University of California, Santa Barbara

Analysis and Forecasting of Quarterly Production of Beer in Australia

PSTAT 174

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Contents

Abstract

The purpose of this proposal is to analyze the quarterly production of beer in Australia between March of 1956 and June 1992 in order to forecast the projections for the third quarter of year 1993 through second quarter of 1994 by utilizing time series functions. Since the data is seasonal and demonstrated a positive trend, it needed to be transformed and differenced in order to use the lowest AICs and BICs to create an accurate model. The model was then checked by running diagnostic checking to finalize the model which was then used in forecasting. Our predicted values are within a 95% confidence interval showcasing that our forecasted model is relatively accurate. Also, when we compare our predicted values to the actual observed values, they appear reasonably close, again proving the point that our selected model is fairly accurate when compared to the original dataset.

1. Introduction

Being students at UC Santa Barbara, which is dubbed a party school, it is understandable as to why we would be curious to observe what have been previous trends in beer production and our willingness to try to predict future production. This dataset showcases the quarterly data of beer production in Australia from March 1956 to June of 1994. We chose this dataset because while production of beer is interesting in itself, the data is quarterly which demonstrates which season (summer, spring, fall, winter) required more production of beer and which had a lower demand in supply. We plan to predict the last two years' worth of data points and compare it with the actual recorded values to see if the trend remains consistent throughout the data. By performing a Box-Cox transformation to stabilize variance, and differencing the data to ensure the data is stationary and detrended, we were then able to identify an adequate model that would allow accurate forecasting. The first two models we used were $SARIMA(0,1,2)x(0,1,1)_4$ which has an AIC value of -0.9514 and BIC value of -1.9058 and secondly, $SARIMA(1,1,1)x(0,1,1)_4$ with an AIC of -0.9172 and BIC of -1.8715. Both models prove to have very low AIC and BIC values so we proceeded to perform diagnostic checking to test if the models are normal. After the diagnostic check, it was concluded that the best model was $SARIMA(0,1,2)x(0,1,1)_4$. After finalizing the best model, forecasting was performed, and the last eight observations from the data were compared with the predicted values. Results concluded that the predicted values fell within a 95% confidence interval further confirming the model selected is fairly accurate. This dataset can be found on the DataMarket website where they cite this data from Australian Bureau of Statistics.

2. Data Analysis

2.1 Data Exploration

The data represents the quarterly beer production in Australia, the time variable is in quarters (Q1, Q2, Q3, Q4) and the production of beer is recorded in megaliters. In the original dataset, there were 154 observations. By cutting the last 8 observations from the data set, we aimed to test the results from our forecasted values to these 8 observations to ensure accurate predictions; therefore, we utilize 146 observations for our future analysis.

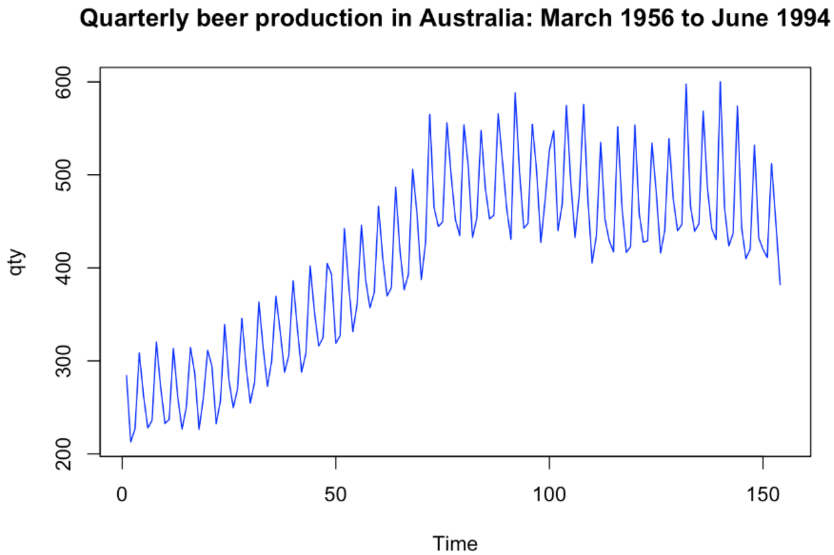


Figure 2.1

From the original plot of the dataset with all 154 observations, as illustrated in Figure 2.1, there appears to be an increasing trend. The plot above demonstrates that production steadily increases in the beginning and eventually appears to plateau. The plot also seems to have a repeating sharp zig-zag motion which alludes to seasonality.

From the Seasonal graph below (Figure 2.2), we see that the majority of the production of beer is during the fourth quarter and looks to roll over to the first quarter of the next year. If we stop to think about when Australia's summer time is, it is clear that since summer starts end of November early December (Quarter 4) and ends somewhere in February (Quarter 1) these quarters would demand higher production. Also, there are around eight notable holidays all during the fourth quarter that could give reason to drink, which could also explain the higher production level than any of the other quarters. Nevertheless, despite the reasons, there is noticeable variation in production levels between the four quarters, which demonstrates clearly there is in fact a seasonality component to this data. Therefore, we were right before to assume from the original plot that the zig-zag motion of the line did represent seasonality.

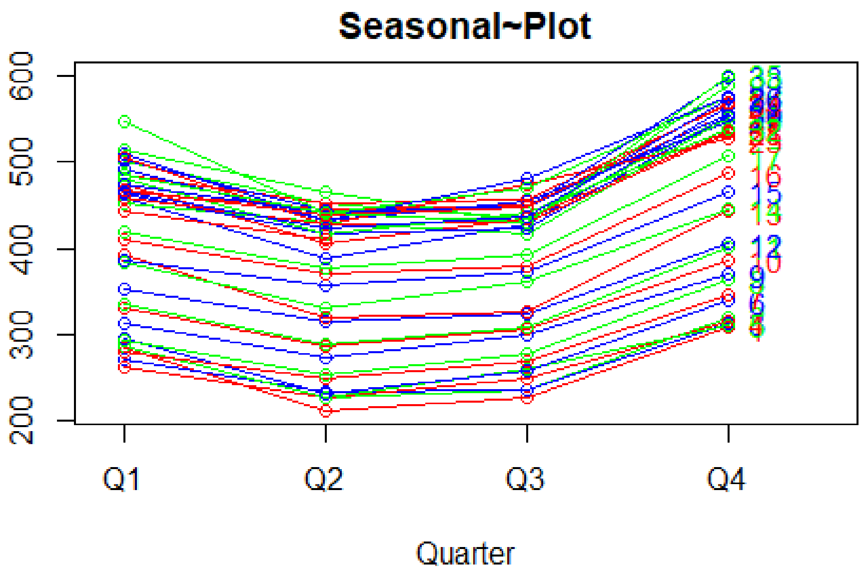


Figure 2.2

In conclusion, in the first plot it was clear there is an increasing trend with the data and potential seasonality and from the seasonal plot it became clearer that there is in fact seasonality with the data, therefore the data is not stationary and further analysis and transformations are required.

