Capstone Project

Urmidola Raye

Prediction of crude oil export volume in 2015 between Canada and USA based on ARIMA forecasting method in R

Abstract: Disparity between production and demand of energy product (crude oil) is the root cause of the downturn of current oil market. Organization of the petroleum exporting countries (OPEC) declined to cut production which forced other oil producers to drop oil prices. There are virtually no wells in the United States that are profitable to drill and US also lost the market of being the sole import market of crude oil from Nigeria and Algeria as they started competing for Asian markets. In such a scenario, this study is based on the historical data of import volume of crude oil from Canada into US. There are two major producing areas in Canada, the Western Canada Sedimentary Basin, which includes Alberta, Saskatchewan and parts of British Columbia and offshore eastern part. Forecasting of the crude oil volume between Canada and the United States using ARIMA method was executed based on historical data from 2000 till 2014 to obtain any correlation between drop in oil price and export volume of crude oil in 2015. The forecasted values were then compared with the actual values of 2015 and accuracy of the model was checked. It was found that the forecasted values fell within the 95% confidence interval and thus performed more or less a satisfactory forecasting. The increasing trend in crude oil export volume even in the downturn of oil market were related to the displacement of energy imports from other oil-producing countries, the addition of new pipeline capacity and more U.S. refinery space for the heavy oils

1. Introduction: The oil industry is going through its deepest downturn since the 1990s. Saudi, Nigerian and Algerian oil that once was sold in the United States is suddenly competing for Asian markets, and the producers are forced to drop prices. Canadian and Iraqi oil production and exports are rising year after year. Even the Russians, with all their economic problems, manage to keep pumping at record levels. On the demand side, the economies of Europe and

developing countries are weak and vehicles are becoming more energy-efficient. So demand for fuel is lagging a bit, although there are signs that demand is growing in the United States. In the United States, there are now virtually no wells that are profitable to drill. In recent months, Iran, Venezuela, Ecuador and Algeria have all pressed OPEC to cut production to help firm up prices. At the same time, Iraq is actually pumping more, and Iran is expected to become a major exporter again. OPEC countries, at a recent meeting, decided to make no change, citing the recent rise in prices.

In this study, an attempt has been made to create a time series model to forecast the export trade volume of energy product (crude oil) between the United States and Canada during 2015 based on the historical data (from 2000-2014) and correlation between drop in global oil price with export of crude oil was searched for to explain the economic scenario of current oil market.

Research shows that the export volume of crude oil between Canada and USA in 2015 shows some correlation with the current economic oil market scenario and can be explained due to the following reasons. The displacement of energy imports from other oil-producing countries, the addition of new pipeline capacity and more U.S. refinery space for the heavy oils are all factors that helped cement Canada's position as the top foreign oil-supplier to the United States. Canada has abundant resources of crude oil. Of this, oil sands account for 90 per cent and conventional oil 10 per cent. The U.S. remains Canada's sole market with plans to build pipelines linking the oil sands to global markets. Our forecast also suggests that the Canadian export surge in the U.S. echoes OPEC mopping up global market share as non-OPEC production recedes. Canadian oil now accounts for 45 per cent of all U.S. import crude imports, from about 30 per cent three years ago.

2. The dataset:

The data was downloaded from http://open.canada.ca/data/. The data on origin country, destination country, number of megabarrels exported per day and number of days in a month in which export took place will be considered. The data was initially in excel format and contained data from 2000 to 2015. The excel file was saved as .csv file and the column containing US import of crude oil from Canada till 2014 was only used. Another .csv file containing only 2015 data was used to compare with the predicted data of our study. The dataset represents a univariate time series as it is a sequence of measurement of the same variable megabarrels/day (Mb/d) collected over time. These measurements were made at regular time intervals.

3. Analysis procedure:

Install.packages("forecast")

library(forecast)

Importing data in R

The data was read into Rstudio using read.csv().

Exploratory Data Analysis: Preliminary investigations showed that the data set was clean and tidy and had no missing values.

export <- read.csv("Crudeoil.csv", header = FALSE)

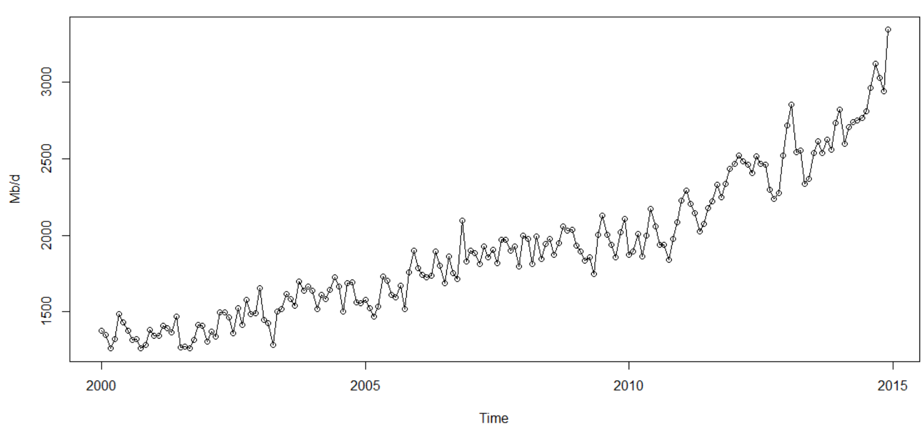
Once the time series was read in, the next step was to store the data in a time series object in R, so that we could use R's many functions for analyzing time series data. To store the data in a time series object, we used the ts() function in R.

Converting data into time series and plotting it in R. The data starts at January of 2000 and ends at December of 2014.

exportts <- ts(export, frequency = 12, start = c(2000,1), end = c(2014, 12))

exports

plot(exportts, type = "o", ylab = "Mb/d")



The data clearly shows an increasing upward trend. The time series is not stationary as the mean and variance are not constant but a function of time. However it is not clear from the plot whether it has a seasonality component in it or not.

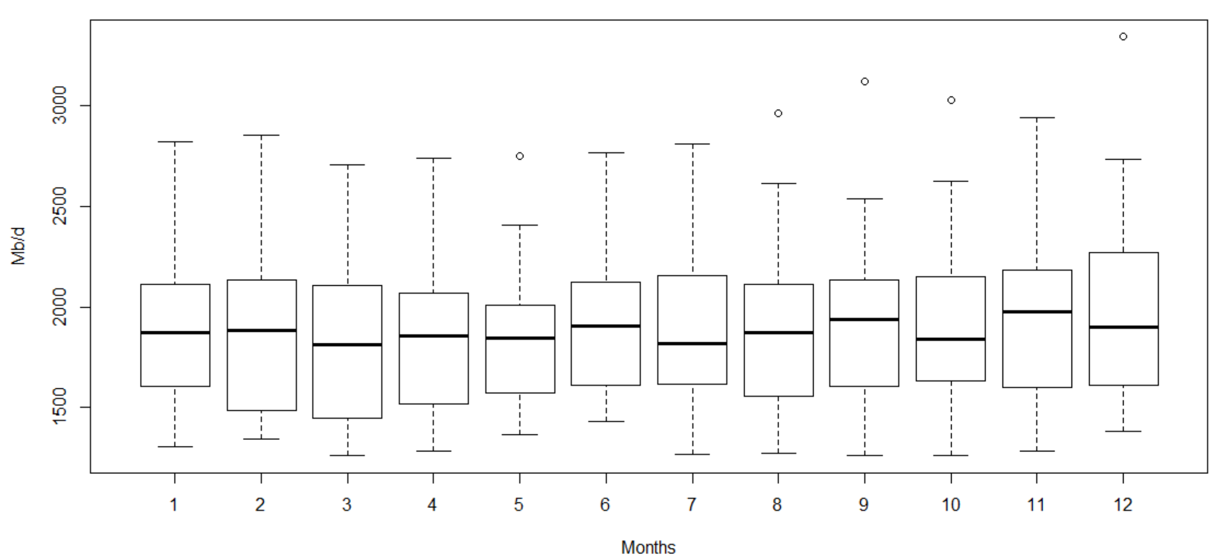
class(exportts) # This shows that it is a time series data

```
[1] “ts”
```

