Data624 - Project1

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Contents

Overview

This project includes 3 time series dataset and requires to select best forecasting model for all 3 datasets.

- Part A - ATM Forecast
- Part B - Forecasting Power
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Part A - ATM Forecast

The dataset contains cash withdrawals from 4 different ATM machines from May 2009 to Apr 2010. The variable 'Cash' is provided in hundreds of dollars and data is in a single file. Before starting our analysis we will first download the excel from github and then read it through read_excel.

Exploratory Analysis

```
temp.file <- tempfile(fileext = ".xlsx")
download.file(url="https://github.com/amit-kapoor/data624/blob/main/Project1/ATM624Data.xlsx?raw=true",
              destfile = temp.file,
```

```
              mode = "wb",
              quiet = TRUE)
atm.data <- read_excel(temp.file, skip=0, col_types = c("date","text","numeric"))

glimpse(atm.data)
```

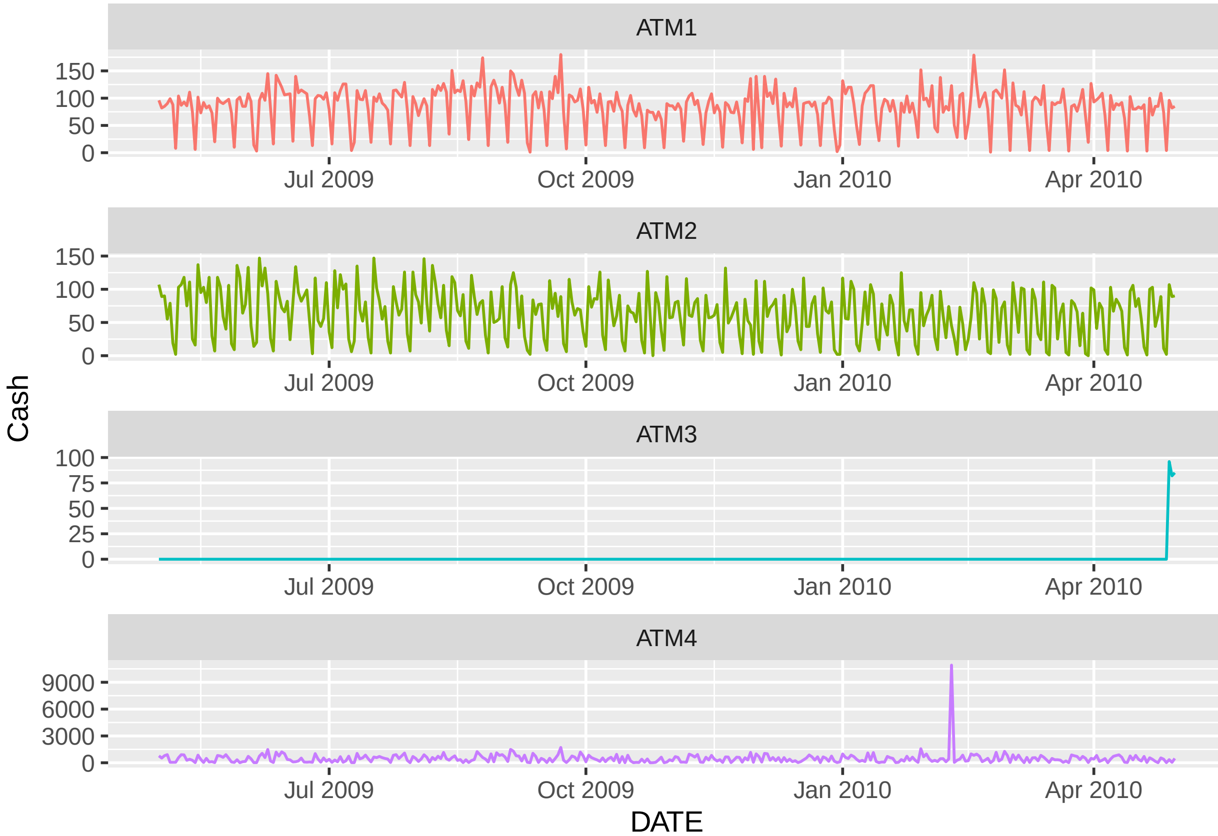
```
## Rows: 1,474
## Columns: 3
## $ DATE <dttm> 2009-05-01, 2009-05-01, 2009-05-02, 2009-05-02, 2009-05-03, 2009~
## $ ATM  <chr> "ATM1", "ATM2", "ATM1", "ATM2", "ATM1", "ATM2", "ATM1", "ATM2", "~
## $ Cash <dbl> 96, 107, 82, 89, 85, 90, 90, 55, 99, 79, 88, 19, 8, 2, 104, 103, ~
```

```
# rows missing values
atm.data[!complete.cases(atm.data),]
```

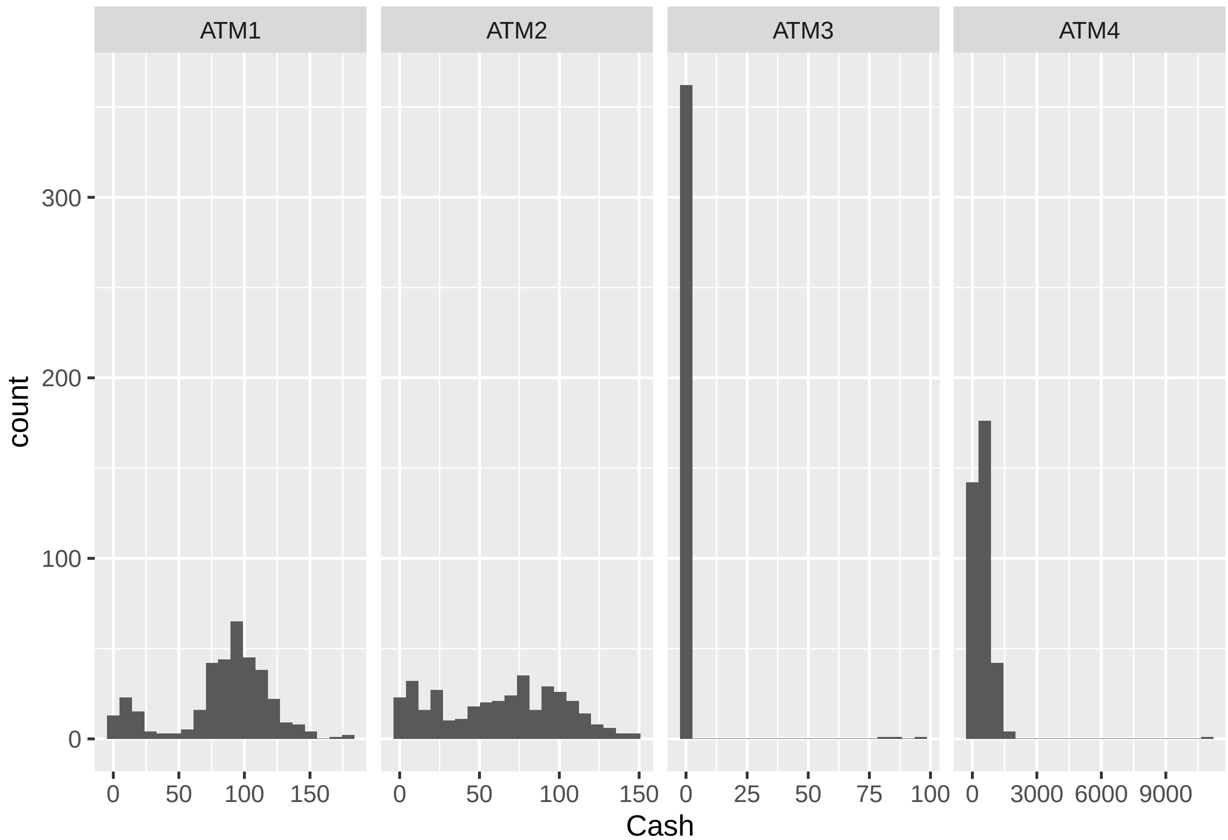
```
## # A tibble: 19 x 3
##    DATE                ATM    Cash
##    <dttm>              <chr> <dbl>
##  1 2009-06-13 00:00:00 ATM1     NA
##  2 2009-06-16 00:00:00 ATM1     NA
##  3 2009-06-18 00:00:00 ATM2     NA
##  4 2009-06-22 00:00:00 ATM1     NA
##  5 2009-06-24 00:00:00 ATM2     NA
##  6 2010-05-01 00:00:00 <NA>     NA
##  7 2010-05-02 00:00:00 <NA>     NA
##  8 2010-05-03 00:00:00 <NA>     NA
##  9 2010-05-04 00:00:00 <NA>     NA
## 10 2010-05-05 00:00:00 <NA>     NA
## 11 2010-05-06 00:00:00 <NA>     NA
## 12 2010-05-07 00:00:00 <NA>     NA
## 13 2010-05-08 00:00:00 <NA>     NA
## 14 2010-05-09 00:00:00 <NA>     NA
## 15 2010-05-10 00:00:00 <NA>     NA
## 16 2010-05-11 00:00:00 <NA>     NA
## 17 2010-05-12 00:00:00 <NA>     NA
## 18 2010-05-13 00:00:00 <NA>     NA
## 19 2010-05-14 00:00:00 <NA>     NA
```

In the next set of plots, we will see the data distribution for all ATMs alongwith individual summaries.

```
ggplot(atm.data[complete.cases(atm.data),] , aes(x=DATE, y=Cash, col=ATM )) +
  geom_line(show.legend = FALSE) +
  facet_wrap(~ATM, ncol=1, scales = "free")
```




```
ggplot(atm.data[complete.cases(atm.data),] , aes(x=Cash )) +
  geom_histogram(bins=20) +
  facet_grid(cols=vars(ATM), scales = "free")
```




```
# consider complete cases
atm.comp <- atm.data[complete.cases(atm.data),]
# pivot wider with cols from 4 ATMs and their values as Cash
atm.comp <- atm.comp %>% pivot_wider(names_from = ATM, values_from = Cash)
head(atm.comp)
```

```
## # A tibble: 6 x 5
##   DATE                 ATM1  ATM2  ATM3  ATM4
##   <dttm>              <dbl> <dbl> <dbl> <dbl>
## 1 2009-05-01 00:00:00    96   107     0 777.
## 2 2009-05-02 00:00:00    82    89     0 524.
## 3 2009-05-03 00:00:00    85    90     0 793.
## 4 2009-05-04 00:00:00    90    55     0 908.
## 5 2009-05-05 00:00:00    99    79     0  52.8
## 6 2009-05-06 00:00:00    88    19     0  52.2
```

```
# summary
atm.comp %>% select(-DATE) %>% summary()
```

```
##       ATM1             ATM2             ATM3              ATM4
##  Min.   :  1.00   Min.   :  0.00   Min.   : 0.0000   Min.   :    1.563
##  1st Qu.: 73.00   1st Qu.: 25.50   1st Qu.: 0.0000   1st Qu.:  124.334
##  Median : 91.00   Median : 67.00   Median : 0.0000   Median :  403.839
##  Mean   : 83.89   Mean   : 62.58   Mean   : 0.7206   Mean   :  474.043
##  3rd Qu.:108.00   3rd Qu.: 93.00   3rd Qu.: 0.0000   3rd Qu.:  704.507
##  Max.   :180.00   Max.   :147.00   Max.   :96.0000   Max.   :10919.762
##  NA's   :3        NA's   :2
```

Per above exploratory analysis, all ATMs show different patterns. We would perform forecasting for each

ATM separately.

- ATM1 and ATM2 shows similar pattern (approx.) throughout the time. ATM1 and ATM2 have 3 and 2 missing entries respectively.
- ATM3 appears to become online in last 3 days only and rest of days appears inactive. So tha data available for this ATM is very limited.
- ATM4 requires replacement for outlier and we can assume that one day spike of cash withdrawal is unique. It has an outlier showing withdrawl amount 10920.

Data Cleaning

For this part we will first apply ts() function to get required time series. Next step is to apply tsclean function that will handle missing data along with outliers. To estimate missing values and outlier replacements, this function uses linear interpolation on the (possibly seasonally adjusted) series. Once we get the clean data we will use pivot_longer to get the dataframe in its original form.

```
atm.ts <- ts(atm.comp %>% select(-DATE))
head(atm.ts)
```

```
## Time Series:
## Start = 1
## End = 6
## Frequency = 1
##   ATM1 ATM2 ATM3      ATM4
## 1   96  107    0 776.99342
## 2   82   89    0 524.41796
## 3   85   90    0 792.81136
## 4   90   55    0 908.23846
## 5   99   79    0  52.83210
## 6   88   19    0  52.20845
```

```
# apply tsclean
atm.ts.cln <- sapply(X=atm.ts, tsclean)
atm.ts.cln %>% summary()
```

```
##       ATM1             ATM2             ATM3              ATM4
##  Min.   :  1.00   Min.   :  0.00   Min.   : 0.0000   Min.   :   1.563
##  1st Qu.: 73.00   1st Qu.: 26.00   1st Qu.: 0.0000   1st Qu.: 124.334
##  Median : 91.00   Median : 67.00   Median : 0.0000   Median : 402.770
##  Mean   : 84.15   Mean   : 62.59   Mean   : 0.7206   Mean   : 444.757
##  3rd Qu.:108.00   3rd Qu.: 93.00   3rd Qu.: 0.0000   3rd Qu.: 704.192
##  Max.   :180.00   Max.   :147.00   Max.   :96.0000   Max.   :1712.075
```