2.2 Box-Cox Transformation

In order to make the data stationary, we plan to transform and difference the data to do the future analysis. The variance for the original data is 9845.175. Since it is relatively large, we need to stabilize the variance. Then we can remove the seasonality and trend of the data to get the best model.

Since it is confirmed the data is seasonal and it demonstrates an increasing trend, it is necessary to perform transformations in order to achieve stationarity. Box Cox transformation is needed in order to stabilize the variance. As we can see from the graph below (Figure 2.3), lambda appears to be about 0.5, and further analysis confirms that lambda is 0.505, therefore the transformation used on the data is a square root transformation, such as: $V_t = Y_t^{0.50}$. The variance is reduced significantly, to 6.39539. Then from here, differencing is needed to remove the seasonality of the data.

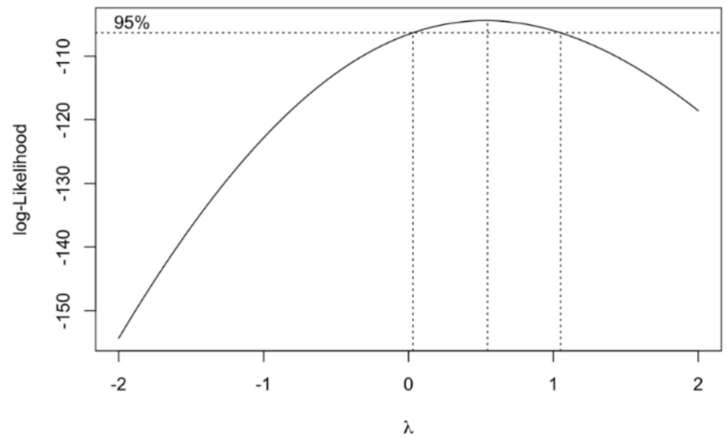


Figure 2.3

2.3 Deseasonalizing and Detrending the Data

First, the data will be differenced at lag four due to the fact the data is represented quarterly. By doing so we are removing the seasonality of the data and the resulting data is represented in Figure 2.4. From Figure 2.4, the graph appears to be more randomized and has less of the uniform peak and valley structure that was originally exhibited in Figure 2.1. The variance of the model is fairly small (.2195557). While the seasonality appears to be fixed, there still appears to be a trend within the data, which is illustrated clearly with the red line. Even though the trend in Figure 2.1 looked to be increasing, after differencing at lag 4 the trend appears to be decreasing; nevertheless, additional modification is necessary to remove the trend in order to make the model stationary.

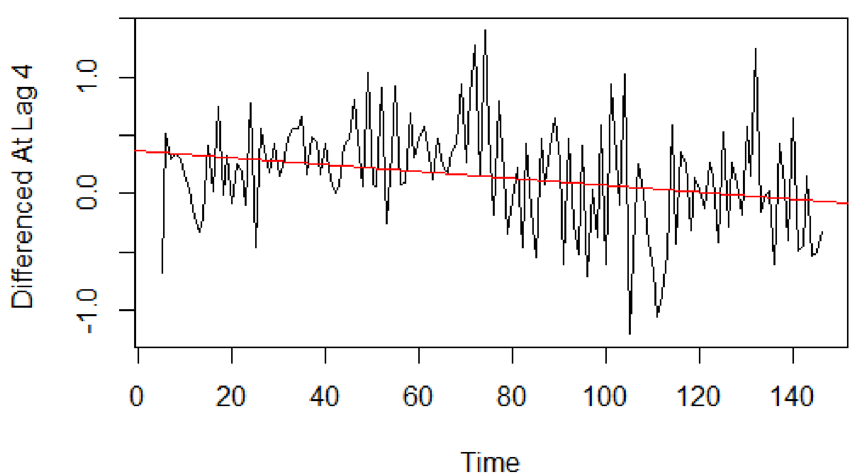


Figure 2.4

By differencing once more, the trend component is removed, as shown below in Figure 2.5. Again, as represented by the red line, it is clear that the data is detrended since the line appears to be fairly constant around 0. The variance for this model is .41797, and while this is greater than the variance of the previous model, we will keep this model due to the fact the data is now detrended and deseasonalized, while the prior was only deseasonalized. Despite the fact this model looks adequate, the data will be differenced again to ensure the best model.

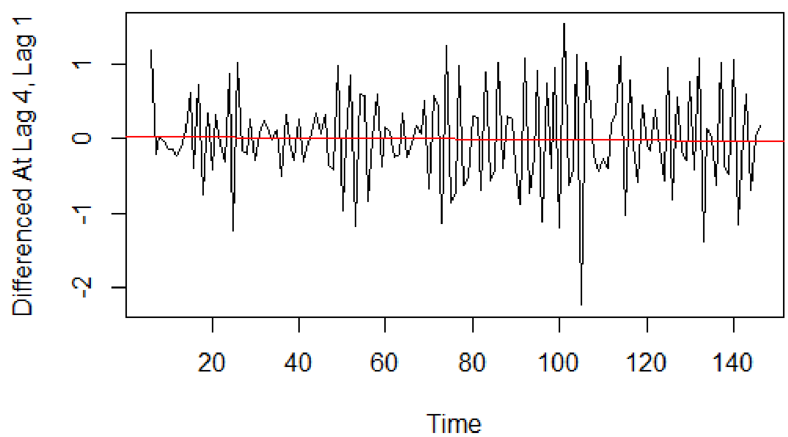


Figure 2.5

When the data is differenced once more variance is then 1.34731 which is substantially greater than the variances before. This increase in variance demonstrates an over differencing in the data, therefore the best model would be when we differenced at lag 4 and then again at lag 1. While it is noted that the variance between the model where it was only differenced at lag 4 and the one that is differenced at lag 4 and then at lag 1 does exemplify a slightly increased variance, the model still manages to remove the trend so model differenced at lag 4 lag 1 is adequate. The data is now stationary and can be used to distinguish the proper model by using ACF and PACF plots.

