

M7: Seasonal ARIMA Models in R

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02/25/2021

Setting R code chunk options

First R code chunk is used for setting the options for all R code chunks. The choice `echo=TRUE` means both code and output will appear on report, `include = FALSE` neither code nor output is printed.

Loading packages and initializing

Second R code chunk is for loading packages. By setting `message = FALSE`, the code will appear but not the output.

```
library(lubridate)
library(ggplot2)
library(forecast)
library(Kendall)
library(tseries)
library(outliers)
library(tidyverse)
```

Importing data

For this module we will work with monthly average for electricity retail price in US. The data is from the U.S. Energy Information Administration and can be download [here][[https://www.eia.gov/electricity/data/browser/#/topic/7?agg=2,0,1&geo=g&freq=M%2013:41:41%20GMT-0500%20\(EST\)](https://www.eia.gov/electricity/data/browser/#/topic/7?agg=2,0,1&geo=g&freq=M%2013:41:41%20GMT-0500%20(EST))].

```
#Importing time series data from text file#
electricity_price <- read.csv(file="./Data/Average_retail_price_of_electricity_United_States_monthly.csv")

#Inspect data
head(electricity_price)
```

```
##      Month all.sectors.cents.per.kilowatthour
## 1 Nov 2020                                10.45
## 2 Oct 2020                                10.64
## 3 Sep 2020                                11.07
## 4 Aug 2020                                11.11
## 5 Jul 2020                                 11.14
## 6 Jun 2020                                 10.96
## residential.cents.per.kilowatthour commercial.cents.per.kilowatthour
## 1                                13.35                                10.59
## 2                                13.60                                10.73
## 3                                13.55                                11.07
## 4                                13.31                                10.95
## 5                                13.26                                10.90
## 6                                13.28                                10.95
```

```
## industrial.cents.per.kilowatthour
## 1 6.48
## 2 6.72
## 3 7.01
## 4 7.09
## 5 7.17
## 6 6.94

nvar <- ncol(electricity_price) - 1
nobs <- nrow(electricity_price)

#Preparing the data - create date object and rename columns
electricity_price_processed <-
  electricity_price %>%
  mutate( Month = my(Month) ) %>%
  rename( All.sectors = all.sectors.cents.per.kilowatthour ) %>%
  rename( Residential = residential.cents.per.kilowatthour ) %>%
  rename( Commercial = commercial.cents.per.kilowatthour ) %>%
  rename( Industrial = industrial.cents.per.kilowatthour ) %>%
  arrange( Month )

head(electricity_price_processed)
```

	Month	All.sectors	Residential	Commercial	Industrial
## 1	2001-01-01	6.75	7.73	7.25	4.73
## 2	2001-02-01	6.87	8.04	7.51	4.80
## 3	2001-03-01	7.01	8.32	7.70	4.86
## 4	2001-04-01	7.02	8.46	7.73	4.87
## 5	2001-05-01	7.17	8.83	7.77	5.00
## 6	2001-06-01	7.58	9.07	8.13	5.23

```
summary(electricity_price_processed)
```

```
##      Month      All.sectors      Residential      Commercial
## Min.   :2001-01-01  Min.    : 6.750  Min.    : 7.73  Min.    : 7.250
## 1st Qu.:2005-12-16  1st Qu.: 8.520  1st Qu.: 9.82  1st Qu.: 9.070
## Median :2010-12-01  Median : 9.720  Median :11.77  Median :10.080
## Mean   :2010-11-30  Mean   : 9.381  Mean   :11.23  Mean   : 9.746
## 3rd Qu.:2015-11-16  3rd Qu.:10.305  3rd Qu.:12.64  3rd Qu.:10.540
## Max.   :2020-11-01  Max.    :11.140  Max.    :13.60  Max.    :11.170
##      Industrial
## Min.    :4.71
## 1st Qu.:5.99
## Median :6.58
## Mean   :6.37
## 3rd Qu.:6.89
## Max.    :7.72
```

```
#No NAs so we don't need to worry about missing values
```

Transforming data into time series object

Many of the functions we will use require a time series object. You can transform your data in a time series using the function `ts()`.

```
ts_electricity_price <- ts(electricity_price_processed[,2:(nvar+1)],
                          start=c(year(electricity_price_processed$Month[1]),month(electricity_price_p
                          frequency=12)
#note that we are only transforming columns with electricity price, not the date columns
head(ts_electricity_price,15)
```

```
##           All.sectors Residential Commercial Industrial
## Jan 2001      6.75          7.73          7.25          4.73
## Feb 2001      6.87          8.04          7.51          4.80
## Mar 2001      7.01          8.32          7.70          4.86
## Apr 2001      7.02          8.46          7.73          4.87
## May 2001      7.17          8.83          7.77          5.00
## Jun 2001      7.58          9.07          8.13          5.23
## Jul 2001      7.88          9.03          8.41          5.57
## Aug 2001      7.84          9.01          8.35          5.50
## Sep 2001      7.62          8.92          8.22          5.31
## Oct 2001      7.43          8.84          8.27          5.07
## Nov 2001      7.02          8.47          7.73          4.78
## Dec 2001      7.03          8.29          7.66          4.78
## Jan 2002      6.95          8.07          7.49          4.73
## Feb 2002      6.97          8.19          7.68          4.76
## Mar 2002      6.95          8.17          7.72          4.73
```