cycle(exportts) # This prints the cycle across years

```
     Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
2000   1   2   3   4   5   6   7   8   9  10  11  12
2001   1   2   3   4   5   6   7   8   9  10  11  12
2002   1   2   3   4   5   6   7   8   9  10  11  12
2003   1   2   3   4   5   6   7   8   9  10  11  12
2004   1   2   3   4   5   6   7   8   9  10  11  12
2005   1   2   3   4   5   6   7   8   9  10  11  12
2006   1   2   3   4   5   6   7   8   9  10  11  12
2007   1   2   3   4   5   6   7   8   9  10  11  12
2008   1   2   3   4   5   6   7   8   9  10  11  12
2009   1   2   3   4   5   6   7   8   9  10  11  12
2010   1   2   3   4   5   6   7   8   9  10  11  12
2011   1   2   3   4   5   6   7   8   9  10  11  12
2012   1   2   3   4   5   6   7   8   9  10  11  12
2013   1   2   3   4   5   6   7   8   9  10  11  12
2014   1   2   3   4   5   6   7   8   9  10  11  12
```

boxplot(exportts~cycle(exportts)) # Boxplot across months gives us an idea about the seasonal effect.

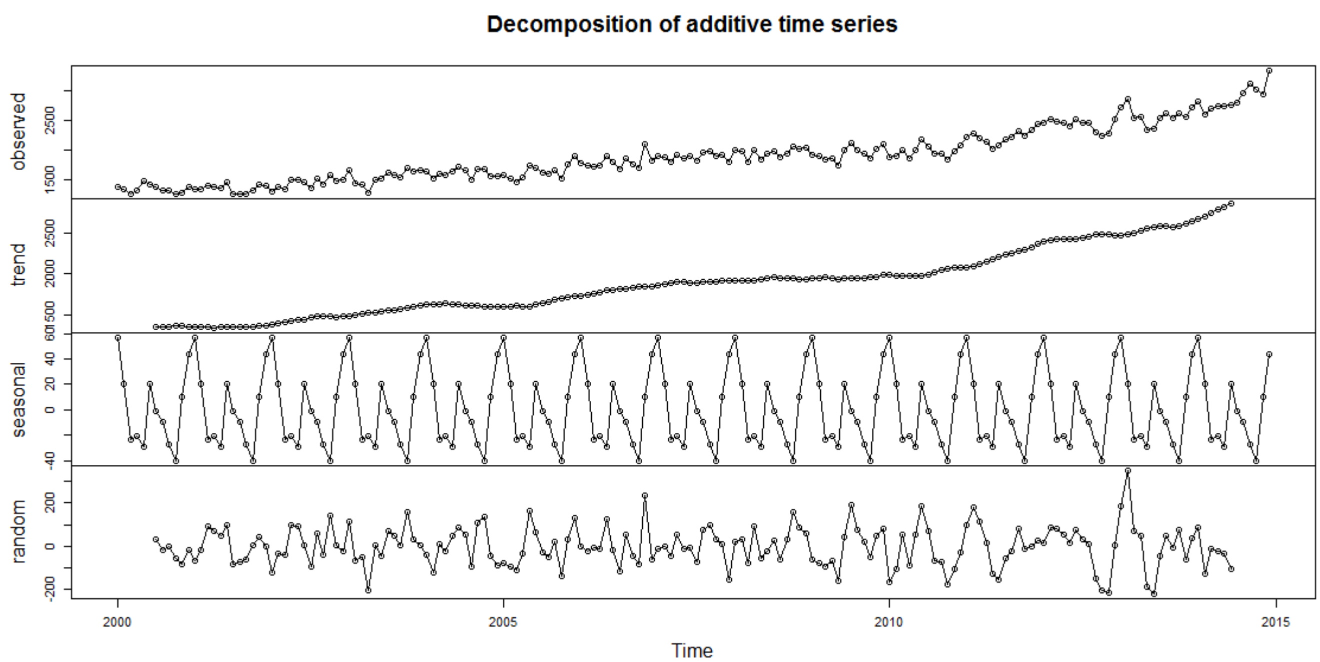


The boxplot shows that the data has a very weak seasonal effect. The boxplot also showed some outliers in the month of May, August, September, October and December as the export volume in these months in 2014 were much larger compared to other years. In order to check for seasonality, time series data can be decomposed into a trend component, a seasonal component and an irregular component. The function “decompose()” returns a list object as its result, where the estimates of the seasonal component, trend component and irregular component can be shown as “seasonal”, “trend”, and “random” respectively.

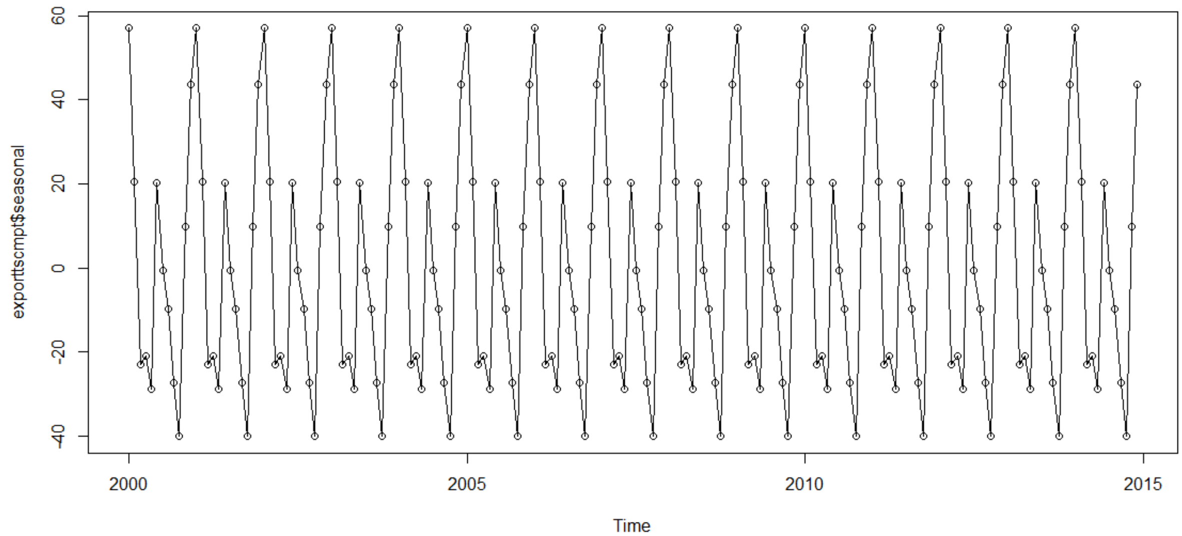
3.1 Decomposing the time series

exporttscmpt <- decompose(exportts)

plot(exporttscmpt, type = “o”)



plot(exporttscmpt$seasonal)



The above plot shows that the crude oil export volume is highest during January, gradually decreases February onwards and again increases in June followed by gradual decrease and hits lowest in October and again rises in November and December each year.

