Final Project

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

Change working directory here

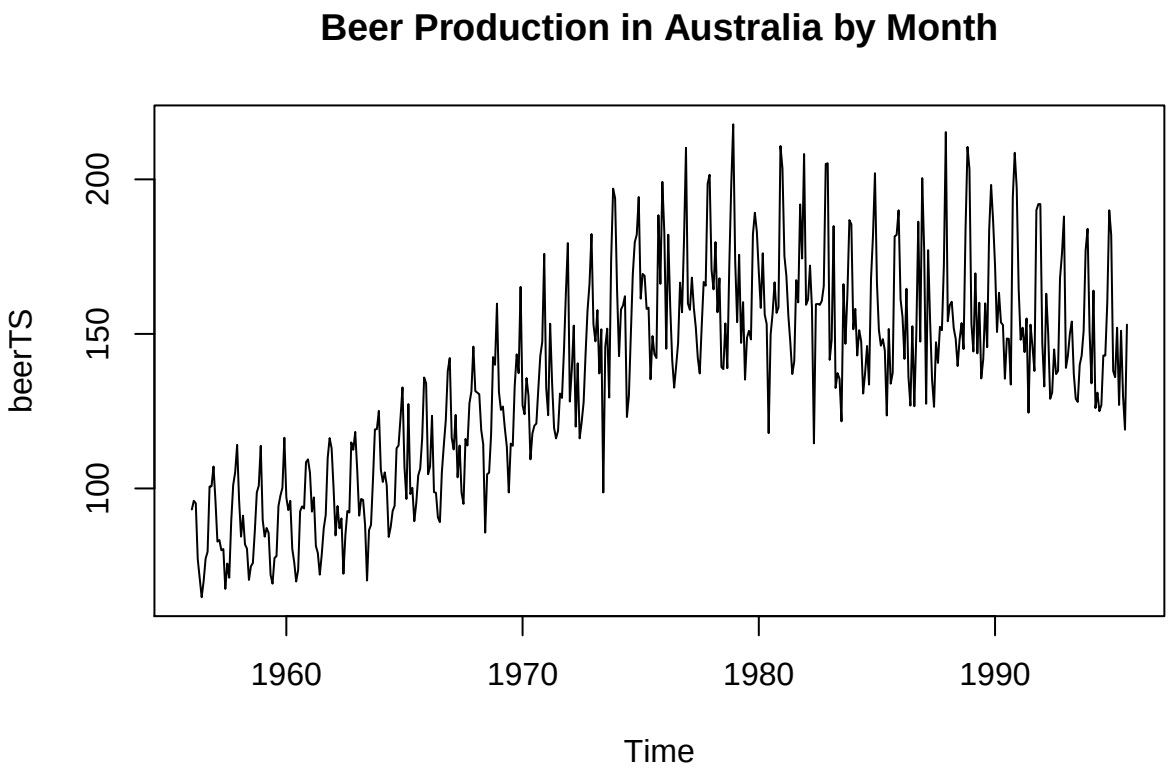
Load data (assumes file is in working directory)