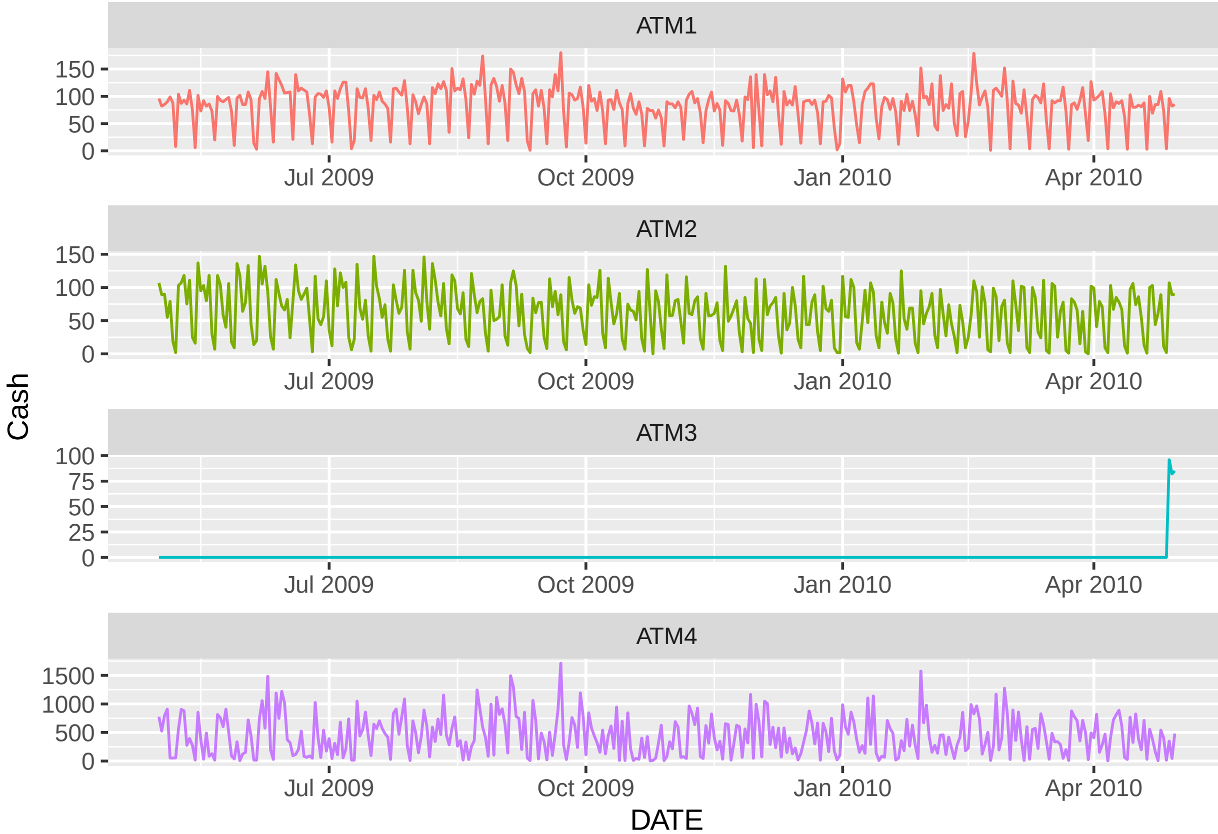
If we compare this summary with previous one of original data, ATM1 and ATM2 has nomore NAs and ATM4 outlier value (10919.762) is handled and now the max value is 1712.075.

```
# convert into data frame, pivot longer , arrange by ATM and bind with dates
atm.new <- as.data.frame(atm.ts.cln) %>%
  pivot_longer(everything(), names_to = "ATM", values_to = "Cash") %>%
  arrange(ATM)

atm.new <- cbind(DATE = seq(as.Date("2009-05-1"), as.Date("2010-04-30"), length.out=365),
                 atm.new)

head(atm.new)
```

```
##         DATE  ATM Cash
## 1 2009-05-01 ATM1   96
```

```
## 2 2009-05-02 ATM1   82
## 3 2009-05-03 ATM1   85
## 4 2009-05-04 ATM1   90
## 5 2009-05-05 ATM1   99
## 6 2009-05-06 ATM1   88
```

```
ggplot(atm.new , aes(x=DATE, y=Cash, col=ATM )) +
  geom_line(show.legend = FALSE) +
  facet_wrap(~ATM, ncol=1, scales = "free")
```



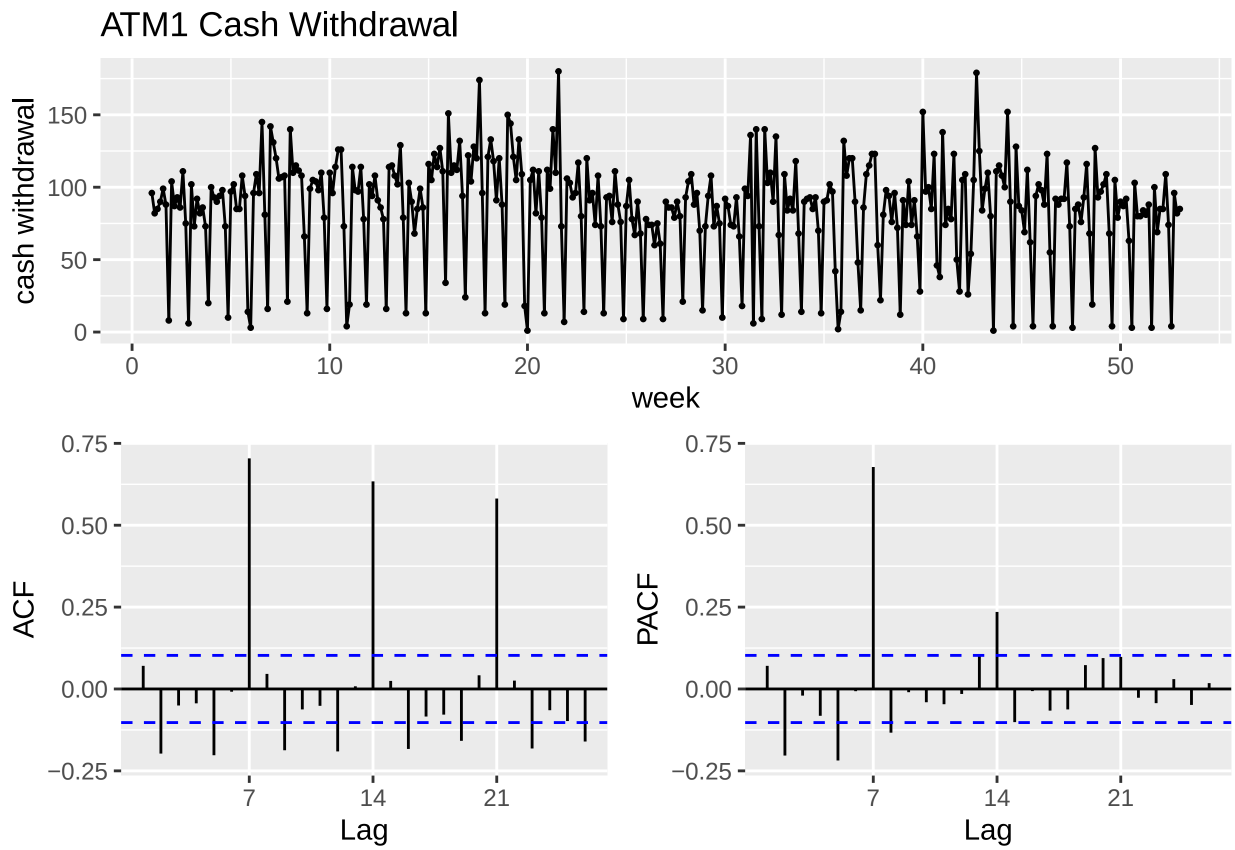
Though above plot doesn't show much differences for ATM1,2,3 but tsclean handled the ATM4 data very well after replacing the outlier.

Time Series

ATM1

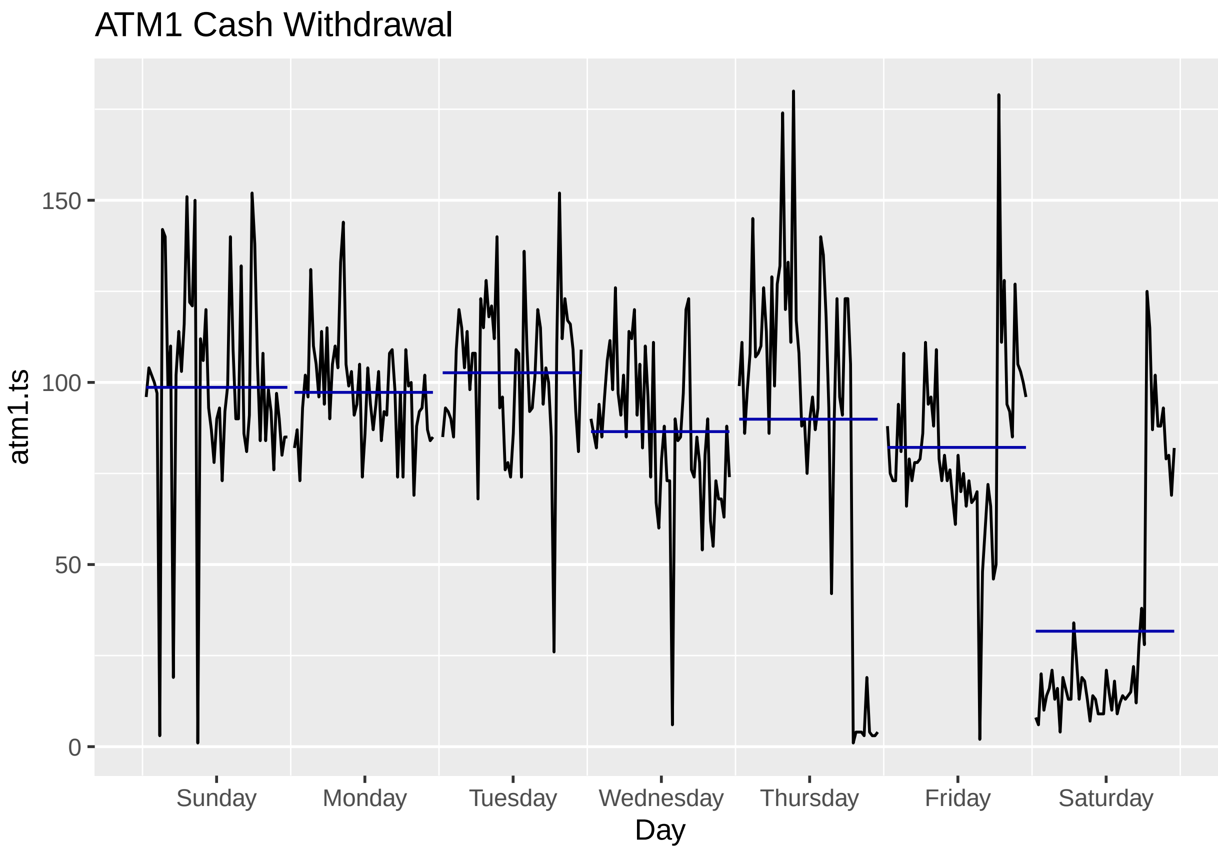
Seeing the time series plot, it is clear that there is a seasonality in the data. We can see increasing and decreasing activities over the weeks in below plot. From the ACF plot, we can see a slight decrease in every 7th lag due to trend. PACF plot shows some significant lags at the beginning.

```
atm1.ts <- atm.new %>% filter(ATM=="ATM1") %>% select(Cash) %>% ts(frequency = 7)
ggtsdisplay(atm1.ts, main="ATM1 Cash Withdrawal", ylab="cash withdrawal", xlab="week")
```



From the above plots it is evident that the time series is non stationary, showing seasonality and will require differencing to make it stationary.

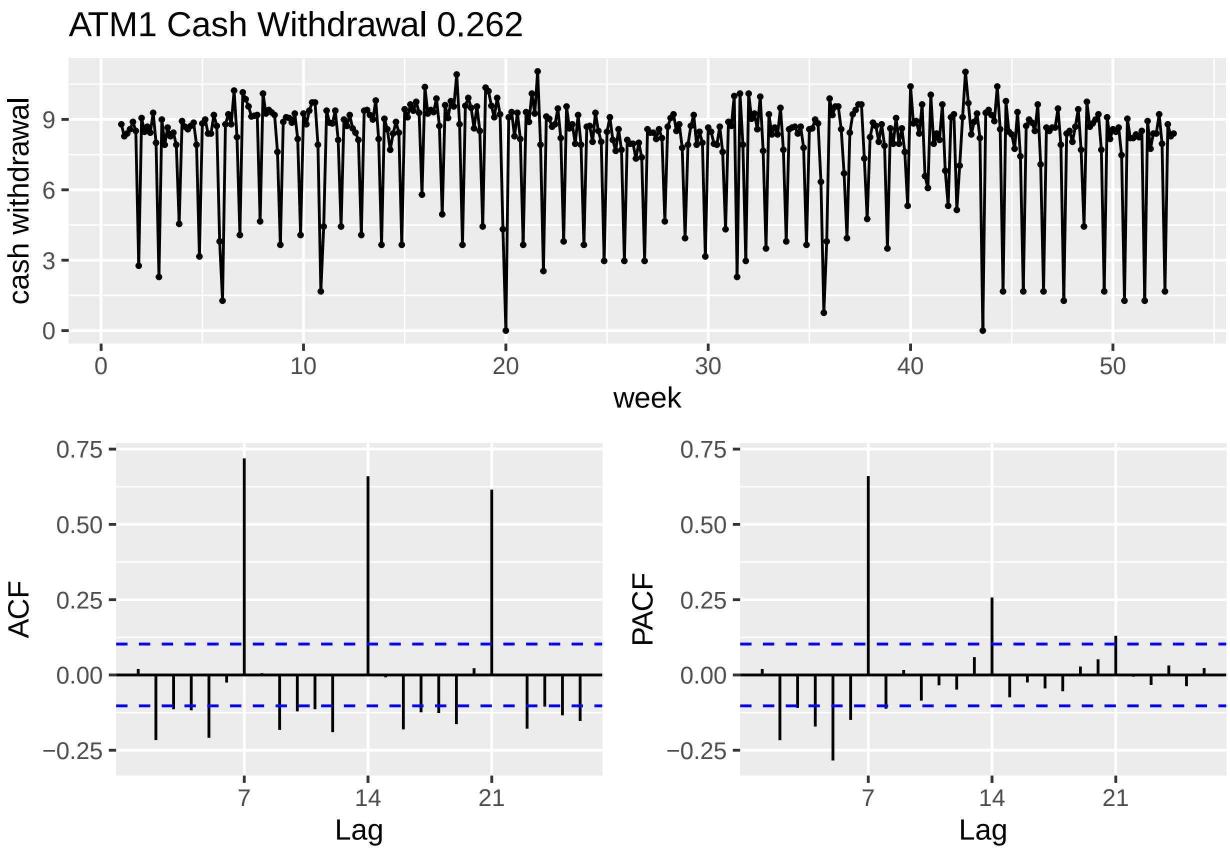
```
ggsubseriesplot(atm1.ts, main="ATM1 Cash Withdrawal")
```



From the subseries plot, it is apparent that Tuesdays having highest mean of ash withdrawl while Saturdays being the lowest.