exporttscmpt$seasonal

	Jan	Feb	Mar	Apr
2000	57.0347222	20.5972222	-23.0605159	-21.0099206
2001	57.0347222	20.5972222	-23.0605159	-21.0099206
2002	57.0347222	20.5972222	-23.0605159	-21.0099206
2003	57.0347222	20.5972222	-23.0605159	-21.0099206
2004	57.0347222	20.5972222	-23.0605159	-21.0099206
2005	57.0347222	20.5972222	-23.0605159	-21.0099206
2006	57.0347222	20.5972222	-23.0605159	-21.0099206
2007	57.0347222	20.5972222	-23.0605159	-21.0099206
2008	57.0347222	20.5972222	-23.0605159	-21.0099206
2009	57.0347222	20.5972222	-23.0605159	-21.0099206
2010	57.0347222	20.5972222	-23.0605159	-21.0099206
2011	57.0347222	20.5972222	-23.0605159	-21.0099206
2012	57.0347222	20.5972222	-23.0605159	-21.0099206
2013	57.0347222	20.5972222	-23.0605159	-21.0099206
2014	57.0347222	20.5972222	-23.0605159	-21.0099206

	May	Jun	Jul	Aug
2000	-28.8283730	20.1299603	-0.6855159	-9.8968254
2001	-28.8283730	20.1299603	-0.6855159	-9.8968254
2002	-28.8283730	20.1299603	-0.6855159	-9.8968254
2003	-28.8283730	20.1299603	-0.6855159	-9.8968254
2004	-28.8283730	20.1299603	-0.6855159	-9.8968254
2005	-28.8283730	20.1299603	-0.6855159	-9.8968254
2006	-28.8283730	20.1299603	-0.6855159	-9.8968254
2007	-28.8283730	20.1299603	-0.6855159	-9.8968254
2008	-28.8283730	20.1299603	-0.6855159	-9.8968254
2009	-28.8283730	20.1299603	-0.6855159	-9.8968254
2010	-28.8283730	20.1299603	-0.6855159	-9.8968254
2011	-28.8283730	20.1299603	-0.6855159	-9.8968254
2012	-28.8283730	20.1299603	-0.6855159	-9.8968254
2013	-28.8283730	20.1299603	-0.6855159	-9.8968254

```
2014 -28.8283730  20.1299603  -0.6855159  -9.8968254
            Sep         Oct         Nov         Dec
2000 -27.3908730 -40.1765873   9.7222222  43.5644841
2001 -27.3908730 -40.1765873   9.7222222  43.5644841
2002 -27.3908730 -40.1765873   9.7222222  43.5644841
2003 -27.3908730 -40.1765873   9.7222222  43.5644841
2004 -27.3908730 -40.1765873   9.7222222  43.5644841
2005 -27.3908730 -40.1765873   9.7222222  43.5644841
2006 -27.3908730 -40.1765873   9.7222222  43.5644841
2007 -27.3908730 -40.1765873   9.7222222  43.5644841
2008 -27.3908730 -40.1765873   9.7222222  43.5644841
2009 -27.3908730 -40.1765873   9.7222222  43.5644841
2010 -27.3908730 -40.1765873   9.7222222  43.5644841
2011 -27.3908730 -40.1765873   9.7222222  43.5644841
2012 -27.3908730 -40.1765873   9.7222222  43.5644841
2013 -27.3908730 -40.1765873   9.7222222  43.5644841
2014 -27.3908730 -40.1765873   9.7222222  43.5644841
```

The estimated seasonal factors are given for the months January-December, and are the same for each year. The largest seasonal factor is for January (about 57.034), and the lowest is for October (about -40.176), indicating that there seems to be a peak of export volume in January and a trough in October each year. So our time series has a seasonal component. Next, we check for stationarity of our data in various ways as time series models can be build only on stationary data.

summary(exportts)

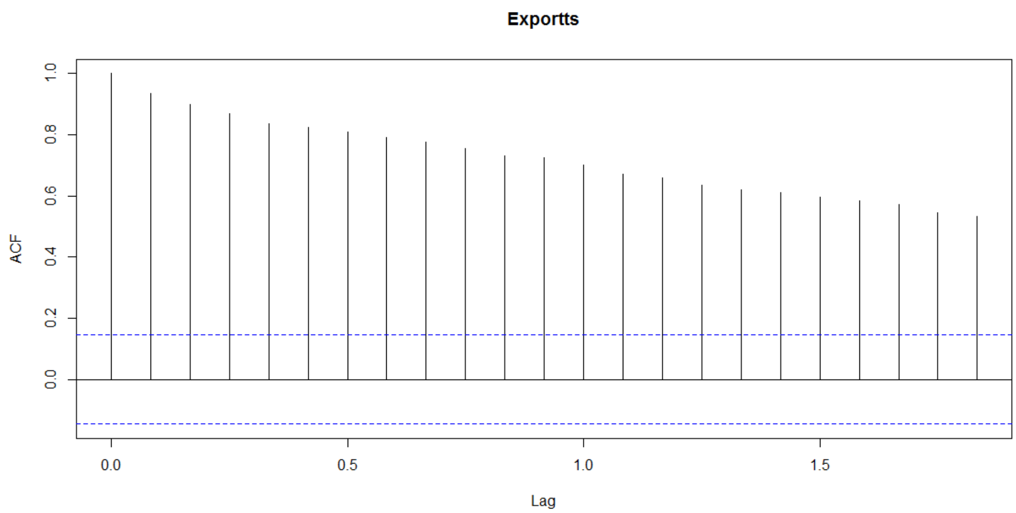
```
Min.   :1261
1st Qu.:1534
Median :1858
Mean   :1908
3rd Qu.:2175
Max.   :3339
```

The summary of the timeseries shows that it is non-stationary and has a non-zero mean of a large value (1908). In order to build time series models or execute forecasting, the data has to be stationary. So if a time series is non-stationary, the first criterion is to make the time series stationary. Another way of checking whether the data is stationary or not is to plot the ACF and PACF of the time series.

The sample autocorrelation function (ACF) for a series (x_t) gives correlations between the series x_t and lagged values of the series i.e. x_{t-1}, x_{t-2}, x_{t-3} and so on. The ACF can be used to identify the possible structure of time series data. For an ACF to make sense, the series must be a weakly stationary series. This means that the autocorrelation for any particular lag is the same regardless of where we are in time.