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

#turn into time series (cuts off last entry which is NA)
beerTS<-ts(beerData[1:(nrow(beerData)-1),2], frequency=12, start=c(1956,1))
```

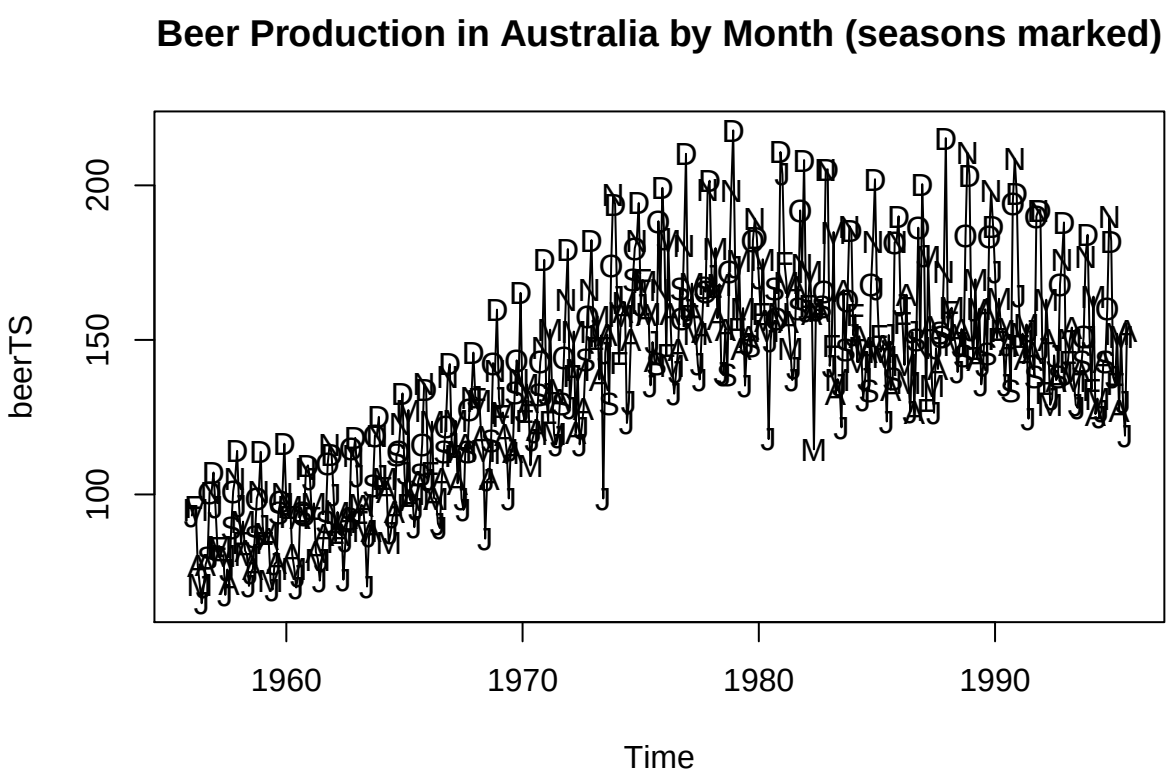
```
#load population data
#pop_totalData<-read.csv("Pop_total.csv", row.names=1)
#pop_total<-t(pop_totalData["Total",])
#pop_totalTS<-ts(pop_total[,1], frequency=1, start=c(1921))
```

Plot data

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




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



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.

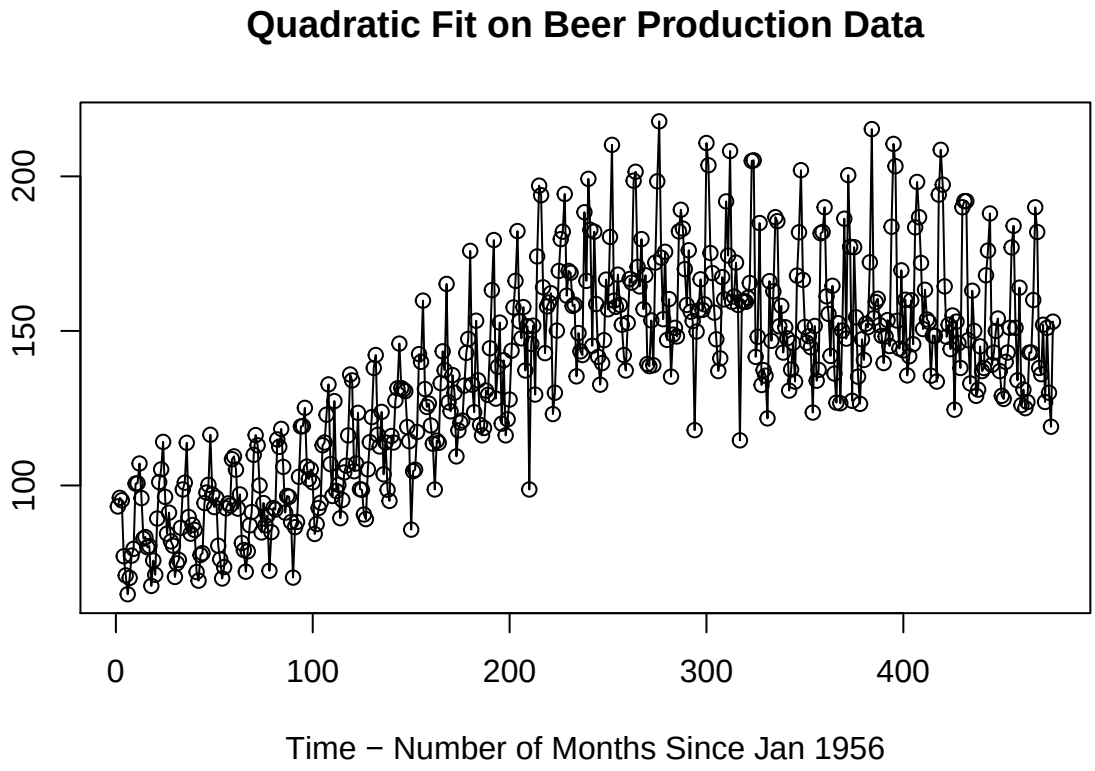
Try to figure out deterministic trend

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

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

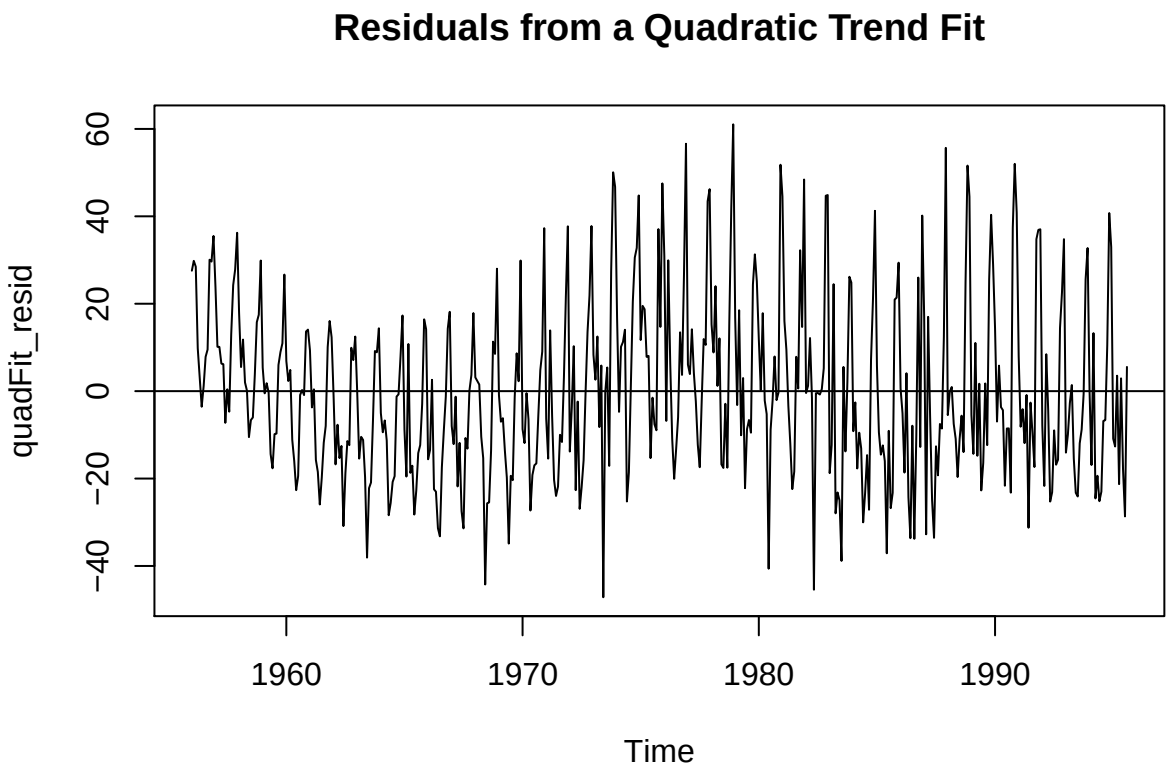
```
##
## Call:
## lm(formula = beerTS ~ t + t2)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
```