3. SARIMA Model Identification

3.1 Preliminary Model Identification

By looking at just the ACF and PACF for the stationary model (Figure 3.1), we can start to develop a SARIMA model.

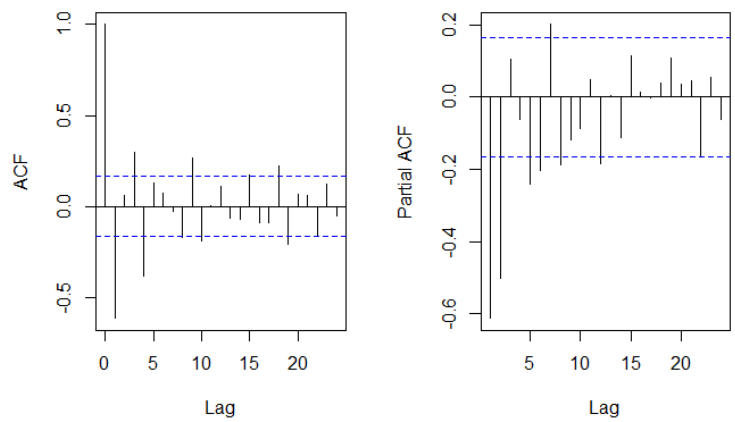


Figure 3.1

Since we already know the data exhibited seasonality, we note that S equals 4 and we differenced once to remove trend, so D=d=1. We plot the ACF and PACF of stationary time series X_t in order to calculate the seasonal terms P and Q from Figure 3.1 above. Since our seasonal component s=4, we need to check ACF and PACF at seasonal lag 4, 8, 12, 16, 20, etc. Therefore, for the seasonal terms P and Q, ACF plot cuts off after lag 4 (Q = 1) and PACF plot tails off (P = 0). Then, we find p and q by looking at ACF and PACF plots. Therefore, for the non-seasonal terms p and q, we ran different combinations of non-seasonal terms p(0,1,2,3,4,5) and q(0, 1, 2,3,4,5) to see which model would be the best. We have 25 possible models to consider. Therefore, further analysis is required to ensure an accurate model and in order to do so, we will look at the AIC and BIC in order to perform the model checking analysis section.

3.2 Model Selection

The Akaike Information Criterion (Table 3.1) and Bayesian Information Criterion (Table 3.2) can be used in order to choose the best model from all possible models that were identified previously. The smaller the score is for both AIC and BIC, the better the model. From the AIC selection, the models with the lowest AIC scores were p=2,q=5 and p=5,q=5 however we selected model p=0,q=2 because it had the lowest BIC score and one of the lowest AIC scores. We selected this model because of the principle of parsimony – it had fewer parameters. This allowed us to select our second model, as well. The AIC and BIC scores when p=1 and q=1 are relatively low and the principle of parsimony states that we should pick a model with few parameters.

Table 3.1:AIC

	q=0	q=1	q=2	q=3	q=4	q=5
p=0	-0.2661	-0.8219	-0.9514	-0.9373	-0.9239	-0.909
p=1	-0.7942	-0.9172	-0.9375	-0.923	-0.9117	-0.8972
p=2	-0.9142	-0.9193	-0.9236	-0.9109	-0.9751	-0.9618
p=3	-0.9278	-0.915	-0.9093	-0.8958	-0.9284	-0.9144
p=4	-0.9155	-0.9001	-0.9297	-0.8814	-0.9013	-0.9311
p=5	-0.9008	-0.8965	-0.8809	-0.925	-0.9219	-0.9614

Table 3.2: BIC

	q=0	q=1	q=2	q=3	q=4	q=5
p=0	-1.26	-1.7959	-1.9058	-1.8722	-1.8396	-1.8056
p=1	-1.7682	-1.8715	-1.8723	-1.8387	-1.8084	-1.775
p=2	-1.8686	-1.8542	-1.8393	-1.8075	-1.8529	-1.8211
p=3	-1.8627	-1.8306	-1.8059	-1.7737	-1.7876	-1.7553
p=4	-1.8311	-1.7968	-1.8076	-1.7406	-1.7422	-1.754
p=5	-1.7975	-1.7743	-1.7402	-1.7659	-1.7447	-1.7664

First model: SARIMA (0,1,2) x $(0,1,1)_4$ with AIC = -0.9514499 and BIC = -1.905785

Second model: SARIMA (1,1,1) x $(0,1,1)_4$ with AIC = -.9171915 and BIC =-1.871526

3.3 Model Estimation

Let X_t be the transformed and differenced data.

$X_t = \nabla \nabla_4 Y_t^{0.5}$

Table 3.3: Model 1 and Model 2 Coefficients

	Model 1: SARIMA (0,1,2) x $(0,1,1)_4$	Model 2: SARIMA $(1,1,1)\text{x}(0,1,1)_4$
AR(1)	-	-0.4229
MA(1)	-0.9663	-0.4926
MA(2)	0.4146	-
SMA(1)	-0.8019	-0.7603

Model 1: SARIMA (0,1,2) x $(0,1,1)_4$

AICc = -0.9514499 BIC = -1.905785

$X_t = (1 - \mathbf{0.9663}B + \mathbf{0.4146}B^2)(1 - \mathbf{0.8019}B^4)Z_t$

$X_t = Z_t - \mathbf{0.9663}Z_{t-1} + \mathbf{0.4146}Z_{t-2} - \mathbf{0.8019}Z_{t-4} + \mathbf{0.7749}Z_{t-5} - \mathbf{0.3325}Z_{t-6}$