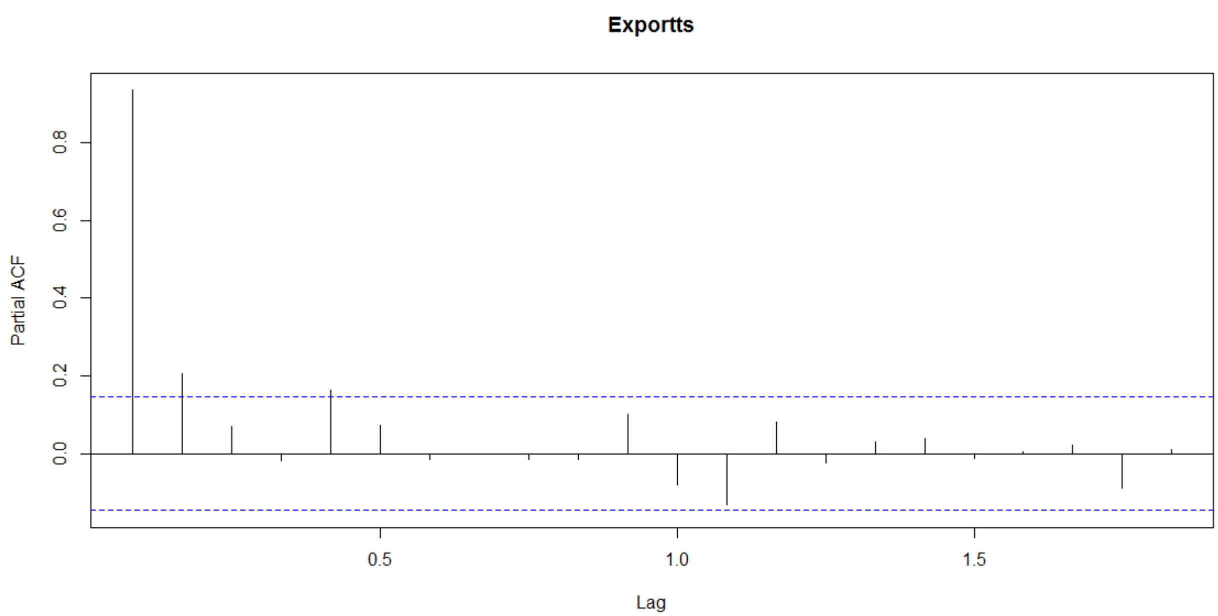
A partial correlation (PACF) is a conditional correlation. For a time series, the partial autocorrelation between x_t and x_{t-h} is defined as the conditional correlation between x_t and x_{t-h}, conditional on $x_{t-h+1},\ldots\ldots,x_{t-1}$, the set of observations that come between the time points t and t-h. For an AR model, the theoretical PACFs are equal to zero past the order of the model. The number of non-zero partial autocorrelations gives the order of the AR model.

acf(exportts)



The above plot indicates non-stationarity of our data as at each lag, as the ACF values are well above the confidence bands (blue dashed lines) and decays very slowly with increasing lag which imply that there is significant correlations among within the data at each lag.

pacf(exportts)



In the PACF plot, we observe one very strong lag and the PACF cuts off after the 2nd lag.

Another method to check stationarity of the time series is the Dickey Fuller test. In this test, null hypothesis of whether a unit root is present in an autoregressive model is present or not is tested. If unit root is present, then the process is non-stationary.

adf.test(exportts, alternative = "stationary", k = 0)

```
        Augmented Dickey-Fuller Test

data:  exportts
Dickey-Fuller = -4.5715, Lag order = 0, p-value
= 0.01
alternative hypothesis: stationary
```

adf.test(exportts, alternative = "explosive", k = 0)

```
        Augmented Dickey-Fuller Test

data:  exportts
Dickey-Fuller = -4.5715, Lag order = 0, p-value
= 0.99
alternative hypothesis: explosive
adf.test(exportts)
```

The augmented Dickey-Fuller test shows that based on p-value (< 0.05), we cannot reject our null hypothesis that our data is non-stationary and based on another p value (>> 0.05) we accept the alternative hypothesis that our data is explosive. Our next step is to make our data stationary.

3.2 Differencing the time series

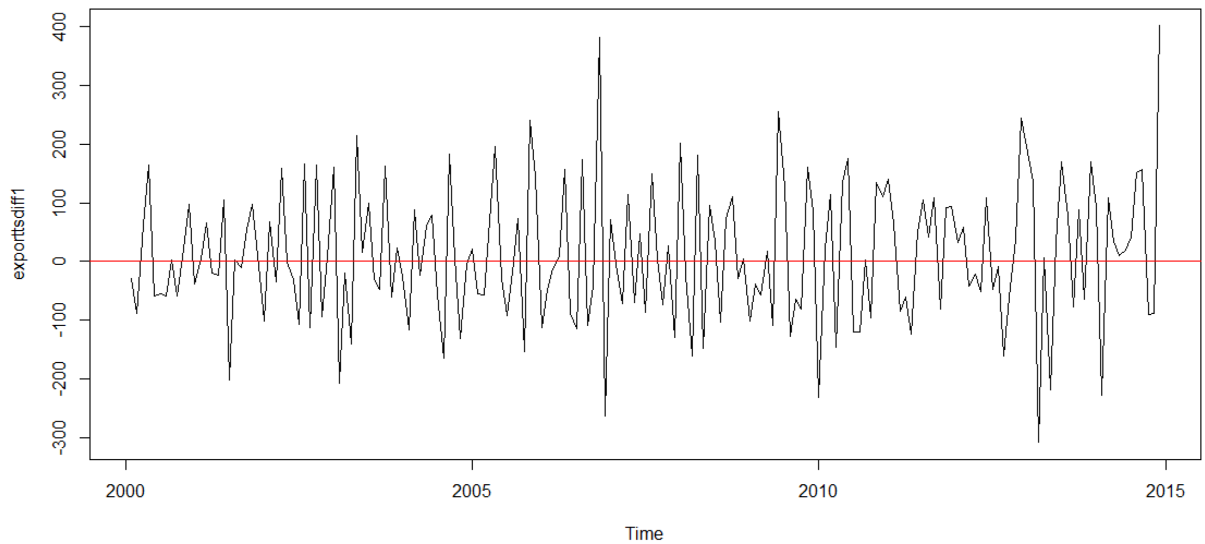
For a non-stationary data set, differencing is done to make it stationary. Time series models such as ARIMA (Auro regressive integrated moving average) are defined for stationary time series only. When a time series is differenced d times, to obtain a stationary series, then an ARIMA (p,d,q) model is used, where d is the order of differencing used. Differencing help stabilize the mean of a time series by removing changes in the level of a time series, and so eliminating trend and seasonality. Differencing of a time series is done using the diff() function.

Exporttsdiff1 <- diff(exportts, differences = 1)

summary(exporttsdiff1)

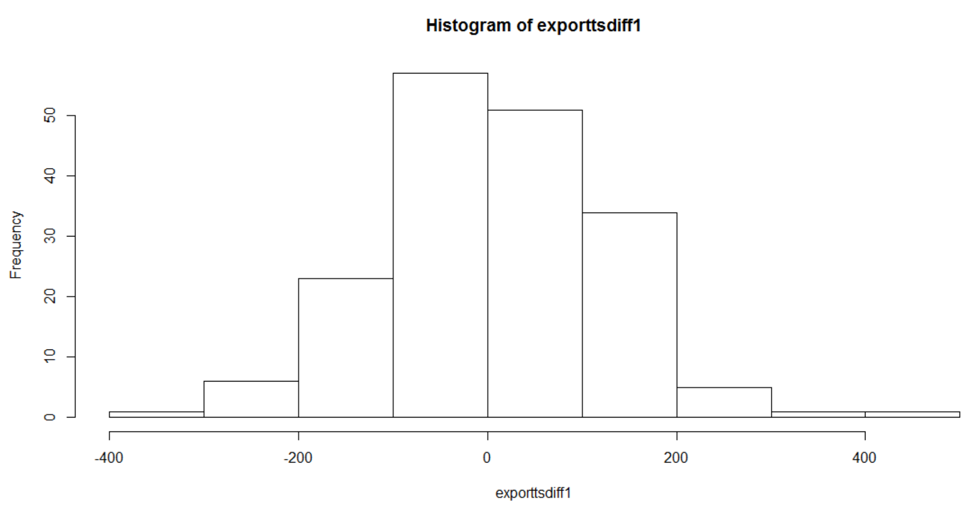
```
Min.   :-308.00
 1st Qu.: -67.00
 Median :   3.00
 Mean   :  10.96
 3rd Qu.:  95.00
 Max.   : 401.00
```

plot.ts(exporttsdiff1)
abline(h = 0, col = “red”)



The summary statistics shows that the mean is still non zero and has a value of 10.96 and a variable variance but the upward increasing trend of the time series is removed.

hist(exporttsdiff1)



The resulting time series of first difference does not appear to be stationary in mean. Therefore, the time series was differenced twice, to see if that gives us a stationary time series.