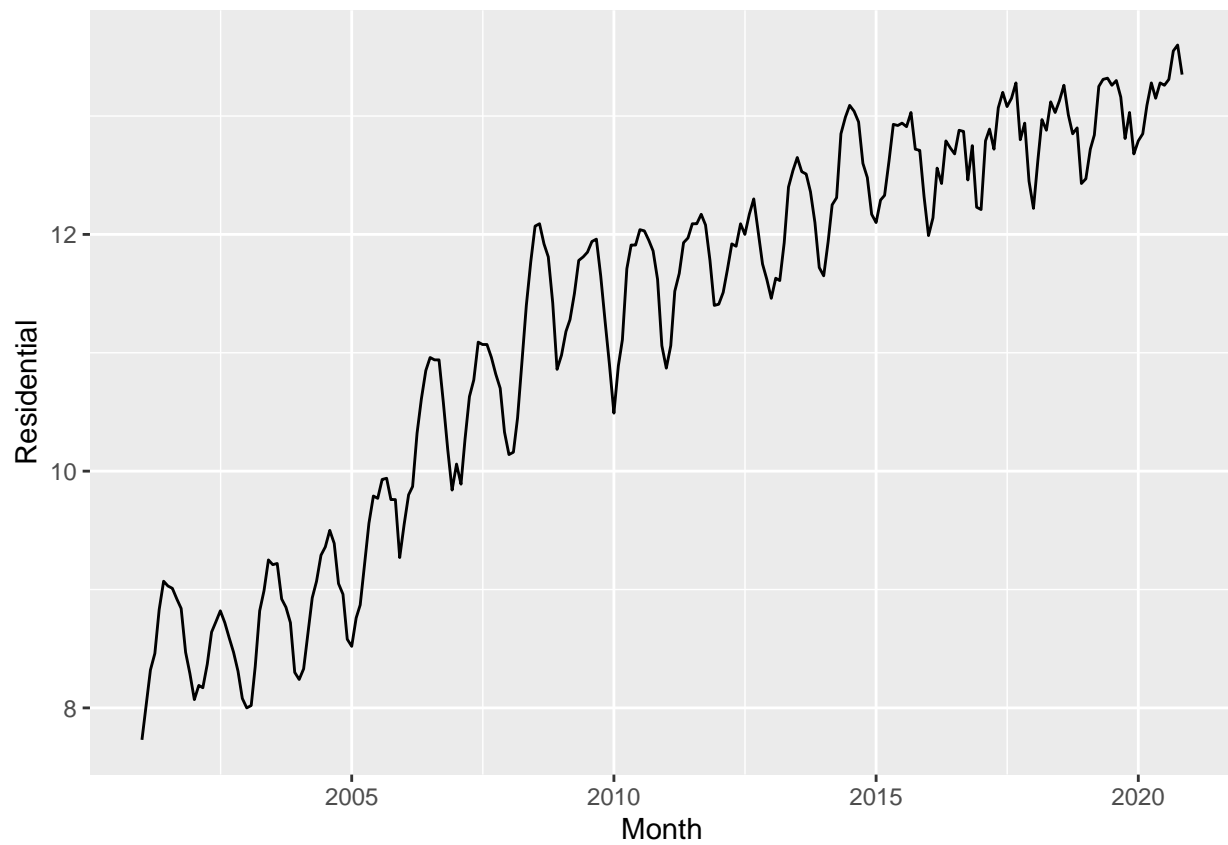
```
tail(ts_electricity_price,15)
```

```
##           All.sectors Residential Commercial Industrial
## Sep 2019      10.82         13.16         10.96          7.06
## Oct 2019      10.39         12.81         10.74          6.84
## Nov 2019      10.38         13.03         10.57          6.72
## Dec 2019      10.22         12.68         10.32          6.38
## Jan 2020      10.28         12.79         10.24          6.33
## Feb 2020      10.29         12.85         10.36          6.41
## Mar 2020      10.29         13.09         10.41          6.38
## Apr 2020      10.42         13.28         10.42          6.40
## May 2020      10.47         13.15         10.46          6.53
## Jun 2020      10.96         13.28         10.95          6.94
## Jul 2020      11.14         13.26         10.90          7.17
## Aug 2020      11.11         13.31         10.95          7.09
## Sep 2020      11.07         13.55         11.07          7.01
## Oct 2020      10.64         13.60         10.73          6.72
## Nov 2020      10.45         13.35         10.59          6.48
```

Initial Plots

#Generating a box plot by factor where factor is month of the year

```
TS_Plot <-
  ggplot(electricity_price_processed, aes(x=Month, y=Residential)) +
    geom_line()
plot(TS_Plot)
```



#Note that although the date is reversed on the data frame, since we are using the ggplot and a date ob.

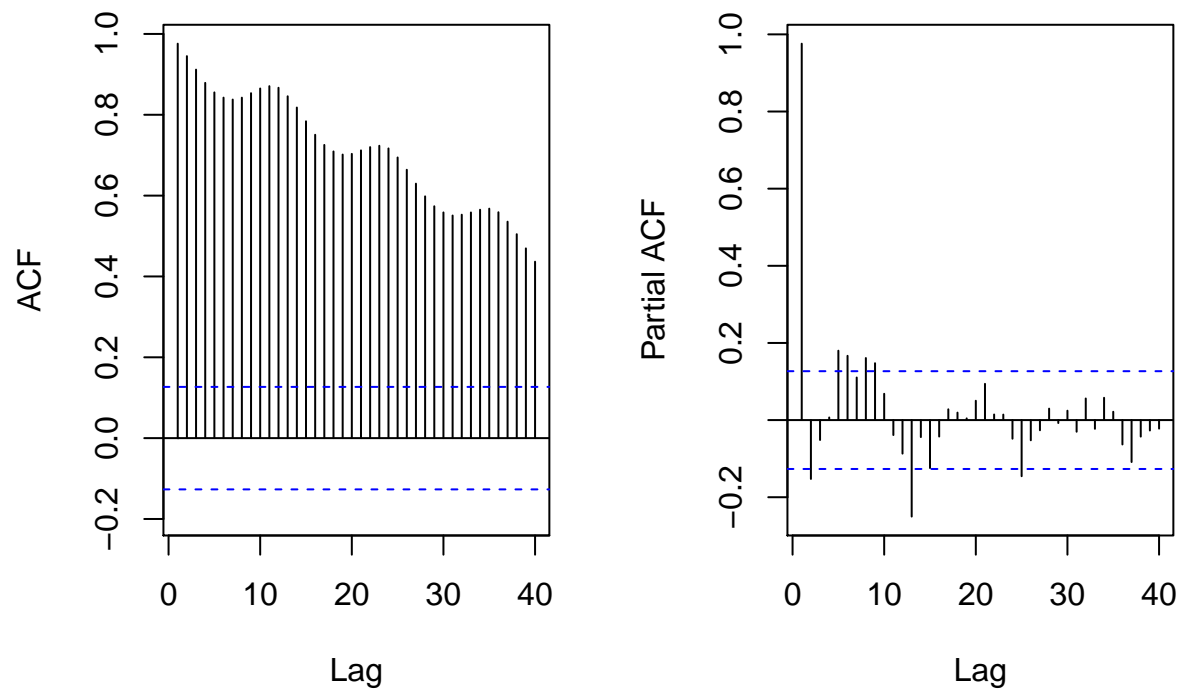
#ACF and PACF plots

`par(mfrow=c(1,2))`

`ACF_Plot <- Acf(electricity_price_processed$Residential, lag = 40, plot = TRUE)`