Model 2: SARIMA (1,1,1) x $(0,1,1)_4$

AICc = -0.9171915 BIC = -1.871526

$(1 + \mathbf{0.4229}B)X_t = (1 - \mathbf{0.4926}B)(1 - \mathbf{0.7603}B^4)Z_t$

$X_t + \mathbf{0.4229}X_{t-1} = Z_t - \mathbf{0.4926}Z_{t-1} - \mathbf{0.7603}Z_{t-4} + \mathbf{0.3745}Z_{t-5}$

Model 1 & Model 2 Roots

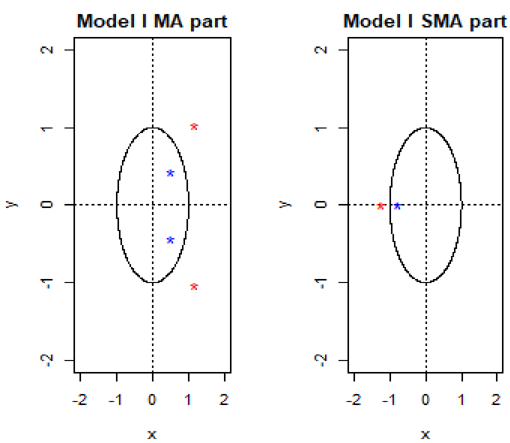


Figure 3.2

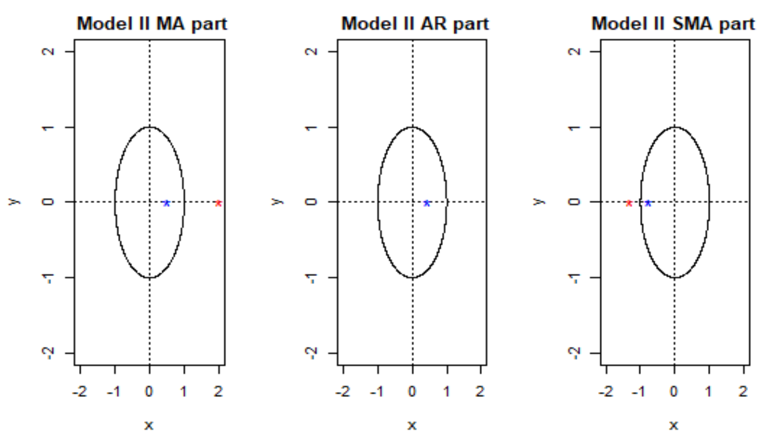


Figure 3.3

By plotting the roots of the polynomials AR and MA, we are able to check causality and invertibility. The red star corresponds to the roots, and if they lie outside of the unit circle, we can conclude that the absolute values for all the coefficients are less than 1, and therefore AR parts are stationary and MA parts are invertible. Model I satisfies both causality and invertibility and is the better model since the roots of Model II did not appear in the graph of the AR part.

3.4 Diagnostic Checking

In order to check the assumptions of the two models to determine whether or not it satisfies the assumptions of SARIMA, we can perform diagnostic checking on normality, heteroscedasticity, and serial correlation by utilizing the ACF and PACF, Shapiro-Wilk normality test, Box-Pierce test, and Ljung-Box test.

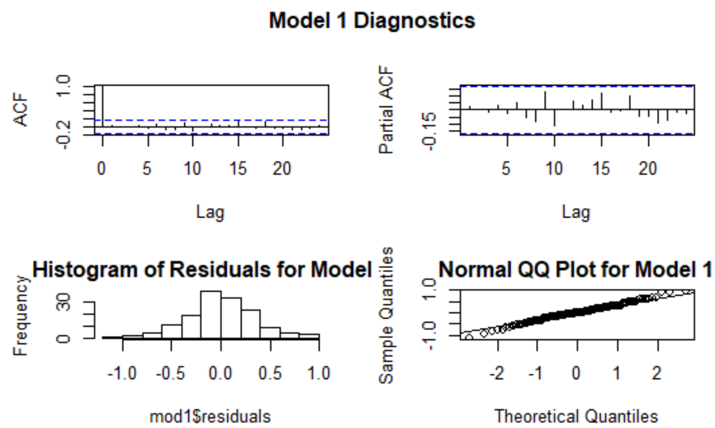


Figure 3.4

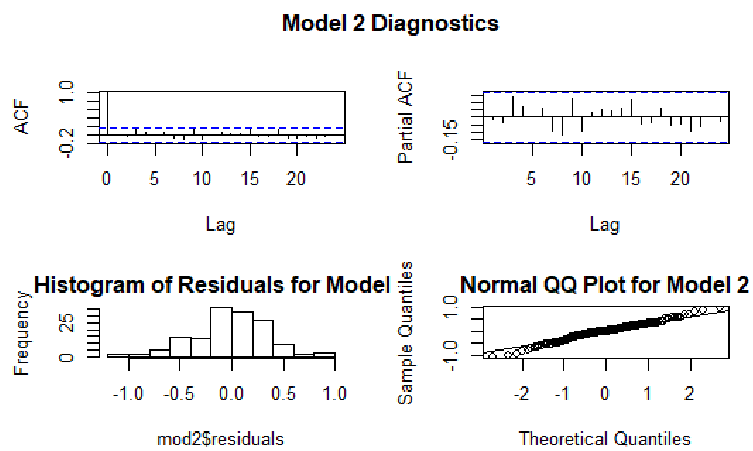


Figure 3.5

The histogram of residuals for both Model I and Model II appear to be normal, since they are symmetrical and bell shaped. Moreover, the normal QQ Plots and residual plots suggest the errors are normal.

ACF and PACF of squared residuals can be used to determine heteroscedasticity. For both models it appears to resemble white noise, and the residuals appear to be within 95% of the white noise. Thus, we can conclude both models are not heteroscedastic.

Since the Shapiro Wilk test is used to test if residuals approximately follow identical and independent Gaussian distribution, we see that the p-value obtained is greater than 0.05, thus we fail to reject the null hypothesis. We can conclude the residuals for both models are normally distributed.

Lastly, we used the Ljung-Box tests and Box-Pierce test to test serial correlation. With the maximum lag set to seasonal s=4, and the p-value obtained is greater than 0.05, we fail to reject the null hypothesis. We can also conclude there is no serial correlation at a 95% confidence interval among the residuals for both models.

