Final Project

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April 9, 2016

Notes: Possible source of population data: http://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/3105.0.65.0012014?OpenDocument

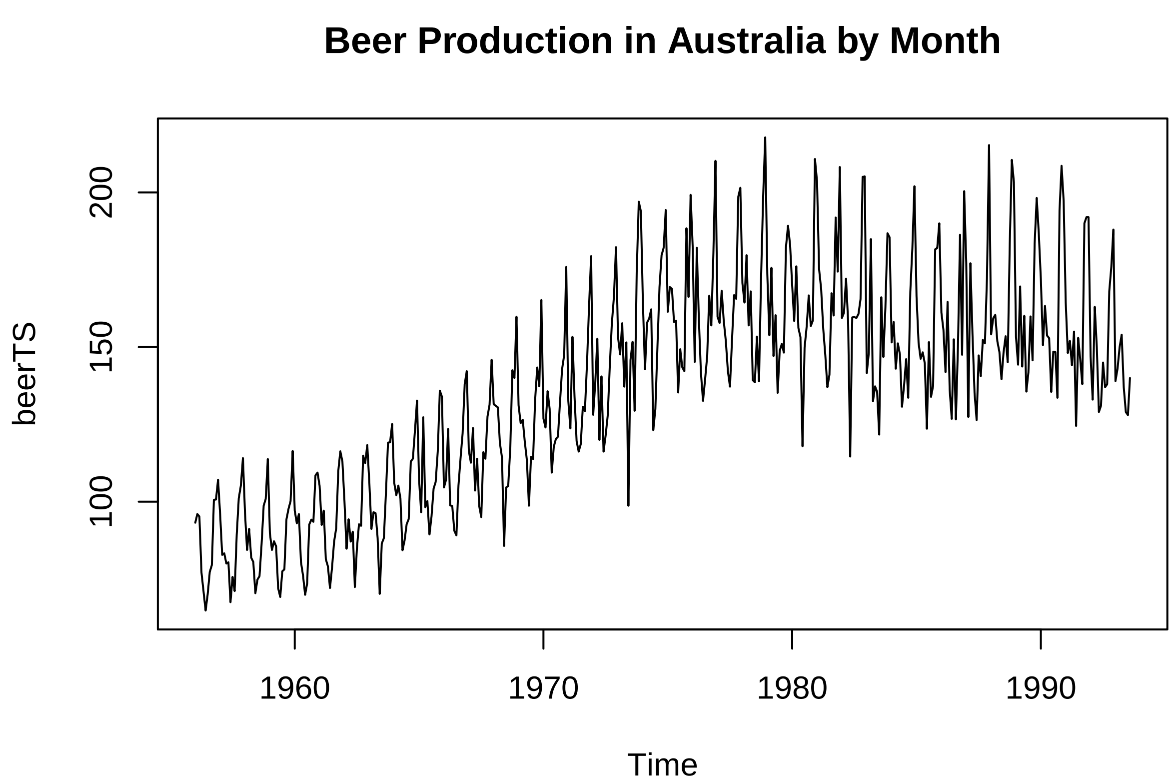
Change working directory here

Load data (assumes file is in working directory)

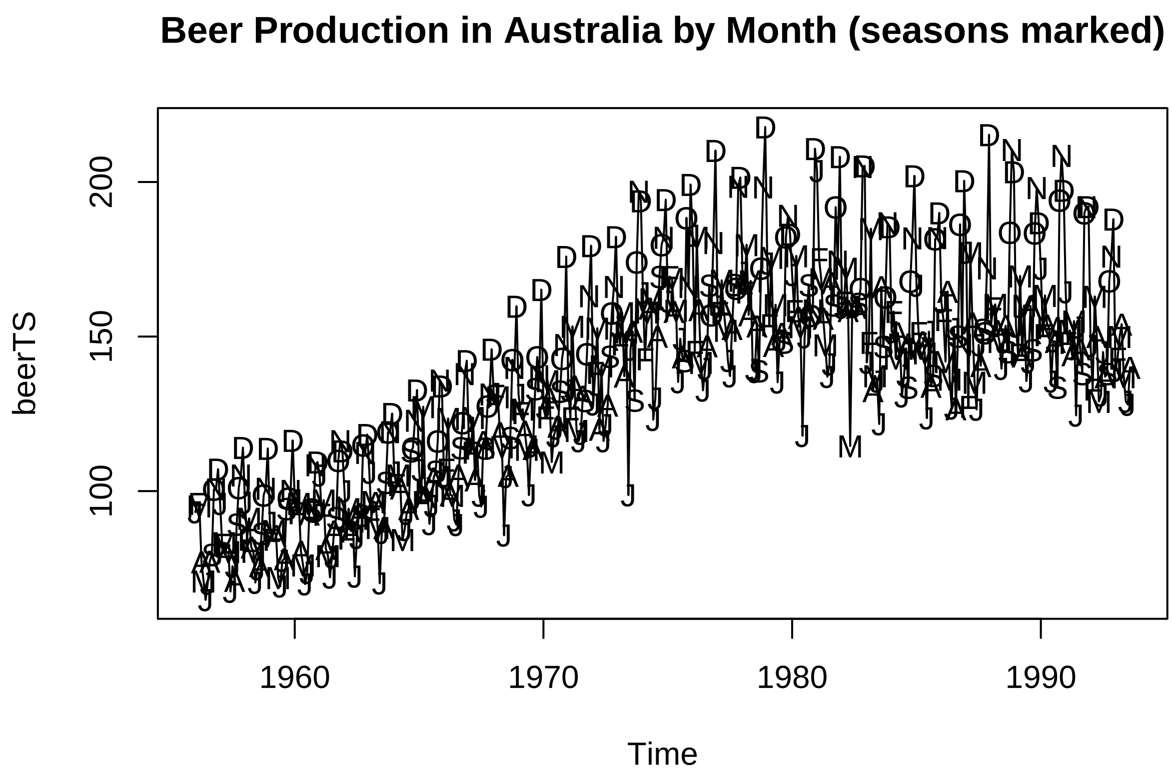
```r
#load the data
beerData<-read.csv("monthly-beer-production-in-austr.csv")

#cut off the last row which is NA
beerData<-beerData[-nrow(beerData),]
colnames(beerData)<-c("Month", "Production")

#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)
```

Plot data

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

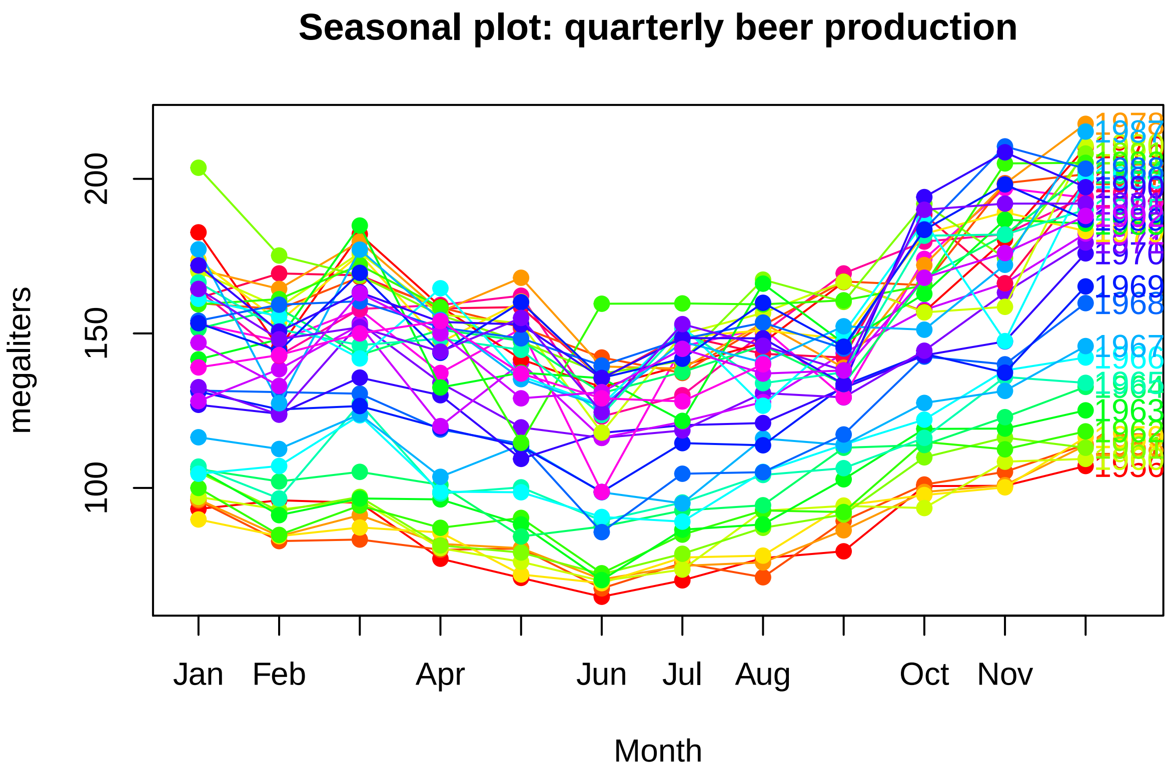


```r
plot(beerTS, main="Beer Production in Australia by Month (seasons marked)", type="l")
points(y=beerTS, x=time(beerTS), pch=as.vector(season(beerTS)))
```



Another plot to show seasonality

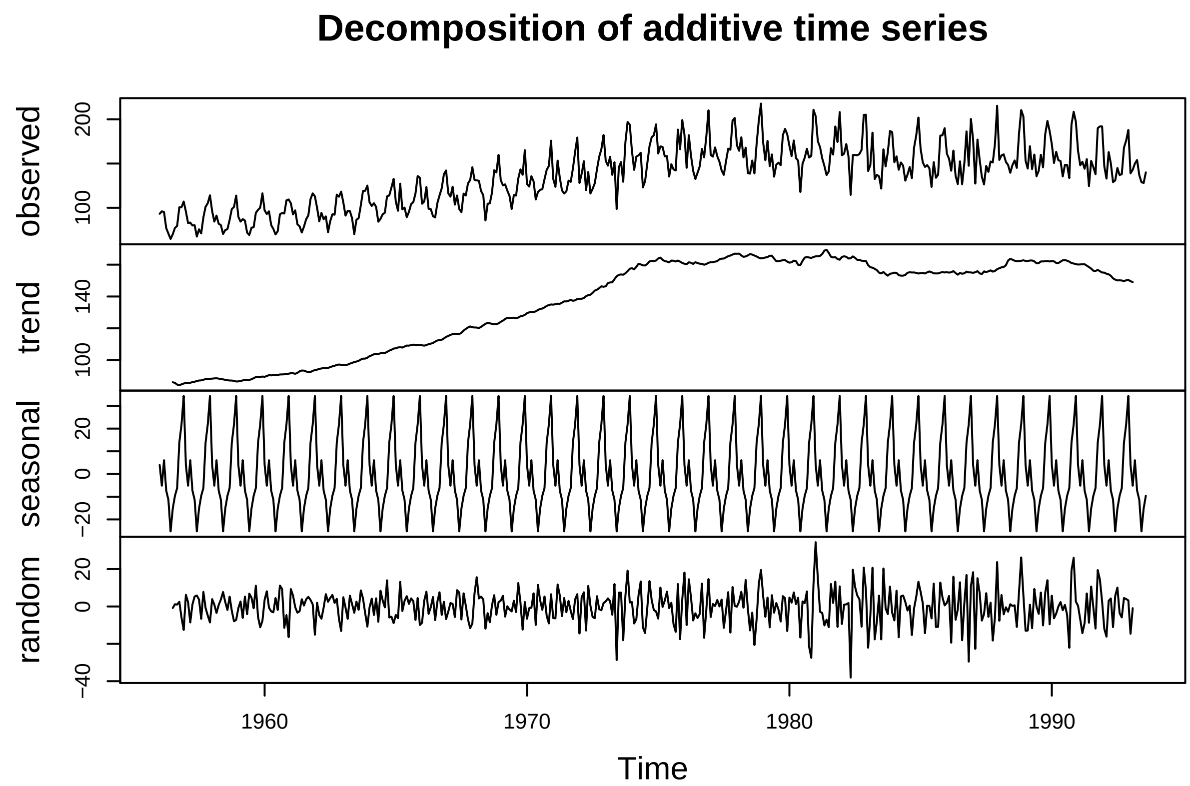
```r
require(fpp)
seasonplot(beerTS,year.labels=TRUE,ylab="megaliters",main="Seasonal plot: quarterly beer production", col=rain
```



In the plot we see obvious seasonality with higher production in November and December and lower production in June and July. There is a trend which may be difficult to fit as it doesn't appear to be a "well known" function like a linear or quadratic function, so we'll have to experiment. It also looks like the variance of the data is larger in the middle, so we will probably want to take the log of our data to correct that varaince issue.

Decompsing the time series to see trends and patterns

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



by looking at the decomposed figures,i was wondering what if we plot a harmonic function with a quadradit polynomial… like imposing a sine curve with 2nd order poly ?