Next step is to apply BoxCox transformation. With λ being 0.26, the resulting transformation does handle the variablity in time series as shown in below transformed plot.

```
atm1.lambda <- BoxCox.lambda(atm1.ts)
atm1.ts.bc <- BoxCox(atm1.ts, atm1.lambda )
ggtsdisplay(atm1.ts.bc, main=paste("ATM1 Cash Withdrawal",round(atm1.lambda, 3)), ylab="cash withdrawal
```



Next we will see the number of differences required for a stationary series and the number of differences required for a seasonally stationary series.

```
# Number of differences required for a stationary series
ndiffs(atm1.ts.bc)
```

```
## [1] 0
```

```
# Number of differences required for a seasonally stationary series
nsdiffs(atm1.ts.bc)
```

```
## [1] 1
```

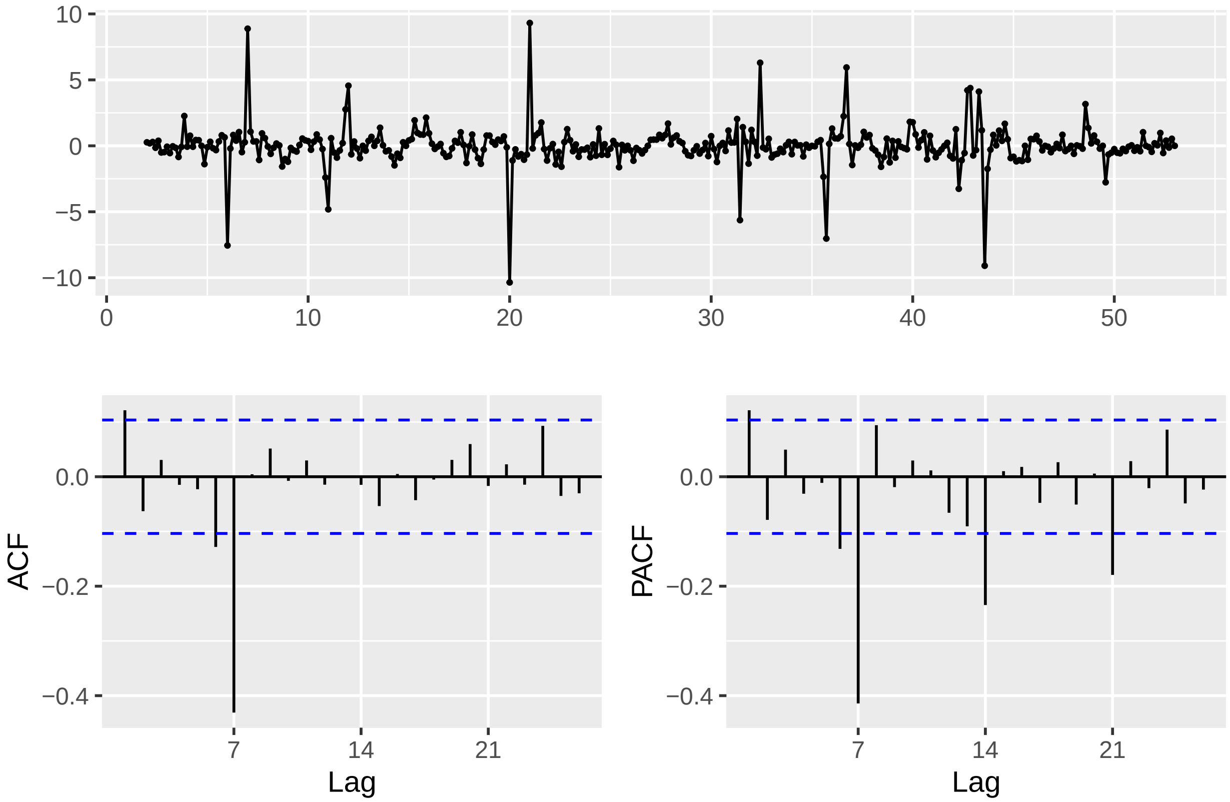
It shows number of differences required for a seasonality stationary series is 1. Next step is to check kpss summary.

```
atm1.ts.bc %>% diff(lag=7) %>% ur.kpss() %>% summary()
```

```
##
## #######################
## # KPSS Unit Root Test #
## #######################
##
## Test is of type: mu with 5 lags.
##
## Value of test-statistic is: 0.0153
##
## Critical value for a significance level of:
##                 10pct  5pct 2.5pct  1pct
## critical values 0.347 0.463  0.574 0.739
```

We can see the test statistic small and well within the range we would expect for stationary data. So we can conclude that the data are stationary.

```
atm1.ts.bc %>% diff(lag=7) %>% ggtsdisplay()
```



The data is non-stationary with seasonality so there will be a seasonal difference of 1. Finally, the differencing of the data has now made it stationary. From the ACF plot, it is apparent now that there is a significant spike at lag 7 but none beyond lag 7.

Lets start with Holt-Winter's additive model with damped trend since the seasonal variations are roughly constant through out the series.

```
# Holt Winters with damped True
atm1.ts %>% hw(h=31, seasonal = "additive", lambda = atm1.lambda, damped = TRUE)
```

```
##          Point Forecast      Lo 80     Hi 80      Lo 95     Hi 95
## 53.14286      86.726308 48.2873323 144.09156 34.0075240 183.86219
## 53.28571      99.656005 56.7502143 162.78119 40.5780934 206.17461
## 53.42857      74.268913 40.2785592 125.84028 27.8645027 161.94499
## 53.57143       3.946722  0.9101988  11.36403  0.3067520  18.00566
## 53.71429      99.554782 56.6834213 162.63577 40.5259535 206.00148
## 53.85714      78.851329 43.2063605 132.58498 30.1007501 170.06058
## 54.00000      85.114307 47.2424187 141.74438 33.2015587 181.05113
## 54.14286      86.658670 45.6127105 150.10813 30.9111908 195.01621
## 54.28571      99.582554 53.7351794 169.36386 37.0454815 218.30796
## 54.42857      74.210981 37.9429783 131.29091 25.1978202 172.11308
## 54.57143       3.940224  0.7732156  12.30036  0.2189239  20.04980
## 54.71429      99.485702 53.6737241 169.22060 36.9987686 218.13522
## 54.85714      78.794338 40.7477446 138.25412 27.2771480 180.60622
## 55.00000      85.055212 44.6156330 147.70043 30.1637147 192.09415
```

```
## 55.14286       86.599982 43.2340302 155.85781 28.2323452 205.80698
## 55.28571       99.518822 51.0490613 175.64880 33.9793617 230.03192
## 55.42857       74.160715 35.8698562 136.50504 22.8992462 181.96358
## 55.57143        3.934588  0.6604831  13.21942  0.1555673  22.09545
## 55.71429       99.425760 50.9921256 175.50745 33.9371713 229.85958
## 55.85714       78.744887 38.5634686 143.67495 24.8394878 190.81691
## 56.00000       85.003935 42.2795812 153.39265 27.5361909 202.77913
## 56.14286       86.549058 41.0923732 161.39633 25.8838357 216.31745
## 56.28571       99.463519 48.6265521 181.69785 31.2829118 241.43875
## 56.42857       74.117099 34.0067798 141.53228 20.8914243 191.57013
## 56.57143        3.929701  0.5664429  14.12646  0.1096150  24.14933
## 56.71429       99.373745 48.5734860 181.55814 31.2445441 241.26666
## 56.85714       78.701976 36.5988213 148.89936 22.7069013 200.76969
## 57.00000       84.959439 40.1763734 158.87600 25.2333014 213.18774
## 57.14286       86.504867 39.1457044 166.76293 23.8038208 226.60572
## 57.28571       99.415528 46.4210490 187.55457 28.8873888 252.59311
## 57.42857       74.079250 32.3163685 146.40758 19.1195026 200.98424
```

Next is to apply exponential smoothing method on this time series. It shows that the ETS(A, N, A) model best fits for the transformed ATM4, i.e. exponential smoothing with additive error, no trend component and additive seasonality.

```r
atm1.ts %>% ets(lambda = atm1.lambda )
```

```
## ETS(A,N,A)
##
## Call:
##  ets(y = ., lambda = atm1.lambda)
##
##   Box-Cox transformation: lambda= 0.2616
##
##   Smoothing parameters:
##     alpha = 1e-04
##     gamma = 0.3513
##
##   Initial states:
##     l = 7.9717
##     s = -4.5094 0.5635 1.0854 0.5711 0.9551 0.5582
##            0.7761
##
##   sigma:  1.343
##
##      AIC     AICc      BIC
## 2379.653 2380.275 2418.652
```

Next we will find out the appropriate ARIMA model for this time series. The suggested model seems ARIMA(0,0,2)(0,1,1)[7].

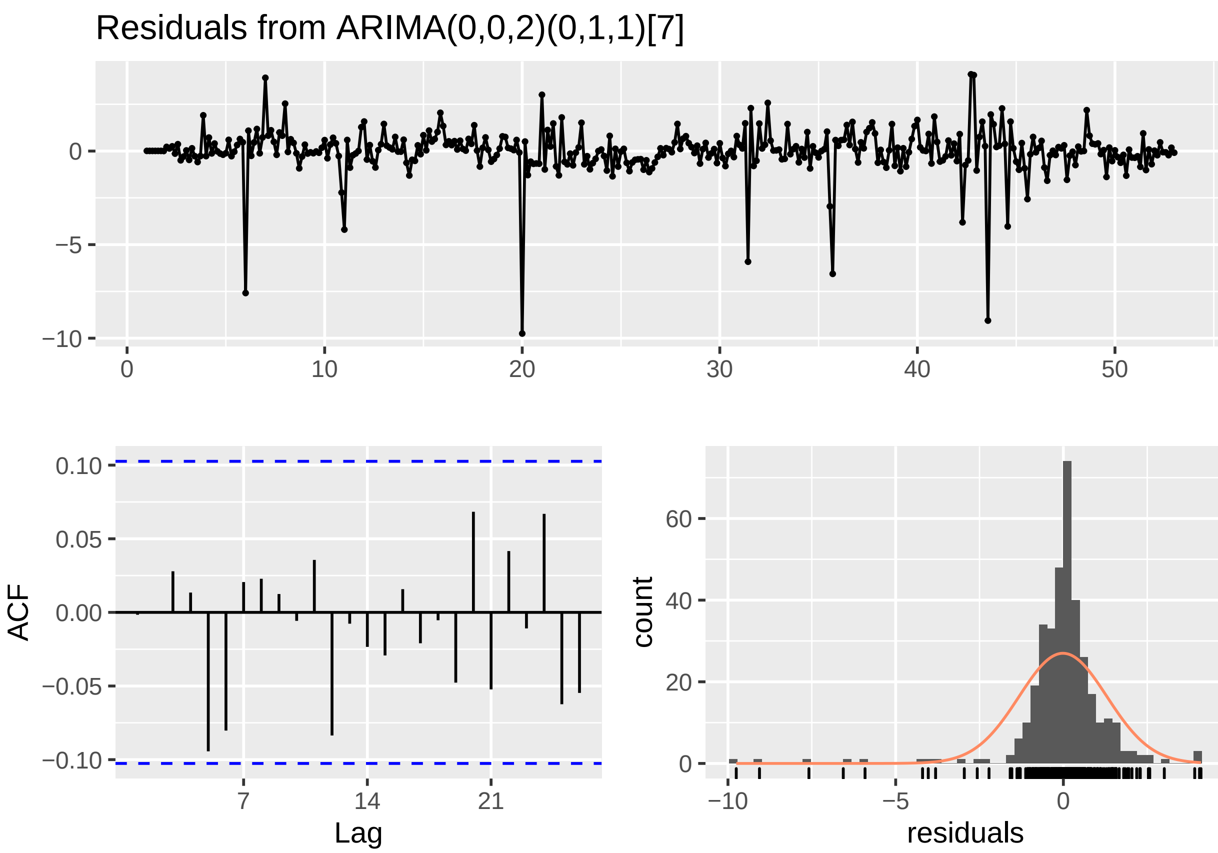
```r
atm1.fit3 <- atm1.ts %>% auto.arima(lambda = atm1.lambda )
atm1.fit3
```

```
## Series: .
## ARIMA(0,0,2)(0,1,1)[7]
## Box Cox transformation: lambda= 0.2615708
##
## Coefficients:
##          ma1      ma2     sma1
```

```
##       0.1126  -0.1094  -0.6418
## s.e.  0.0524   0.0520   0.0432
##
## sigma^2 estimated as 1.764:  log likelihood=-609.99
## AIC=1227.98   AICc=1228.09   BIC=1243.5
```

Next is to see residuals time series plot which shows residuals are being near normal with mean of the residuals being near to zero. Also there is no significant autocorrelation that confirms that forecasts are good.

```
checkresiduals(atm1.fit3)
```




```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(0,0,2)(0,1,1)[7]
## Q* = 9.8626, df = 11, p-value = 0.5428
##
## Model df: 3.   Total lags used: 14
```

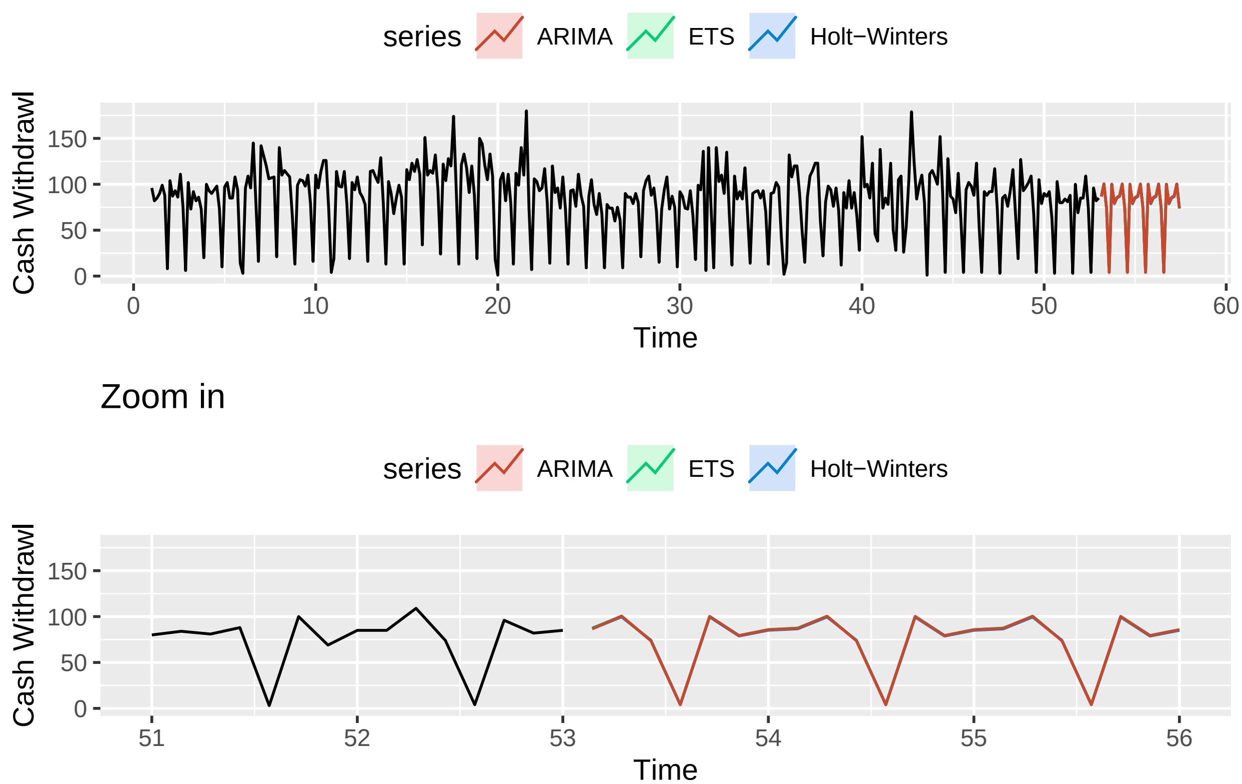
Let's plot the forecast for all the considered models above which will shows a nice visual comparison. it will also show a zoomed in plot to have a clearer view. For this, we will create a generic function which will accept the time series and plot the forecast using all the models.

```
# function to plot forecast(s)
atm.forecast <- function(timeseries) {
  # lambda value
  lambda <- BoxCox.lambda(timeseries)
  # models for forecast
  hw.model <- timeseries %>% hw(h=31, seasonal = "additive", lambda = lambda, damped = TRUE)
```

```
  ets.model <- timeseries %>% ets(lambda = lambda)
  arima.model <- timeseries %>% auto.arima(lambda = lambda)
  # forecast
  atm.hw.fcst <- forecast(hw.model, h=31)
  atm.ets.fcst <- forecast(ets.model, h=31)
  atm.arima.fcst <- forecast(arima.model, h=31)
  # plot forecasts
  p1 <- autoplot(timeseries) +
    autolayer(atm.hw.fcst, PI=FALSE, series="Holt-Winters") +
    autolayer(atm.ets.fcst, PI=FALSE, series="ETS") +
    autolayer(atm.arima.fcst, PI=FALSE, series="ARIMA") +
    theme(legend.position = "top") +
    ylab("Cash Withdrawl")
  # zoom in plot
  p2 <- p1 +
    labs(title = "Zoom in ") +
    xlim(c(51,56))

  grid.arrange(p1,p2,ncol=1)

}
```

```
atm1.arima.fcst <- forecast(atm1.fit3, h=31)
atm.forecast(atm1.ts)
```

```
## Scale for 'x' is already present. Adding another scale for 'x', which will
## replace the existing scale.
```