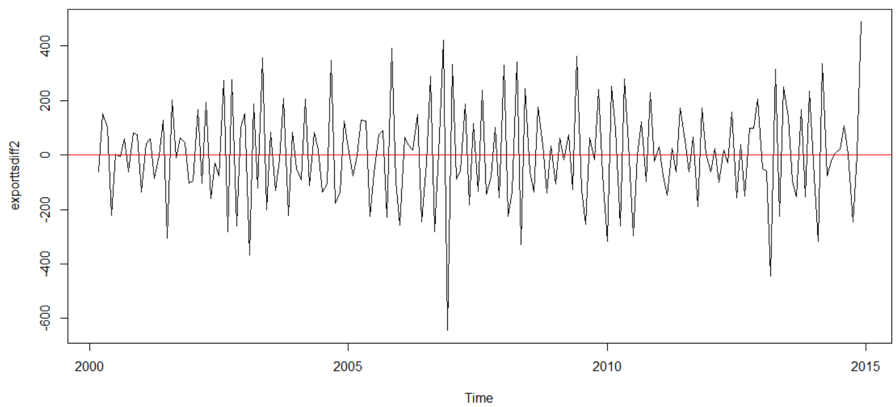
Exporttsdiff2 <- diff(exportts, differences = 2)

summary(exporttsdiff2)

```
Min.   :-644.00
 1st Qu.:-119.75
```

```
 Median :   0.50
 Mean   :   2.41
 3rd Qu.: 114.25
 Max.   : 489.00
```

plot.ts(exporttsdiff2)



The result shows that the mean is still non-zero but has a lower value 2.41 than the previous one and the median has a value of 0.50. The time series of second differences does appear to be more stationary in mean and variance than the first differenced one, as the level of the series stays roughly constant over time, and the variance of the series appear roughly constant over time. To check whether the mean can be made zero, we difference it for the third time.

Exporttsdiff3 <- diff(exportts, differences = 3)

summary(exporttsdiff3)

```
Min.   :-1066.000
 1st Qu.: -220.000
 Median :   -1.000
 Mean   :    3.107
 3rd Qu.:  227.000
 Max.   :  978.000
```

The data after third differencing shows quite similar values as that of the twice differenced data. So we choose the twice differenced data set for modeling. Stationary was also checked using the Dickey-Fuller test.

adf.test(exporttsdiff2, k = 0)

```
        Augmented Dickey-Fuller Test

data:  exporttsdiff2
Dickey-Fuller = -23.472, Lag order = 0, p-value
= 0.01
alternative hypothesis: stationary
```

adf.test(exporttsdiff2)

```
        Augmented Dickey-Fuller Test

data:  exporttsdiff2
Dickey-Fuller = -11.231, Lag order = 5, p-value
= 0.01
alternative hypothesis: stationary
```

The Dickey-Fuller test shows that based on the p-value (<0.05) we accept the alternative hypothesis that our differenced time series is stationary. By taking the time series of first differences, we have removed the trend and seasonal component. The irregular or random component of the time series is still there and ARIMA models include an explicit statistical model for the irregular component of a time series, that allows for non-zero autocorrelations in the irregular component.

The next step is to proceed for time series modeling. The AR of the ARMA stands for auto regressive process and MA stands for moving average process. The autoregressive model (AR) specifies that the output variable depends linearly on its own previous values. Moving average is used to analyze data points by creating series of averages of different subsets of the full dataset. A moving average is a set of numbers each of which is the average of the corresponding subset of a larger set of datum points. A moving average is used with time series data to smooth out short-term fluctuations and highlight longer-term trends or cycles.

3.3 Forecasting choosing the best ARIMA model for the 2015 export volume of crude oil from Canada to US

When we need to difference our original time series data d times in order to obtain a stationary time series, we can use an ARIMA(p,d,q) model for our time series, where d is the order of differencing used. In this case, we had to difference the time series twice, and so the order of differencing (d) is 2. This means that we can use an ARIMA (p,2,q) model here. The next step is to figure out the values of p and q for the ARIMA model. To choose the p and q values, either the ACF and PACF diagrams are taken into account or autoarima() function can be used which provides us with the p,d,q values.

 # Ran couple of ARIMA models to choose the best fit

```
fit <- auto.arima(exporttsdiff2)

fit
Series: exporttsdiff2
ARIMA(5,0,1)(1,0,0)[12] with zero mean
```

```
Coefficients:
          ar1      ar2      ar3      ar4      ar5
      -0.4036  -0.3626  -0.2268  -0.3696  -0.1569
s.e.   0.0777   0.0776   0.0807   0.0785   0.0783
          ma1    sar1
      -0.9758  0.1777
s.e.   0.0207  0.0797

sigma^2 estimated as 10916:  log likelihood=-
1079.36
AIC=2174.72   AICc=2175.57   BIC=2200.17
```

```
 exparima <- arima(exporttsdiff2, order =
c(5,0,1))

 exparima
```

```
Call:
arima(x = exporttsdiff2, order = c(5, 0, 1))

Coefficients:
          ar1      ar2      ar3      ar4      ar5
      -0.4164  -0.3637  -0.2523  -0.3900  -0.1528
s.e.   0.0771   0.0768   0.0787   0.0774   0.0778
          ma1  intercept
      -0.9996     0.1348
s.e.   0.0194     0.0600

sigma^2 estimated as 10457:  log likelihood = -
1080.15,  aic = 2176.31
```

Several other arima models were also run with different p,d,q values

exparima1 <- arima(exporttsdiff2, order = c(5, 1, 1), seasonal = c(1,0,0))

exparima1

exparima2 <- arima(exporttsdiff2, order = c(4, 1, 1), seasonal = c(1,0,0))

exparima2

exparima3 <- arima(exporttsdiff2, order = c(3, 1, 1), seasonal = c(1,0,0))

exparima3

exparima5 <- arima(exporttsdiff2, order = c(5, 0, 1), seasonal = c(1,0,0))

exparima5

exparima6 <- arima(exporttsdiff2, order = c(4, 1, 2),seasonal = c(1,0,0))

exparima6

exparima7 <- arima(exporttsdiff2, order = c(3, 1, 3), seasonal = c(1,0,0)) *exparima7*

Out of all of these, autoarima (exparima5) gave the lowest AIC value .

expforecasts <- forecast.Arima(exparima, h=12)

expforecasts

exparima.pred1 <- predict(exparima, n.ahead = 12)

