[1]+start(beer_forecast)[2]/12,2)</pre>
endDate<-round(end(beer forecast)[1]+end(beer forecast)[2]/12,2)
numToFor<-length(beer_forecast)</pre>
allBeerData<-ts(c(beerTS, beer_forecast), start=c(1956, 1), frequency=12)
#Pull data for population
lag6_10_14new<-subset(monthlyLag6Long, as.numeric(rownames(monthlyLag6Long))>=startDate)
lag6_10_14new<-subset(lag6_10_14new, as.numeric(rownames(lag6_10_14new))<=endDate)
tnew<-1:length(allBeerData)</pre>
t2new<-tnew^2
t3new<-tnew<sup>3</sup>
t4new<-tnew<sup>4</sup>
newRegData<-data.frame(t=tnew, t2=t2new, t3=t3new, t4=t4new)
newRegData<-newRegData[(nrow(newRegData)-numToFor+1):nrow(newRegData),]</pre>
newRegData<-data.frame(lag6_10_14=lag6_10_14new, newRegData)
colnames(newRegData)<-c("lag6_10_14", colnames(newRegData)[2:5])
predFromPop<-predict(monthlyPopModel_log, newdata=newRegData, se.fit=TRUE)</pre>
\label{local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_local_loc
lci_lm<-ts(predFromPop$fit-2*predFromPop$se.fit, start=c(1993, 9), frequency = 12)</pre>
ymin=min(c(as.vector(lci),logBeer))-1
ymax=max(c(as.vector(uci),logBeer))+1
plot(logBeer,xlim=c(1993, 1996), ylim=c(4.5,5.5),main=modelString, ylab='Logged Beer Production (Megalitres)')
lines(ts(predFromPop$fit, start=c(1993, 9), frequency = 12),col=2)
lines(uci_lm,col=3)
lines(lci_lm,col=3)
lines(log(beer_forecast), col="black")
```

SARIMA(12,0,0)(1,0,1)[12] with Population Data



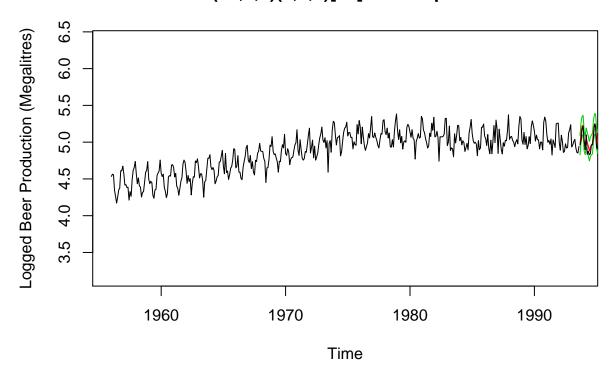
Plot the model forecasts

```
predictions<-predict(chosenMod, n.ahead=24)

pred_raw<-(predictions$pred+predFromPop$fit)
pred<-predictions$pred+predFromPop$fit
uci<-pred_raw+2*predictions$se
lci<-pred_raw-2*predictions$se
uci_lm<-pred_raw-2*(predictions$se+predFromPop$se.fit)
lci_lm<-pred_raw-2*(predictions$se+predFromPop$se.fit)
sumSqErrSARIMA<-sum((log(beer_forecast)-pred)^2)

ymin=min(c(as.vector(lci),logBeer))-1
ymax=max(c(as.vector(uci),logBeer))+1
plot(logBeer,ylim=c(ymin,ymax),main=modelString, ylab='Logged Beer Production (Megalitres)')
lines(pred,col=2)
lines(uci,col=3)
lines(lci,col=3)
lines(log(beer_forecast), col="black")</pre>
```

SARIMA(12,0,0)(1,0,1)[12] with Population Data



```
ymin=min(c(as.vector(lci),log(beer_forecast)))-0.1
ymax=max(c(as.vector(uci),log(beer_forecast)))+0.1
plot(logBeer,xlim=c(1993, 1996), ylim=c(ymin,ymax),main=modelString, ylab='Logged Beer Production (Megalitres)
lines(pred,col=2)
lines(uci,col=3)
lines(lci,col=3)
lines(uci_lm,col="blue")
lines(lci_lm,col="blue")
lines(log(beer_forecast), col="black")
```

SARIMA(12,0,0)(1,0,1)[12] with Population Data