Table 3.4: P-values of residual tests

	Model 1	Model 2
Shapiro-Wilk Test	0.4368	0.1724
Box-Pierce Test	0.8472	0.1734
Ljung-Box Test	0.8424	0.1628

3.5 Forecasting

Forecasting is used to predict future observations based on past data, so here we forecasted 8 values ahead. We forecasted the original data shown in Figure 3.6, and forecasted the transformed data shown in Figure 3.7.

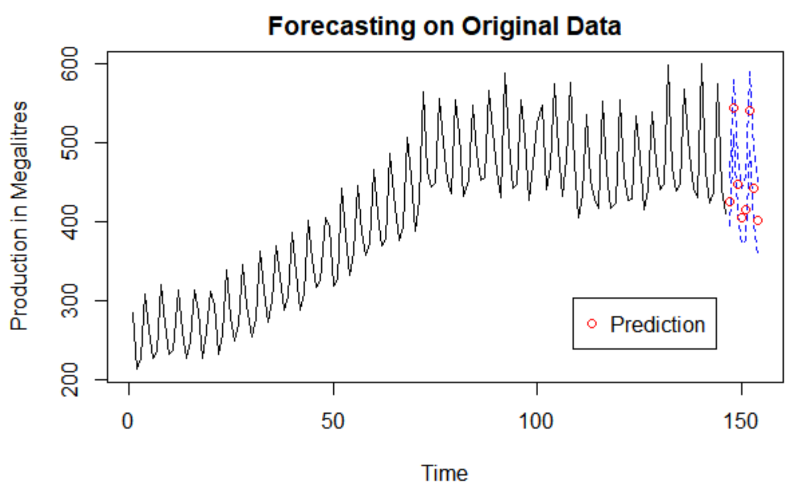


Figure 3.6

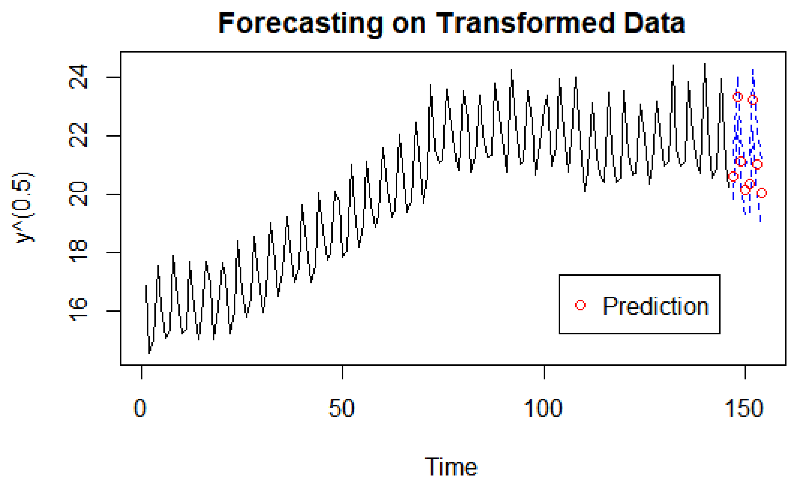


Figure 3.7

The red dot represents the prediction value, blue lines represent the boundaries of the confidence interval. In Figure 3.8, we can see that the forecasted values lie inside the confidence interval, and the observed values also lie closely to the predicted values. Furthermore, our forecasted model still reflects the seasonality and trend of the data. This means our forecasting model is successful.

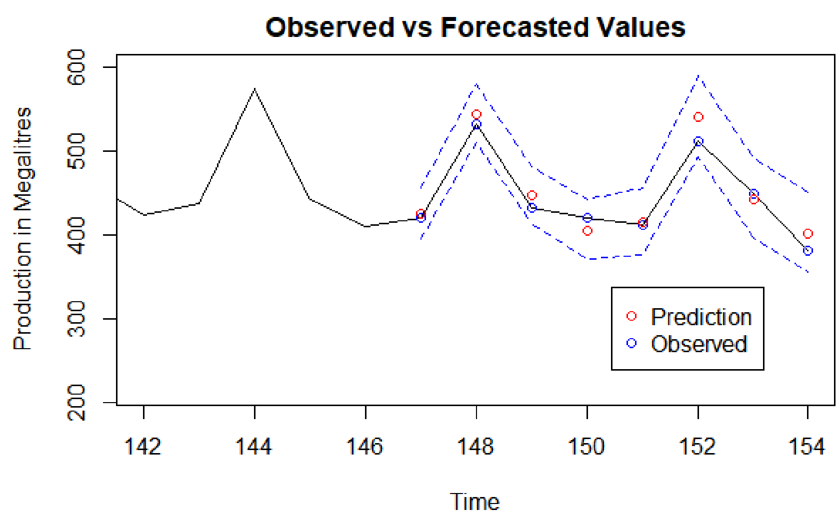


Figure 3.8

4. Conclusion

Our quarterly data consisted of Australian beer production measurements in megaliters, from 1956 to 1994. We initially sought out to create a model which could forecast potential future measurements. Our data originally displayed seasonality, demonstrated by the spike in production during the year's 4th quarter and the drop in production during the 2nd and 3rd quarters. Our data also displayed an upward trend, likely caused by an increase in population and an increase in demand for beer. In order to stabilize variance, we employed a Box-Cox transformation and obtained a lambda value of 0.5. In order to remove seasonality, we differenced our data at lag 4. We differenced once again to remove the trend.

By analyzing our ACF and PACF plots of our newly transformed data, we were able to identify parameter values for a *SARIMA* model. We decided that P = 0, D = 1, and Q = 1, since the ACF plot appeared to cut off after lag 4 and the PACF plot simply tailed off. We identified acceptable values of p and q, given that d would equal 1. We selected two models: p = 0 / q = 2 and p=1 / q=1. After diagnostic checking, we selected our first model.