Investigate possible relationship with population data

```
#load population data
library(reshape)
```

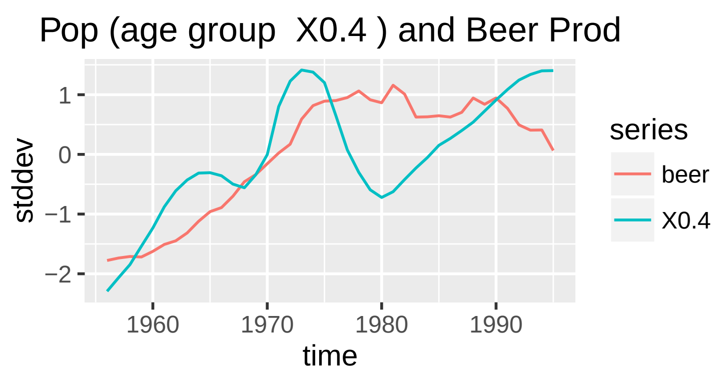
```
## Warning: package 'reshape' was built under R version 3.2.5
```

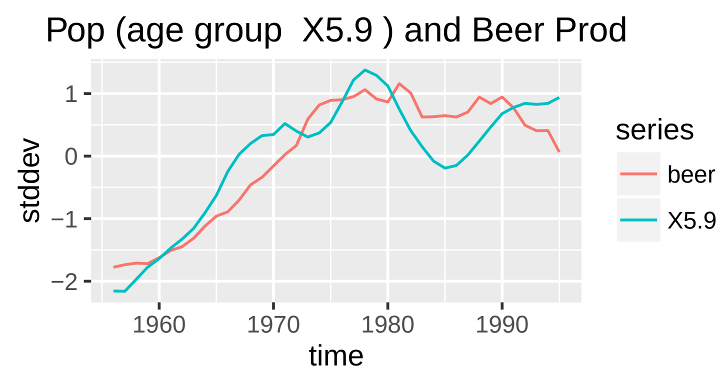
```
library(ggplot2)
```

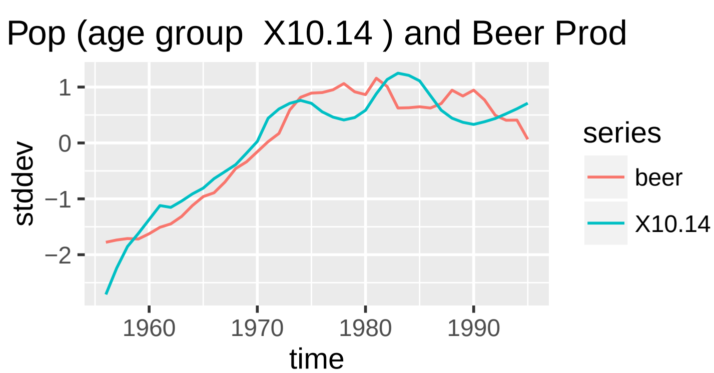
```
## Warning: package 'ggplot2' was built under R version 3.2.5
```

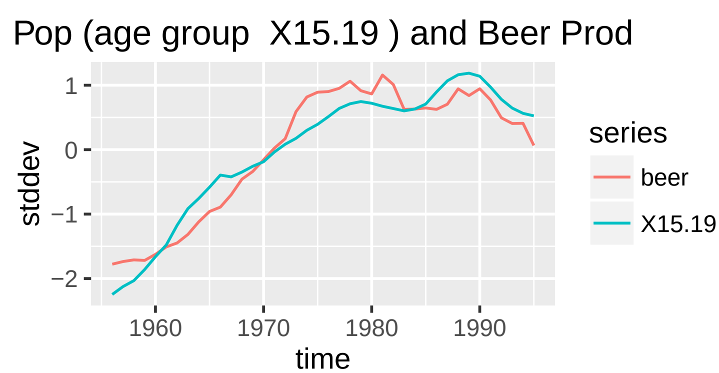
```
#Clean up population data
pop_totalData<-t(read.csv("Pop_total.csv", row.names=1))
dropCols<-colnames(pop_totalData) %in% c("Unspecified","Period not indicated")
rownames(pop_totalData)<-c(1921:2011)
pop_totalDataLong<-pop_totalData[,!dropCols]
pop_totalData<-pop_totalData[paste(1956:1995),!dropCols]

#Aggregate beer data
beerYear<-seq(from=1956, to=1996, by=1)
beerYear<-rep(beerYear, each=12)
beerYear<-beerYear[1:nrow(beerData)]
beerAg<-aggregate(beerData[,2], FUN=mean, by=list(year=beerYear))

#Attach to beer data
```

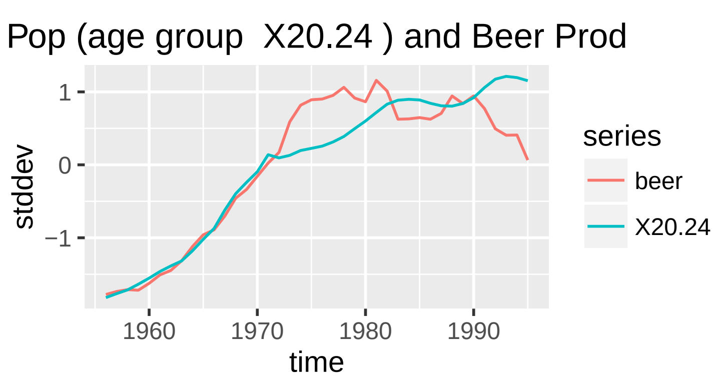
```
beerPop<-data.frame(cbind(beer=beerAg[,2],pop_totalData))
beerPopScale<-scale(beerPop)

beerPopRes<-melt(beerPopScale, variable.name="series")
colnames(beerPopRes)<-c("time", "series", "stddev")

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))
  newPlot<-ggplot(subset_data, aes(time,stddev)) + geom_line(aes(colour = series)) +ggtitle(paste("Pop (age gr
  print(newPlot)
}
```

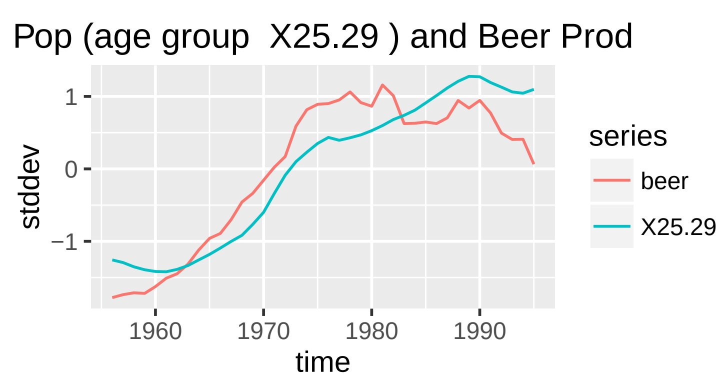


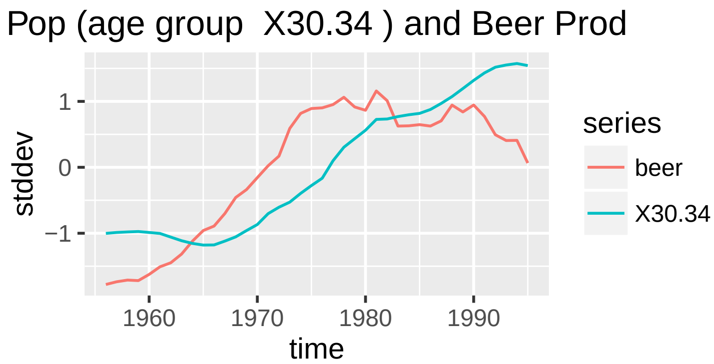


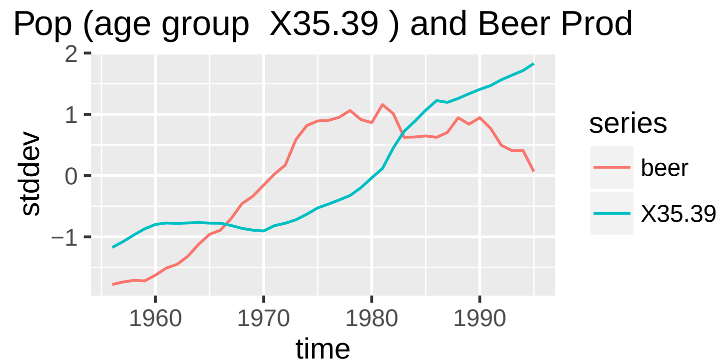


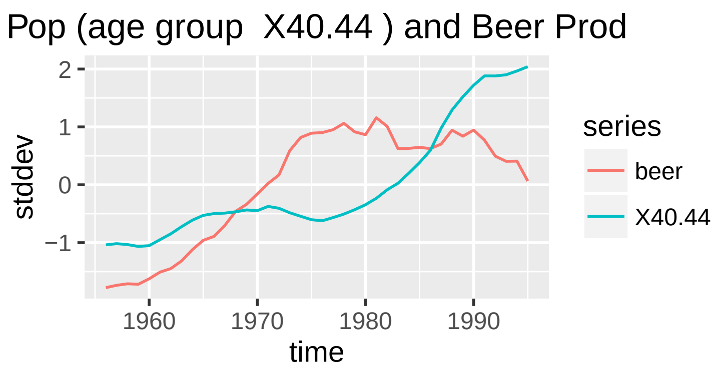


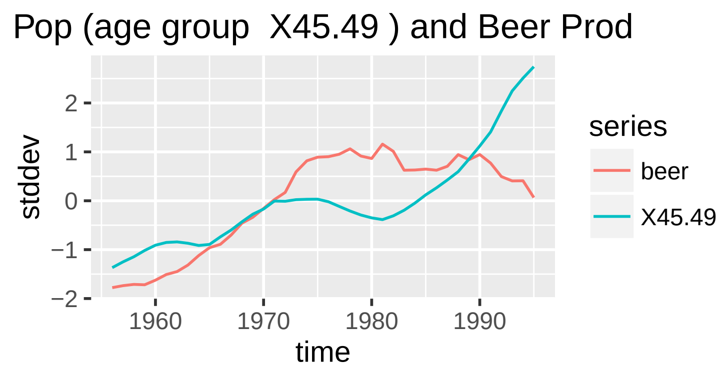


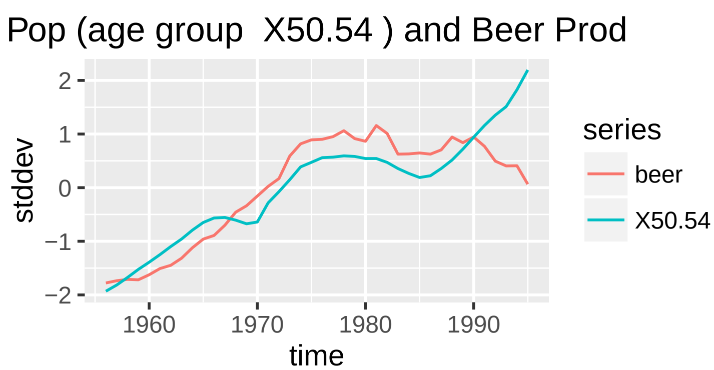


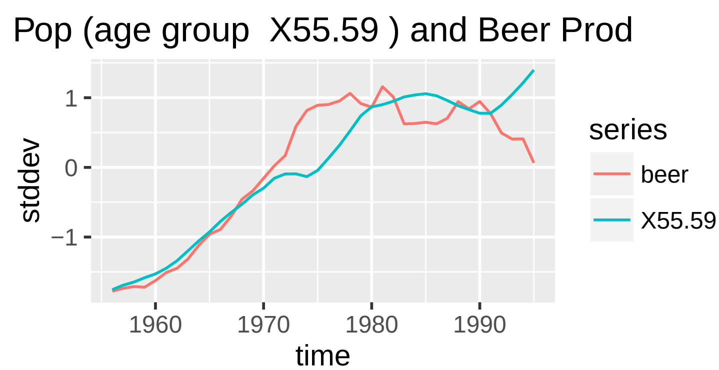

Pop (age group X30.34) and Beer Prod
stddev
1
0
−1
1960
1970
1980
1990
time
series
beer
X30.34

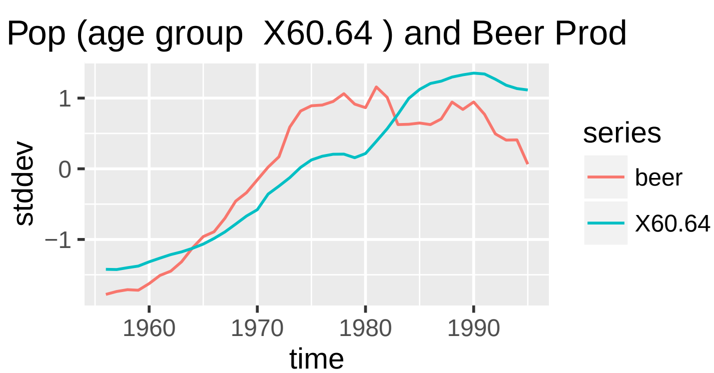

Pop (age group X35.39) and Beer Prod
stddev
2
1
0
−1
1960
1970
1980
1990
time
series
beer
X35.39

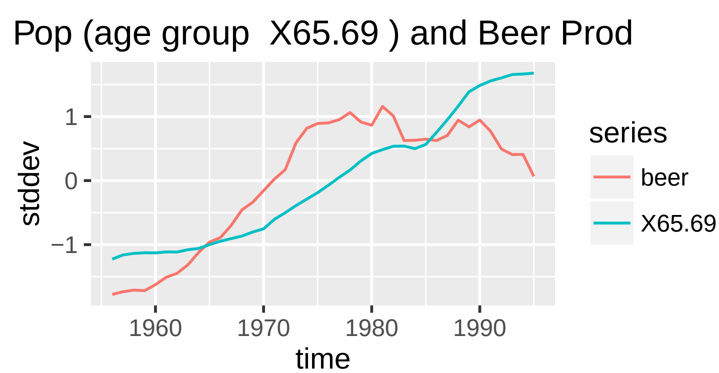

Pop (age group X40.44) and Beer Prod
stddev
2
1
0
−1
1960
1970
1980
1990
time
series
beer
X40.44

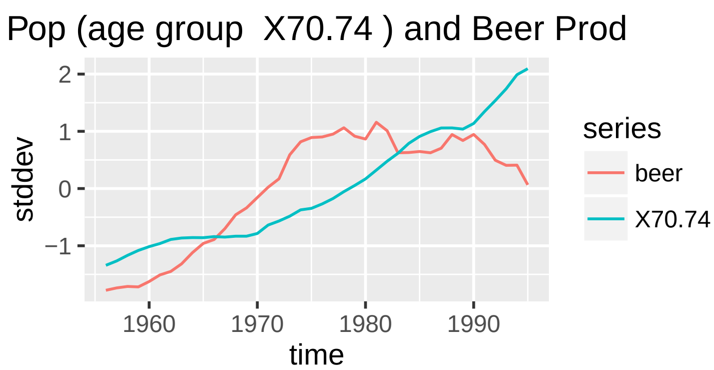

Pop (age group X45.49) and Beer Prod
stddev
2
1
0
−1
−2
1960
1970
1980
1990
time
series
beer
X45.49