Now we will check the accuracy of all the models considered above. Again for this purpose, we have created a function that accepts the timeseries and atm num. In this function we will first divide the data for training and testing, train all models with train set and then find out RMSE using test data.

```r
model_accuracy <- function(timeseries, atm_num) {
  # lambda value
  lambda <- BoxCox.lambda(timeseries)

  # split the data to train and test
  train <- window(timeseries, end=c(40, 3))
  test <- window(timeseries, start=c(40, 4))

  # models for forecast
  hw.model <- train %>% hw(h=length(train), seasonal = "additive", lambda = lambda, damped = TRUE)
  ets.model <- train %>% ets(model='ANA', lambda = lambda)

  # Arima model
  if (atm_num == 1) {
    # for ATM1
    arima.model <- train %>% Arima(order=c(0,0,2),
                                     seasonal = c(0,1,1),
                                     lambda = lambda)
  } else if(atm_num == 2) {
    # for ATM2
    arima.model <- train %>% Arima(order=c(3,0,3),
                                     seasonal = c(0,1,1),
                                     include.drift = TRUE,
                                     lambda = lambda,
                                     biasadj = TRUE)
  } else {
    # for ATM4
    arima.model <- train %>% Arima(order=c(0,0,1),
                                   seasonal = c(2,0,0),
                                   lambda = lambda)
  }

  # forecast
  hw.frct = forecast(hw.model, h = length(test))$mean
  ets.frct = forecast(ets.model, h = length(test))$mean
  arima.frct = forecast(arima.model, h = length(test))$mean

  # dataframe having rmse
  rmse = data.frame(RMSE=cbind(accuracy(hw.frct, test)[,2],
                               accuracy(ets.frct, test)[,2],
                               accuracy(arima.frct, test)[,2]))
  names(rmse) = c("Holt-Winters", "ETS", "ARIMA")
  # display rmse
  rmse
}
```

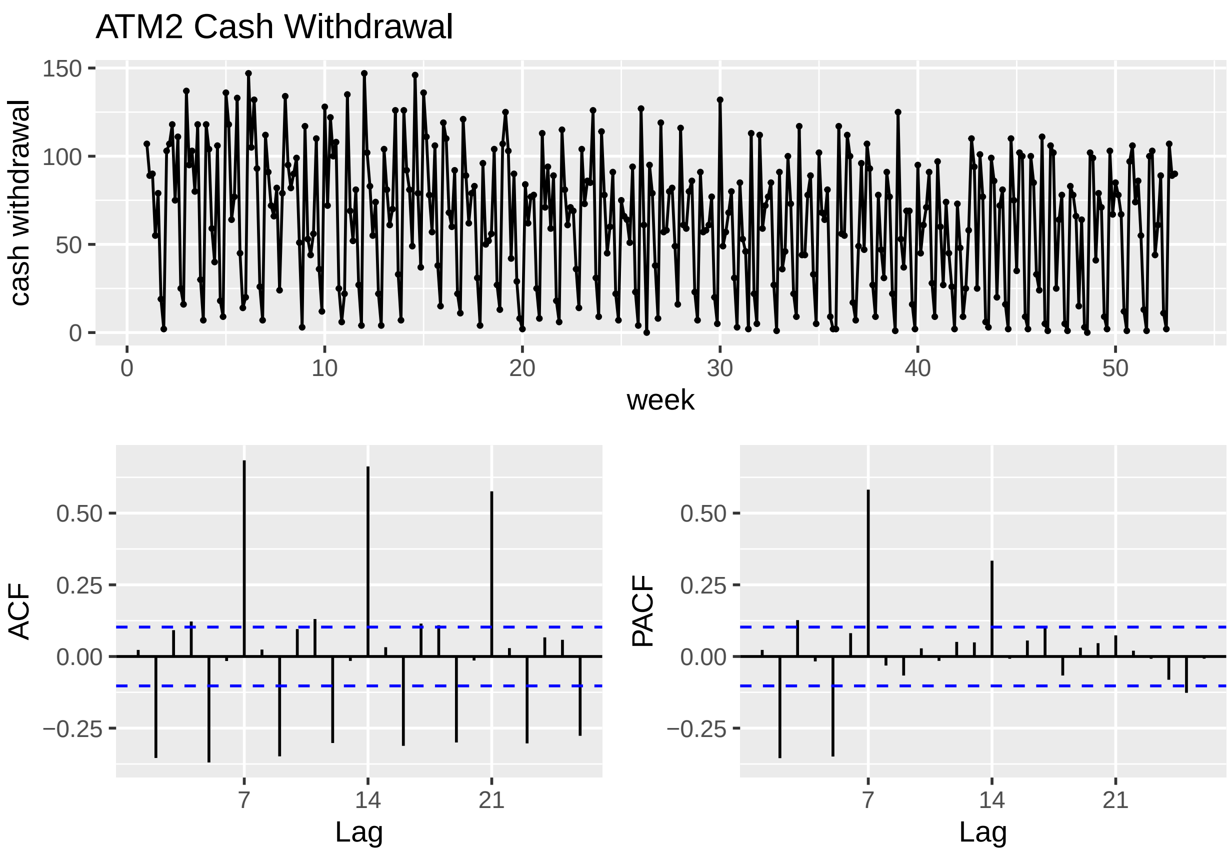
```r
model_accuracy(atm1.ts,1)
```

```
##   Holt-Winters      ETS    ARIMA
## 1     49.35115 49.22521 49.18074
```

ATM2

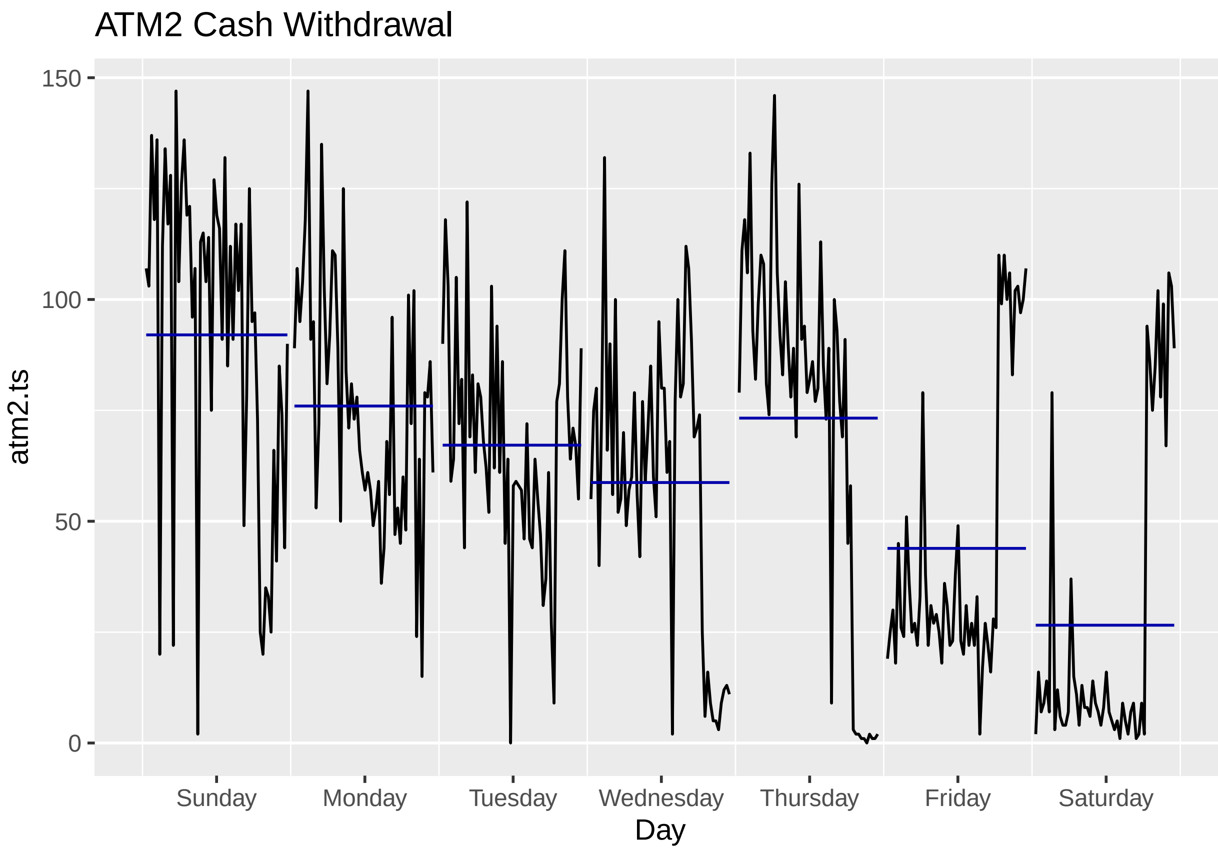
From the time series plot, it is apparent that there is a seasonality in the data but dont see a trend over the period. ACF shows teh significant lags at 7,14 and 21 confirming seasonality. From the PACF, there are few significant lags at the beginning but others within critical limit. Overall, it is non stationary, having seasonality and would require differencing for it to become stationary.

```
atm2.ts <- atm.new %>% filter(ATM=="ATM2") %>% select(Cash) %>% ts(frequency = 7)
ggtsdisplay(atm2.ts, main="ATM2 Cash Withdrawal", ylab="cash withdrawal", xlab="week")
```



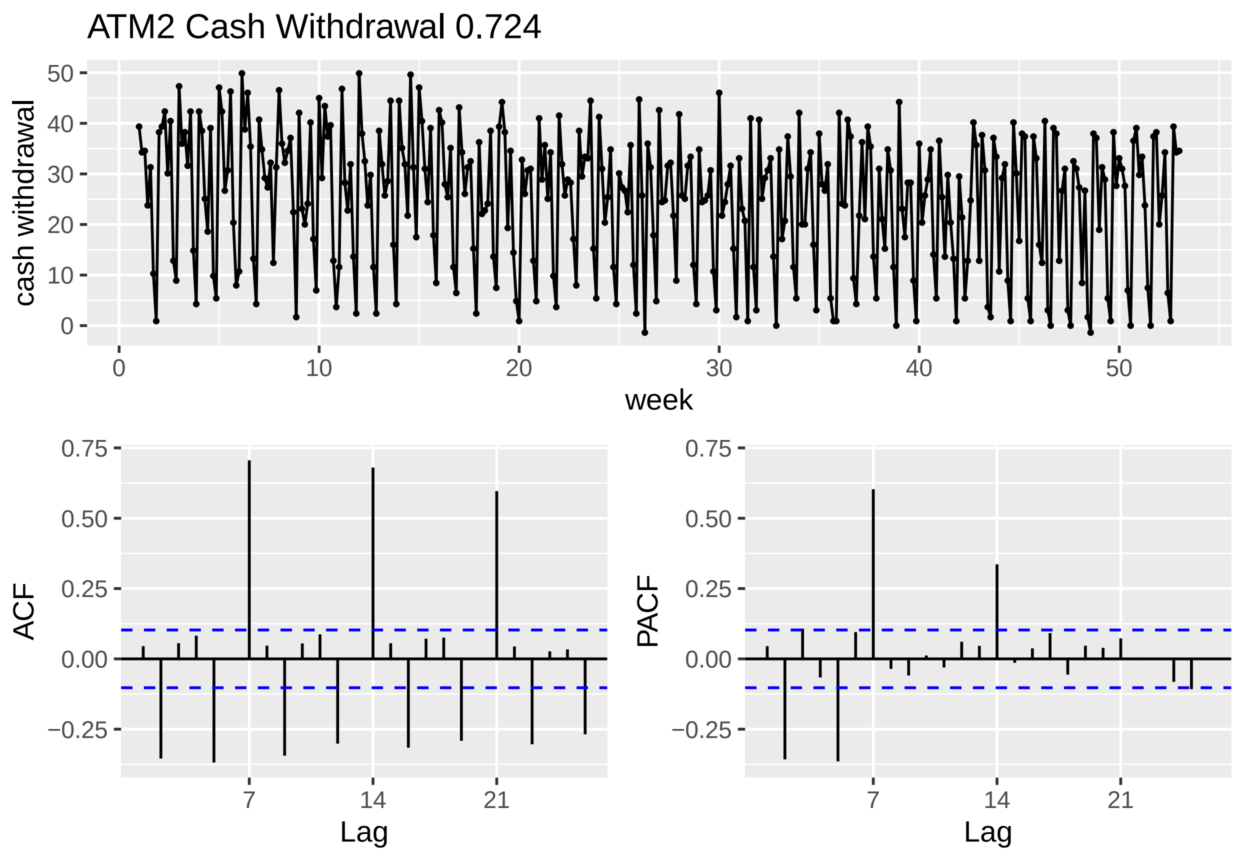
From the subseries plot, it is clear that Sunday is having highest mean for cash withdrawl while Saturday has the lowest.

```
ggsubseriesplot(atm2.ts, main="ATM2 Cash Withdrawal")
```