```
## -47.157 -14.220  -2.119  11.721  61.046
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  6.509e+01  2.754e+00   23.64   <2e-16 ***
## t            5.517e-01  2.666e-02   20.69   <2e-16 ***
## t2          -7.954e-04  5.412e-05  -14.70   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 19.94 on 473 degrees of freedom
## Multiple R-squared:  0.6521, Adjusted R-squared:  0.6506
## F-statistic: 443.3 on 2 and 473 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="Qu
curve(expr = coef(quadFit)[1]+coef(quadFit)[2]*x+coef(quadFit)[3]*x^2+coef(quadFit)[4]*x^3,lty=1,add = T
```



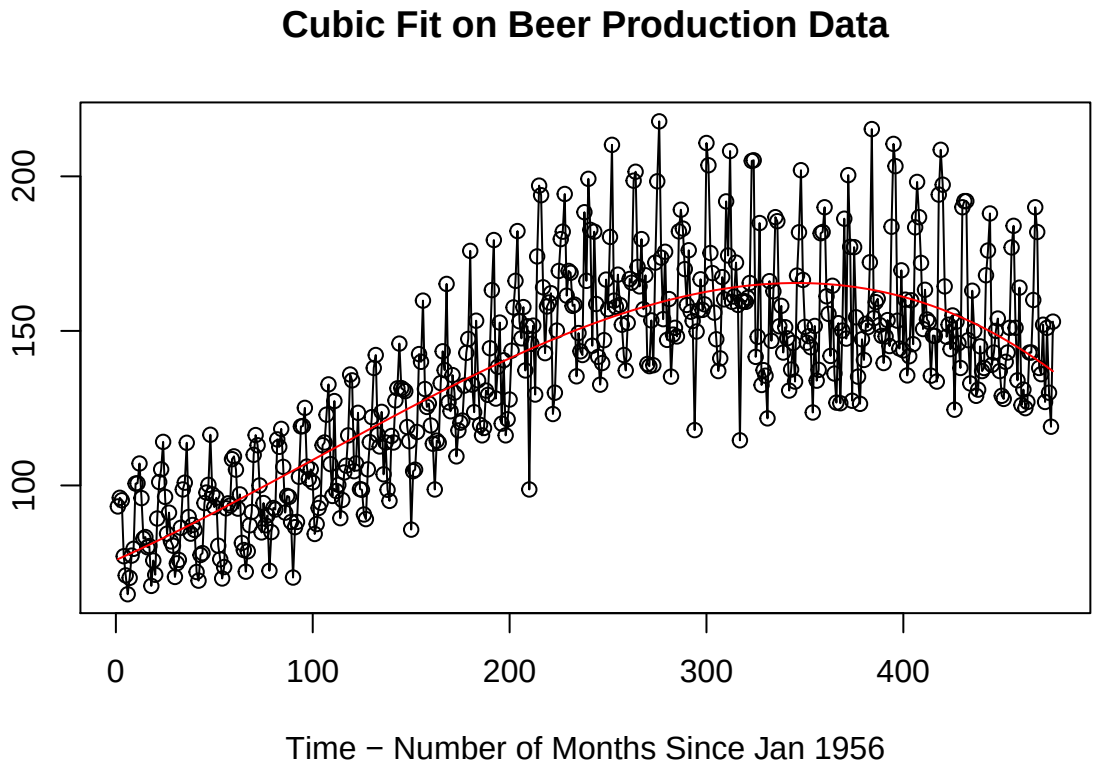

```
quadFit_resid<-ts(residuals(quadFit),frequency=12, start=c(1956,1))
plot(quadFit_resid, main="Residuals from a Quadratic Trend Fit")
abline(h=0)
```



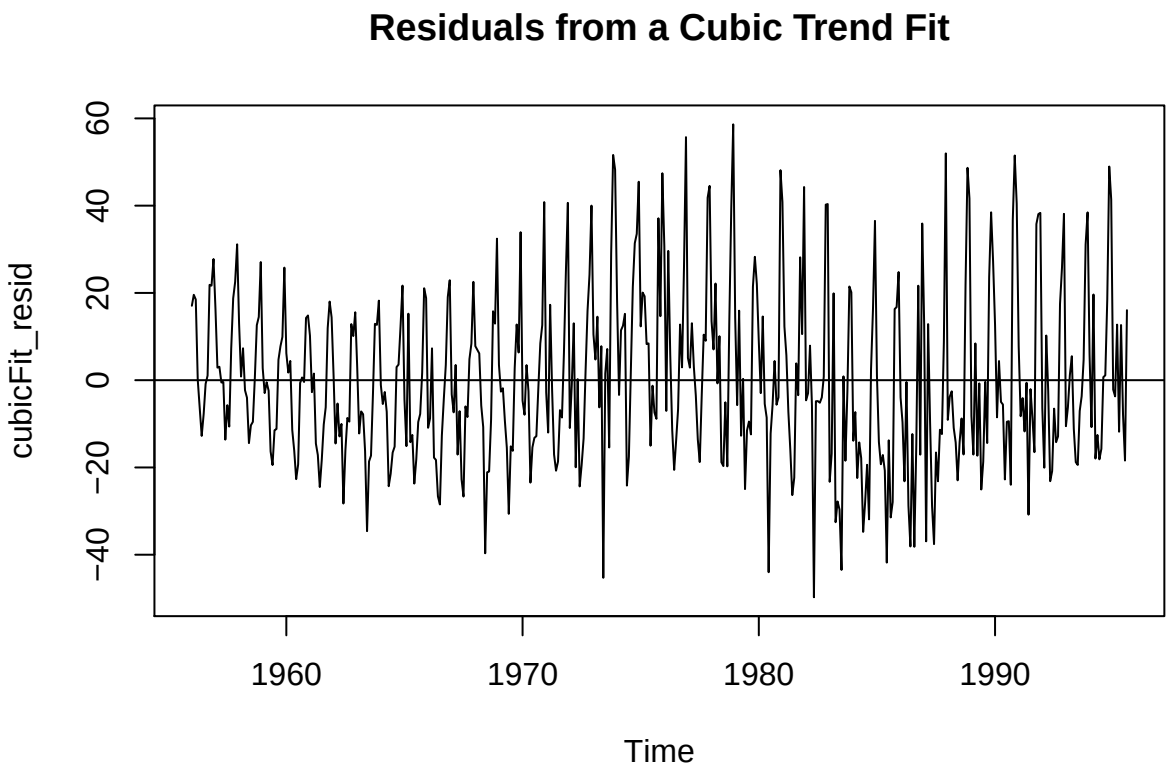