If we allow X_t to be the transformed and differenced data,

$$X_t = \nabla\nabla_4 Y_t^{0.5}$$

Our final model is:

$$SARIMA\ (0, 1, 2) \times (0, 1, 1)_4$$

$$X_t = (1 - \mathbf{0.9663}B + \mathbf{0.4146}B^2)(1 - \mathbf{0.8019}B^4)Z_t \quad \text{where } Z_t \sim N(0, 0.1342)$$

$$X_t = Z_t - \mathbf{0.9663}Z_{t-1} + \mathbf{0.4146}Z_{t-2} - \mathbf{0.8019}Z_{t-4} + \mathbf{0.7749}Z_{t-5} - \mathbf{0.3325}Z_{t-6}$$

Both potential models were acceptable, according to our diagnostic checking. We chose this model however, because its AIC and BIC scores were lower than our second model. This model had the single lowest BIC score and one of the lowest AIC scores. Since it has a small number of parameters, it is compliant with the principle of parsimony, as well. Our forecasted values were similar to the actual recorded values, and lied well within our confidence interval. Our model building appears to have been successful.

Regardless, there are improvements to the model building that could have been applied. For instance, our data exhibited an upward linear trend in the first half of its domain. In the second half, the trend appears to disappear. This implies some kind of non-linear, perhaps exponential, trend. We differenced at lag 1 to remove this trend, yet other strategies may be explored in order to remove this exponential trend. In addition, our model is based purely off of past measurements. If there is some kind of jump or drop in beer production, perhaps caused by economic upturns or downturns, we would need to build a new model, or employ different regression strategies to account for anomalies.

Although we humorously decided to use this dataset with UCSB's "party school" reputation in mind, our model does have value in that it allows for prediction of supply and demand of Australian goods. Beer is a highly sought-after commodity around the world, let alone Australia. By analyzing the increases of supply in accordance with the increases in demand at the end of every year, we are able to predict how much of this commodity will be supplied to the public and relay this information to economic researchers.

Thank you Professor Bapat, for the great quarter and the information we have gained about time series. Also, thanks for the opportunity to demonstrate what we have learned this quarter through this project. We would also like to thank Sunpeng Duan and Nicole Yang on their help and input during office hours and section.

References

Quarterly Beer Production in Australia: megaliters. March 1956- June1994

https://datamarket.com/data/set/22ry/quarterly-beer-production-in-australia-megalitres-march-1956-june-1994#!ds=22ry&display=line

Appendix

Libraries

```
```{r}

#Load Packages

library(MASS)

library(forecast)

library(tseries)

library(astsa)

library(dse)

library(knitr)

library(gridExtra)

library(grid)

```
```

Read in CSV, Initial Time Series Analysis

```
```{r}

beer <- read.csv(file = "beer.csv",  header = TRUE, sep = ",", nrows = 146)[,-1]

beerall <- read.csv(file = "beer.csv",  header = TRUE, sep = ",", nrows = 154)[,-1]

ts.plot(beer, ylab = "Production in Megalitres",xlab = "Time(Quarterly)")

title(expression(Beer~Production~In~Australia~March~1956~-~June~1992))

```
```

ACF and PACFs for Beer Production

```{r}
# Beer.ts with 8 points removed
beer.ts <- ts(beer, frequency = 1)

# Beer.ts with all points
beerall.ts <- ts(beerall, frequency = 1)

acf(beer.ts, lag.max =10,main = "" )
pacf(beer.ts, lag.max=10, main = "")
```

Seasonal Plot

```{r}
# Seasonal Plot
seasonplot(beer.ts, 4, col=rainbow(3), year.labels = TRUE, main = "Seasonal~Plot")

```

Box Cox Transformations

```{r}
# Finding Lambda
bcbeer <- boxcox(beer.ts~as.numeric(1:length(beer)))
# Lambda
lambda1 <- bcbeer$x[which.max(bcbeer$y)]
# Lambda is 1/2
# Log transformed data
beer.tr <- beer.ts^(1/2)
ts.plot(beer.tr, ylab = "Production in Megalitres",xlab = "Time(Quarterly)", main = "Box Cox Transformed Data")
```

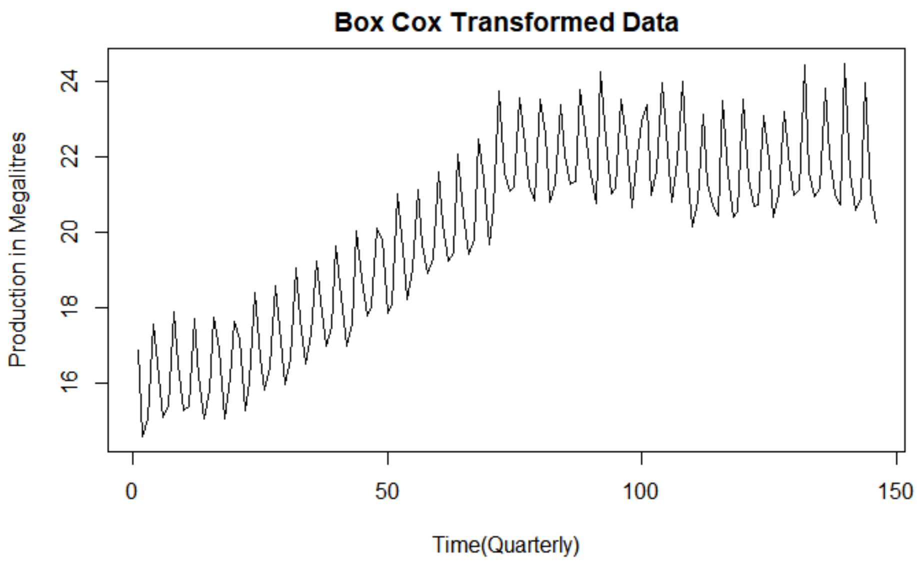
Variance of nontransformed data

var(beer.ts)

Variance of transformed data

var(beer.tr)

```




Removing Trend and Seasonality

```{r}

# Differencing Seasonality at lag 4

beerdiff4 <- diff(beer.tr, lag =4)

var(beerdiff4)

ts.plot(beerdiff4, ylab = "Differenced At Lag 4 ")

abline(lm(beerdiff4~as.numeric(1:length( beerdiff4))), col ="red")