Next step is to apply BoxCox transformation. With λ being 0.72, the resulting transformation does handle the variablity in time series as shown in below transformed plot.

```
atm2.lambda <- BoxCox.lambda(atm2.ts)
atm2.ts.bc <- BoxCox(atm2.ts, atm2.lambda )
ggtsdisplay(atm2.ts.bc, main=paste("ATM2 Cash Withdrawal",round(atm2.lambda, 3)), ylab="cash withdrawal
```




```r
# Number of differences required for a stationary series
ndiffs(atm2.ts.bc)
```

```
## [1] 1
```

```r
# Number of differences required for a seasonally stationary series
nsdiffs(atm2.ts.bc)
```

```
## [1] 1
```

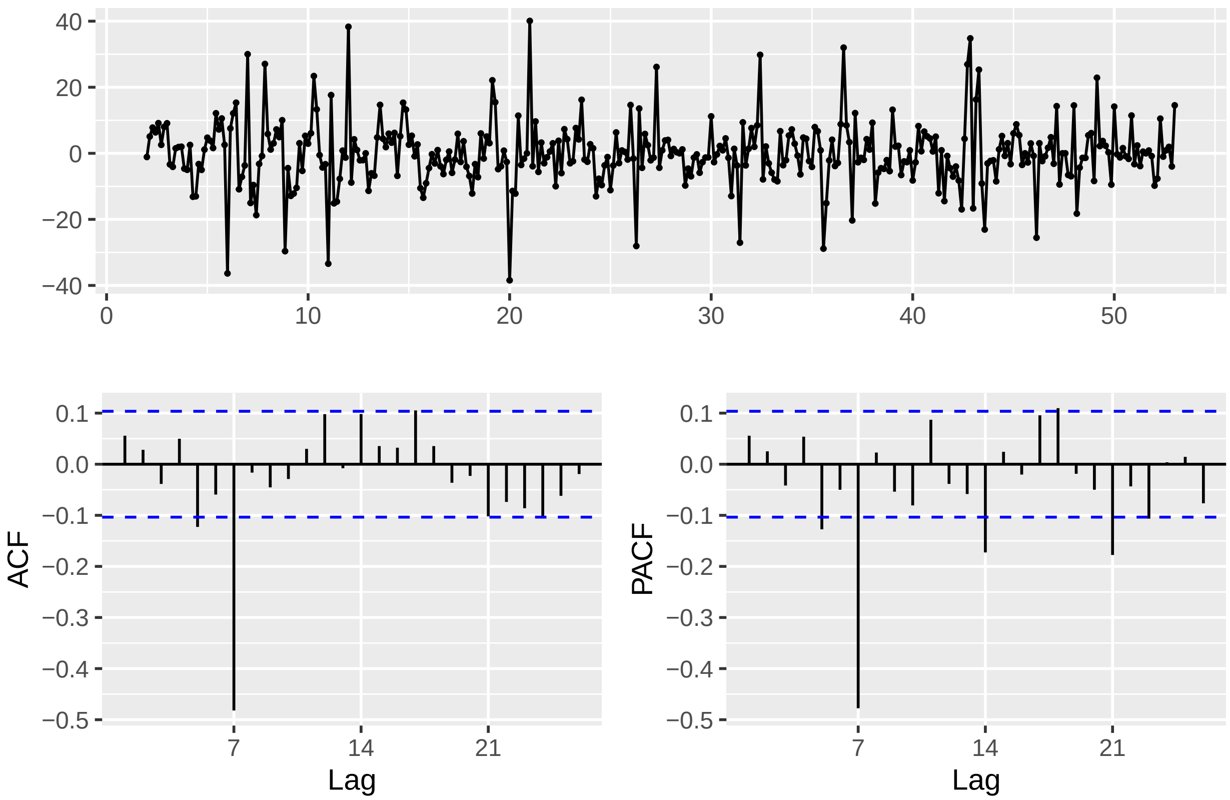
It shows number of differences required is 1 for boxcox transformed data.

```r
atm2.ts.bc %>% diff(lag=7) %>% ur.kpss() %>% summary()
```

```
##
## #######################
## # KPSS Unit Root Test #
## #######################
##
## Test is of type: mu with 5 lags.
##
## Value of test-statistic is: 0.0162
##
## Critical value for a significance level of:
##                 10pct  5pct 2.5pct  1pct
## critical values 0.347 0.463  0.574 0.739
```

We can see the test statistic small and well within the range we would expect for stationary data. So we can conclude that the data are stationary

```
atm2.ts.bc %>% diff(lag=7) %>% ggtsdisplay()
```



First we will start with Holt-Winters damped method. Damping is possible with both additive and multiplicative Holt-Winters' methods. This method often provides accurate and robust forecasts for seasonal data is the Holt-Winters method with a damped trend.

```
# Holt Winters
atm2.ts %>% hw(h=31, seasonal = "additive", lambda = atm2.lambda, damped = TRUE)
```

```
##          Point Forecast        Lo 80     Hi 80     Lo 95     Hi 95
## 53.14286      67.727881  35.291267 105.26894  20.74561 126.87010
## 53.28571      74.012766  40.580383 112.34286  25.35441 134.30920
## 53.42857      10.844773  -3.254323  36.70434 -13.45333  53.31462
## 53.57143       1.648706 -13.353074  22.08418 -26.56518  36.83677
## 53.71429     101.948220  64.792300 143.32926  47.14368 166.72907
## 53.85714      92.500300  56.498440 132.92025  39.58380 155.86508
## 54.00000      68.866332  36.243721 106.55382  21.56968 128.22256
## 54.14286      67.775348  33.216555 108.21505  18.01659 131.58961
## 54.28571      74.059485  38.420870 115.33960  22.46113 139.10021
## 54.42857      10.871202  -4.387783  38.91404 -15.98503  57.04338
## 54.57143       1.663821 -14.982817  24.01057 -29.59257  40.21221
## 54.71429     101.993433  62.324951 146.52593  43.68529 171.80421
## 54.85714      92.542577  54.122362 136.04975  36.29148 160.84582
## 55.00000      68.903765  34.144880 109.49813  18.80244 132.94355
## 55.14286      67.811143  31.293904 110.99079  15.54866 136.05209
## 55.28571      74.094716  36.416629 118.16249  19.82956 143.62898
## 55.42857      10.891142  -5.535746  41.01325 -18.47284  60.59806
## 55.57143       1.675242 -16.563883  25.85263 -32.52085  43.44674
## 55.71429     102.027528  60.025873 149.53496  40.49965 176.59647
```

```
## 55.85714      92.574457  51.911131 138.99687  33.26820 165.55113
## 56.00000      68.931993  32.200914 112.27407  16.29845 137.40928
## 56.14286      67.838136  29.500528 113.62437  13.30674 140.29932
## 56.28571      74.121282  34.544212 120.84032  17.42301 147.93815
## 56.42857      10.906182  -6.688629  43.01959 -20.91749  64.00567
## 56.57143       1.683868 -18.101954  27.62307 -35.36252  46.56110
## 56.71429     102.053237  57.869192 152.38739  37.54566 181.15191
## 56.85714      92.598496  49.839436 141.79169  30.47392 170.02576
## 57.00000      68.953279  30.388346 114.90931  14.02175 141.66104
## 57.14286      67.858490  27.819168 116.13717  11.26493 144.36295
## 57.28571      74.141315  32.785857 123.39486  15.21412 152.06003
## 57.42857      10.917527  -7.840726  44.94651 -23.32042  67.28683
```

Next is to apply exponential smoothing method on this time series. It shows that the ETS(A, N, A) model best fits for the transformed ATM4, i.e. exponential smoothing with additive error, no trend component and additive seasonality.

```
# ETS
atm2.ts %>% ets(lambda = atm2.lambda)
```

```
## ETS(A,N,A)
##
## Call:
##  ets(y = ., lambda = atm2.lambda)
##
##   Box-Cox transformation: lambda= 0.7243
##
##   Smoothing parameters:
##     alpha = 1e-04
##     gamma = 0.3852
##
##   Initial states:
##     l = 26.7912
##     s = -17.8422 -13.3191 10.8227 1.8426 4.2781 5.7994
##            8.4185
##
##   sigma:  8.5054
##
##      AIC     AICc      BIC
## 3727.060 3727.682 3766.059
```

We will now find out the appropriate ARIMA model for this time series. The suggested model seeems ARIMA(3,0,3)(0,1,1)[7] with drift.

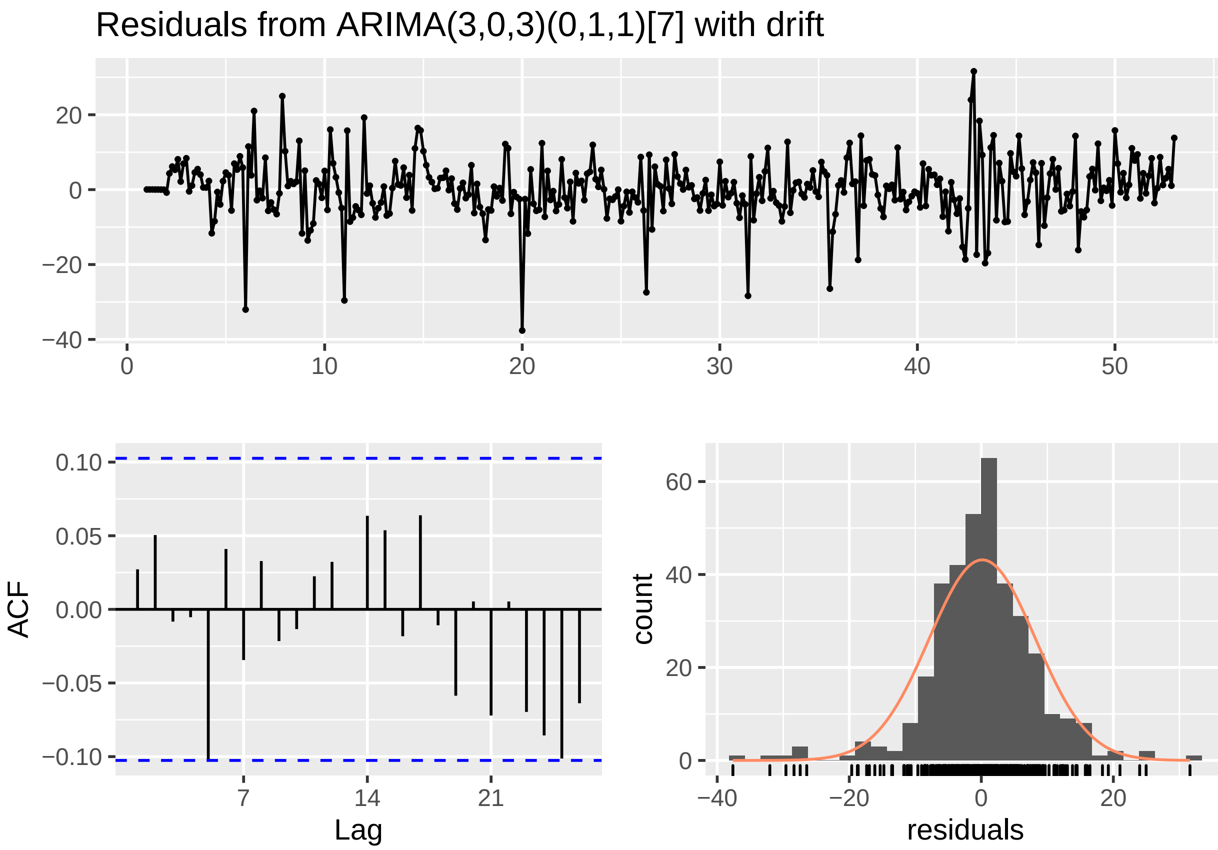
```
atm2.fit3 <- atm2.ts %>% auto.arima(lambda = atm2.lambda )
atm2.fit3
```

```
## Series: .
## ARIMA(3,0,3)(0,1,1)[7] with drift
## Box Cox transformation: lambda= 0.7242585
##
## Coefficients:
##          ar1      ar2     ar3      ma1     ma2      ma3     sma1    drift
##       0.4902  -0.4948  0.8326  -0.4823  0.3203  -0.7837  -0.7153  -0.0203
## s.e.  0.0863   0.0743  0.0614   0.1060  0.0941   0.0621   0.0453   0.0072
##
## sigma^2 estimated as 67.52:  log likelihood=-1260.59
```

```
## AIC=2539.18   AICc=2539.69   BIC=2574.1
```

Next is to see residuals time series plot which shows residuals are being near normal with mean of the residuals being near to zero. Also there is no significant autocorrelation that confirms that forecasts are good.

```
checkresiduals(atm2.fit3)
```

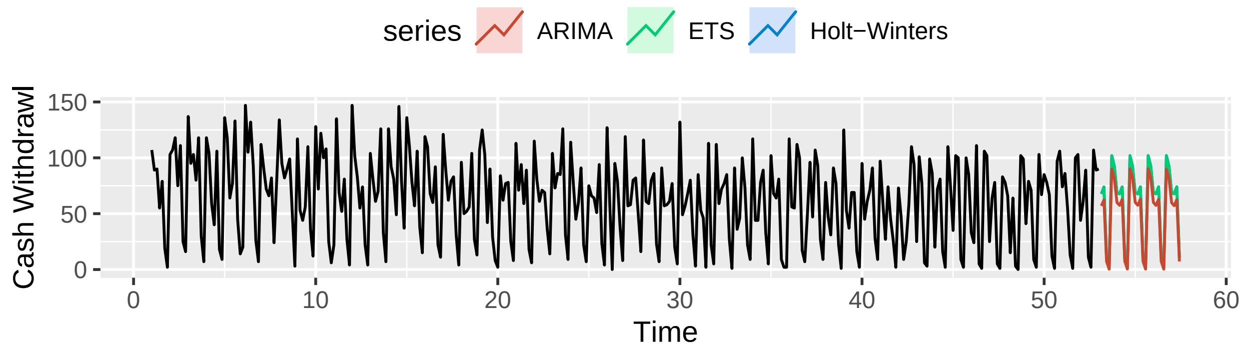



```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(3,0,3)(0,1,1)[7] with drift
## Q* = 8.944, df = 6, p-value = 0.1768
##
## Model df: 8.   Total lags used: 14
```