```
cubicFit<-lm(beerTS~t+t2+t3)
summary(cubicFit)
```

```
##
## Call:
## lm(formula = beerTS ~ t + t2 + t3)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -49.744 -13.812  -2.959  12.679  58.635
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  7.586e+01  3.613e+00  20.998  < 2e-16 ***
## t            2.820e-01  6.552e-02   4.304 2.04e-05 ***
## t2           6.165e-04  3.190e-04   1.932   0.0539 .
## t3          -1.973e-06  4.397e-07  -4.488 9.05e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 19.55 on 472 degrees of freedom
## Multiple R-squared:  0.6663, Adjusted R-squared:  0.6642
## F-statistic: 314.2 on 3 and 472 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="Cu
curve(expr = coef(cubicFit)[1]+coef(cubicFit)[2]*x+coef(cubicFit)[3]*x^2+coef(cubicFit)[4]*x^3,lty=1,ad
```



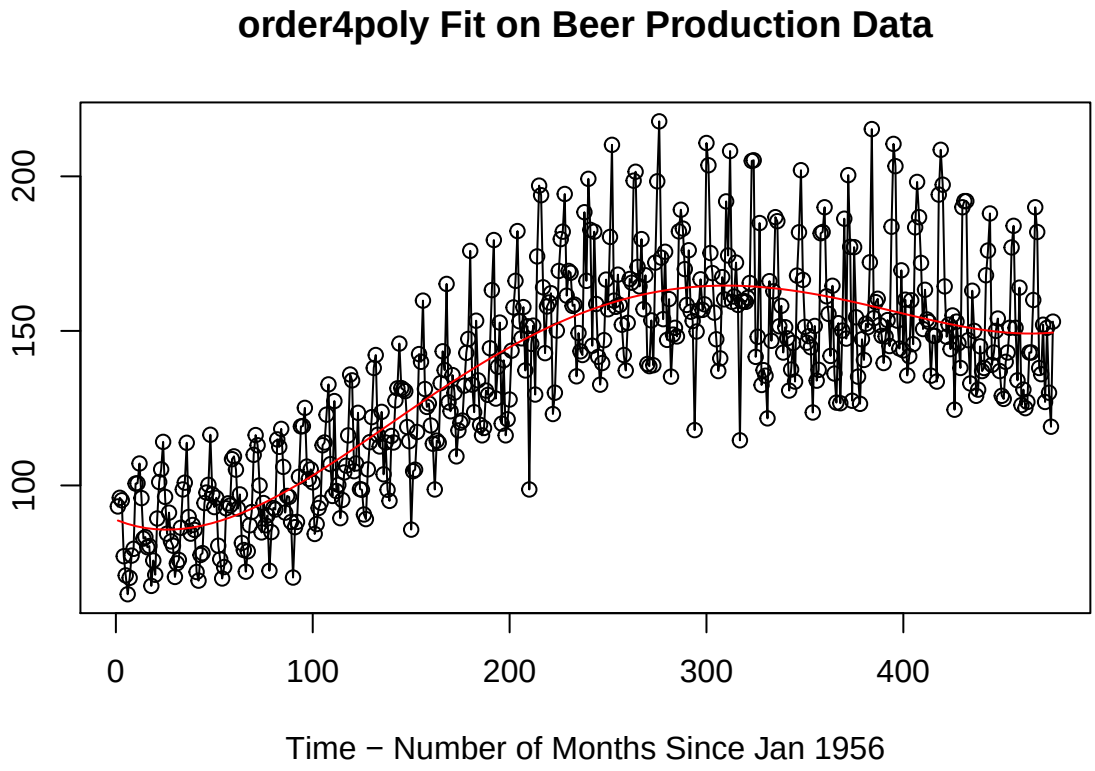

```
cubicFit_resid<-ts(residuals(cubicFit),frequency=12, start=c(1956,1))
plot(cubicFit_resid, main="Residuals from a Cubic Trend Fit")
abline(h=0)
```



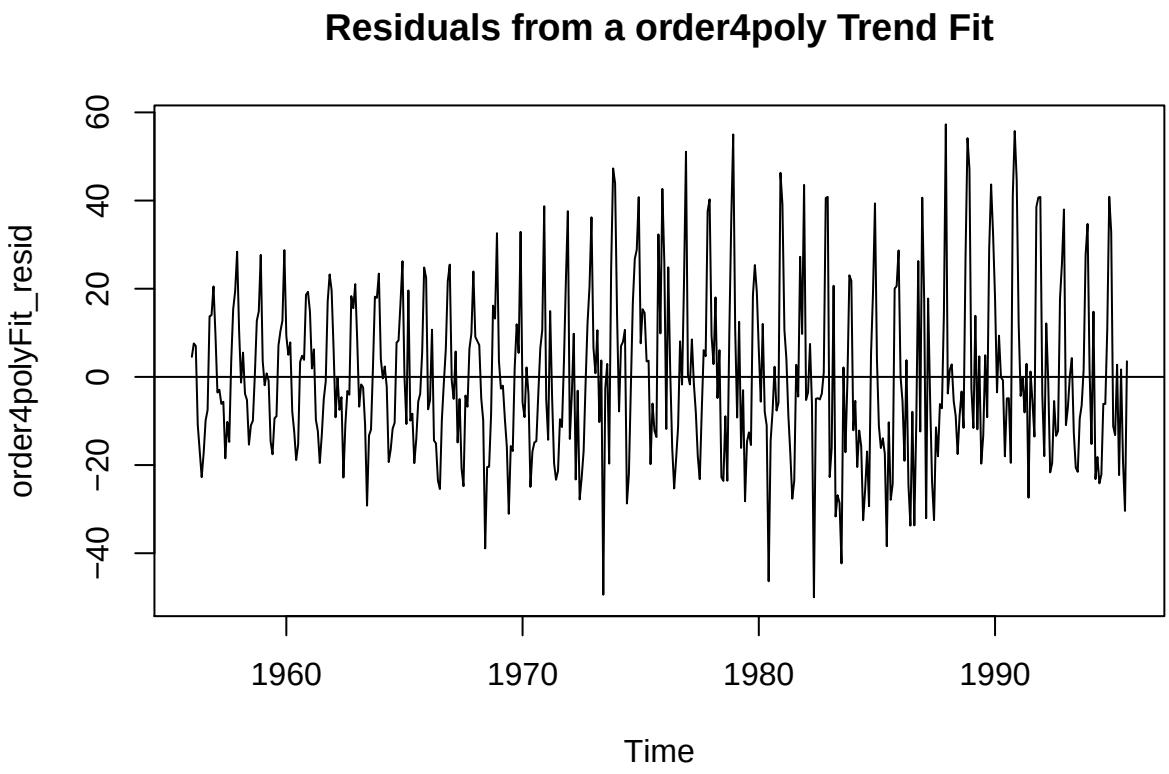