`PACF_Plot <- Pacf(electricity_price_processed$Residential, lag = 40)`

es electricity_price_processed\$Rees electricity_price_processed\$Re

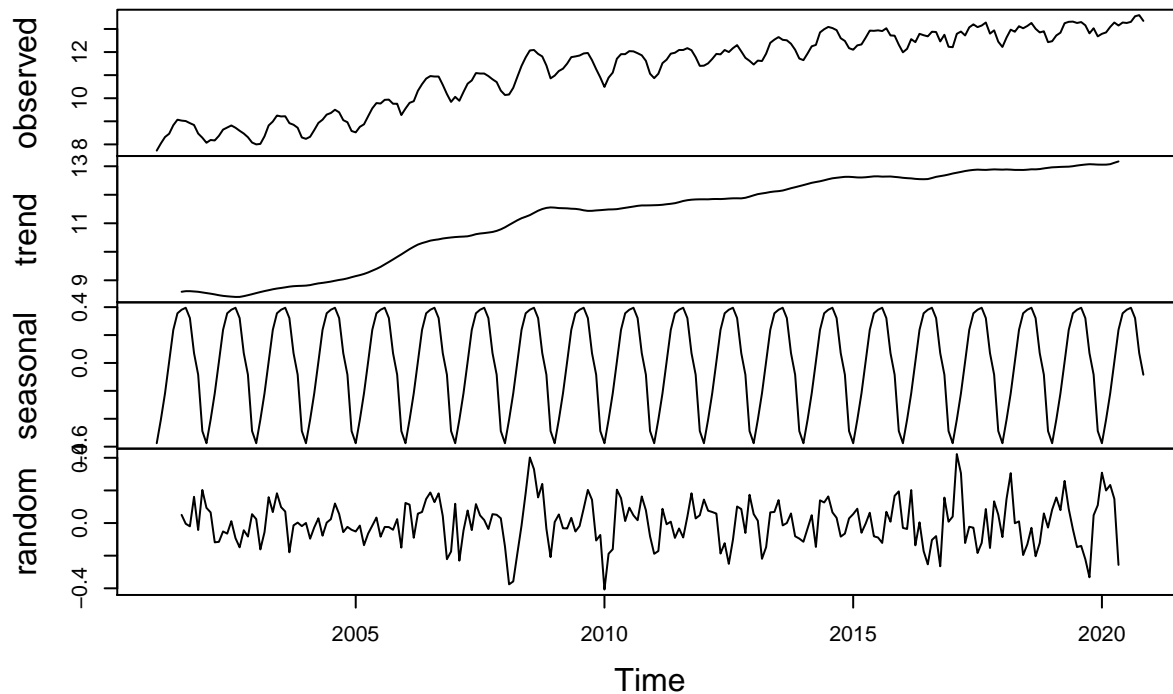


Decomposing the time series

The plots from the previous section show the data has a seasonal component. Since we are working with non-seasonal ARIMA, we need to decompose the series and eliminate the seasonality.

```
#Using R decompose function  
decompose_residential_price <- decompose(ts_electricity_price[, "Residential"], "additive")  
plot(decompose_residential_price)
```

Decomposition of additive time series



#The ACF plot show a slow decay which is a sign of non-stationarity.

This time we will not remove seasonality to enter the Arima(). But we still need to remove seasonal component to run stationarity test and find the order of the non-seasonal part of the ARIMA, i.e., (p,d,q).