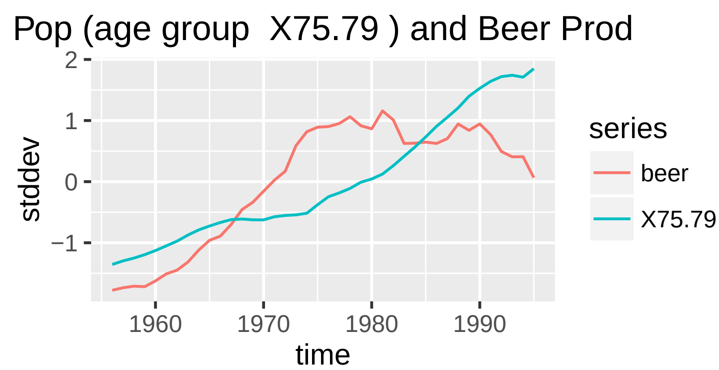

Pop (age group X50.54) and Beer Prod
stddev
2
1
0
−1
−2
1960
1970
1980
1990
time
series
beer
X50.54

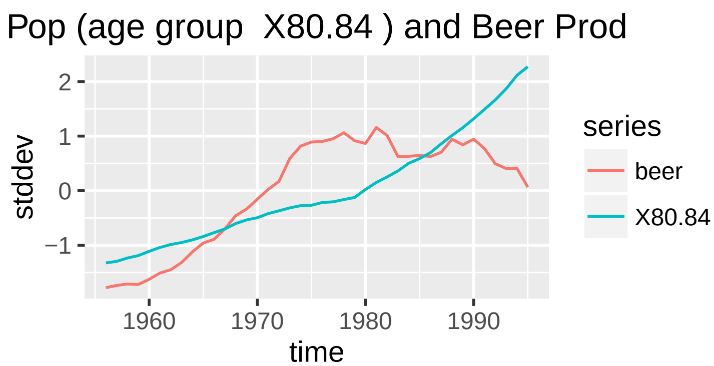

Pop (age group X55.59) and Beer Prod
stddev
1
0
−1
1960
1970
1980
1990
time
series
beer
X55.59

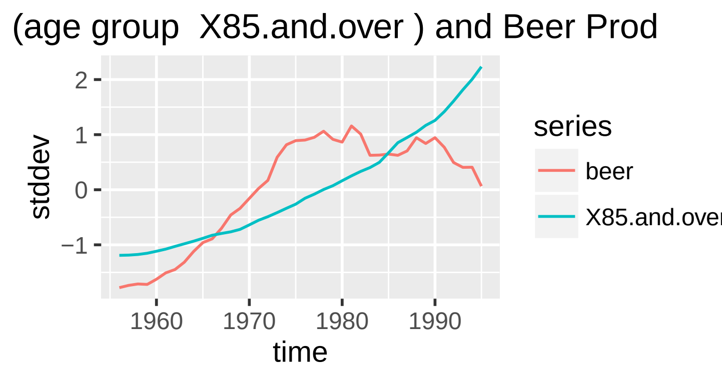

Pop (age group X60.64) and Beer Prod
stddev
1
0
−1
1960
1970
1980
1990
time
series
beer
X60.64

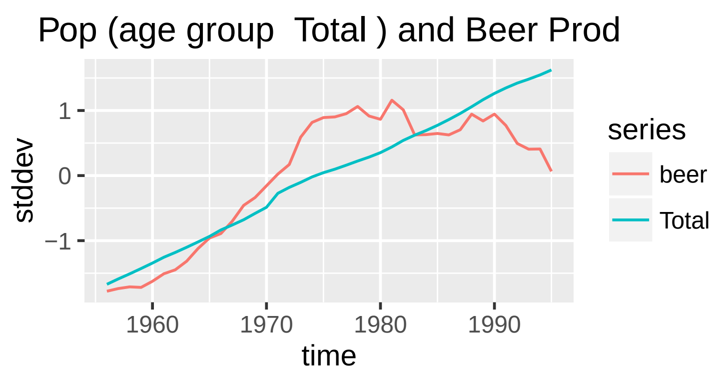

Pop (age group X65.69) and Beer Prod
stddev
1
0
−1
1960
1970
1980
1990
time
series
beer
X65.69









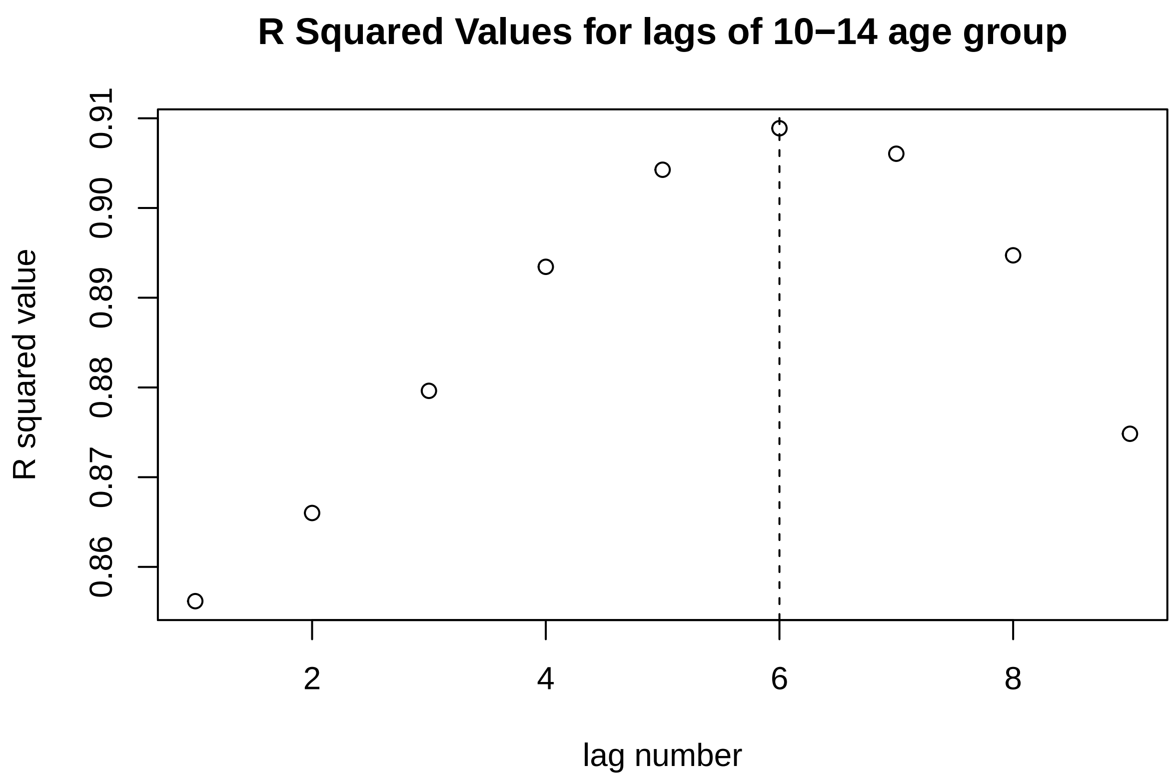



```
par(mfrow=c(1,1))

#Make a model based on the 15-19 age group
yearModel1<-lm(beer ~ X15.19, data=beerPop)
```

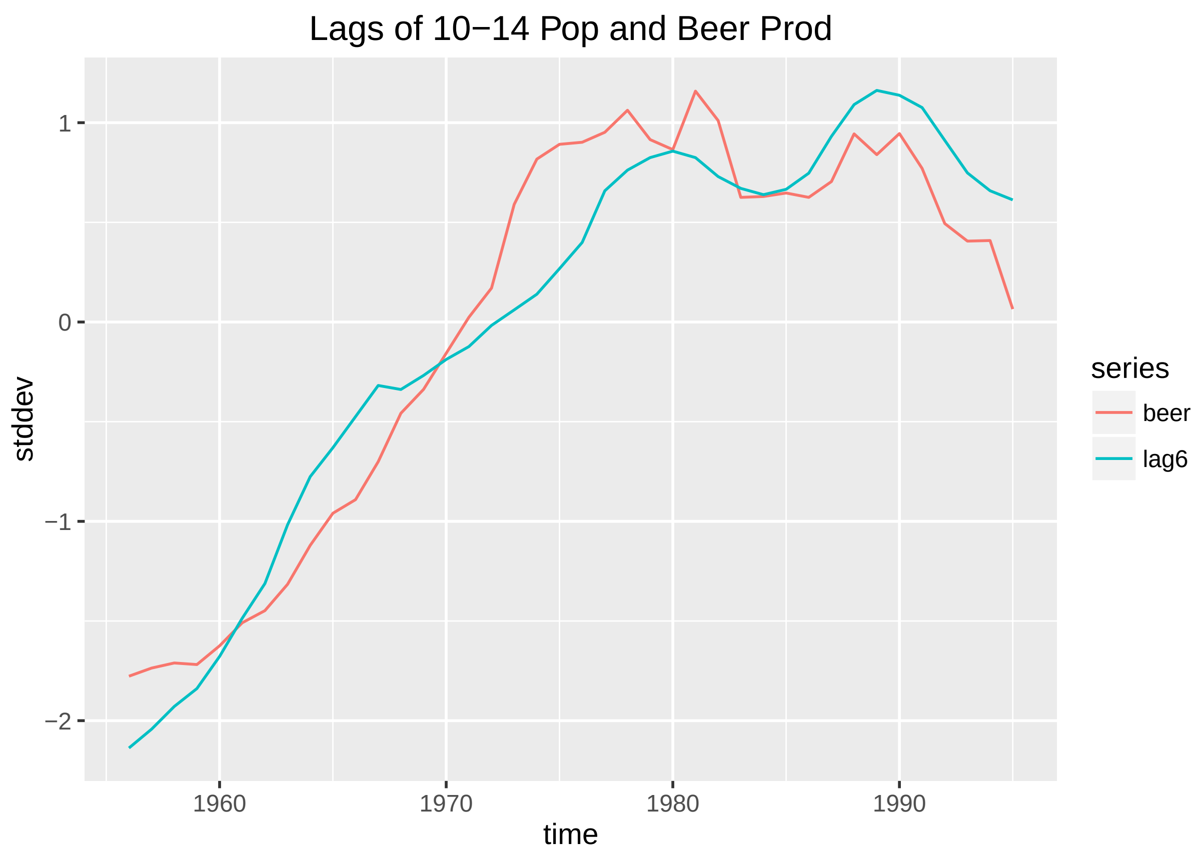
It appears that there may be a relationship with the 15-19 age block, which makes sense since the legal drinking age is 18. We may be able to use this to remove some of our trend. However, the 10-14 age group numbers look like they might have potential if shifted forward a few years. This makes sense since these children will grow up and start drinking beer.

```
#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
```

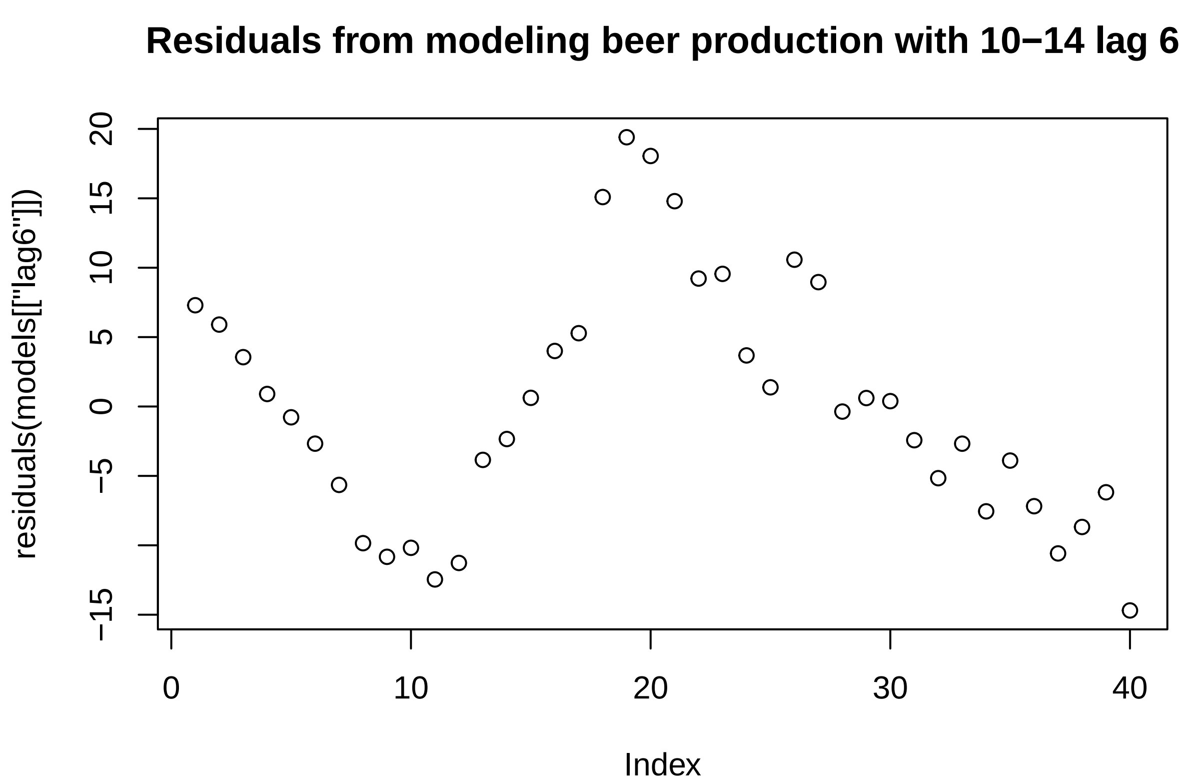
```
}

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)
```




```
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)
```




```r
plot(residuals(models[["lag6"]]), main="Residuals from modeling beer production with 10-14 lag 6")
```