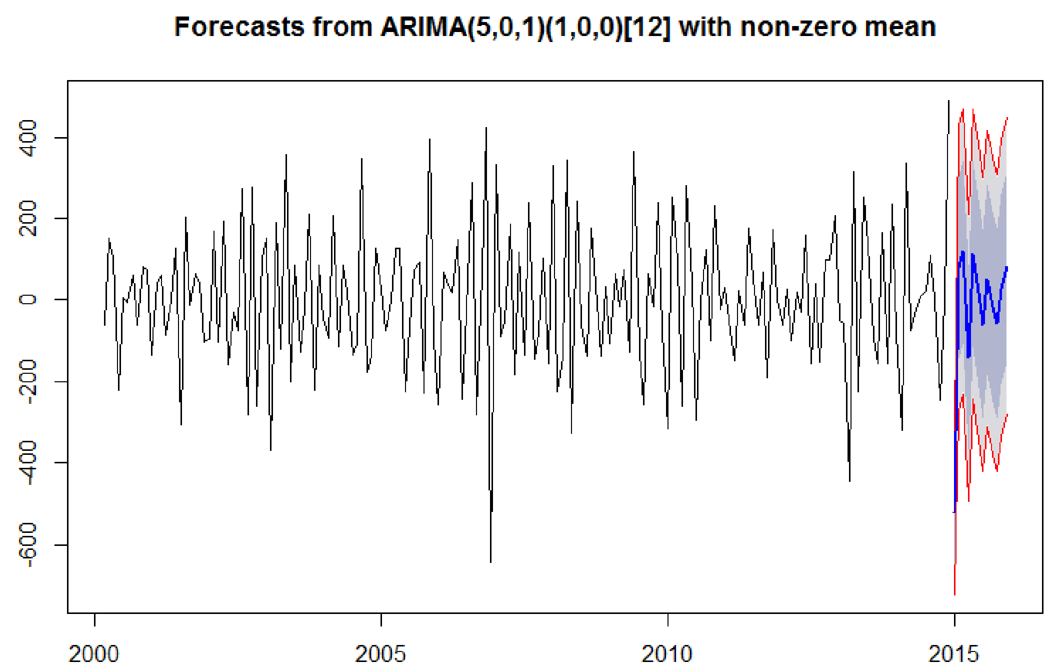
exparima.pred1

plot(exparima.pred1)

lines(exparima.pred1$pred, col = "blue")

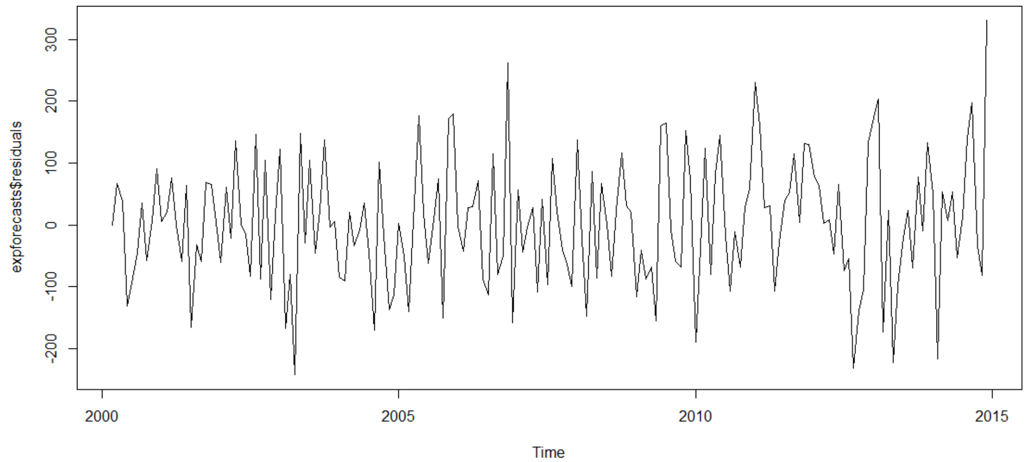
lines(exparima.pred1$pred+2*dataarima.pred1$se, col = "red")

lines(exparima.pred1$pred-2*dataarima.pred1$se, col = "red")

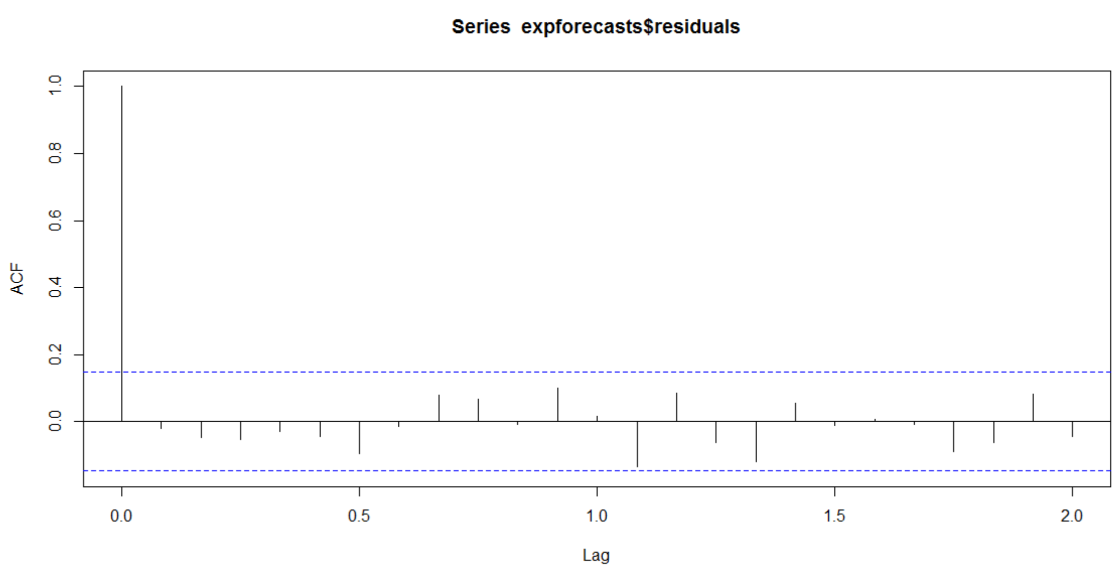


In the above plot, the forecasts for 2015 are plotted as a blue line, the 80% prediction interval (dark grey shaded area) are bounded by red lines and 95% prediction interval is shown by light grey shaded area. The forecast errors or residuals are calculated as the observed values minus predicted values, for each time point. One measure of the accuracy of the predictive model is the sum-of-squared errors(SSE) for the in-sample forecast errors. The ACF of the residuals for a model is also useful. A Ljung-Box test is also done to check whether any of a group of autocorrelations of a time series are different from zero. The ideal for a sample ACF of residuals is that there aren't any significant correlations for any lag. To investigate whether the forecast errors are normally distributed with mean close to zero and constant variance, a time plot and histogram of the forecast errors is essential.

plot.ts(expforecasts$residuals)



acf(expforecasts$residuals, lag.max = 24)



Box.test(expforecasts$residuals, lag = 24, type = "Ljung-Box")

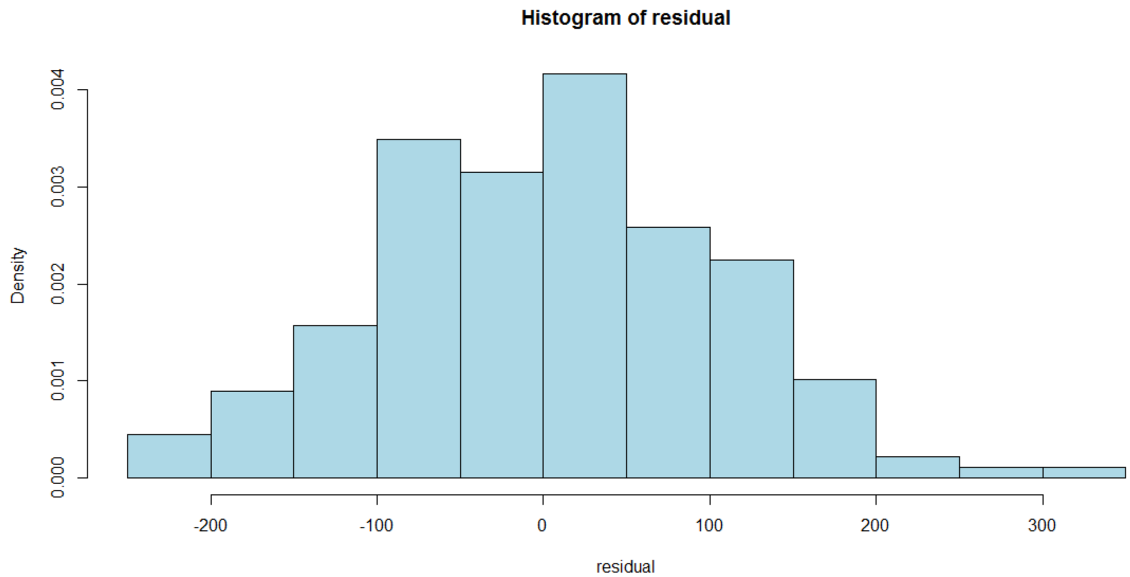
```
                Box-Ljung test

data:  expforecasts$residuals
```

```
X-squared = 20.815, df = 24, p-value = 0.6496
```

residual <- resid(exparima5)

hist(residual)