Modeling the non-seasonal part

Remember from previous scripts that the electricity price series has a stochastic trend. A useful function to help determine how many times you should difference your series is the `ndiffs()` from package 'forecast'.

```
#Creating non-seasonal residential price time series
deseasonal_residential_price <- seasadj(decompose_residential_price)

# Find out how many time we need to difference
n_diff <- ndiffs(deseasonal_residential_price)
cat("Number of differencing needed: ",n_diff)

## Number of differencing needed: 1

#Lets difference the series once at lag 1 to remove the trend.
deseasonal_residential_price_diff <- diff(deseasonal_residential_price,differences=1,lag=1)

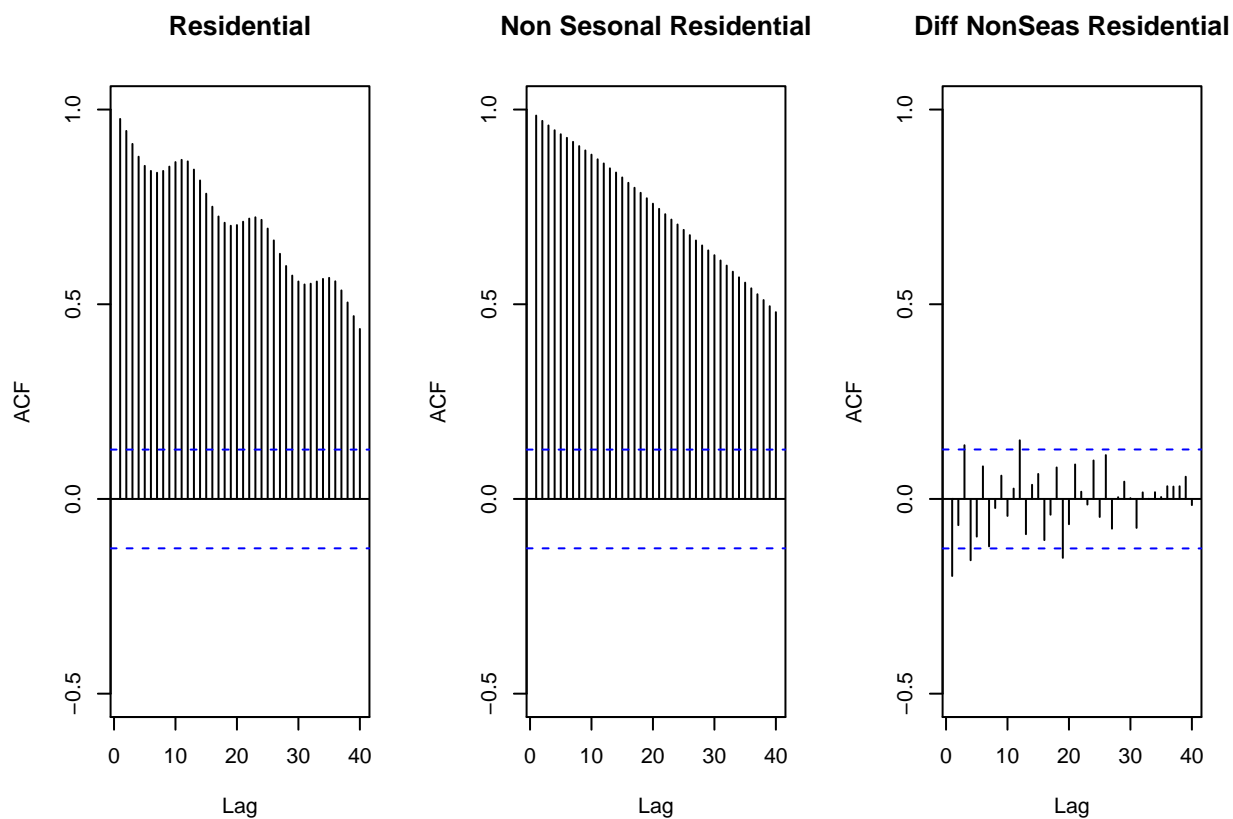
#Add the new series to our data frame
df_residential_full <- data.frame( Month = electricity_price_processed$Month,
                                   Residential = electricity_price_processed$Residential,
                                   NonSeasonalResidential = as.numeric(deseasonal_residential_price),
                                   ResidentialDiff = c(NA,as.numeric(deseasonal_residential_price_diff)))

#Check autocorrelation plot again
#Comparing ACFs
par(mfrow=c(1,3))
```

```

Acf(df_residential_full$Residential,lag.max=40,main="Residential",ylim=c(-.5,1))
Acf(df_residential_full$NonSeasonalResidential,lag.max=40,main="Non Sesonal Residential",ylim=c(-.5,1))
Acf(df_residential_full$ResidentialDiff,lag.max=40,main="Diff NonSeas Residential",ylim=c(-.5,1))

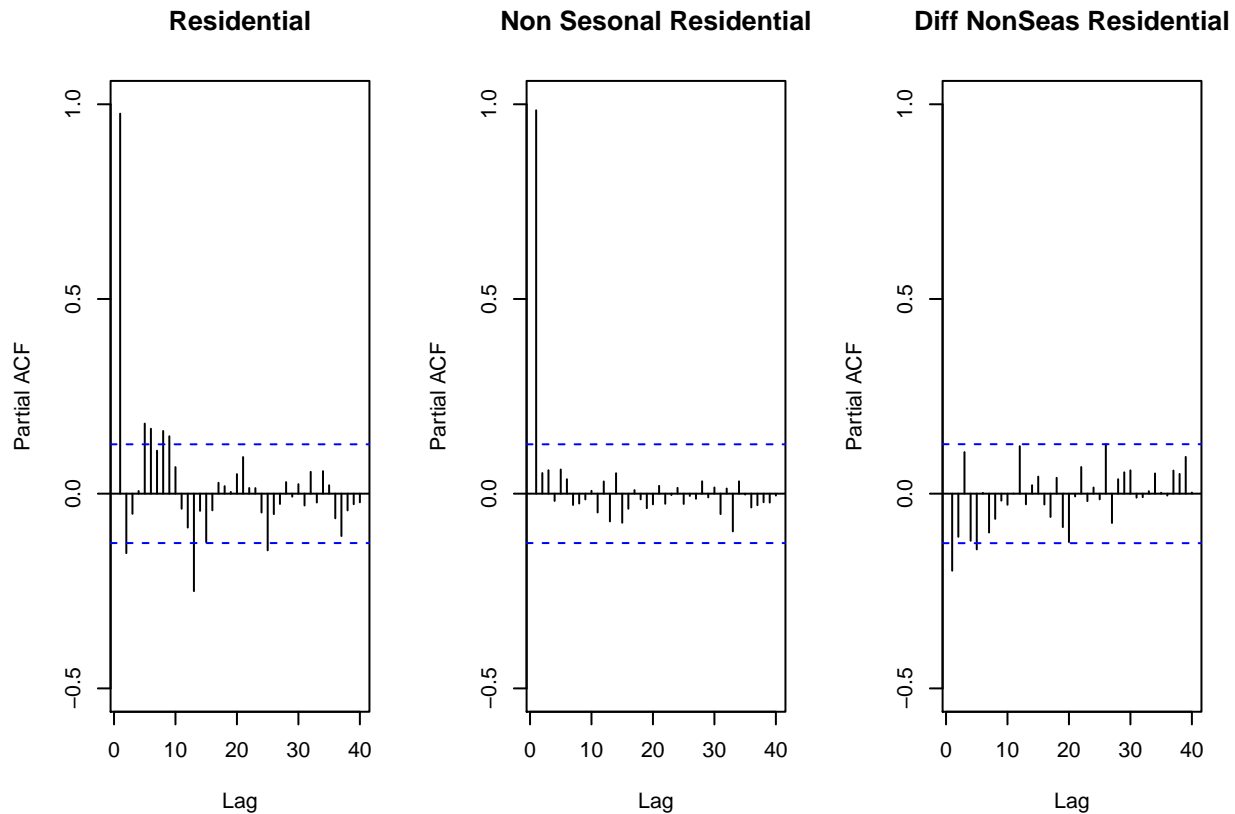
```



```

#Comparing PACFs
par(mfrow=c(1,3))
Pacf(df_residential_full$Residential,lag.max=40,main="Residential",ylim=c(-.5,1))
Pacf(df_residential_full$NonSeasonalResidential,lag.max=40,main="Non Sesonal Residential",ylim=c(-.5,1))
Pacf(df_residential_full$ResidentialDiff,lag.max=40,main="Diff NonSeas Residential",ylim=c(-.5,1))