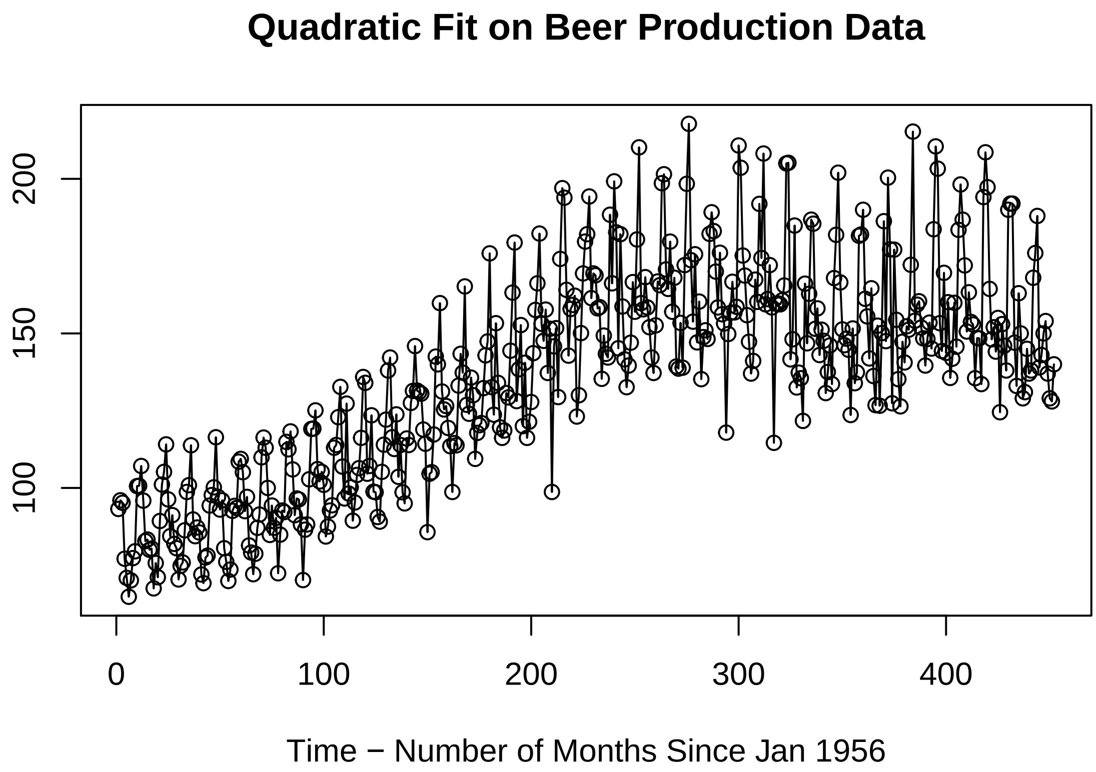
We see that lag 6 is the optimal lag in terms of R-squared values. This makes sense because in 6 years, this age group will be 16-20, or right around drinking age. We can see in the residuals that it isn't perfect, but this pattern may be easier to model than what we had before, it looks much more like a regular polynomial.

Try to figure out deterministic trend

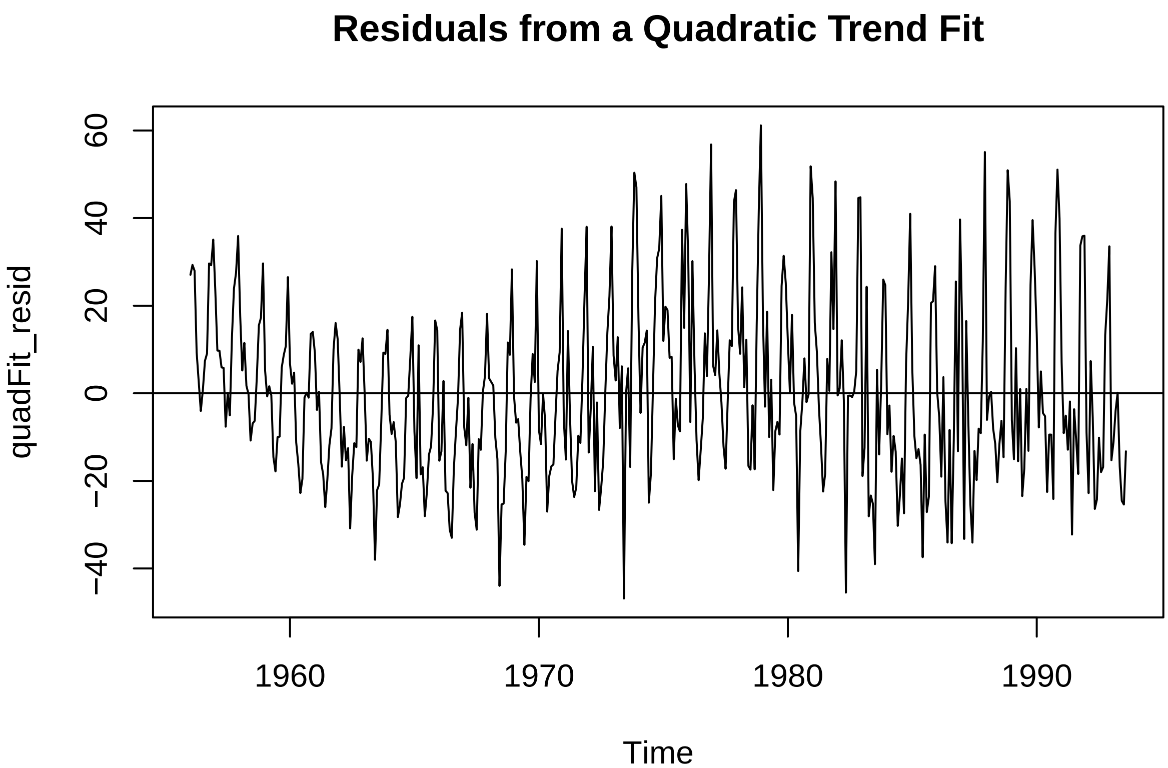
```
t<-1:length(beerTS)
t2<-t^2
t3<-t^3
t4<-t^4
t5<-t^5

quadFit<-lm(beerTS~t+t2)
summary(quadFit)
```

```
##
## Call:
## lm(formula = beerTS ~ t + t2)
##
## Residuals:
##     Min      1Q  Median      3Q     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 ***
## t2          -7.721e-04  6.163e-05  -12.53   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## 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
```

```
#### 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
```



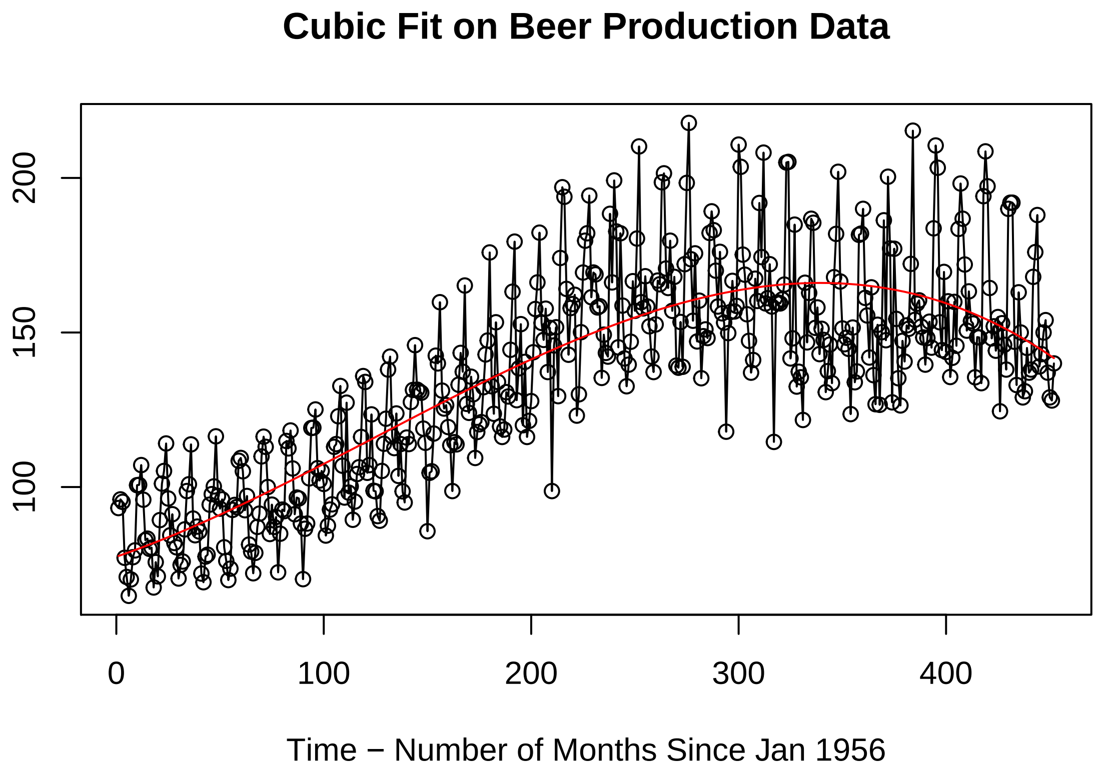

```
quadFit_resid<-ts(residuals(quadFit),frequency=12, start=c(1956,1))
plot(quadFit_resid, main="Residuals from a Quadratic Trend Fit")
abline(h=0)
```



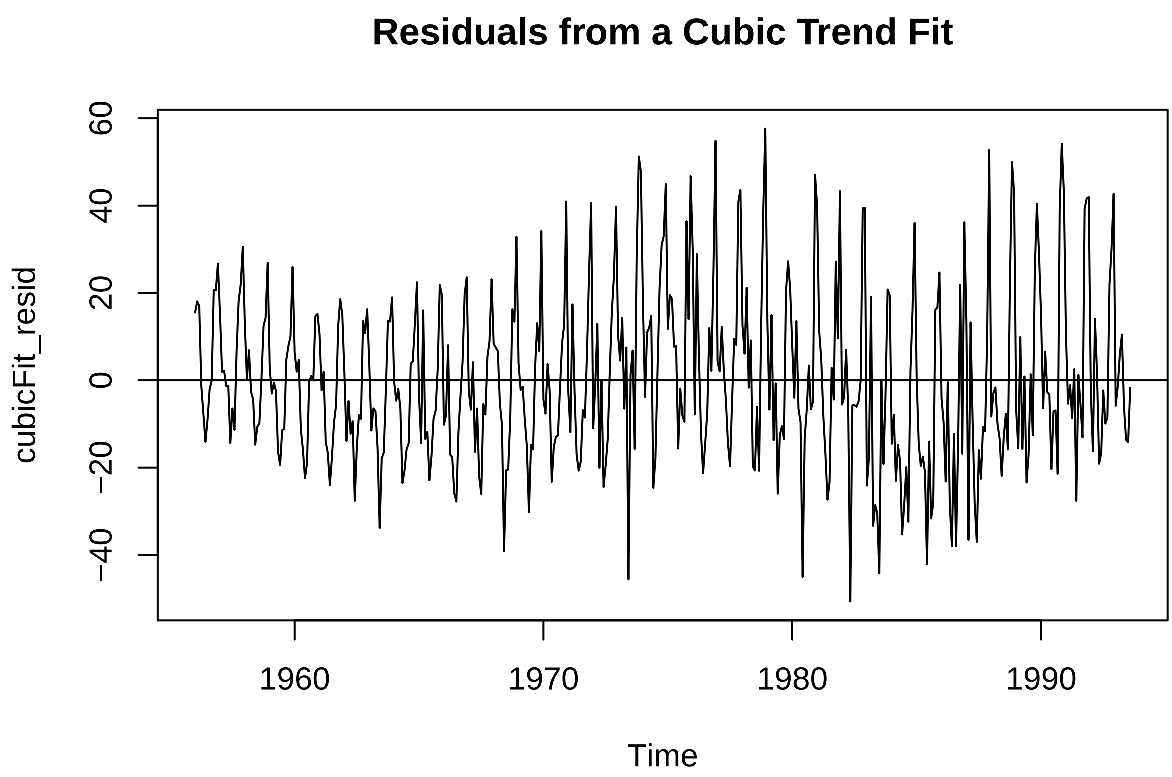
```r
cubicFit<-lm(beerTS~t+t2+t3)
summary(cubicFit)
```

```
##
## Call:
## lm(formula = beerTS ~ t + t2 + t3)
##
## Residuals:
##     Min      1Q  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 ***
## t            2.307e-01  7.056e-02   3.270  0.00116 **
## t2           9.490e-04  3.617e-04   2.624  0.00900 **
## t3          -2.533e-06  5.249e-07  -4.826 1.92e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## 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
```

```r
#### 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
```



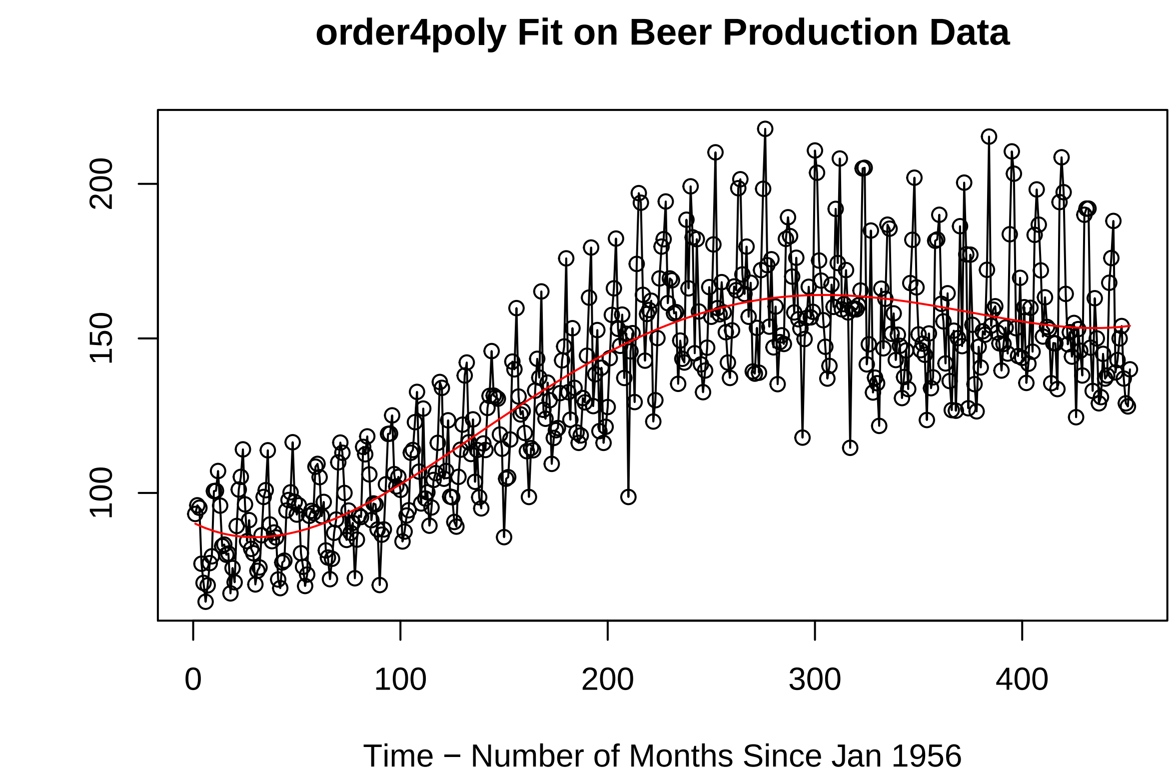

```r
cubicFit_resid<-ts(residuals(cubicFit),frequency=12, start=c(1956,1))
plot(cubicFit_resid, main="Residuals from a Cubic Trend Fit")
abline(h=0)
```