```
order4polyFit<-lm(beerTS~t+t2+t3+t4)
summary(order4polyFit)
```

```
##
## Call:
## lm(formula = beerTS ~ t + t2 + t3 + t4)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -49.98 -12.80  -3.25  10.61  57.29
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  8.890e+01  4.432e+00  20.058  < 2e-16 ***
## t           -2.598e-01  1.285e-01  -2.022   0.0437 *
## t2           5.715e-03  1.094e-03   5.226 2.61e-07 ***
## t3          -1.859e-05  3.443e-06  -5.399 1.06e-07 ***
## t4           1.742e-08  3.581e-09   4.864 1.57e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 19.1 on 471 degrees of freedom
## Multiple R-squared:  0.6823, Adjusted R-squared:  0.6796
## F-statistic: 252.9 on 4 and 471 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="o
curve(expr = coef(order4polyFit)[1]+coef(order4polyFit)[2]*x+coef(order4polyFit)[3]*x^2+coef(order4polyl
```



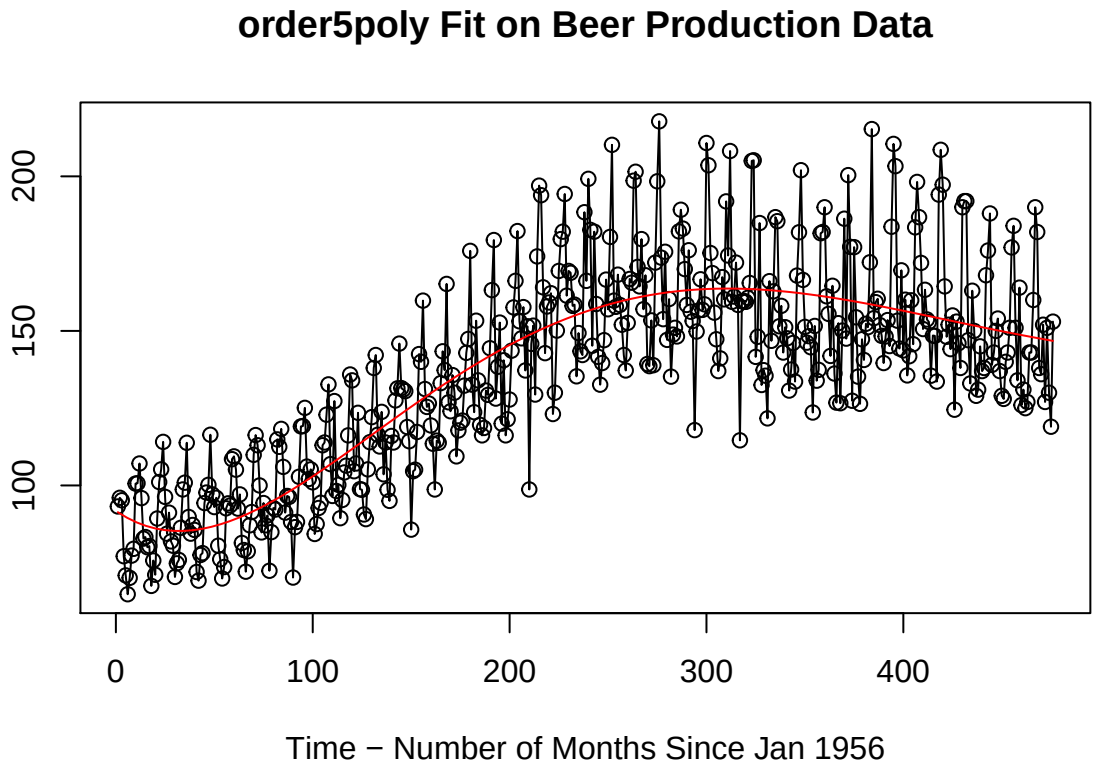

```
order4polyFit_resid<-ts(residuals(order4polyFit),frequency=12, start=c(1956,1))
plot(order4polyFit_resid, main="Residuals from a order4poly Trend Fit")
abline(h=0)
```



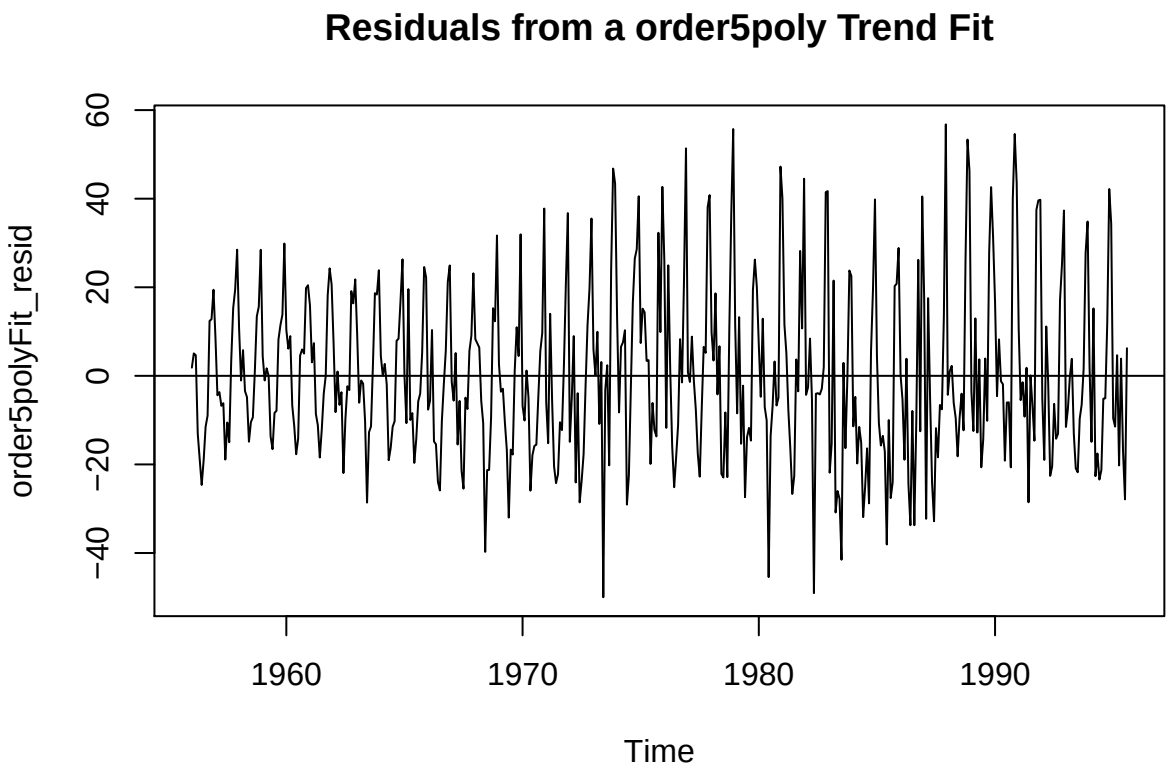

```
order5polyFit<-lm(beerTS~t+t2+t3+t4+t5)
summary(order5polyFit)
```

```
##
## Call:
## lm(formula = beerTS ~ t + t2 + t3 + t4 + t5)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -49.99 -12.86  -3.47  10.48  56.79
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  9.177e+01  5.351e+00  17.152  < 2e-16 ***
## t           -4.376e-01  2.258e-01  -1.938  0.05328 .
## t2           8.313e-03  2.926e-03   2.841  0.00469 **
## t3          -3.309e-05  1.554e-05  -2.130  0.03369 *
## t4           5.160e-08  3.589e-08   1.438  0.15118
## t5          -2.866e-11  2.995e-11  -0.957  0.33896
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 19.1 on 470 degrees of freedom
## Multiple R-squared:  0.6829, Adjusted R-squared:  0.6795
## F-statistic: 202.4 on 5 and 470 DF,  p-value: < 2.2e-16
```

```
#### 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="o
curve(expr = coef(order5polyFit)[1]+coef(order5polyFit)[2]*x+coef(order5polyFit)[3]*x^2+coef(order5polyl
```




```
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?)