The time plot of the in-sample forecast errors shows that the variance of the forecast errors seems to be roughly constant over time. The histogram of the time series shows that the forecast errors are roughly normally distributed and the mean seems to be close to zero. Therefore it is plausible that the forecast errors are normally distributed with mean zero and constant variance. Since successive forecast errors do not seem to be correlated, and the forecast errors seem to be normally distributed with mean zero and constant variance, the ARIMA (5, 0, 1) does seem to provide an adequate predictive model for the export volume of crude oil to USA in 2015.

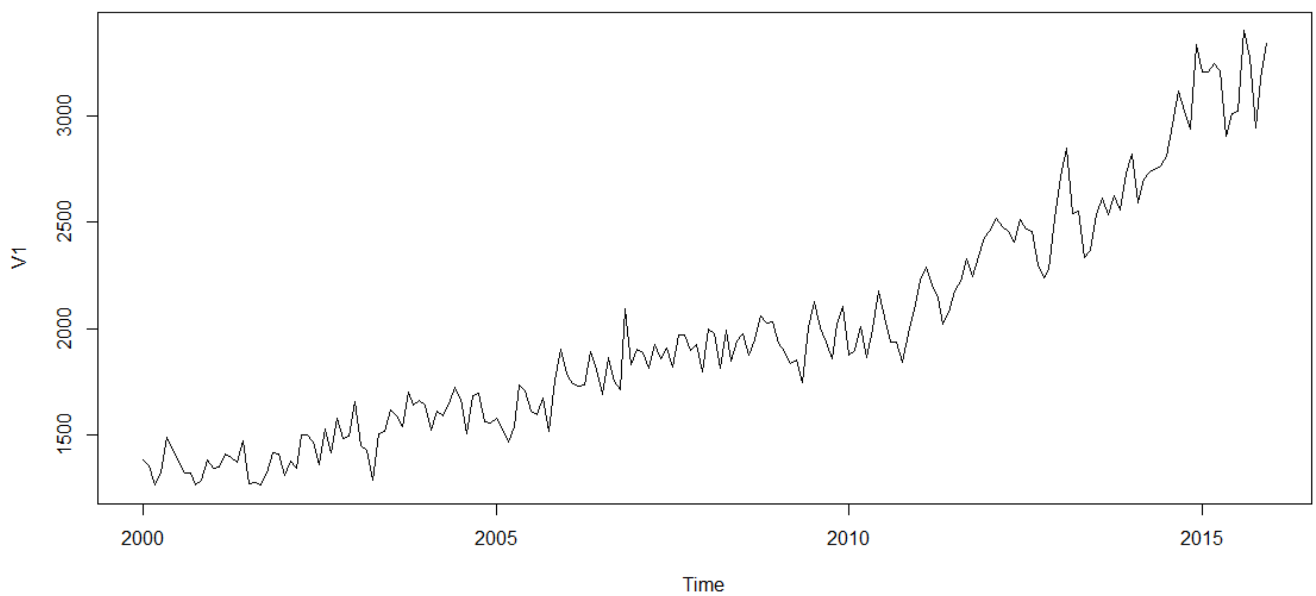
 # Read in .csv file containing data till 2015 and plotting it

checkoil <- read.csv("checkoil.csv", header = FALSE)

checkoilts <- ts(checkoil, frequency = 12, start = c(2000,1), end = c(2015, 12))

checkoilts

plot.ts(checkoilts)



3.4 Plot of predicted versus actual value

plot(checkoiltsdiff2, col = "blue", ann = FALSE, las = 2)

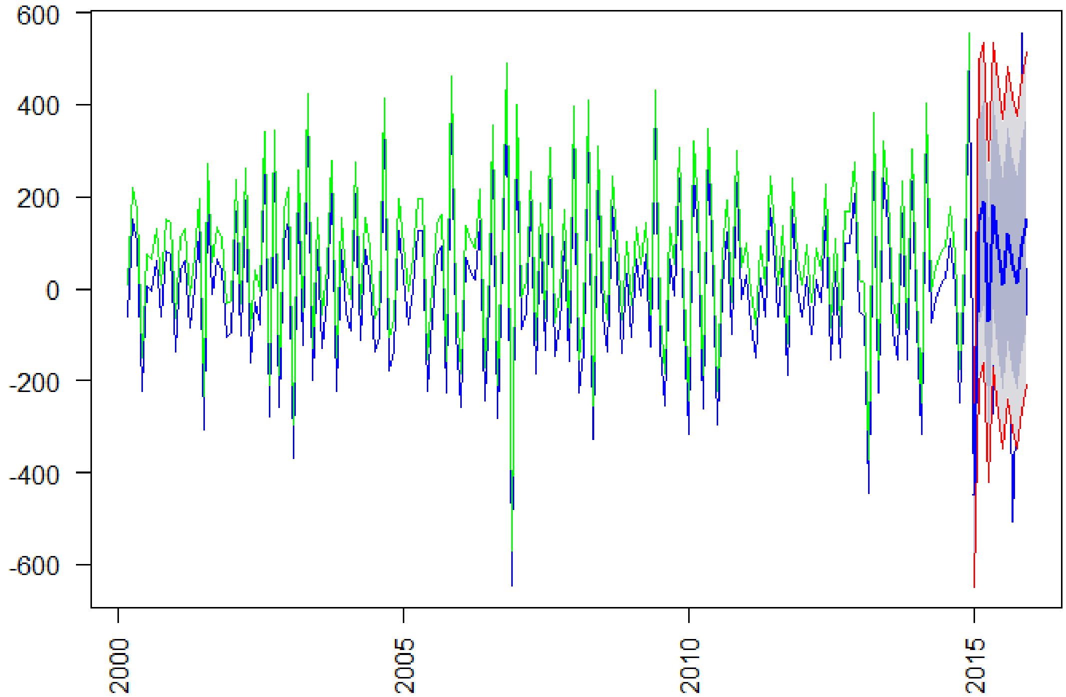
par(new = TRUE)

plot(expforecasts,ann = FALSE, axes = FALSE, col = "green")

lines(exparima.pred1$pred, col = "blue", xlab = "Time", ylab = "exparima.pred1")

lines(exparima.pred1$pred+2*exparima.pred1$se, col = "red")

lines(exparima.pred1$pred-2*exparima.pred1$se, col = "red")



The plot shows that 2015 values exactly overlaps the values predicted by our model. So our analysis resulted in quite satisfactory predictive model for the export volume of crude oil from Canada to US in 2015 based on the historical data from 2000 till 2014.

4. Summary and Future Work

a) The export trade volume of crude oil between Canada and USA is predicted using the auto ARIMA function.

b) The predicted values are well within the 95% confidence interval and overlaps the actual values of 2015 which suggest that the autoARIMA method provides an adequate predictive model for crudeoil export volume in 2015.

c) The export volume shows an increasing trend even in 2015 instead of trough which is also predicted from the ARIMA method. This is explained by the increased supply of crude oil from Canada to USA during oil market recession as other exporters decreased their crude oil supply to USA.

d) Other various time series forecasting models (Holt Winters exponential smoothing) can be executed to compare prediction between various methods and increase accuracy of prediction.