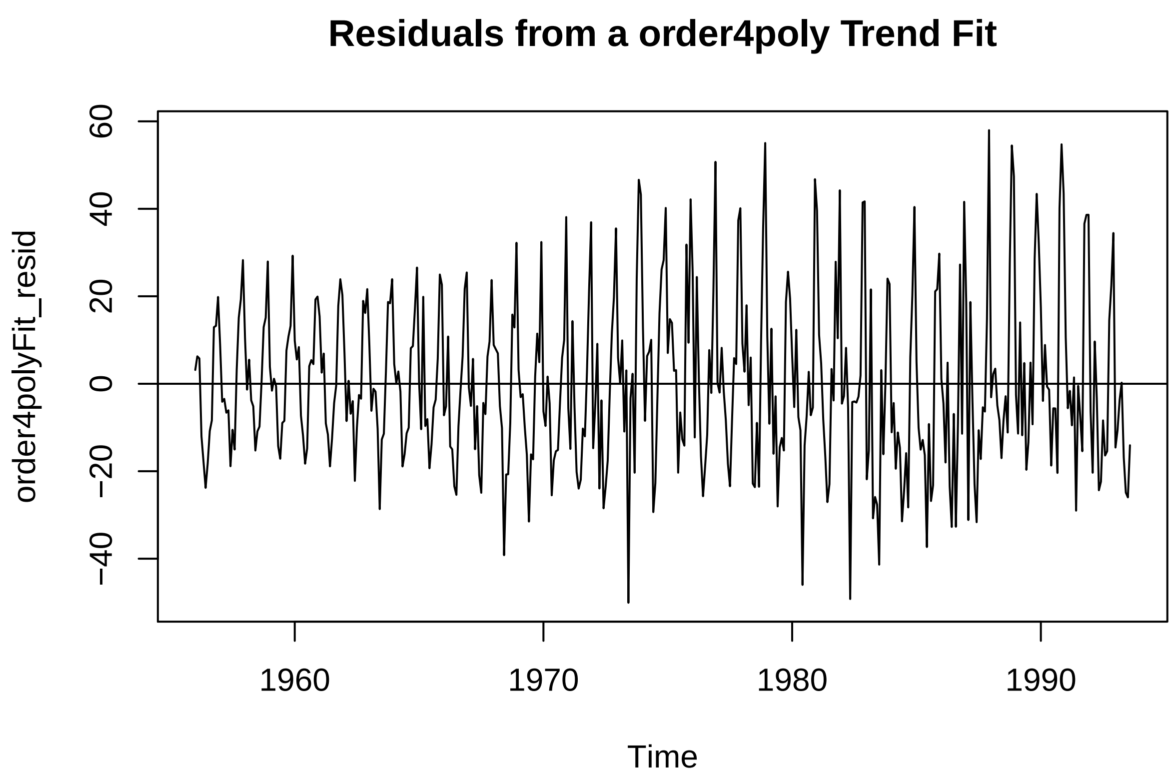

```
order4polyFit<-lm(beerTS~t+t2+t3+t4)
summary(order4polyFit)
```

```
##
## Call:
## lm(formula = beerTS ~ 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 ***
## t3          -2.173e-05  4.113e-06  -5.285 1.97e-07 ***
## t4           2.119e-08  4.504e-09   4.706 3.38e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## 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]
```



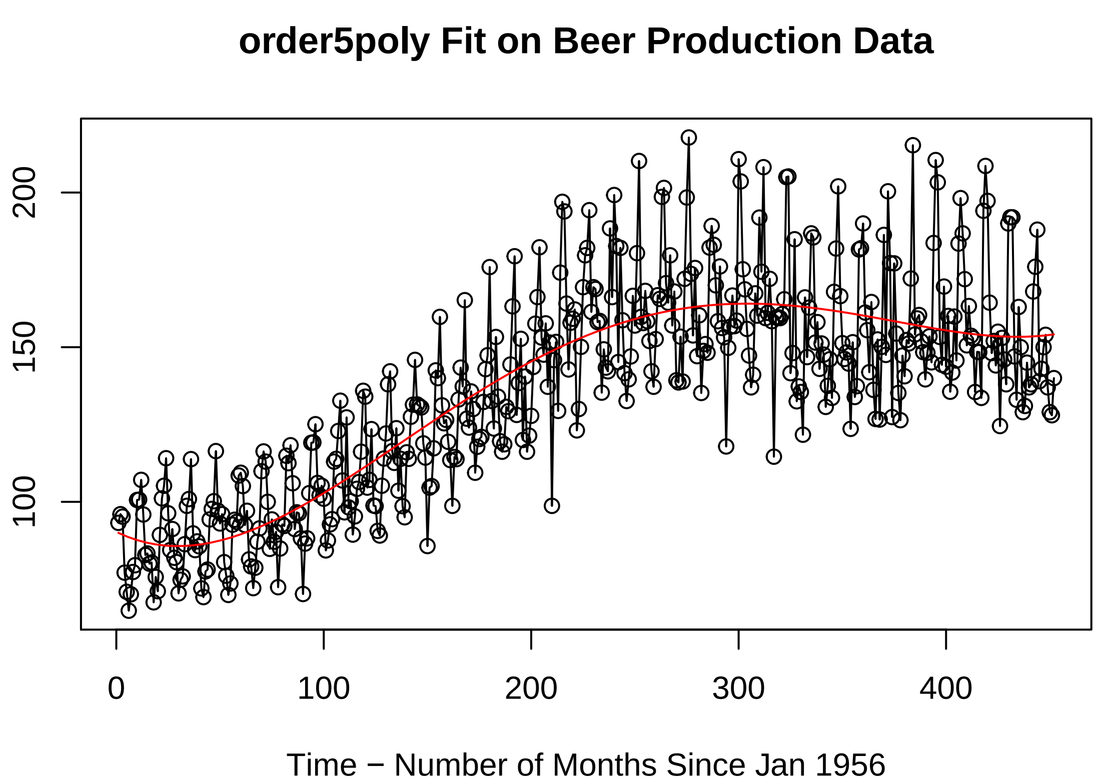

```
order4polyFit_resid<-ts(residuals(order4polyFit),frequency=12, start=c(1956,1))
plot(order4polyFit_resid, main="Residuals from a order4poly Trend Fit")
abline(h=0)
```



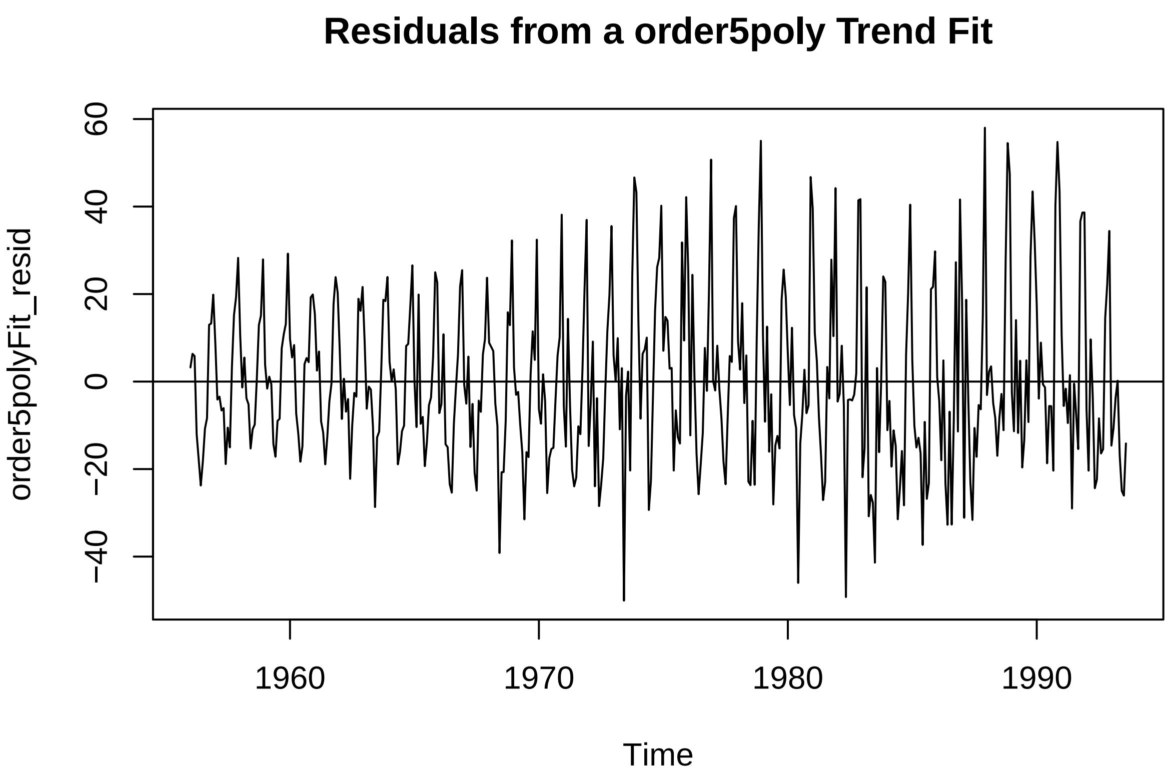
```r
order5polyFit<-lm(beerTS~t+t2+t3+t4+t5)
summary(order5polyFit)
```

```
##
## Call:
## lm(formula = beerTS ~ 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 .
## t3          -2.126e-05  1.858e-05  -1.144   0.2532
## t4           2.000e-08  4.519e-08   0.443   0.6582
## t5           1.049e-12  3.970e-11   0.026   0.9789
## ---
## 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
```

```r
#### plot the data and the fitted 5th order polynomial trend function
plot(x=1:length(beerTS),y=beerTS,type='o',ylab="",xlab="Time - Number of Months Since Jan 1956",main="order5po
curve(expr = coef(order5polyFit)[1]+coef(order5polyFit)[2]*x+coef(order5polyFit)[3]*x^2+coef(order5polyFit)[4]
```



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



It looks like a 4th order polynomial might take care of the worst of it, the question is are we okay with using a 4th order polynomial or should we drop it down to a cubic function and just deal with it? I found population data and I would be interested to see if we can find a good correlation there (total population won't work, I already looked at that, but maybe a specific age group?)

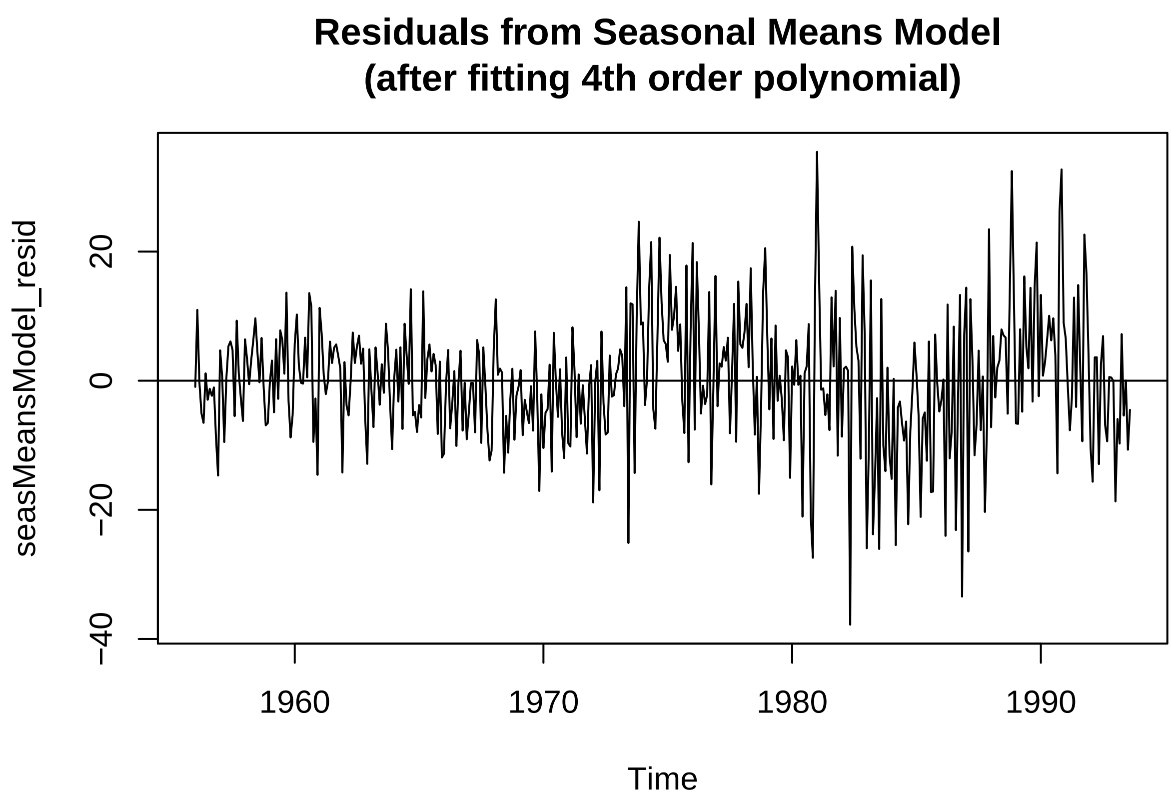
Assume we go with the 4th order polynomial for now. Let's see what we can do about the seasonality with a seasonal means model

```r
library(TSA)
month=season(order4polyFit_resid)
seasMeansModel<-lm(order4polyFit_resid~month)
summary(seasMeansModel)
```

```
##
## Call:
## lm(formula = order4polyFit_resid ~ month)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -37.789  -6.263   0.327   6.128  35.453
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)         4.108      1.652   2.487 0.013268 *
## monthFebruary      -8.810      2.336  -3.771 0.000185 ***
## monthMarch          1.929      2.336   0.826 0.409372
## monthApril        -11.085      2.336  -4.744 2.83e-06 ***
## monthMay          -15.540      2.336  -6.651 8.65e-11 ***
```

```
## monthJune       -29.051      2.336 -12.434  < 2e-16 ***
## monthJuly       -19.403      2.336  -8.304 1.25e-15 ***
## monthAugust     -13.661      2.336  -5.847 9.78e-09 ***
## monthSeptember  -10.151      2.352  -4.316 1.97e-05 ***
## monthOctober      9.861      2.352   4.192 3.34e-05 ***
## monthNovember    17.904      2.352   7.612 1.66e-13 ***
## monthDecember    30.406      2.352  12.927  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 10.18 on 440 degrees of freedom
## Multiple R-squared:  0.7181, Adjusted R-squared:  0.7111
## F-statistic: 101.9 on 11 and 440 DF,  p-value: < 2.2e-16
```

```
seasMeansModel_resid<-ts(residuals(seasMeansModel),frequency=12, start=c(1956,1))
plot(seasMeansModel_resid, main="Residuals from Seasonal Means Model \n(after fitting 4th order polynomial)")
abline(h=0)
```