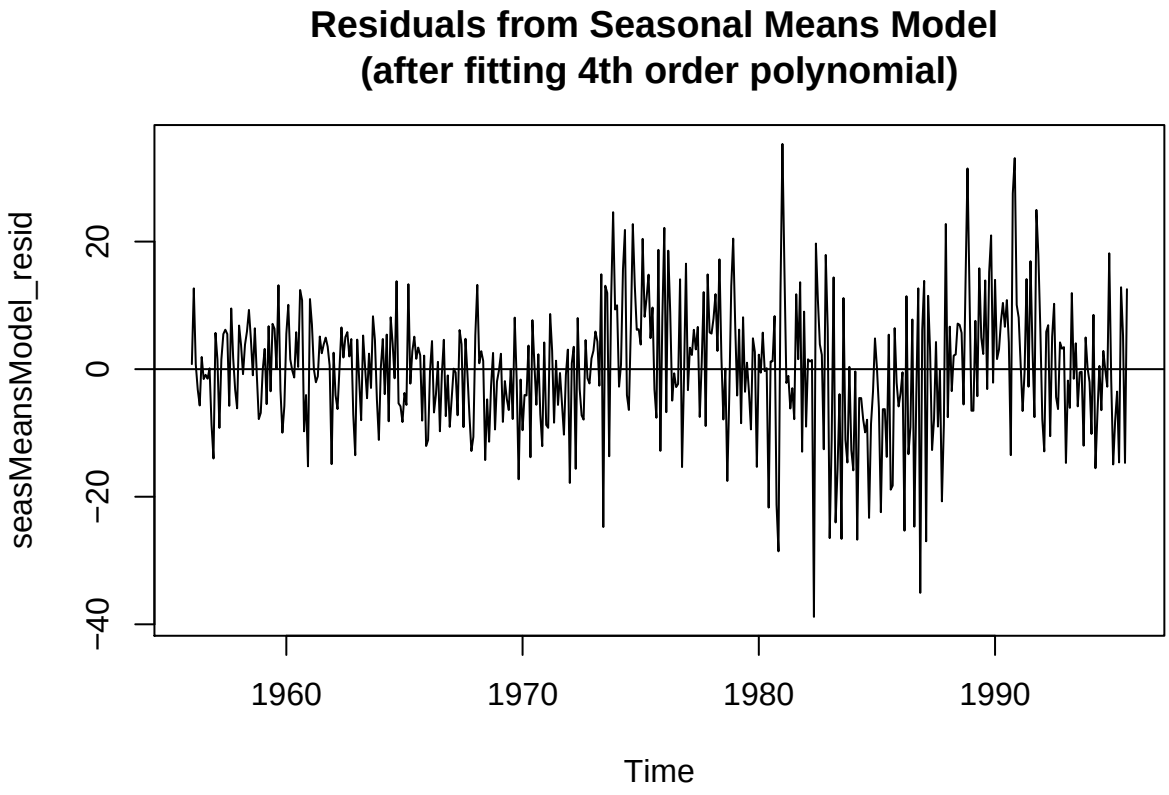
Assume we go with the 4th order polynomial for now. Let's see what we can do about the seasonality with a seasonal means model

```
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
## -38.833  -6.262   0.163   5.865  35.303
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)       3.762      1.619   2.324 0.020577 *
## monthFebruary    -8.838      2.290  -3.860 0.000129 ***
## monthMarch        2.520      2.290   1.100 0.271686
```

```
## monthApril      -11.413      2.290  -4.985 8.79e-07 ***
## monthMay        -14.914      2.290  -6.513 1.91e-10 ***
## monthJune       -28.417      2.290 -12.411  < 2e-16 ***
## monthJuly       -19.470      2.290  -8.503 2.55e-16 ***
## monthAugust     -12.758      2.290  -5.572 4.28e-08 ***
## monthSeptember   -9.781      2.304  -4.245 2.64e-05 ***
## monthOctober      9.852      2.304   4.276 2.31e-05 ***
## monthNovember    18.926      2.304   8.214 2.15e-15 ***
## monthDecember    30.769      2.304  13.353  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 10.24 on 464 degrees of freedom
## Multiple R-squared:  0.7168, Adjusted R-squared:  0.7101
## F-statistic: 106.8 on 11 and 464 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 polynom
abline(h=0)
```