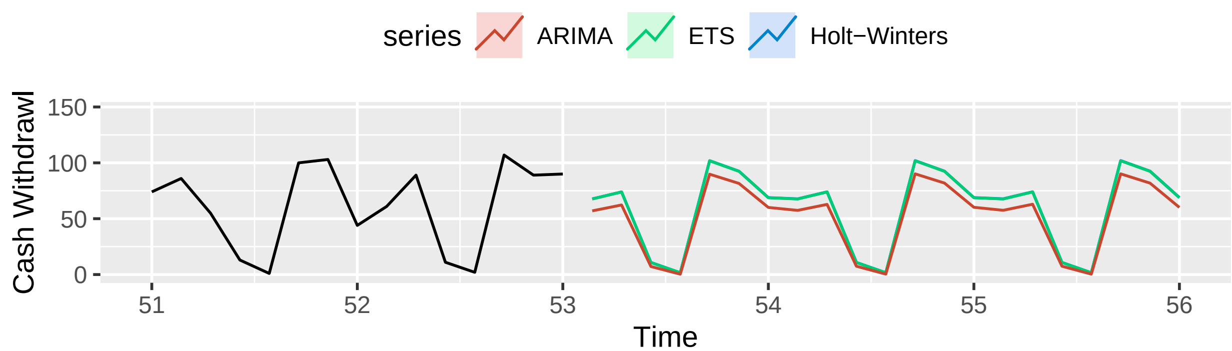
Next step is to plot the forecast for all the considered models above which will shows a nice visual comparison. it will also show a zoomed in plot to have a clearer view.

```
atm2.arima.fcst <- forecast(atm2.fit3, h=31)
atm.forecast(atm2.ts)
```

```
## Scale for 'x' is already present. Adding another scale for 'x', which will
## replace the existing scale.
```



Zoom in

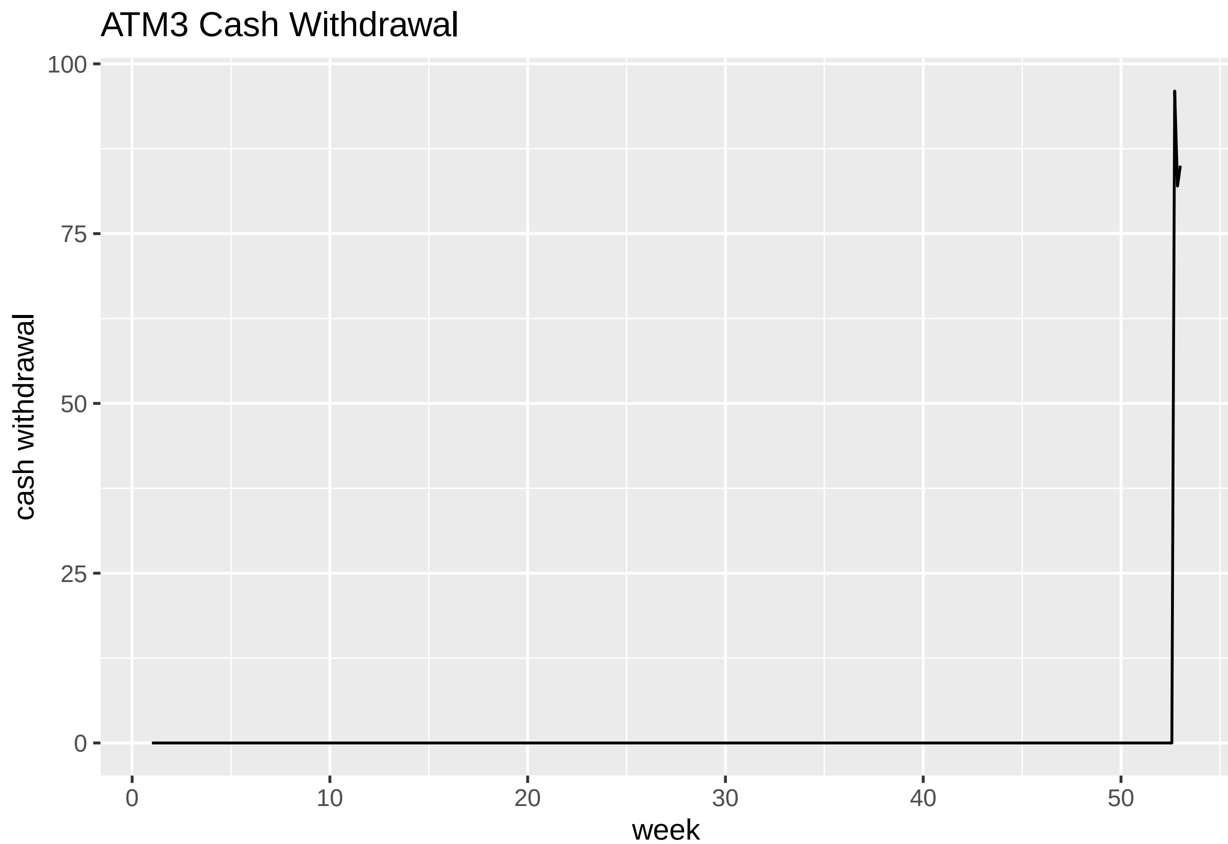



```
model_accuracy(atm2.ts,2)
```

```
##   Holt-Winters      ETS    ARIMA
## 1     57.20467 57.58101 56.58658
```

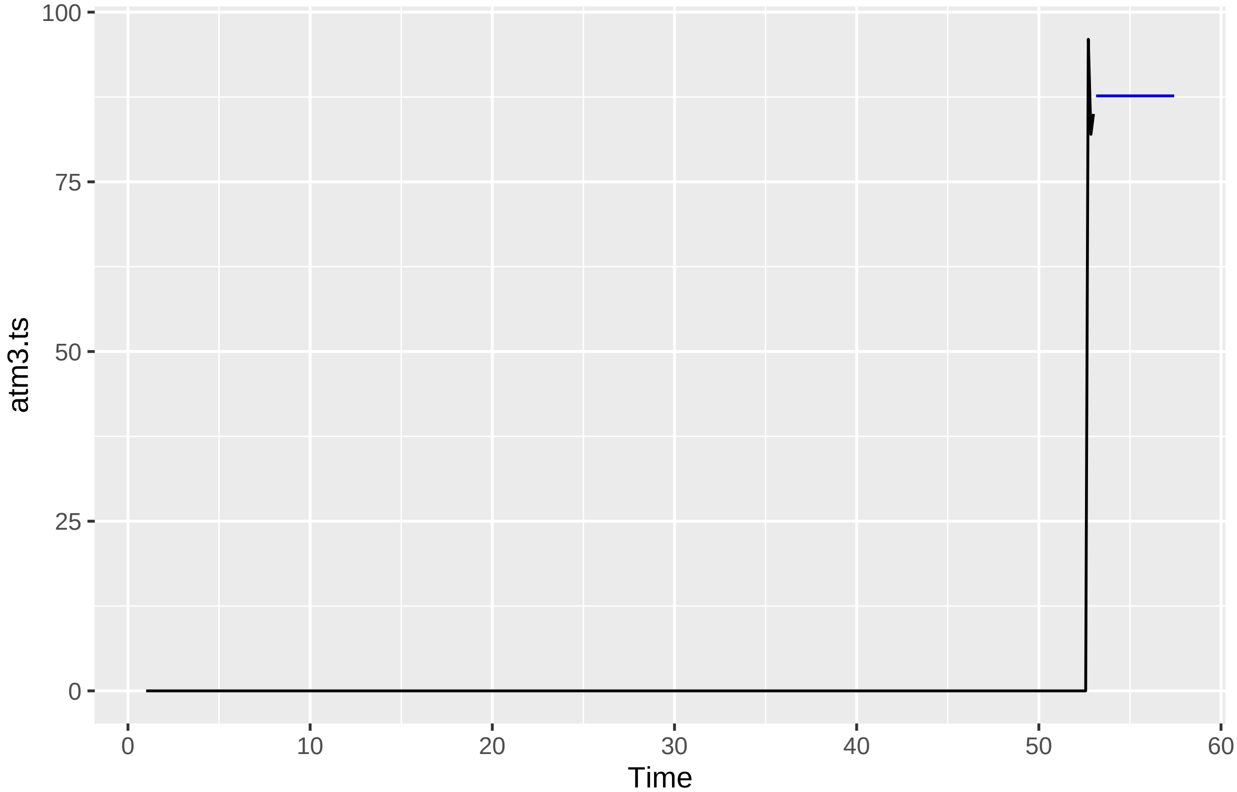
ATM3

```
atm3.ts <- atm.new %>% filter(ATM=="ATM3") %>% select(Cash) %>% ts(frequency = 7)
autoplot(atm3.ts, main="ATM3 Cash Withdrawal", ylab="cash withdrawal", xlab="week")
```



As described and evident above, we only have 3 observations for ATM3 and only these observations will be used for the forecast. Thus, a **Simple mean forecast** will be used for ATM3.

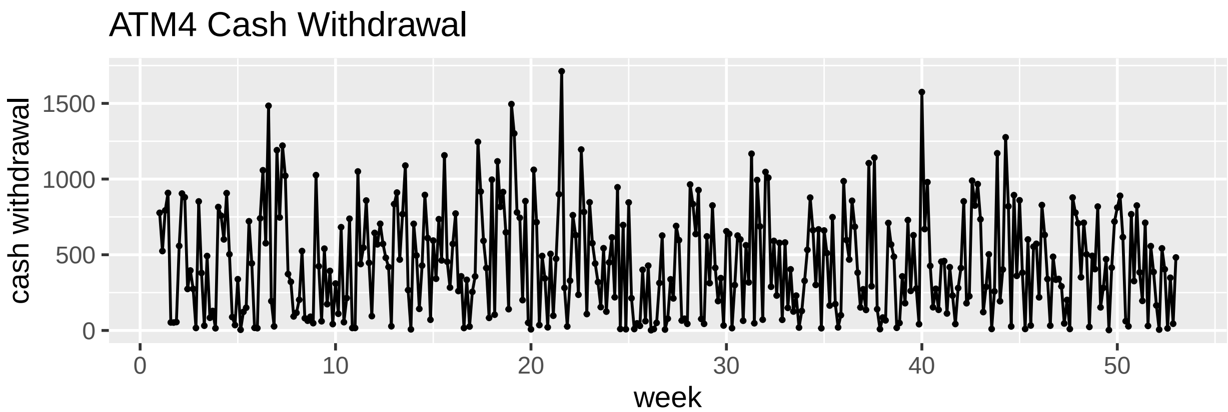
```
# ATM3 forecast
atm3.fcst <- meanf(window(atm3.ts, start=c(52,6)), h=31)
autoplot(atm3.ts) +
  autolayer(atm3.fcst, PI=FALSE)
```

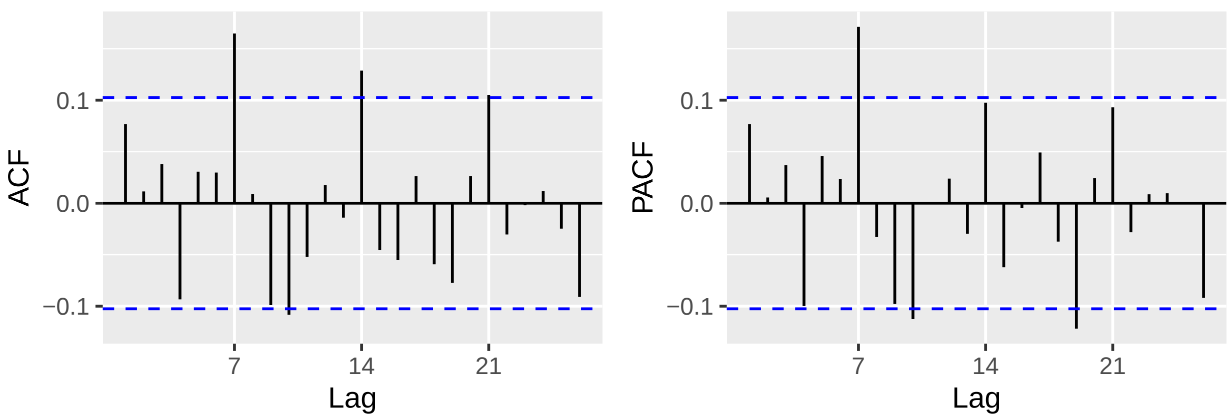


ATM4

Seeing the time series plot, it is apparent that there is seasonality in this series. ACF shows a decrease in every 7th lag. From the PACF, there are few significant lags at the beginning but others within critical limit. Overall, it is non stationary, having seasonality and might require differencing for it to become stationary.

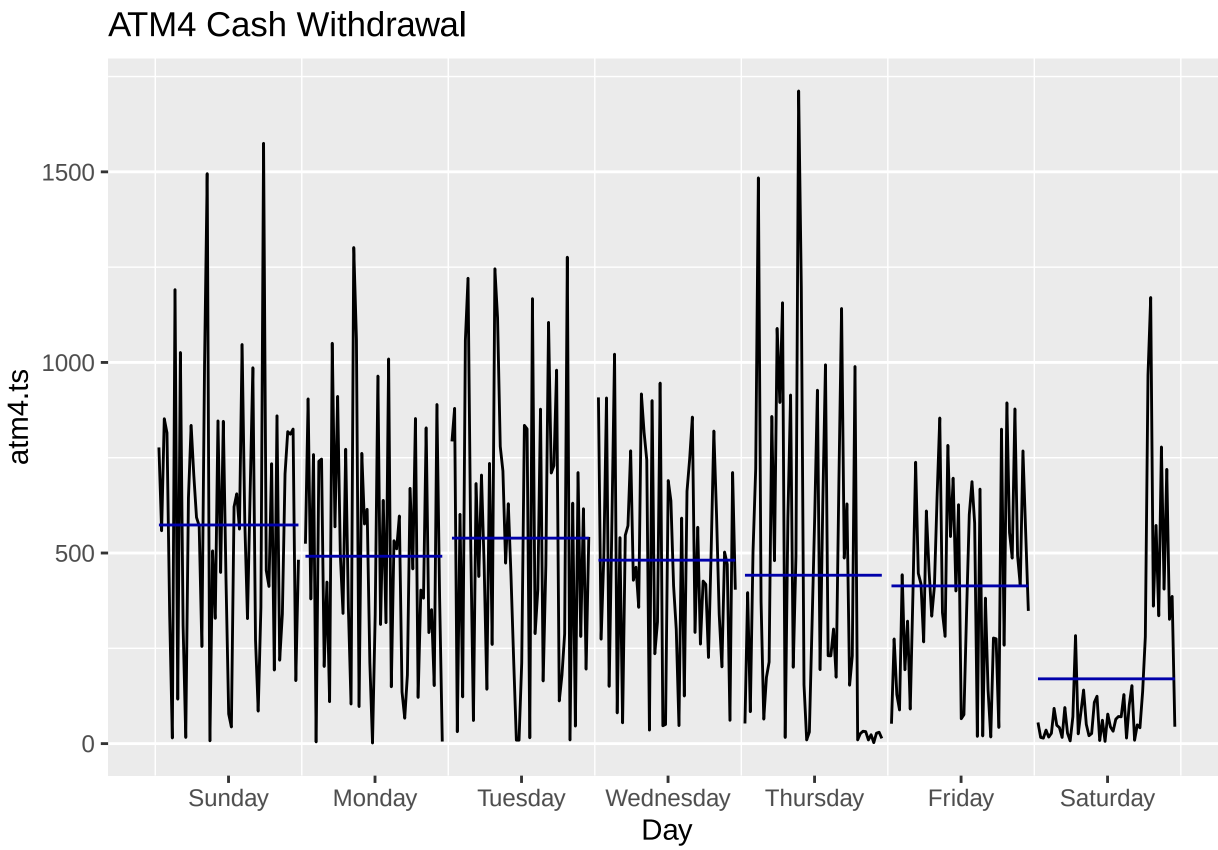
```
atm4.ts <- atm.new %>% filter(ATM=="ATM4") %>% select(Cash) %>% ts(frequency = 7)
ggtsdisplay(atm4.ts, main="ATM4 Cash Withdrawal", ylab="cash withdrawal", xlab="week")
```