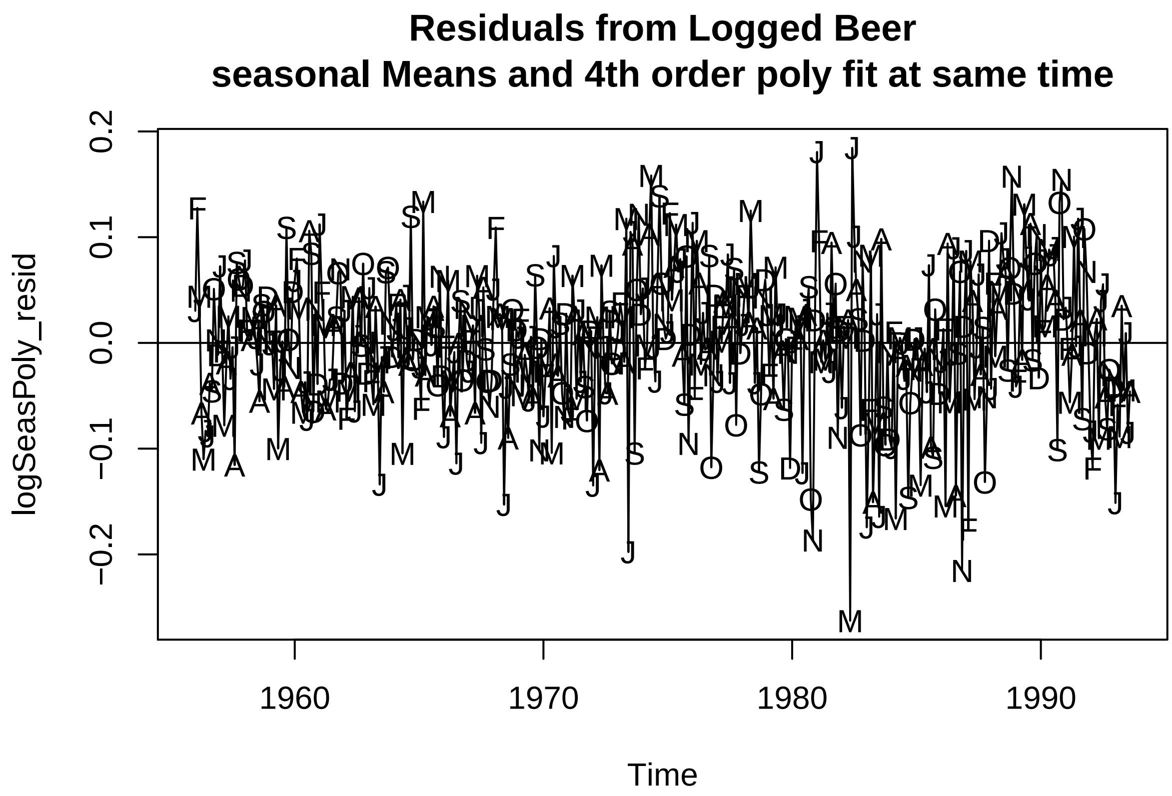


With an adjusted R-squared value of 71%, this is looking pretty good, but in the residual plot you can still the the variance increasing over time. In addition, there is a noticeable "wave" in the residuals that starts around 1970, but I'm not sure what to do about that yet. For now, let's go back, log the data, and apply both the 4th order polynomial and the seasonal means model at the same time.

```
logBeer<-log(beerTS)
t<-1:length(logBeer)
t2<-t^2
t3<-t^3
t4<-t^4
month<-season(logBeer)

logSeasPoly<-lm(logBeer~t+t2+t3+t4+month)
summary(logSeasPoly)
```

```
##
## Call:
## lm(formula = logBeer ~ t + t2 + t3 + t4 + month)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.262750 -0.039816  0.003297  0.043475  0.184483
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)     4.506e+00  1.945e-02 231.675  < 2e-16 ***
## t              -1.796e-03  5.014e-04  -3.583 0.000378 ***
## t2              4.926e-05  4.494e-06  10.962  < 2e-16 ***
## t3             -1.745e-07  1.490e-08 -11.713  < 2e-16 ***
## t4              1.785e-10  1.631e-11  10.941  < 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  < 2e-16 ***
## 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 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## 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
```

```r
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 at same time",
points(y=logSeasPoly_resid, x=time(logSeasPoly_resid), pch=as.vector(season(logSeasPoly_resid)))
abline(h=0)
```



Let's take a look and see if we have a stationary series yet

```
# d
adf.test(logSeasPoly_resid)
```

```
## Warning in adf.test(logSeasPoly_resid): p-value smaller than printed p-
## value
```

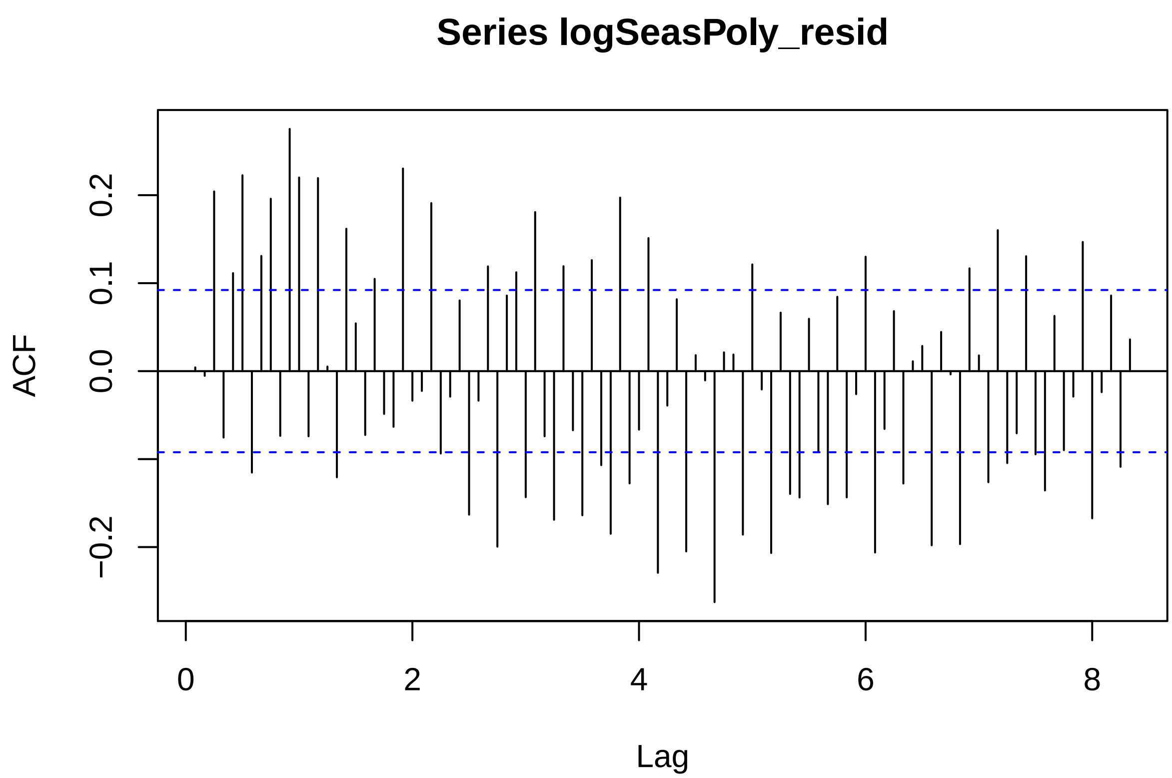
```
##
##  Augmented Dickey-Fuller Test
##
## data:  logSeasPoly_resid
## Dickey-Fuller = -5.3999, Lag order = 7, p-value = 0.01
## alternative hypothesis: stationary
```

```
pp.test(logSeasPoly_resid)
```

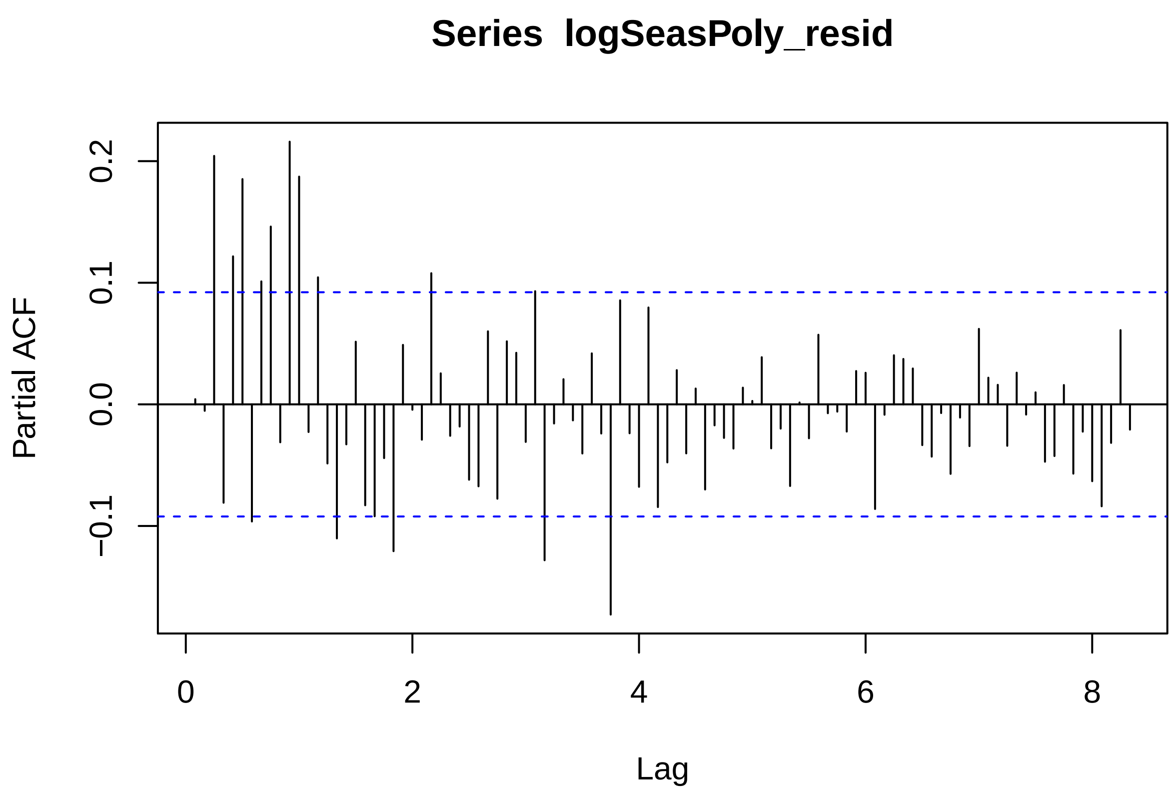
```
## Warning in pp.test(logSeasPoly_resid): p-value smaller than printed p-value
```

```
##
##  Phillips-Perron Unit Root Test
##
## data:  logSeasPoly_resid
## Dickey-Fuller Z(alpha) = -489.81, Truncation lag parameter = 5,
## p-value = 0.01
## alternative hypothesis: stationary
```

```
# p & q
par(mfrow=c(1,1))
acf(logSeasPoly_resid, lag.max=100)
```




```r
pacf(logSeasPoly_resid, lag.max=100)
```



```r
par(mfrow=c(1,1))
eacf(logSeasPoly_resid)
```

```
## AR/MA
##   0 1 2 3 4 5 6 7 8 9 10 11 12 13
## 0 o o x o x x x x x o x  x  o  x
## 1 x o x o o x o o x o x  x  o  x
## 2 o o x o x x o x x x x  x  x  x
## 3 x x x o o o o o o o x  x  x  o
## 4 x x x o o o o o o o o  x  o  o
## 5 x x x x x o o o o o o  x  o  x
## 6 x x x x x o o o o o o  o  o  x
## 7 x x x x x x o o o o o  o  o  x
```

Try an AR(12) model and examine residuals

```r
#Set up external regressors and dummy vars
library(forecast)
monthDummies<-seasonaldummy(logBeer)
externReg<-data.frame(t, t2, t3, t4, monthDummies)

ar12_poly<-arima(logBeer, order=c(12,0,0), xreg=externReg)
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
##          ar9     ar10    ar11    ar12  intercept        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  0.0440  0.0453     0.0781   0.0014  2e-04   0   0
##           Jan      Feb      Mar      Apr      May      Jun      Jul
##       -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
```