# Differencing at Lag 1

beerdiff4diff1 <- diff(beerdiff4, lag =1)

var(beerdiff4diff1)

```
ts.plot(beerdiff4diff1, ylab = "Differenced At Lag 4, Lag 1")
abline(lm(beerdiff4diff1~as.numeric(1:length(beerdiff4diff1))), col ="red")
```

```{r}
# Differenced at lag 4 PACF AND ACF
par(mfrow=c(1,2))
acf(beerdiff4, lag.max = 24, main = "")
pacf(beerdiff4, lag.max = 24, main = "")

# DIFFERENCED at lag 4 and lag 1 PACF AND ACF
par(mfrow=c(1,2))
acf(beerdiff4diff1, lag.max=24, main = "")
pacf(beerdiff4diff1, lag.max=24, main = "")

```

Model Selection for SMA(1)

```{r}

library(qpcR)
AICc<-numeric()
for (p in 0:5) {
  for (q in 0:5) {
    AICc<-round(c(AICc, sarima(beer.tr, p, 1, q, 0, 1, 1, 4, details = FALSE)$AICc),4)
  }
}
```

```
AICc<-matrix(AICc, nrow = 6, byrow = TRUE)
rownames(AICc)<-c("p=0","p=1","p=2", "p=3", "p=4", "p=5")
colnames(AICc)<-c("q=0","q=1", "q=2", "q=3", "q=4", "q=5")
AICc
AICc<-data.frame(AICc)
aicc<-setNames(AICc, c("q=0","q=1", "q=2", "q=3", "q=4", "q=5"))
aicc
grid.table(aicc)

```

```
```{r}

BIC<-numeric()
for (p in 0:5) {
  for (q in 0:5) {
    BIC<- round(c(BIC, sarima(beer.tr, p, 1, q, 0, 1, 1, 4, details = FALSE)$BIC),4)
  }
}

BIC<-matrix(BIC, nrow = 6, byrow = TRUE)
rownames(BIC)<-c("p=0","p=1","p=2", "p=3", "p=4", "p=5")
colnames(BIC)<-c("q=0","q=1","q=2", "q=3", "q=4", "q=5")
BIC
bic<-data.frame(BIC)
bic<-setNames(bic, c("q=0","q=1","q=2", "q=3", "q=4", "q=5"))
```
```

library(grid)

grid.table(bic)

```

From SMA(1) AIC selection, we select

Model Estimation for SMA(1) from AIC (0,1,2)X(1,1,0)4

Model Estimation for SMA(1) from BIC (1,1,1)X(1,1,0)4

```{r}

mod1 <- arima(beer.tr, order = c(0,1,2), seasonal = list(order = c(0,1,1), period = 4))

mod2 <- arima(beer.tr, order = c(1,1,1), seasonal = list(order = c(0,1,1), period = 4))

mod1

mod2
```

Checking Roots on both models

```{r}

#Script for roots

plot.roots <- function(ar.roots=NULL, ma.roots=NULL, size=2, angles=FALSE, special=NULL, sqecial=NULL,my.pch=1,first.col="blue",

```
second.col="red",main=NULL)
{xylims <- c(-size,size)
omegas <- seq(0,2*pi,pi/500)
temp <- exp(complex(real=rep(0,length(omegas)),imag=omegas))
plot(Re(temp),Im(temp),typ="l",xlab="x",ylab="y",xlim=xylims,ylim=xylims,main=main)
abline(v=0,lty="dotted")
abline(h=0,lty="dotted")
if(!is.null(ar.roots))
{
points(Re(1/ar.roots),Im(1/ar.roots),col=first.col,pch=my.pch)
points(Re(ar.roots),Im(ar.roots),col=second.col,pch=my.pch)
}
if(!is.null(ma.roots))
{
points(Re(1/ma.roots),Im(1/ma.roots),pch="*",cex=1.5,col=first.col)
points(Re(ma.roots),Im(ma.roots),pch="*",cex=1.5,col=second.col)
}
if(angles)
{
if(!is.null(ar.roots))
{
abline(a=0,b=Im(ar.roots[1])/Re(ar.roots[1]),lty="dotted")
abline(a=0,b=Im(ar.roots[2])/Re(ar.roots[2]),lty="dotted")
}
if(!is.null(ma.roots))
{
sapply(1:length(ma.roots), function(j) abline(a=0,b=Im(ma.roots[j])/Re(ma.roots[j]),
lty="dotted"))
}
```

```
}
if(!is.null(special))
{
lines(Re(special),Im(special),lwd=2)
}
if(!is.null(sqecial))
{
lines(Re(sqecial),Im(sqecial),lwd=2)
}
}
```

```{r}

# Plotting Roots for Both Models
par(mfrow = c(1,3))
plot.roots(NULL, polyroot (c(1,-0.9663,0.4146)) , main ="Model I MA part")
plot.roots(NULL, polyroot (c (1,0.8019)) , main ="Model I SMA part")
par(mfrow = c(1,3))
plot.roots(NULL, polyroot (c(1,-0.4926)) , main =" Model II MA part")
plot.roots(NULL, polyroot (c(1,-0.4229)) , main =" Model II AR part")
plot.roots(NULL, polyroot (c(1, 0.7603)) , main =" Model II SMA part ")
# normality
par(mfrow = c(2,2))

```

Model1:SARIMA(0,1,2)x(0,1,1)4

AICc = -0.9514499 BIC = -1.905785

Xt = Zt-0.97Zt-1 + 0.41Zt-2

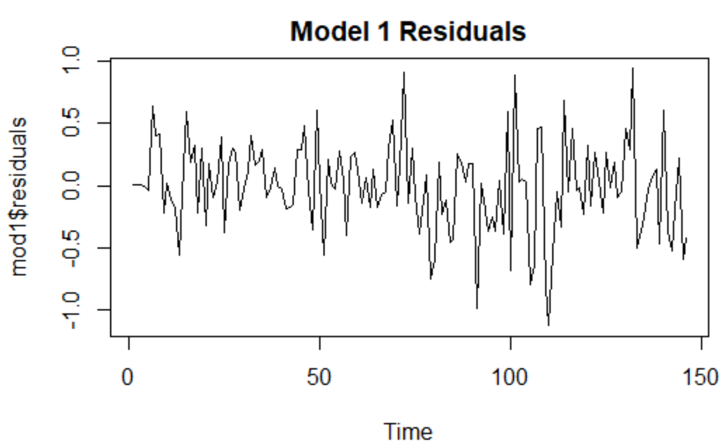
NABLA(4)NABLA(Yt) = (1+0.97B-0.41B^2-0.80B^4)