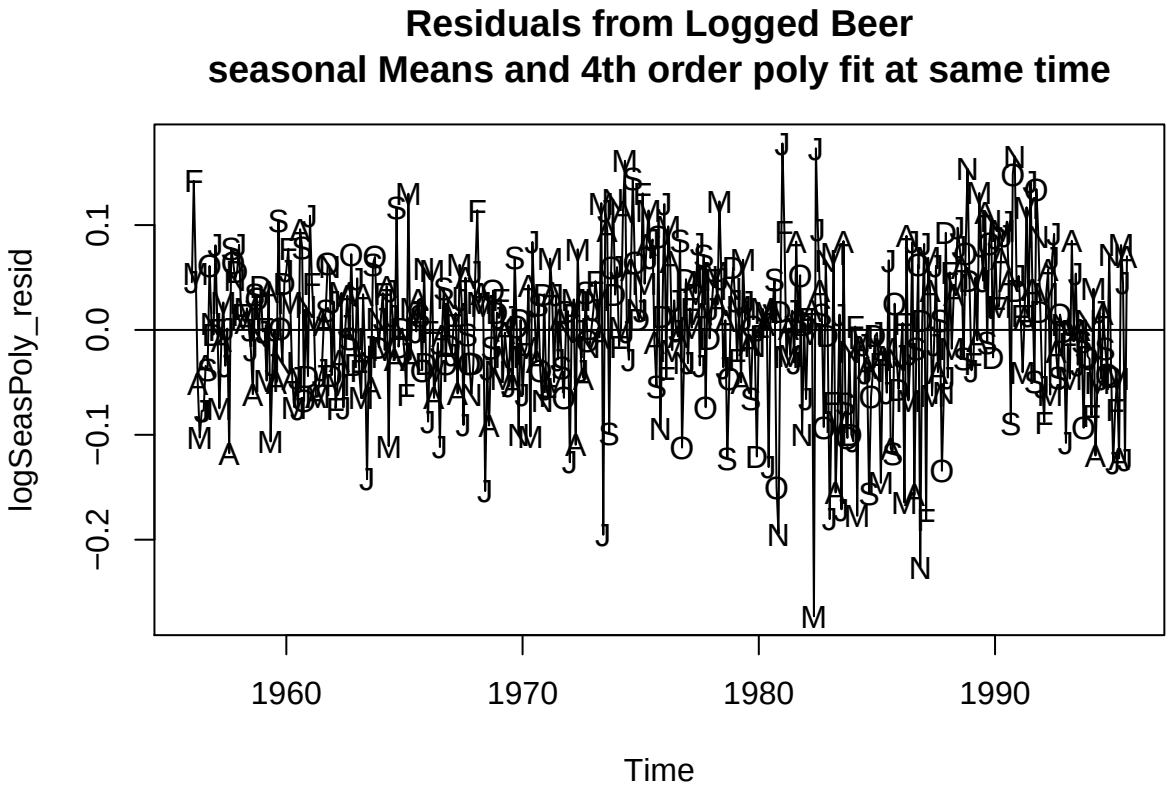


With an adjusted R-squared value of 71%, this is looking pretty good, but in the residual plot you can still the the variance increasing over time. In addition, there is a noticeable "wave" in the residuals that starts around 1970, but I'm not sure what to do about that yet. For now, let's go back, log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

```r
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
## -0.273007 -0.039226  0.002222  0.045637  0.177923
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)     4.490e+00  1.918e-02 234.056  < 2e-16 ***
## t              -1.112e-03  4.694e-04  -2.368   0.0183 *
## t2              4.149e-05  3.996e-06  10.384  < 2e-16 ***
## t3             -1.446e-07  1.258e-08 -11.492  < 2e-16 ***
## t4              1.420e-10  1.308e-11  10.857  < 2e-16 ***
## monthFebruary  -6.604e-02  1.559e-02  -4.235 2.76e-05 ***
## monthMarch      1.470e-02  1.559e-02   0.943   0.3464
## monthApril     -9.043e-02  1.559e-02  -5.799 1.24e-08 ***
## monthMay       -1.219e-01  1.559e-02  -7.818 3.68e-14 ***
## monthJune      -2.366e-01  1.559e-02 -15.172  < 2e-16 ***
## monthJuly      -1.577e-01  1.560e-02 -10.114  < 2e-16 ***
## monthAugust    -1.020e-01  1.560e-02  -6.539 1.65e-10 ***
## monthSeptember -6.994e-02  1.570e-02  -4.456 1.05e-05 ***
## monthOctober    6.689e-02  1.570e-02   4.261 2.47e-05 ***
## monthNovember   1.230e-01  1.570e-02   7.834 3.30e-14 ***
## monthDecember   1.954e-01  1.570e-02  12.449  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.06973 on 460 degrees of freedom
## Multiple R-squared:  0.9328, Adjusted R-squared:  0.9306
## F-statistic: 425.6 on 15 and 460 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
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

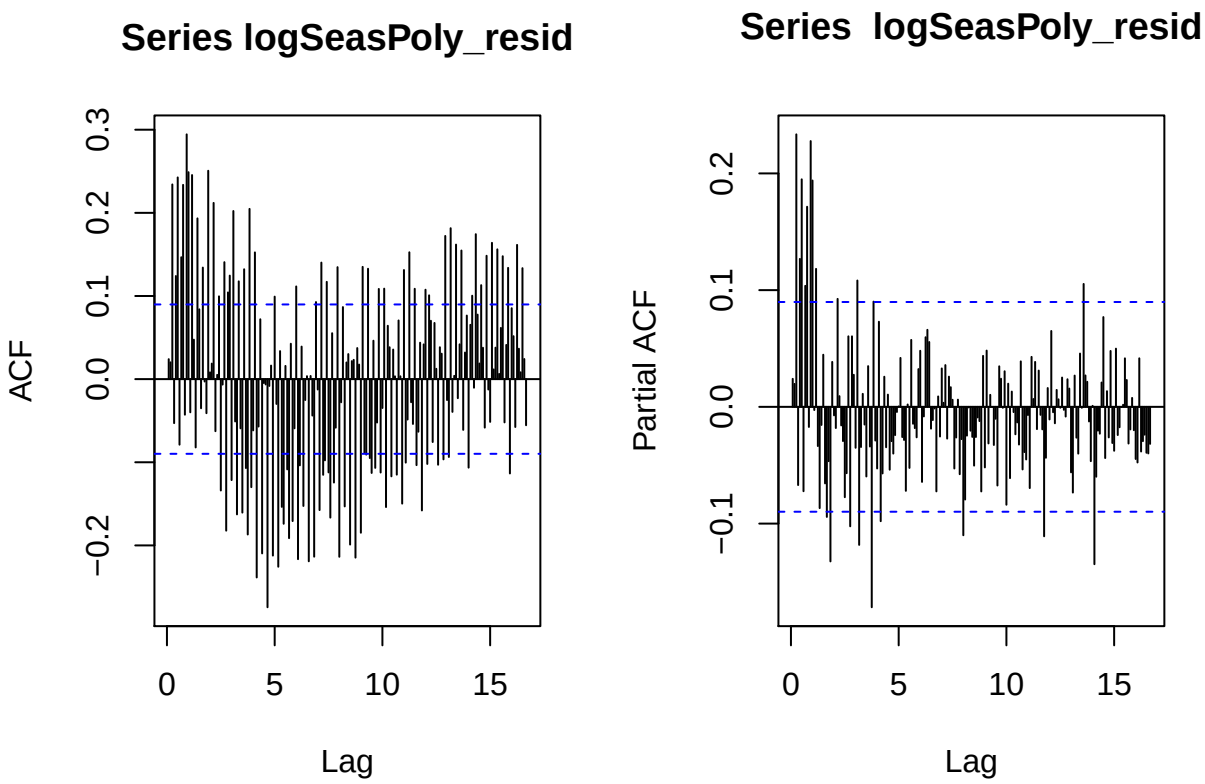
```
# d
adf.test(logSeasPoly_resid)
```

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

##
##  Augmented Dickey-Fuller Test
##
## data:  logSeasPoly_resid
## Dickey-Fuller = -5.1622, 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) = -522.68, Truncation lag parameter = 5,
## p-value = 0.01
## alternative hypothesis: stationary
```

```r
# p & q
par(mfrow=c(1,2))
acf(logSeasPoly_resid, lag.max=200)
pacf(logSeasPoly_resid, lag.max=200)
```