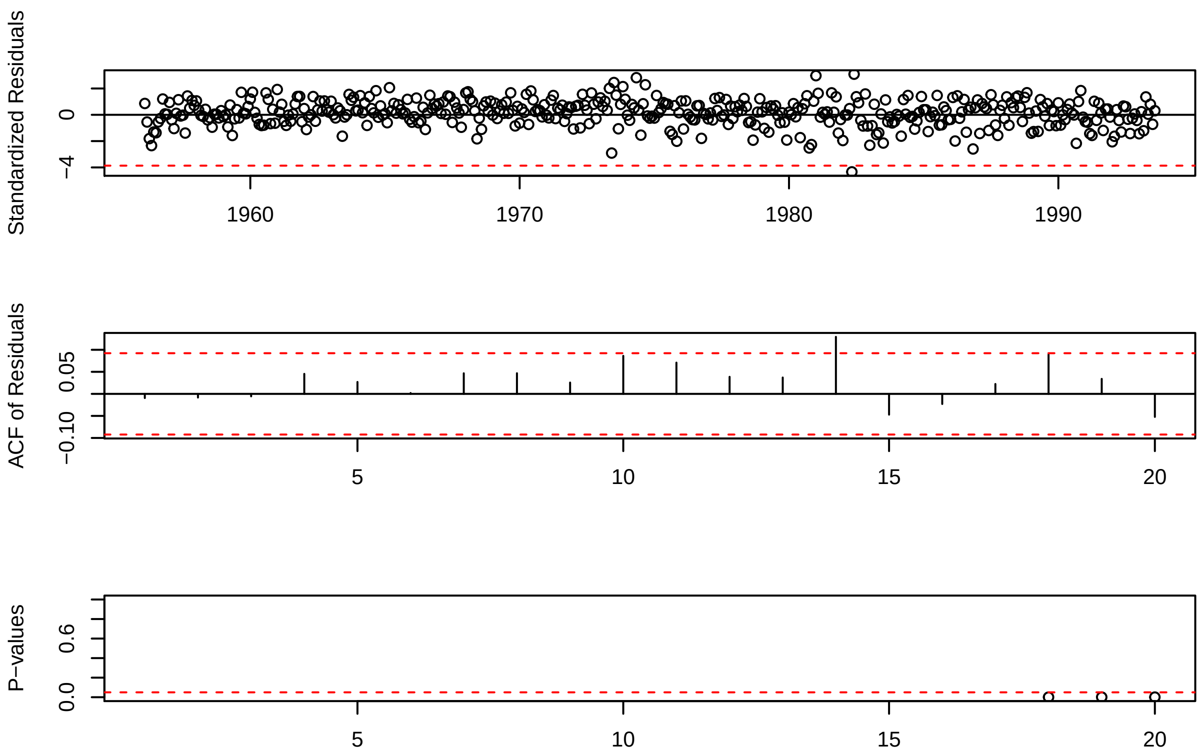
We seem to be having trouble getting fits for the trend line, ask about this Monday, try just using the month dummies.

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

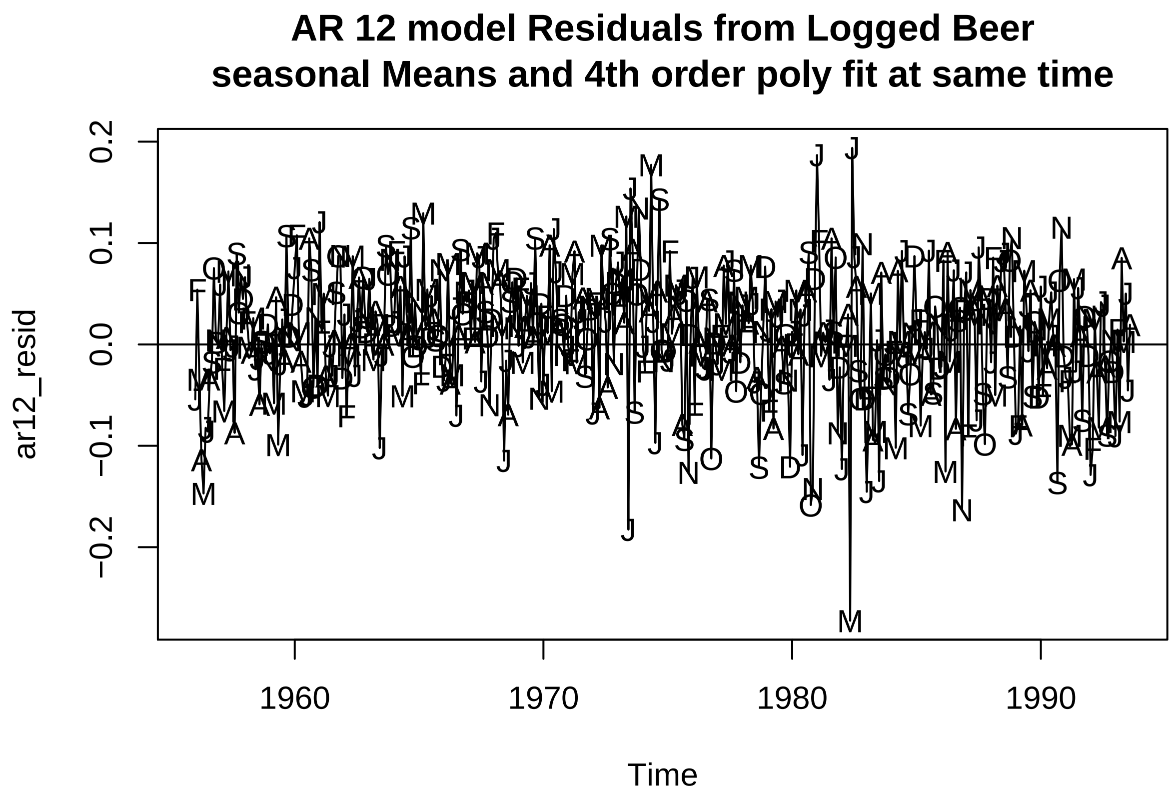
```
##
## Call:
## arima(x = logBeer, order = c(12, 0, 0), xreg = monthDummies)
##
## Coefficients:
##          ar1     ar2     ar3      ar4     ar5     ar6      ar7     ar8
##       0.0631  0.0283  0.1255  -0.0127  0.1286  0.1447  -0.0733  0.0983
## s.e.  0.0464  0.0458  0.0458   0.0457  0.0458  0.0460   0.0461  0.0459
```

```
##          ar9     ar10    ar11    ar12  intercept      Jan      Feb
##       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
##           Mar      Apr      May      Jun      Jul      Aug      Sep
##       -0.1798  -0.2797  -0.3188  -0.4349  -0.3507  -0.3012  -0.2657
## 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
```

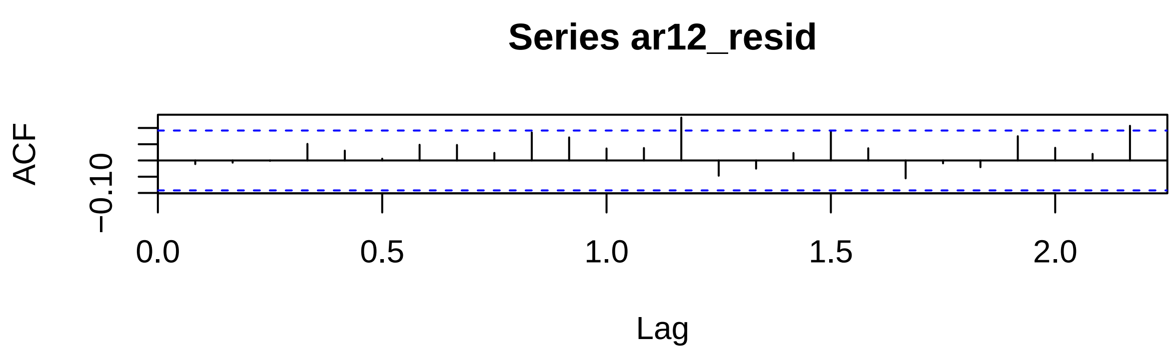
```r
tsdiag(ar12, gof.lag=20)
```

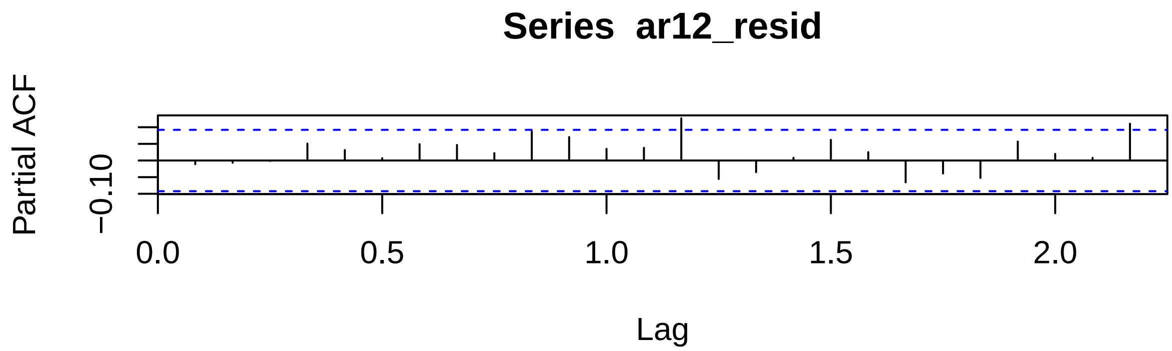



```r
#residuals
ar12_resid<-ts(residuals(ar12), frequency=12, start=c(1956,1))
plot(ar12_resid, main="AR 12 model Residuals from Logged Beer\nseasonal Means and 4th order poly fit at same t
points(y=ar12_resid, x=time(ar12_resid), pch=as.vector(season(ar12_resid)))
abline(h=0)
```




```r
par(mfrow=c(2,1))
acf(ar12_resid)
pacf(ar12_resid)
```

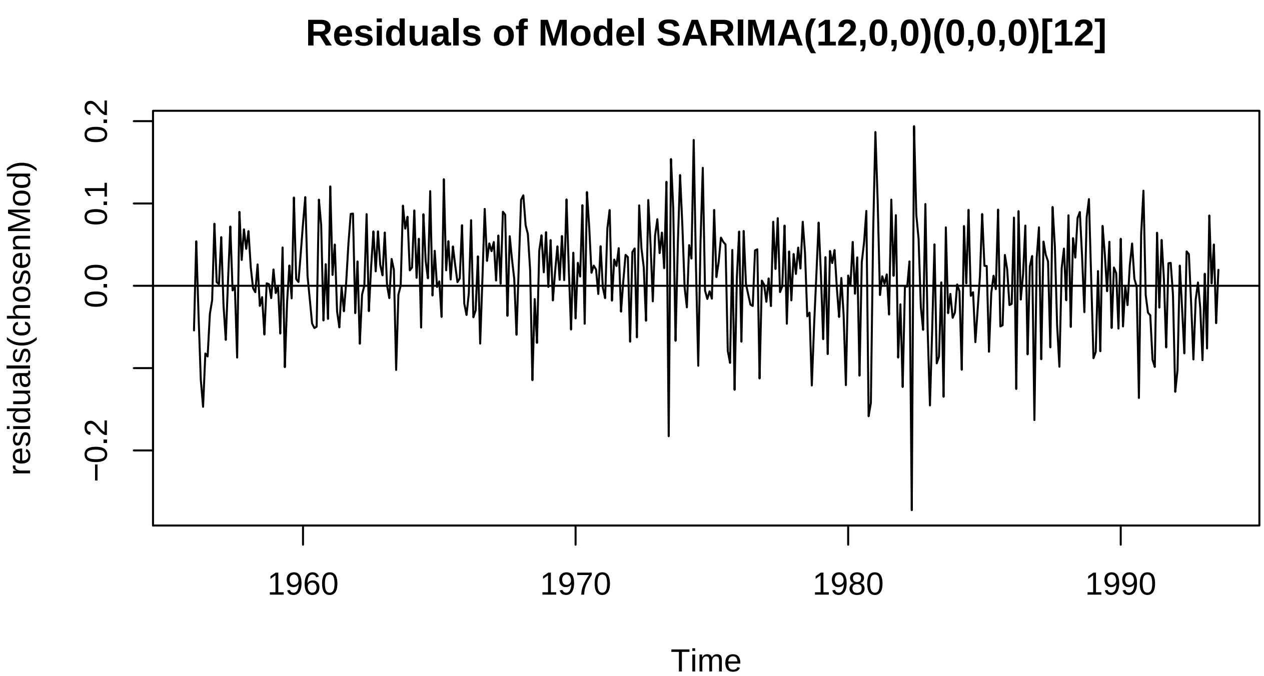




```r
pacf_acf<-data.frame(acfVal=acf(ar12_resid, plot=FALSE)$acf, pacfVal=pacf(ar12_resid, plot=FALSE)$acf)
#print(pacf_acf)
```