```



Modeling the seasonal part

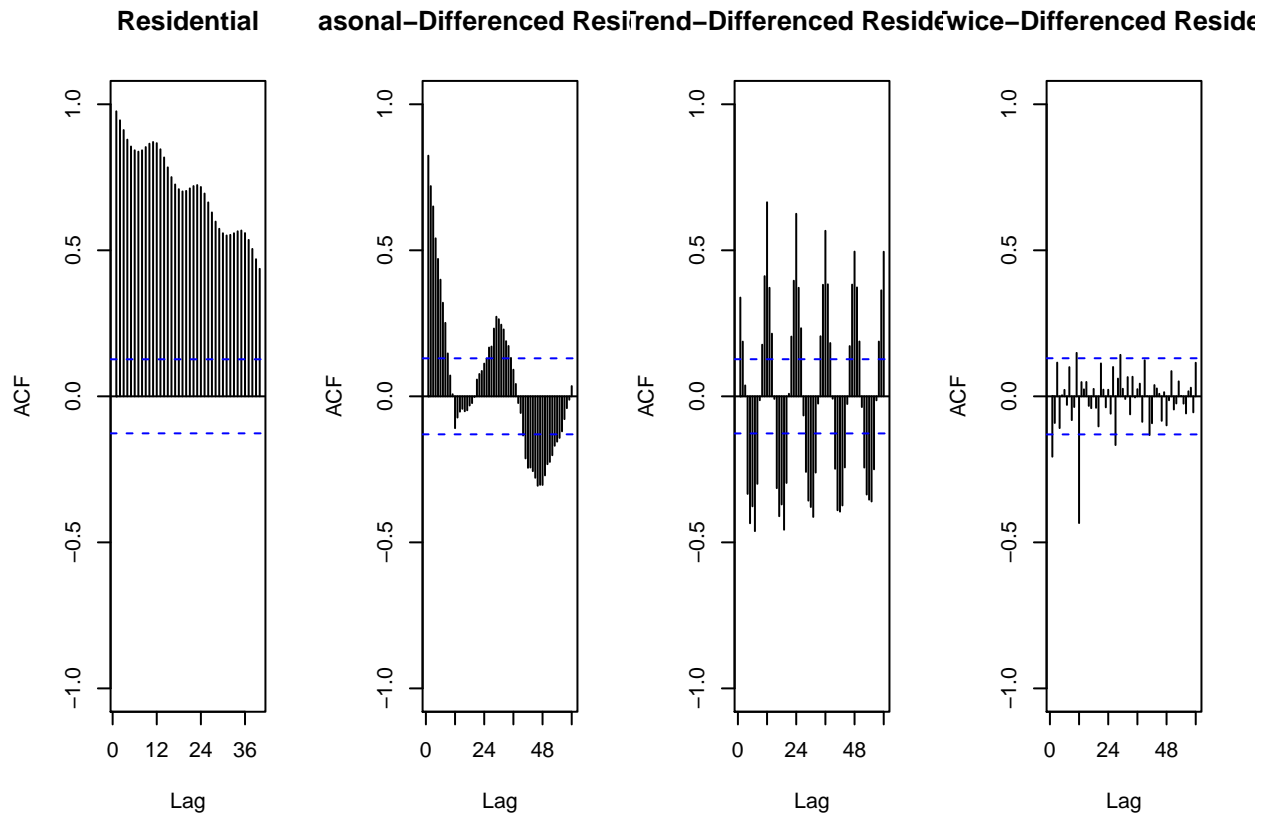
I will not cover the hypothesis test associated with deterministic and stochastic seasonal component. We will use the `nsdiffs()` function to find if our series need differencing at the seasonal lag or not. The function will run the statistical tests internally.

```
# Find out how many time we need to difference
ns_diff <- nsdiffs(ts_electricity_price[, "Residential"])
cat("Number of seasonal differencing needed: ", ns_diff)

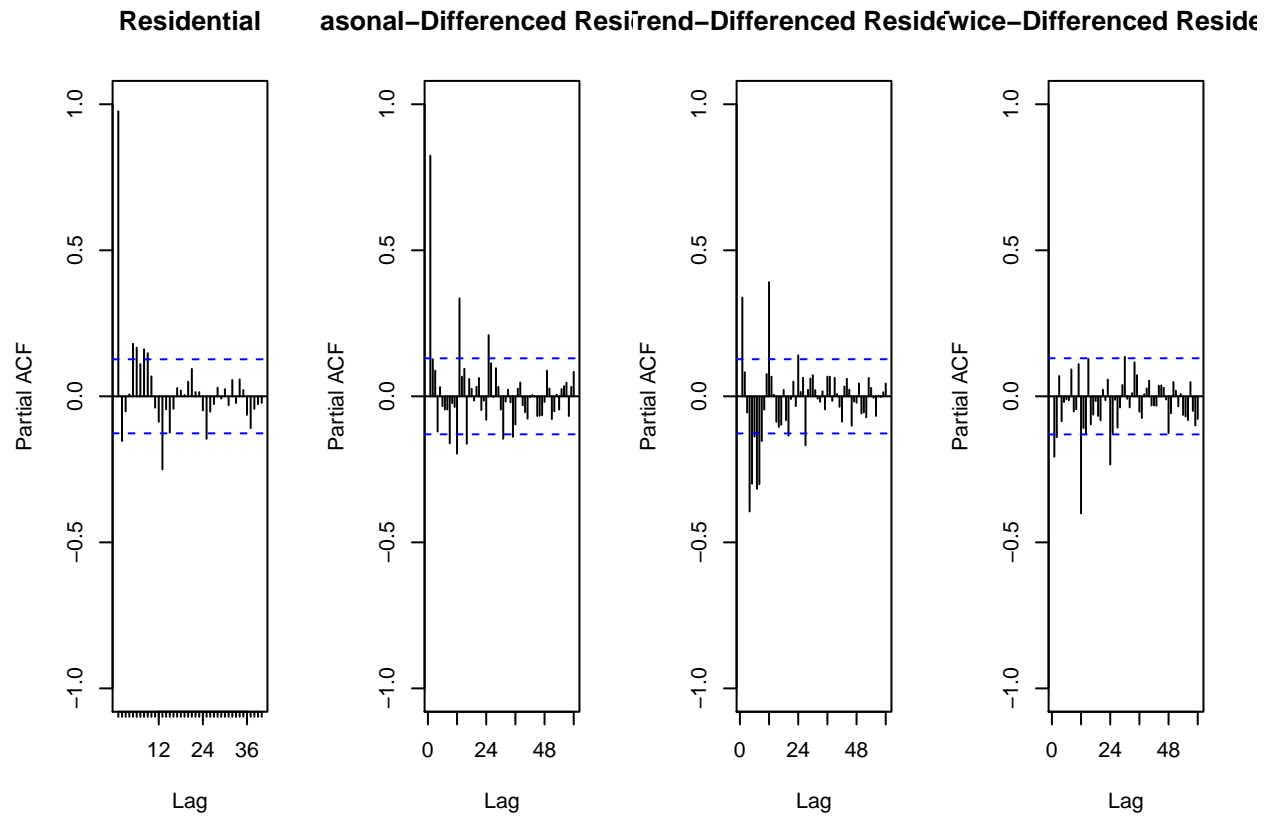
## Number of seasonal differencing needed: 1

# Lets difference the series once at lag 12 to remove the seasonal trend.
residential_price_seas_diff <- diff(ts_electricity_price[, "Residential"], lag=12, differences=1)
residential_price_trend_diff <- diff(ts_electricity_price[, "Residential"], lag=1, differences=1) #diff
residential_price_both_diff <- diff(residential_price_trend_diff, lag=12, differences=1)

# Check autocorrelation plots for differenced series
# Comparing ACFs
par(mfrow=c(1,4))
Acf(ts_electricity_price[, "Residential"], lag.max=40, main="Residential", ylim=c(-1,1))
Acf(residential_price_seas_diff, lag.max=60, main="Seasonal-Differenced Residential", ylim=c(-1,1))
Acf(residential_price_trend_diff, lag.max=60, main="Trend-Differenced Residential", ylim=c(-1,1))
Acf(residential_price_both_diff, lag.max=60, main="Twice-Differenced Residential", ylim=c(-1,1))
```