Client Recommendation: OPEC and other big oil companies (Exxon Mobil, Royal Dutch Shell , BP) can get an idea about the export volume of crude oil between countries. Results of such predictions can put pressure on OPEC to reduce oil production and increase oil prices. Such forecasting can also give an insight about the future shares of OPEC versus other oil companies.

5. References:

1. Coghlan A. (2015). A Little Book of R For Time Series. p.1-75.

2. Dickey DA, Fuller WA (1981). "Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root." *Econometrica*, 49, 1057 -1071.

3. Hyndman RJ (2008c). ***forecast:*** *Forecasting Functions for Time Series.* R package version 1.11, URL http://CRAN. R-project.org/package=forecasting.

4. Hyndman RJ and Khandakar Y (2008). Automatic Time Series Forecasting: The forecast Package for R. *Journal of Statistical Software*, 27, 1-22.

5. Kwiatkowski D, Phillips PC, Schmidt P, Shin Y (1992). "Testing the Null Hypothesis of Stationarity Against the Alternative of a Unit Root." *Journal of Econometrics*, 54, 159-178.

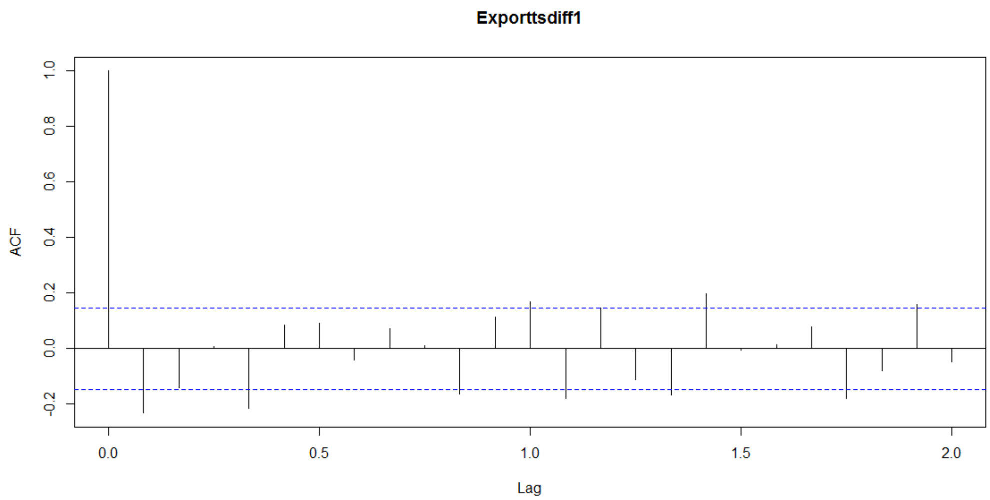
6. Melard G, Pasteels JM (2000). "Automatic ARIMA Modeling Including Intervention, Using Time Series Expert Software." *International Journal of Forecasting*, 16, 497 -508.

7. Zucchini W., and Nenadic O. Time Series Analysis with R – Part 1, 1-23.

Appendix

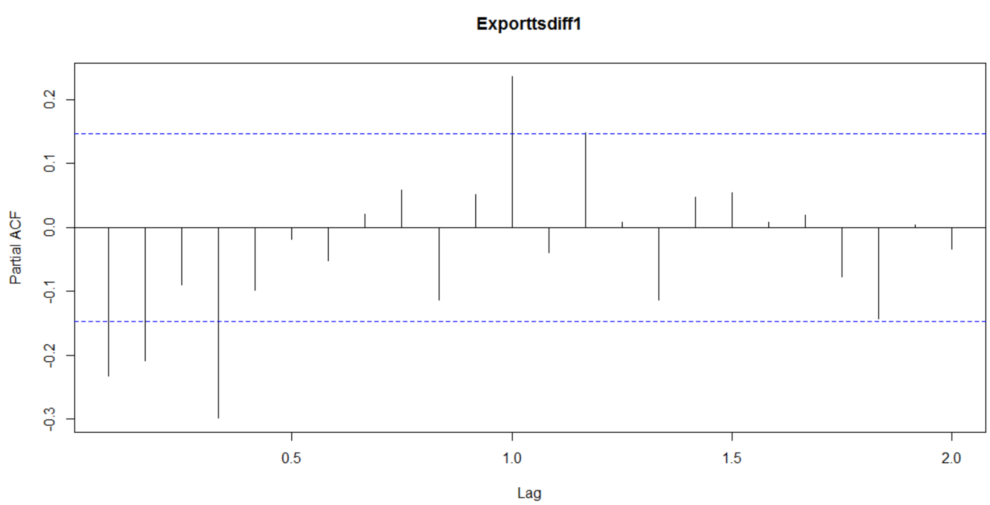
Some other tests were also executed to find the value of AR and MA process without autoarima function. They are as follows:

acf(exporttsdiff1, lag.max = 24)



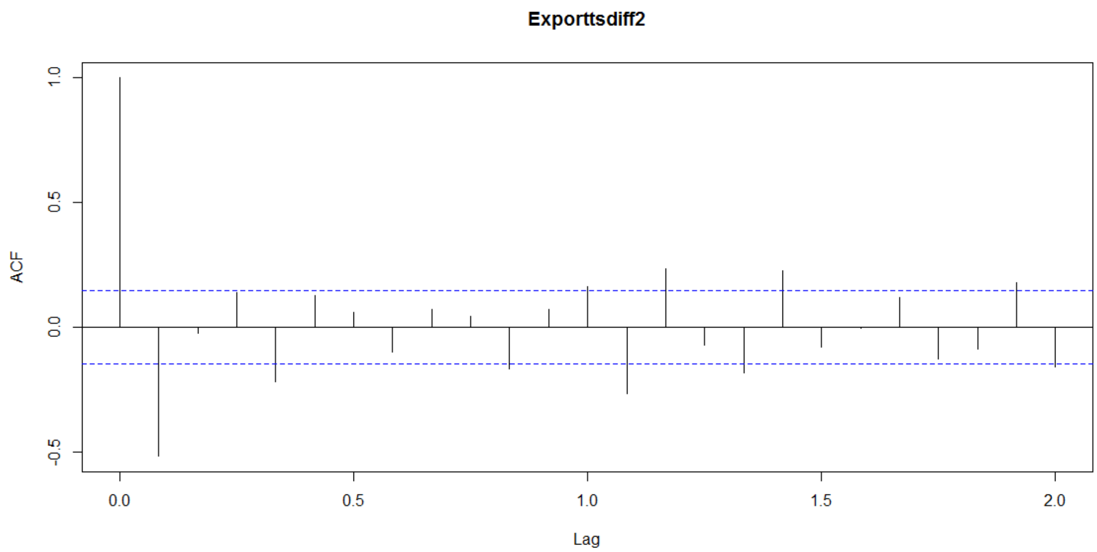
The ACF plot shows that the decay of the spikes doesn't show any pattern and all of them are not within the confidence bands. Thus the first difference of the time series is not stationary.

pacf(exporttsdiff1, lag.max = 24)



The PACF shows significant negative spikes at 1st 2nd and 4th lags and a positive spike afterwards. Since the spikes are not cutting off sharply after a certain lag value, we can consider this time series as non-stationary.

acf(exporttsdiff2, lag.max = 24)



---

pacf(exporttsdiff2, lag.max = 24)