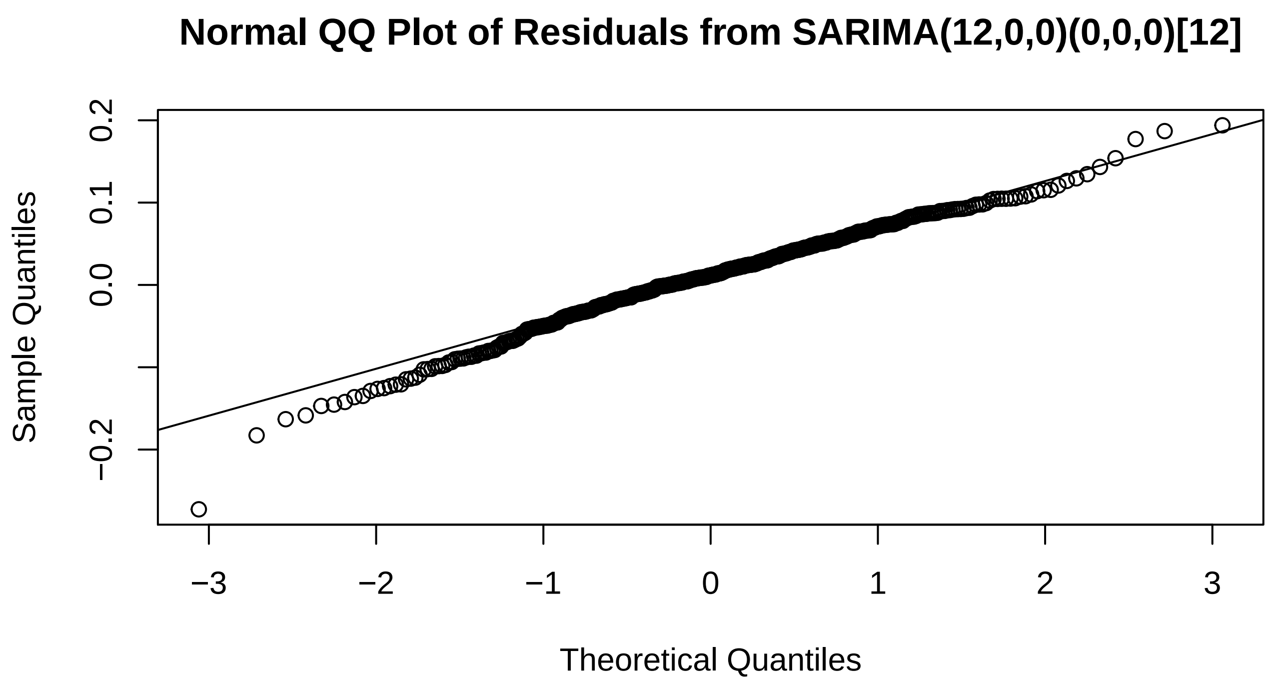
After we choose a model, run all of the diagnostic tests

```r
chosenMod<-ar12
modelString<-"SARIMA(12,0,0)(0,0,0)[12]"

par(mfrow=c(1,1))
plot(residuals(chosenMod), main=paste("Residuals of Model", modelString))
abline(h=0)
```



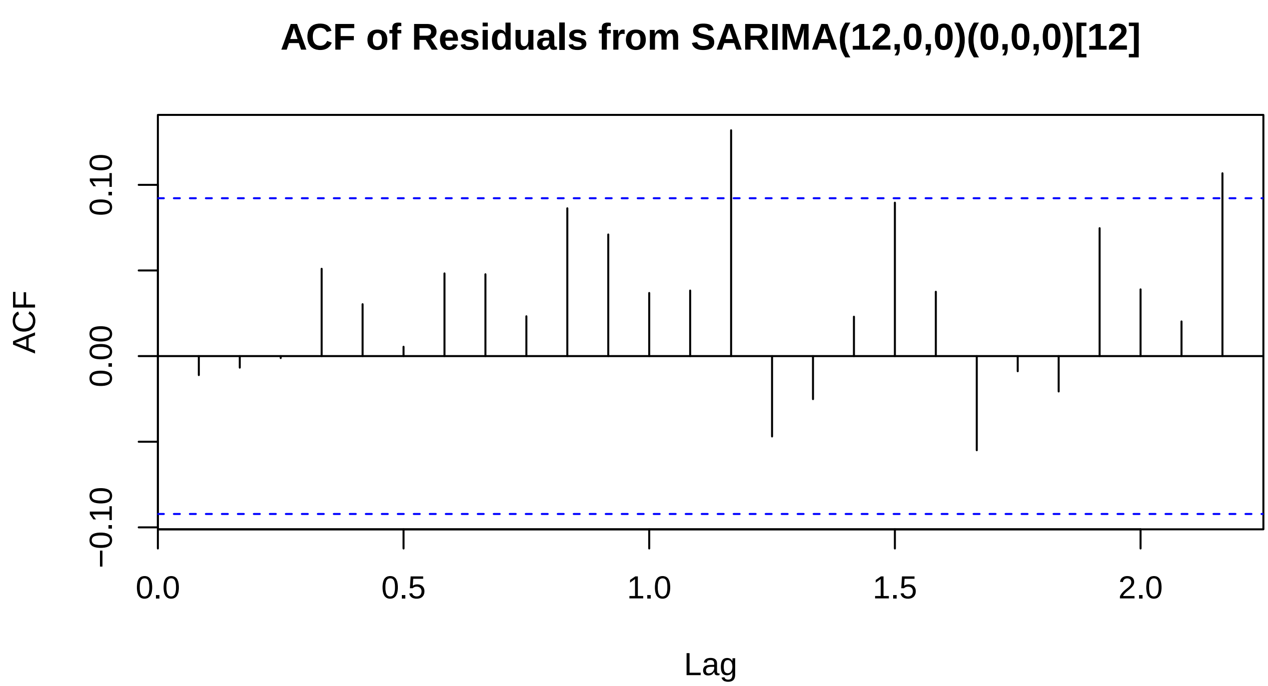
Comment:

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



Comment:

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



Comment:

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

```
##
```

```
##  Shapiro-Wilk normality test
##
## data:  residuals(chosenMod)
## W = 0.98657, p-value = 0.000348
```

Comment:

```
LB.test(chosenMod, lag=24)
```

```
##
##  Box-Ljung test
##
## data:  residuals from  chosenMod
## X-squared = 30.485, df = 12, p-value = 0.002359
```

Comment:

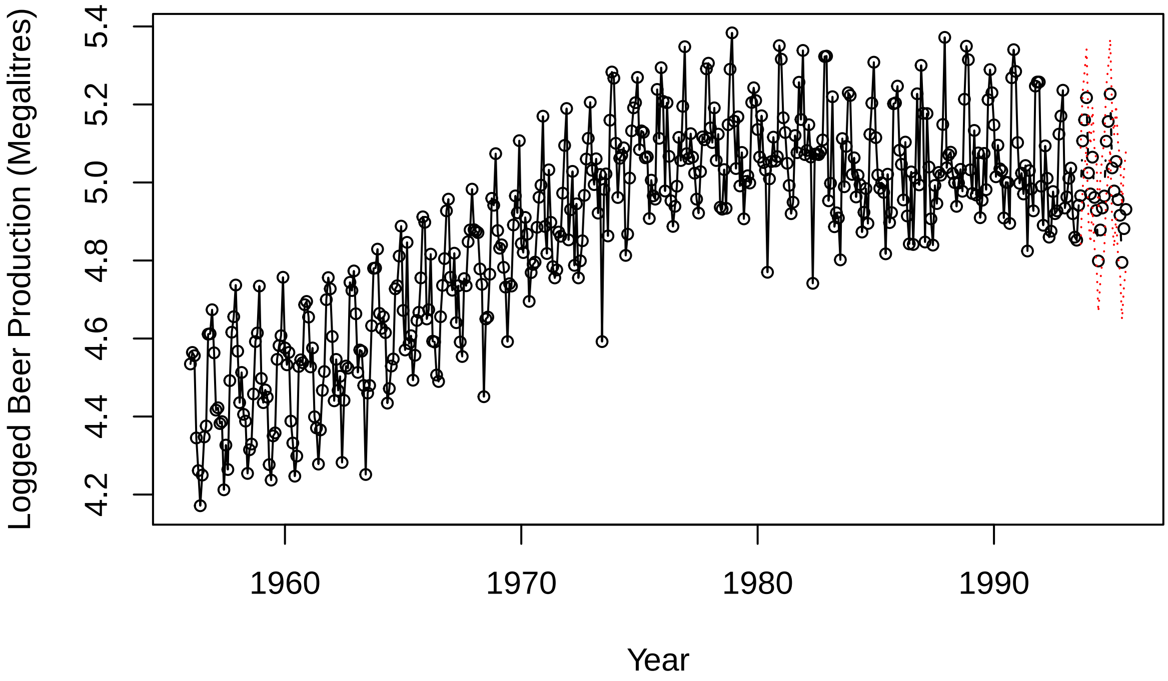
Make the forecasts

Set up external regressor data frame

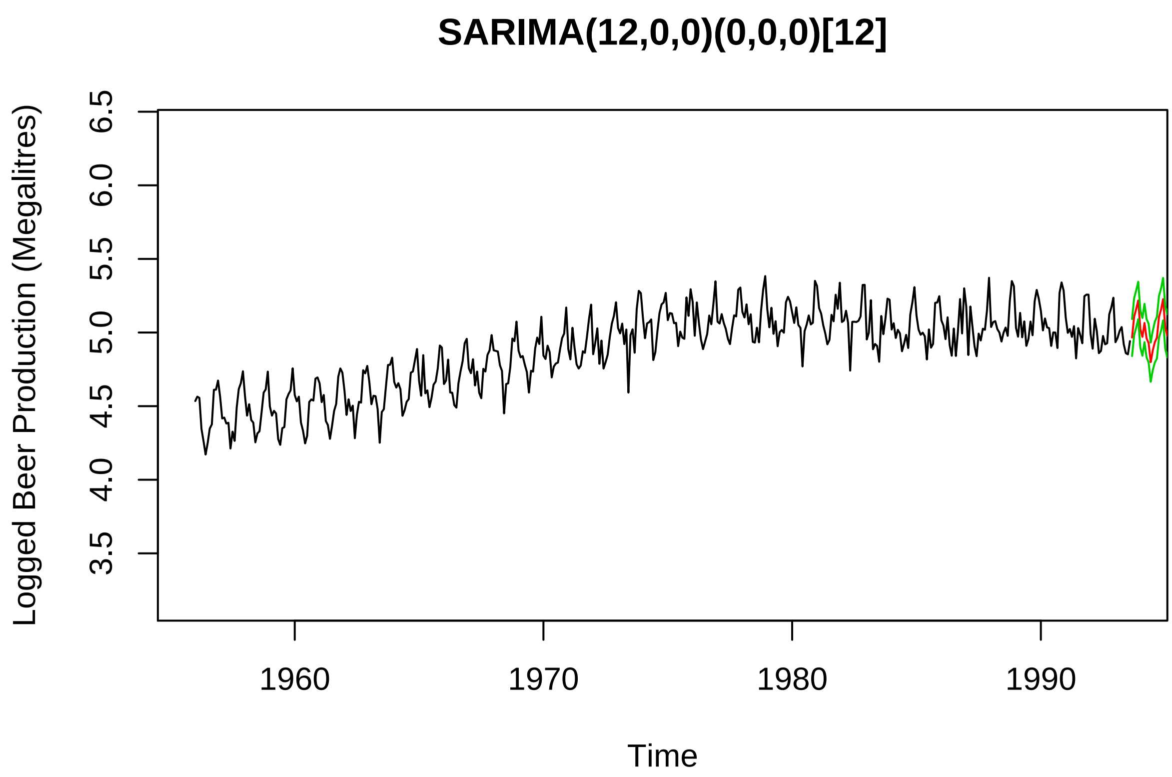
```
newMonthDummy<-seasonaldummy(beer_forecast)
```

Plot the model forecasts

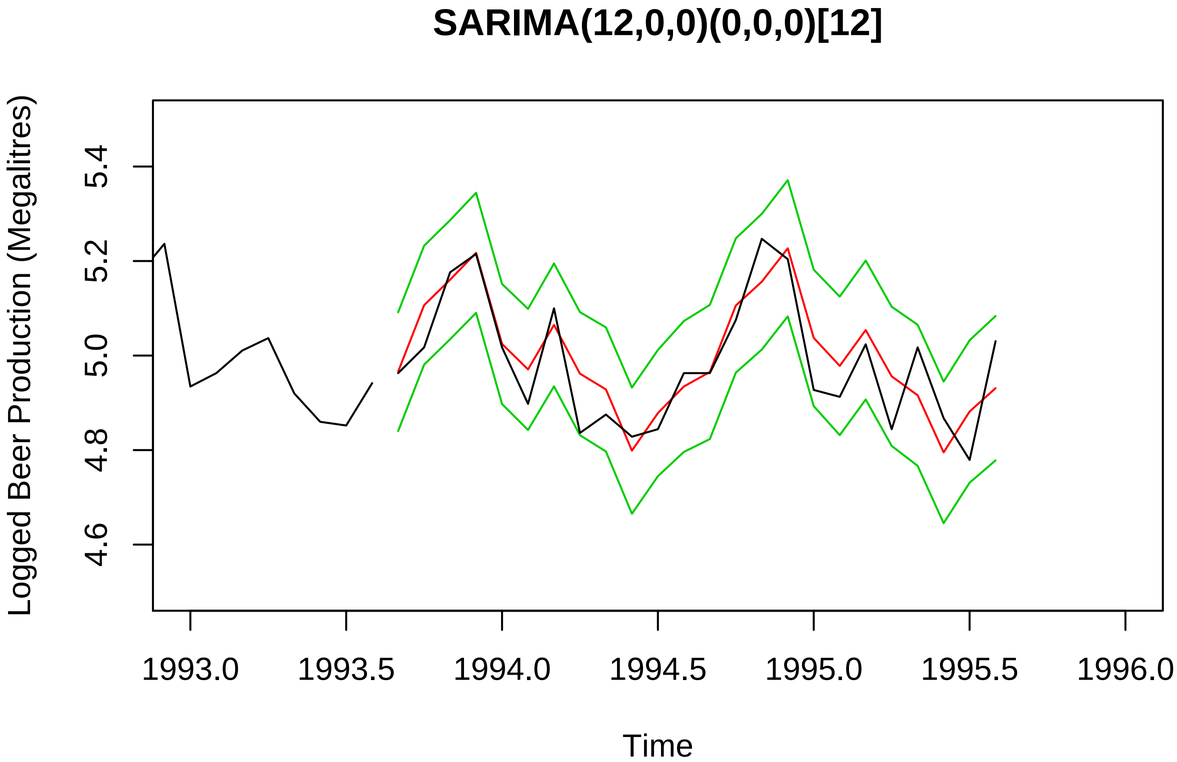
```
library(TSA)

TSA::plot.Arima(chosenMod,n.ahead=24,n1=c(1956,1), newxreg=newMonthDummy,
type='b',ylab='Logged Beer Production (Megalitres)',xlab='Year', col="red", lty=2, cex=.75)
```




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

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)
```




```
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")
```


SARIMA(12,0,0)(0,0,0)[12]
Logged Beer Production (Megalitres)
4.6
4.8
5.0
5.2
5.4
1993.0
1993.5
1994.0
1994.5
1995.0
1995.5
1996.0
Time