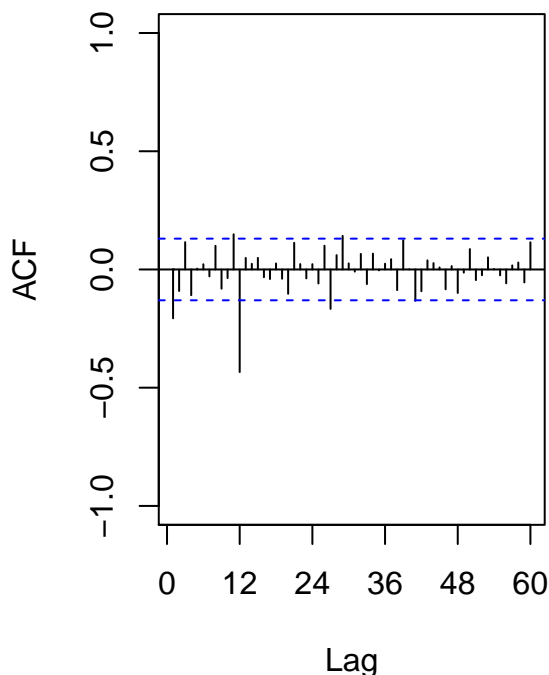



```
#Comparing PACFs
par(mfrow=c(1,4))
Pacf(ts_electricity_price[, "Residential"], lag.max=40, main="Residential", ylim=c(-1,1))
Pacf(residential_price_seas_diff, lag.max=60, main="Seasonal-Differenced Residential", ylim=c(-1,1))
Pacf(residential_price_trend_diff, lag.max=60, main="Trend-Differenced Residential", ylim=c(-1,1))
Pacf(residential_price_both_diff, lag.max=60, main="Twice-Differenced Residential", ylim=c(-1,1))
```

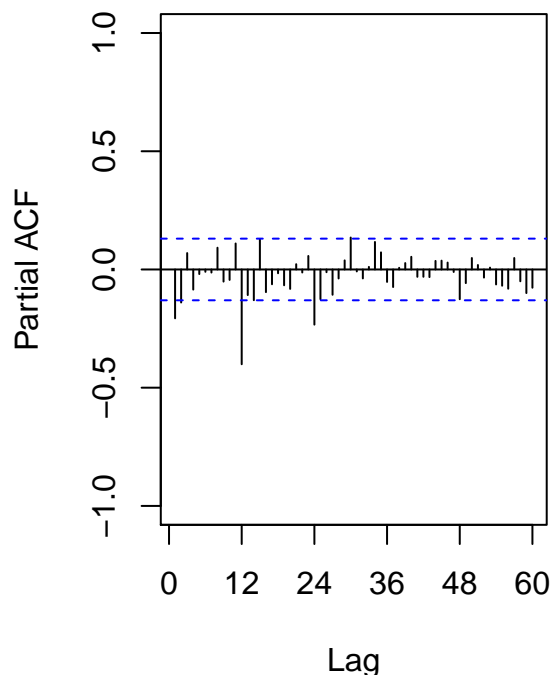


```
#Plot ACF and PACF for twice-differenced series - Steps 3 (order of non-seasonal) and 5 ) order of seas
par(mfrow=c(1,2))
Acf(residential_price_both_diff,lag.max=60,main="Twice-Differenced Residential",ylim=c(-1,1))
Pacf(residential_price_both_diff,lag.max=60,main="Twice-Differenced Residential",ylim=c(-1,1))
```

Twice-Differenced Residential



Twice-Differenced Residential



Look at the twice differenced series to identify model order.

Note that we look at the ACF and PACF plot of the differenced series to try to find the order of the model. Here when we look at the first 12 lags for ACF & PACF we don't see slow decays but it looks like we have cut offs at lag 1 on both plots indicating an ARMA($p=1, q=1$), and we know from `ndiffs` that $d=1$.