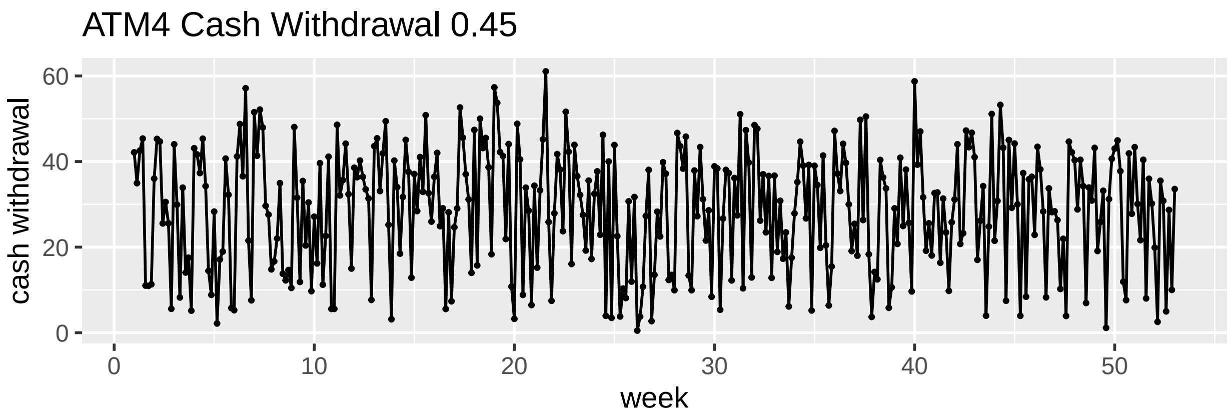
From the subseries plot, it is clear that Sunday is having highest mean for cash withdrawl while Saturday has the lowest.

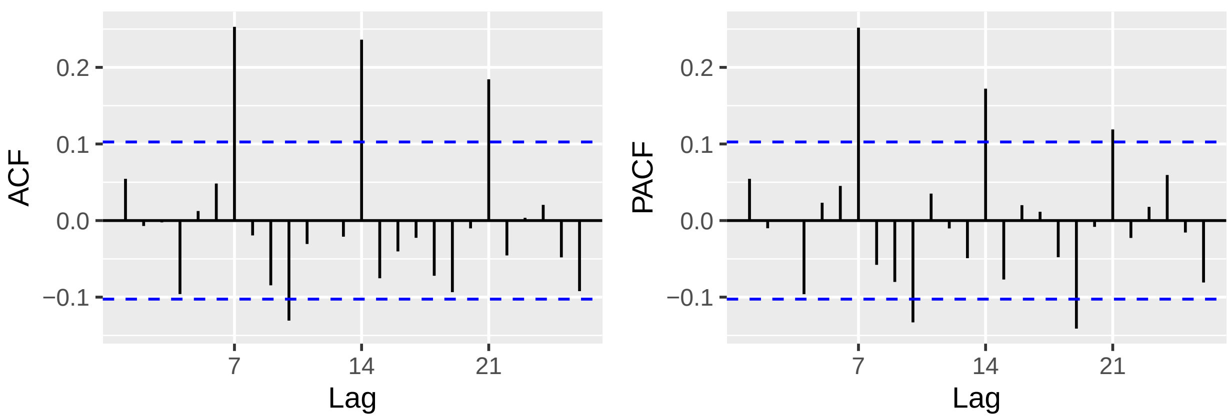
```
ggsubseriesplot(atm4.ts, main="ATM4 Cash Withdrawal")
```



Next step is to apply BoxCox transformation. With λ being 0.45, the resulting transformation does handle the variablity in time series as shown in below transformed plot.

```
atm4.lambda <- BoxCox.lambda(atm4.ts)
atm4.ts.bc <- BoxCox(atm4.ts, atm4.lambda )
ggtsdisplay(atm4.ts.bc, main=paste("ATM4 Cash Withdrawal",round(atm4.lambda, 3)), ylab="cash withdrawal
```






```r
# Number of differences required for a stationary series
ndiffs(atm4.ts.bc)
```

```
## [1] 0
```

```r
# Number of differences required for a seasonally stationary series
nsdiffs(atm4.ts.bc)
```

```
## [1] 0
```

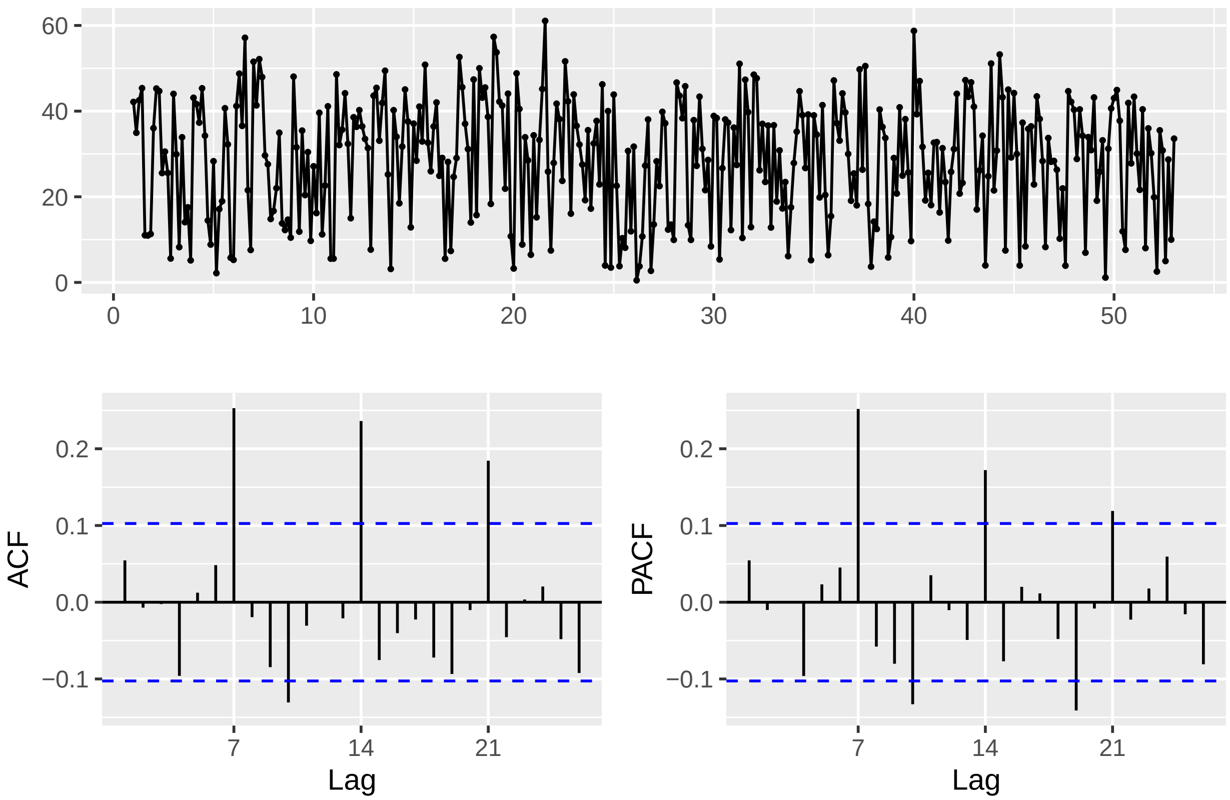
It shows number of differences required is 0 for boxcox transformed data.

```r
atm4.ts.bc %>% ur.kpss() %>% summary()
```

```
##
## #######################
## # KPSS Unit Root Test #
## #######################
##
## Test is of type: mu with 5 lags.
##
## Value of test-statistic is: 0.0792
##
## Critical value for a significance level of:
##                 10pct  5pct 2.5pct  1pct
## critical values 0.347 0.463  0.574 0.739
```

We can see the test statistic small and well within the range we would expect for stationary data. So we can conclude that the data are stationary.

```
atm4.ts.bc %>% ggtsdisplay()
```



First we will start with Holt-Winters damped method. Damping is possible with both additive and multiplicative Holt-Winters' methods. This method often provides accurate and robust forecasts for seasonal data is the Holt-Winters method with a damped trend.

```
# Holt Winters
atm4.ts %>% hw(h=31, seasonal = "additive", lambda = atm4.lambda, damped = TRUE)
```

```
##          Point Forecast         Lo 80     Hi 80       Lo 95     Hi 95
## 53.14286      326.46664  5.361266e+01  872.7889   4.7560920 1283.0394
## 53.28571      390.55947  7.881312e+01  980.9502  12.8286778 1416.0583
## 53.42857      397.88339  8.186526e+01  993.0862  13.9675943 1430.9036
## 53.57143       88.16707 -1.188133e-04  412.7690 -21.7513686  696.1136
## 53.71429      437.83425  9.906165e+01 1058.5849  20.8852913 1510.7692
## 53.85714      284.50971  3.881453e+01  799.7425   1.5164332 1192.4004
## 54.00000      507.20922  1.308726e+02 1169.8559  35.4549744 1645.5454
## 54.14286      324.77262  5.208909e+01  874.0891   4.2406561 1287.4075
## 54.28571      388.90207  7.701404e+01  982.6924  11.9597845 1421.1069
## 54.42857      396.39921  8.010639e+01  995.1580  13.0852412 1436.3713
## 54.57143       87.59346 -4.150601e-03  414.2213 -22.8793652  700.0263
## 54.71429      436.60517  9.725297e+01 1061.2815  19.8415430 1517.0757
## 54.85714      283.65049  3.777331e+01  802.2506   1.2832703 1198.1842
## 55.00000      506.16225  1.288966e+02 1173.1625  34.1181908 1652.7103
## 55.14286      324.04660  5.092781e+01  877.1018   3.8375566 1293.9333
## 55.28571      388.19148  7.560926e+01  986.0591  11.2521458 1428.1862
## 55.42857      395.76275  7.870397e+01  998.6853  12.3531475 1443.6612
## 55.57143       87.34775 -1.273091e-02  416.4752 -23.8878631  705.0385
## 55.71429      436.07791  9.575384e+01 1065.1735  18.9437425 1524.8790
```

```
## 55.85714      283.28192  3.689963e+01  805.6726   1.0925953 1205.1449
## 56.00000      505.71298  1.272021e+02 1177.4724  32.9319224 1661.1294
## 56.14286      323.73508  4.992740e+01  880.8442   3.4901477 1301.3790
## 56.28571      387.88653  7.438035e+01  990.1166  10.6232674 1436.1287
## 56.42857      395.48959  7.746167e+01 1002.8304  11.6956591 1451.7237
## 56.57143       87.24235 -2.513721e-02  419.0707 -24.8511354  710.5204
## 56.71429      435.85159  9.439585e+01 1069.5705  18.1202396 1533.3133
## 56.85714      283.12372  3.610421e+01  809.4805   0.9275239 1212.6021
## 57.00000      505.52010  1.256379e+02 1182.2034  31.8238709 1670.0733
## 57.14286      323.60135  4.900310e+01  884.8928   3.1755185 1309.2095
## 57.28571      387.75561  7.323505e+01  994.4625  10.0390607 1444.4301
## 57.42857      395.37231  7.629643e+01 1007.2323  11.0813715 1460.1059
```

Next is to apply exponential smoothing method on this time series. It shows that the ETS(A, N, A) model best fits for the transformed ATM4, i.e. exponential smoothing with additive error, no trend component and additive seasonality.

```r
# ETS
atm4.ts %>% ets(lambda = atm4.lambda)
```

```
## ETS(A,N,A)
##
## Call:
##  ets(y = ., lambda = atm4.lambda)
##
##   Box-Cox transformation: lambda= 0.4498
##
##   Smoothing parameters:
##     alpha = 1e-04
##     gamma = 0.1035
##
##   Initial states:
##     l = 28.6369
##     s = -18.6503 -3.3529 1.6831 4.7437 5.4471 4.9022
##            5.2271
##
##   sigma:  12.9202
##
##      AIC     AICc      BIC
## 4032.268 4032.890 4071.267
```

Next we will find out the appropriate ARIMA model for this time series. The suggested model seeems ARIMA(0,0,1)(2,0,0)[7] with non-zero mean.