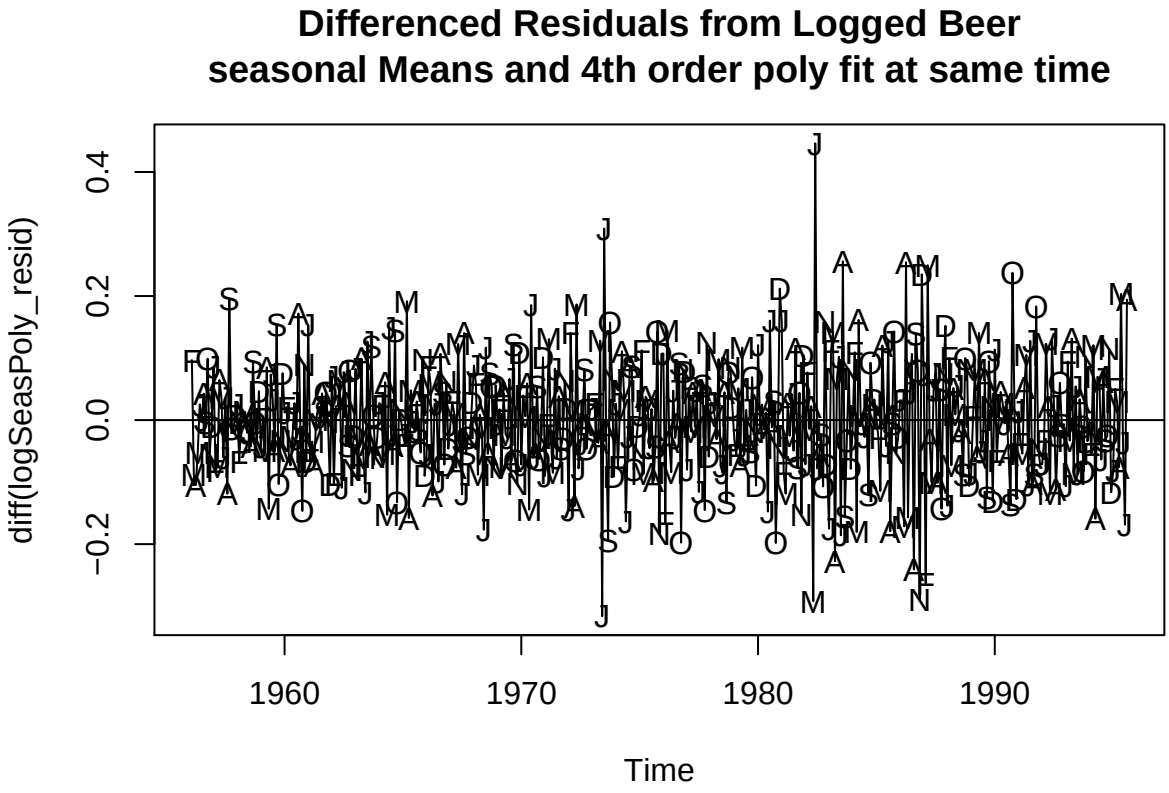



```r
par(mfrow=c(1,1))
eacf(logSeasPoly_resid)
```

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

The variance looks a little better, we still have that wave we should definitely look at, maybe differencing would take care of it?

```r
plot(diff(logSeasPoly_resid), main="Differenced Residuals from Logged Beer\nseasonal Means and 4th orde
points(y=diff(logSeasPoly_resid), x=time(diff(logSeasPoly_resid)), pch=as.vector(season(diff(logSeasPoly
abline(h=0)
```



Now it looks pretty except for a couple outliers. Let's work with this then.

So to summarize what we've done so far

1) Logged data
2) Fit 4th order polynomial and seasonal means at the same time
3) Differenced residuals from step 2

We will rename this series beer2 for convienence

```
beer2TS<-diff(logSeasPoly_resid)
```

Let's look to see if our new series is stationary according to the Augmented Dickey-Fuller Test and a Phillips-Perron Test

```
# d
adf.test(beer2TS)
```

```
## Warning in adf.test(beer2TS): p-value smaller than printed p-value

##
##  Augmented Dickey-Fuller Test
##
## data:  beer2TS
## Dickey-Fuller = -14.857, Lag order = 7, p-value = 0.01
## alternative hypothesis: stationary
```

```
pp.test(beer2TS)
```

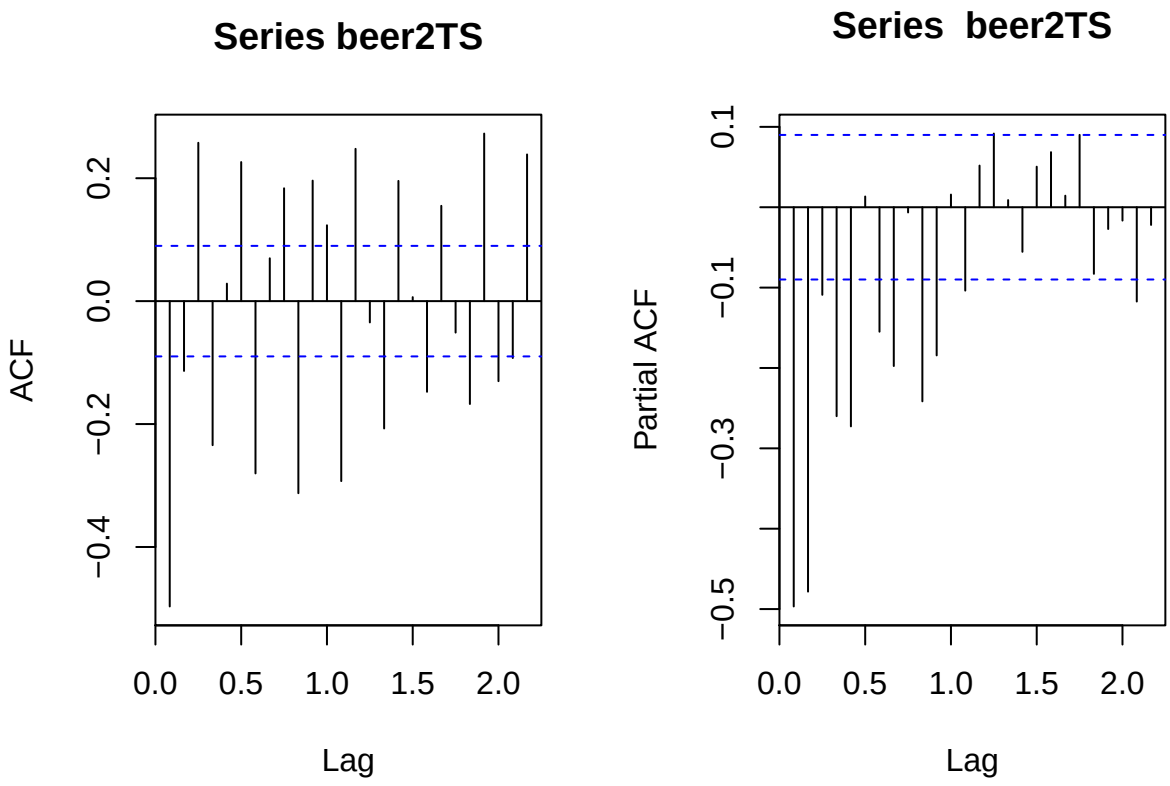
```
## Warning in pp.test(beer2TS): p-value smaller than printed p-value
```

```
##
##  Phillips-Perron Unit Root Test
##
## data:  beer2TS
## Dickey-Fuller Z(alpha) = -572.9, Truncation lag parameter = 5,
## p-value = 0.01
## alternative hypothesis: stationary
```

In both we have small p-values, so we should reject the null hypothesis (that the series is not stationary), so we conclude that our transformed series is stationary.

Now we need to determine p and q

```
# p & q
par(mfrow=c(1,2))
acf(beer2TS)
pacf(beer2TS)
```




```
par(mfrow=c(1,1))
eacf(beer2TS)
```

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

Well clearly this is a mess. The pacf appears to be decreasing nicely as we would like, however the acf doesn't appear to be decreasing at all. Needs to be investigated further, but not tonight.