Now let's look at seasonal lags only (12,24,36,48). ACF has one spike at 12 and PACF has 2 spikes one at 12 and one at 24. This is an indication of a seasonal moving average (SMA). Therefore the order of seasonal component is $P=0$ and $Q=1$. We know from `nsdiffs` that $D=1$.

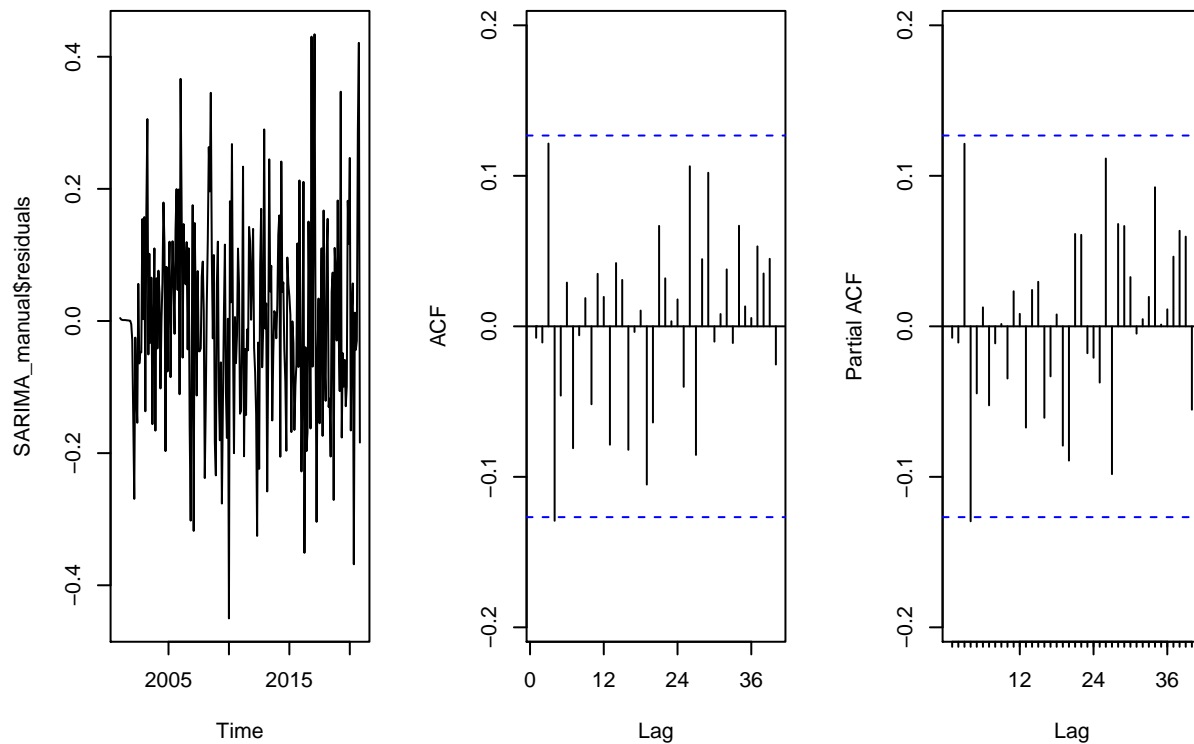
Manually fitting seasonal ARIMA to original series

```
SARIMA_manual <- Arima(ts_electricity_price[, "Residential"], order=c(1,1,1), seasonal=c(0,1,1), include.drift=TRUE)
print(SARIMA_manual)
```

```
## Series: ts_electricity_price[, "Residential"]
## ARIMA(1,1,1)(0,1,1)[12]
##
## Coefficients:
##          ar1          ma1          sma1
##          0.2957   -0.5393   -0.7534
## s.e.    0.3612    0.3266    0.0620
##
## sigma^2 estimated as 0.02352:  log likelihood=99.49
## AIC=-190.98  AICc=-190.8   BIC=-177.3
```

```
par(mfrow=c(1,3))
ts.plot(SARIMA_manual$residuals)
Acf(SARIMA_manual$residuals, lag.max=40)
Pacf(SARIMA_manual$residuals, lag.max=40)
```

Series SARIMA_manual\$residu Series SARIMA_manual\$residu



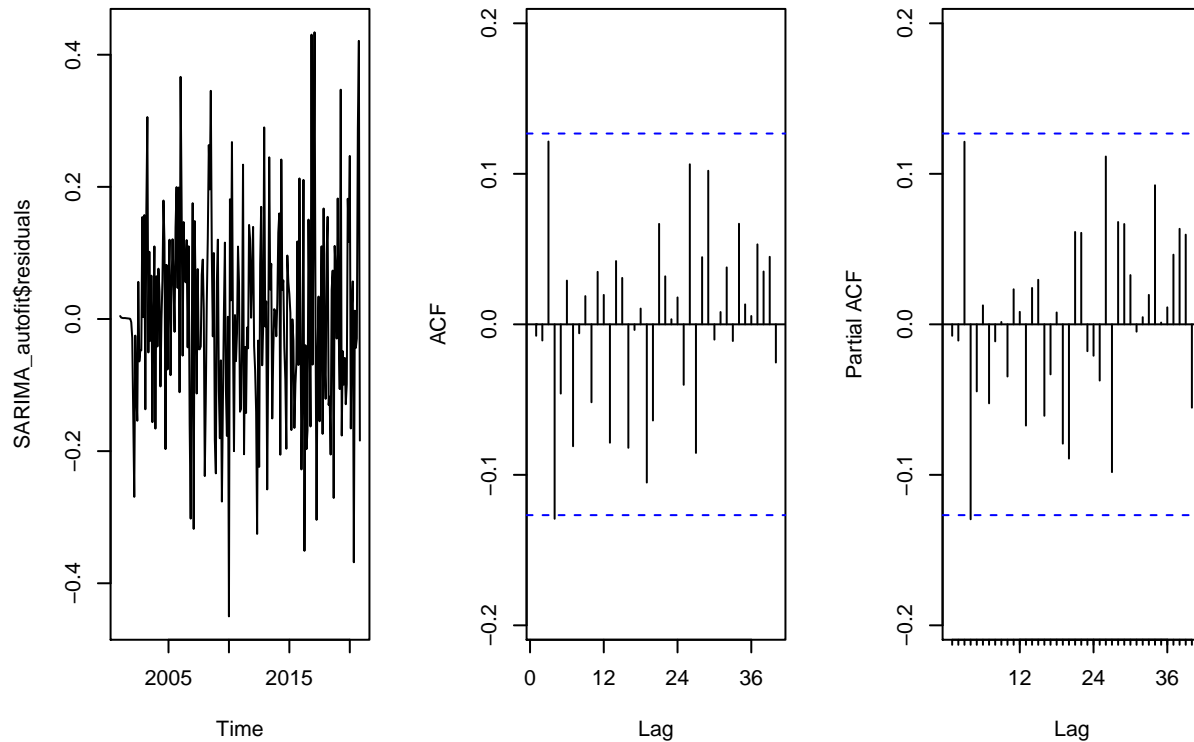
Automatically fitting seasonal ARIMA to original series

```
SARIMA_autofit <- auto.arima(ts_electricity_price[, "Residential"])
print(SARIMA_autofit)
```

```
## Series: ts_electricity_price[, "Residential"]
## ARIMA(1,1,1)(0,1,1)[12]
##
## Coefficients:
##          ar1          ma1          sma1
##          0.2957   -0.5393   -0.7534
## s.e.    0.3612    0.3266    0.0620
##
## sigma^2 estimated as 0.02352:  log likelihood=99.49
## AIC=-190.98  AICc=-190.8   BIC=-177.3
```

```
par(mfrow=c(1,3))
ts.plot(SARIMA_autofit$residuals)
Acf(SARIMA_autofit$residuals,lag.max=40)
Pacf(SARIMA_autofit$residuals,lag.max=40)
```