Model 2:SARIMA(1,1,1)x(0,1,1)4

AICc = -0.9171915   BIC = -1.871526

Model Diagnostics 1

```{r}

# Residual Plot Model 1

ts.plot(mod1$residuals, main = "Model 1 Residuals")

```



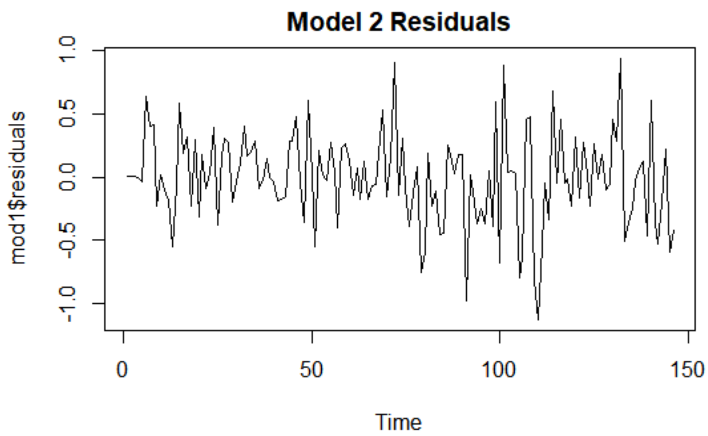
```{r}

par(mfrow=c(1,2),oma=c(0,0,2,0))
op <- par(mfrow=c(2,2))

acf(mod1$residuals, main = "", lag.max = 24)
pacf(mod1$residuals, main = "", lag.max= 24)
# histogram
hist(mod1$residuals, main = "Histogram of Residuals for Model 1")
# qq plot
qqnorm(mod1$residuals, main = "Normal QQ Plot for Model 1")
qqline(mod1$residuals)

title("Model 1 Diagnostics", outer=TRUE)
par(op)


#Normality Tests
shapiro.test(mod1$residuals)
Box.test(mod1$residuals, lag =4, type = "Box-Pierce", fitdf =2)
Box.test(mod1$residuals, lag =4, type = "Ljung-Box", fitdf =2)
```

Model 2 Diagnostics

```{r}

# Residual Plot Model 2
ts.plot(mod1$residuals, main = "Model 2 Residuals")
```

~~~
```
~~~




~~~
```{r}

#Model 2 Diagnostics
par(mfrow=c(1,2),oma=c(0,0,2,0))
op <- par(mfrow=c(2,2))

acf(mod2$residuals, main = "", lag.max = 24)
pacf(mod2$residuals, main = "", lag.max=24)
# histogram
hist(mod2$residuals, main = "Histogram of Residuals for Model 2")
# qq plot
qqnorm(mod2$residuals, main = "Normal QQ Plot for Model 2")
qqline(mod2$residuals)

title("Model 2 Diagnostics", outer=TRUE)
par(op)
~~~

```
#Normality Tests
shapiro.test(mod2$residuals)
Box.test(mod2$residuals, lag =4, type = "Box-Pierce", fitdf =2)
Box.test(mod2$residuals, lag =4, type = "Ljung-Box", fitdf =2)

```

Forecasting

```
```{r}

# Predictions on Transformed Data

pred.log <- predict(mod1, n.ahead=8)

upper.log <- pred.log$pred + 2*pred.log$se
lower.log <- pred.log$pred - 2*pred.log$se

ts.plot(beer.tr, xlim=c(1, length(beer.tr)+8), main = "Forecasting on Transformed Data", ylab= "y^(0.5)")

lines(upper.log, col="blue", lty = "dashed")
lines(lower.log, col="blue", lty = "dashed")

points((length(beer.tr)+1):(length(beer.tr)+8), pred.log$pred, col ="red")

# Add a legend
legend("bottomright",
  legend = c("Prediction"),
  col = c("red"),
```
```

```
  pch = 1,
  bty = "o",
  pt.cex = 1,
  cex = 1,
  text.col = "black",
  horiz = F ,
  inset = c(0.1, 0.1))
```

```{r}
# Predictions on Original Data
pred.original <- pred.log$pred^(1/0.5)
upper <-upper.log^(1/0.5)
lower <-lower.log^(1/0.5)

ts.plot(beer.ts, xlim=c(1, length(beer.ts)+8), main = "Forecasting on Original Data", ylab= "Production in Megalitres")

lines(upper, col="blue", lty = "dashed")
lines(lower, col="blue", lty = "dashed")
points((length(beer.ts)+1):(length(beer.ts)+8), pred.original, col ="red")

# Add a legend
legend("bottomright",
  legend = c("Prediction"),
  col = c("red"),
  pch = 1,
  bty = "o",
```

```
  pt.cex = 1,
  cex = 1,
  text.col = "black",
  horiz = F ,
  inset = c(0.1, 0.1))

```

```{r}
# Zoom Forecast

ts.plot(beerall.ts, xlim = c(length(beerall.ts)-12, length(beerall.ts)), main = "Observed vs Forecasted Values", ylab = "Production in Megalitres")

# Points for Original Data *
points((length(beer.ts)+1):(length(beer.ts)+8), beerall.ts[147:154], col ="blue")

# Points for Forecasted Data Red
points((length(beer.ts)+1):(length(beer.ts)+8), pred.original, col ="red")
lines((length(beer.ts)+1): (length(beer.ts)+8), upper, lty=2, col = "blue")
lines((length(beer.ts)+1): (length(beer.ts)+8), lower, lty=2, col = "blue")

# Add a legend
legend("bottomright",
  legend = c("Prediction", "Observed"),
  col = c("red",
  "blue"),
  pch = 1,
```

```
 bty = "o",

 pt.cex = 1,

 cex = 1,

 text.col = "black",

 horiz = F ,

 inset = c(0.1, 0.1))

```