Series SARIMA_autofit\$residuals Series SARIMA_autofit\$residuals



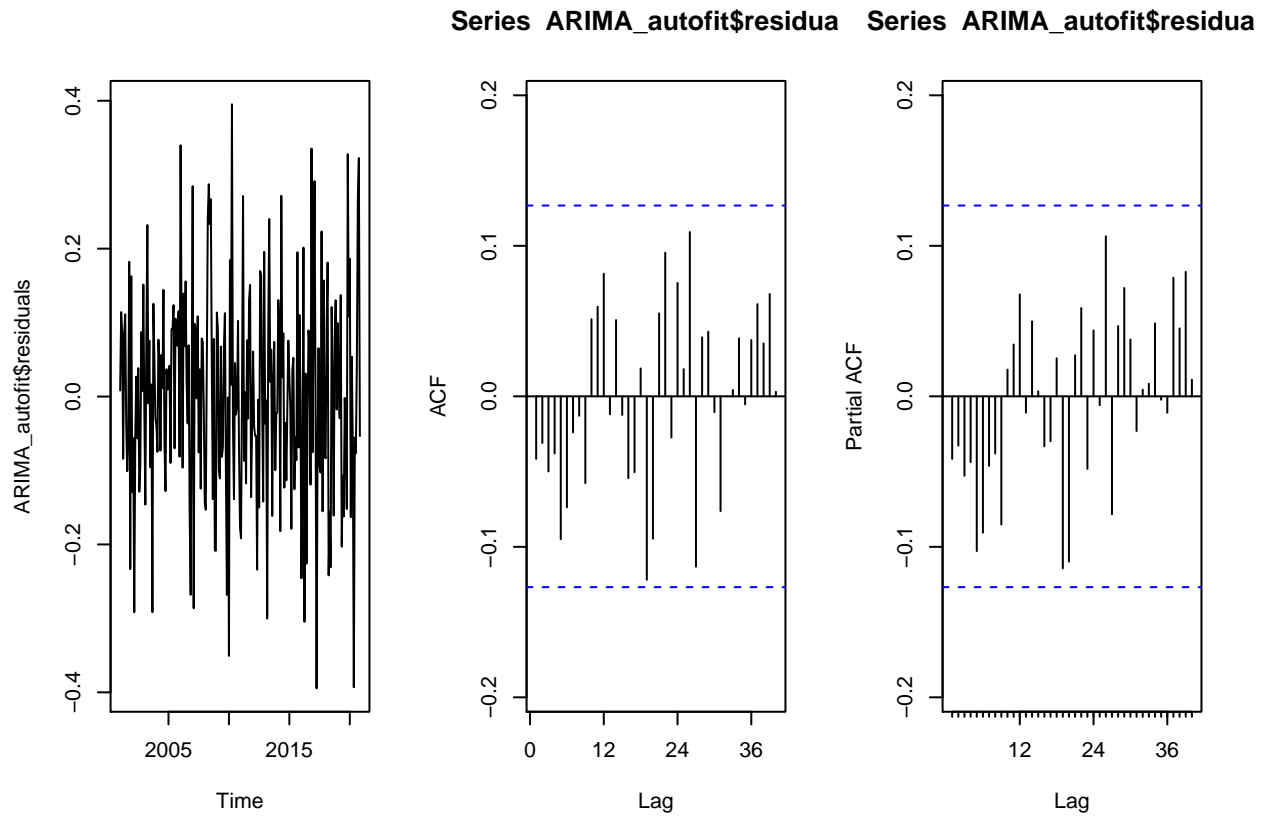
Automatically fitting ARIMA to deseasonal series

Recall from M6 that the best fit for the non-seasonal time series is a ARIMA(2,1,2) with drift.

```
ARIMA_autofit <- auto.arima(deseasonal_residential_price,max.D=0,max.P = 0,max.Q=0)
print(ARIMA_autofit)
```

```
## Series: deseasonal_residential_price
## ARIMA(2,1,2) with drift
##
## Coefficients:
##      ar1      ar2      ma1      ma2      drift
##      -0.9488  -0.8484   0.8040   0.7078   0.0217
## s.e.    0.0867   0.1001   0.1206   0.1391   0.0083
##
## sigma^2 estimated as 0.02052:  log likelihood=127.14
## AIC=-242.29  AICc=-241.93  BIC=-221.46
```

```
par(mfrow=c(1,3))
ts.plot(ARIMA_autofit$residuals)
Acf(ARIMA_autofit$residuals,lag.max=40)
Pacf(ARIMA_autofit$residuals,lag.max=40)
```



Discussion: Which one to do? ARIMA or SARIMA?