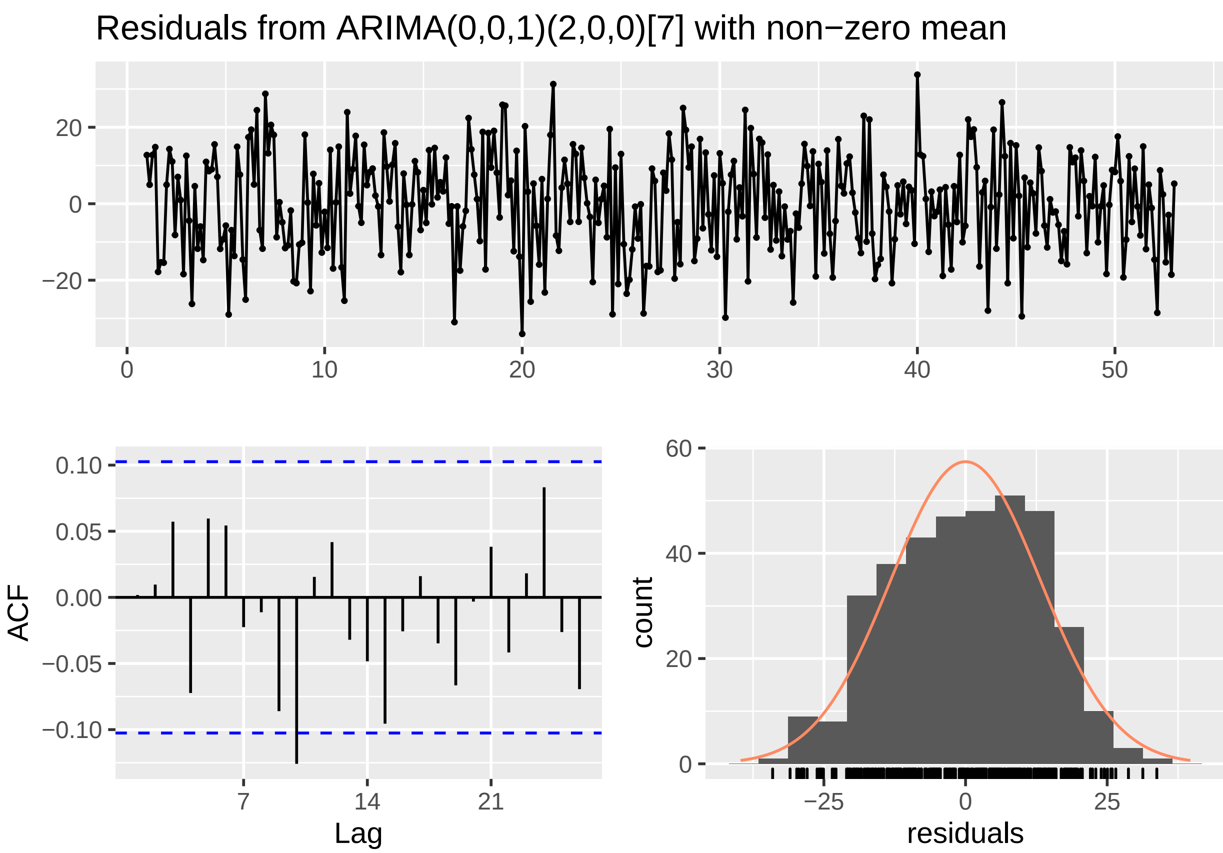
```r
# Arima
atm4.fit3 <- atm4.ts %>% auto.arima(lambda = atm4.lambda)
atm4.fit3
```

```
## Series: .
## ARIMA(0,0,1)(2,0,0)[7] with non-zero mean
## Box Cox transformation: lambda= 0.449771
##
## Coefficients:
##          ma1    sar1    sar2     mean
##       0.0790  0.2078  0.2023  28.6364
## s.e.  0.0527  0.0516  0.0525   1.2405
##
```

```
## sigma^2 estimated as 176.5:  log likelihood=-1460.57
## AIC=2931.14   AICc=2931.3   BIC=2950.64
```

Next is to see residuals time series plot which shows residuals are being near normal with mean of the residuals being near to zero. Also there is no significant autocorrelation that confirms that forecasts are good.

```
checkresiduals(atm4.fit3)
```

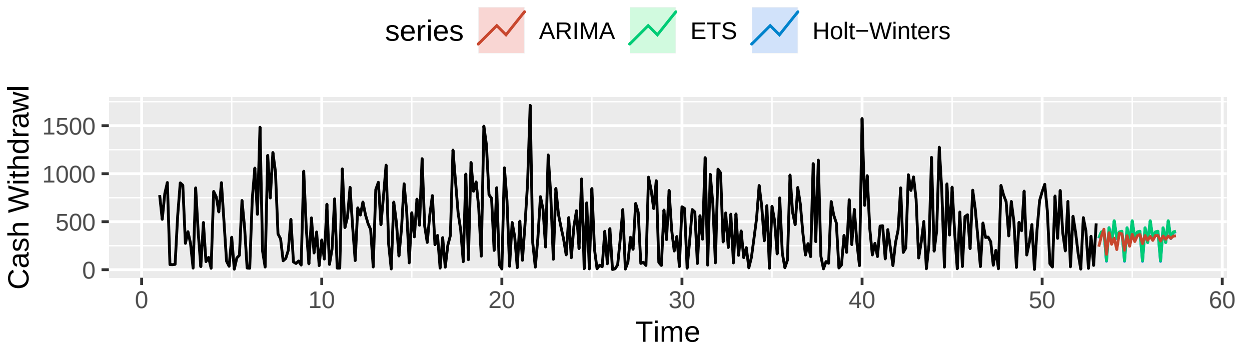



```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(0,0,1)(2,0,0)[7] with non-zero mean
## Q* = 16.645, df = 10, p-value = 0.0826
##
## Model df: 4.   Total lags used: 14
```

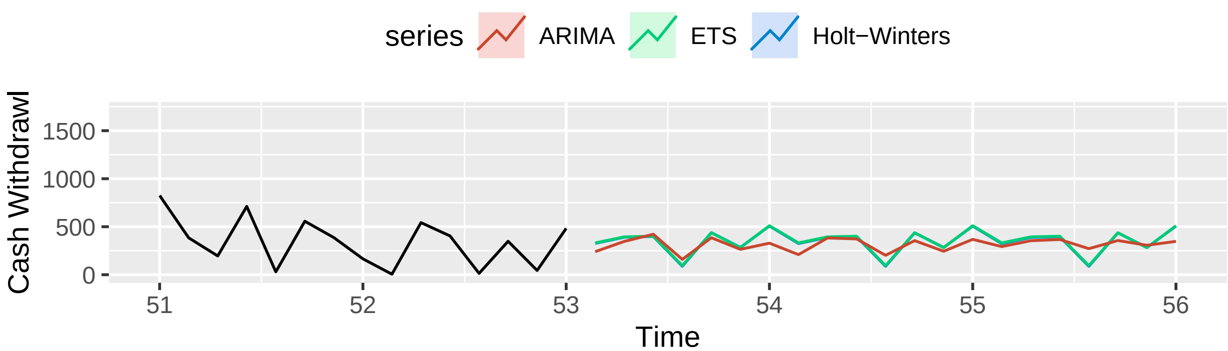
Next is to plot the forecast for all the considered models above which will shows a nice visual comparison. it will also show a zoomed in plot to have a clearer view.

```
atm4.arima.fcst <- forecast(atm4.fit3, h=31)
atm.forecast(atm4.ts)
```

```
## Scale for 'x' is already present. Adding another scale for 'x', which will
## replace the existing scale.
```



Zoom in




```
model_accuracy(atm4.ts,4)
```

```
##   Holt-Winters      ETS    ARIMA
## 1     360.3953 360.7951 315.7226
```

Forecast May, 2010

Finally we will do forecast for May 2010 for all 4 ATMs and save it in an excel. Here are the best fit models for cash withdrawls forecast of all 4 ATMs.

- ATM1 - ARIMA(0,0,2)(0,1,1)[7] with Box-Cox transformation 0.262
- ATM2 - ARIMA(3,0,3)(0,1,1)[7] with drift and Box-Cox transformation 0.724
- ATM3 - Simple Mean Forecast
- ATM4 - ARIMA(0,0,1)(2,0,0)[7] with non-zero mean and Box-Cox transformation 0.45

```
Date <- seq(as.Date('2010-05-01'), as.Date('2010-05-31'), by="day")
ATM <- c(rep('ATM1',31),rep('ATM2',31),rep('ATM3',31),rep('ATM4',31))
Cash=c(atm1.arima.fcst$mean, atm2.arima.fcst$mean, atm3.fcst$mean,atm4.arima.fcst$mean)

write.xlsx(data.frame(Date, ATM, Cash),
           "Kapoor_data624_atm_forecasts.xlsx")
```

```
pow.fcst.ak <- read_excel("Kapoor_data624_atm_forecasts.xlsx", skip=0, col_types = c("date","text","nume
pow.fcst.ak %>%
  kbl() %>%
  kable_paper() %>%
  scroll_box(width = "500px", height = "200px")
```

Date	ATM	Cash
2010-05-01	ATM1	86.6586443
2010-05-02	ATM1	100.5720071
2010-05-03	ATM1	73.7188092
2010-05-04	ATM1	4.2285430
2010-05-05	ATM1	100.1587348
2010-05-06	ATM1	79.3468403
2010-05-07	ATM1	85.7338546
2010-05-08	ATM1	87.1676511
2010-05-09	ATM1	100.3884814
2010-05-10	ATM1	73.7188092
2010-05-11	ATM1	4.2285430
2010-05-12	ATM1	100.1587348
2010-05-13	ATM1	79.3468403
2010-05-14	ATM1	85.7338546
2010-05-15	ATM1	87.1676511
2010-05-16	ATM1	100.3884814
2010-05-17	ATM1	73.7188092
2010-05-18	ATM1	4.2285430
2010-05-19	ATM1	100.1587348
2010-05-20	ATM1	79.3468403
2010-05-21	ATM1	85.7338546
2010-05-22	ATM1	87.1676511
2010-05-23	ATM1	100.3884814
2010-05-24	ATM1	73.7188092
2010-05-25	ATM1	4.2285430
2010-05-26	ATM1	100.1587348
2010-05-27	ATM1	79.3468403
2010-05-28	ATM1	85.7338546
2010-05-29	ATM1	87.1676511
2010-05-30	ATM1	100.3884814
2010-05-31	ATM1	73.7188092
2010-05-01	ATM2	57.0022951
2010-05-02	ATM2	62.2798852
2010-05-03	ATM2	7.2063600
2010-05-04	ATM2	0.3456494
2010-05-05	ATM2	89.8398423
2010-05-06	ATM2	81.5691544
2010-05-07	ATM2	60.0626996
2010-05-08	ATM2	57.4480083
2010-05-09	ATM2	62.8071210
2010-05-10	ATM2	7.4370968
2010-05-11	ATM2	0.4060141
2010-05-12	ATM2	90.1467675
2010-05-13	ATM2	81.8753121
2010-05-14	ATM2	60.1929496
2010-05-15	ATM2	57.5248105
2010-05-16	ATM2	62.9411138
2010-05-17	ATM2	7.4704488
2010-05-18	ATM2	0.3941616
2010-05-19	ATM2	90.1268184
2010-05-20	ATM2	81.8627435
2010-05-21	ATM2	60.0812606
2010-05-22	ATM2	57.3871088
2010-05-23	ATM2	62.8416413
2010-05-24	ATM2	7.3874716
2010-05-25	ATM2	0.3413394
2010-05-26	ATM2	89.9145967

Part B - Forecasting Power

The dataset contains residential power usage for January 1998 until December 2013. Its monthly data from 1998 and power consumed is in KWH column. This dataset contains a total 192 records.

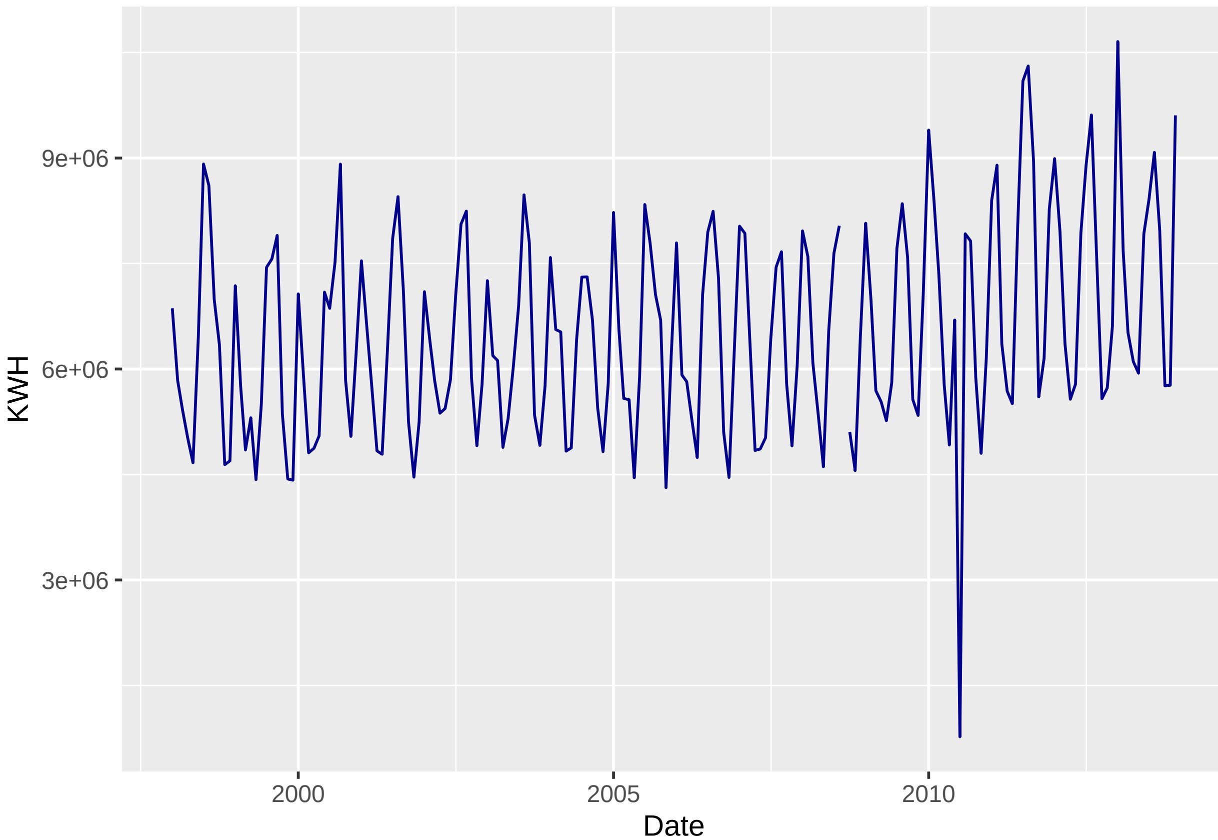
```
download.file(
  url="https://github.com/amit-kapoor/data624/blob/main/Project1/ResidentialCustomerForecastLoad-624.xls
  destfile = temp.file,
  mode = "wb",
  quiet = TRUE)
power.data <- read_excel(temp.file, skip=0, col_types = c("numeric","text","numeric"))

head(power.data)
```

```
## # A tibble: 6 x 3
##   CaseSequence `YYYY-MMM`     KWH
##          <dbl> <chr>        <dbl>
## 1          733 1998-Jan   6862583
## 2          734 1998-Feb   5838198
## 3          735 1998-Mar   5420658
## 4          736 1998-Apr   5010364
## 5          737 1998-May   4665377
## 6          738 1998-Jun   6467147
```

Exploratory Analysis

Seeing the plot closely, it is apparent that there is an outlier and a missing entry too. We will use the tsclean function to take care of missing entry and outlier in the data. Other than this data seems to be good shape.

```
power.data$`YYYY-MMM` <- paste0(power.data$`YYYY-MMM`,"-01")
power.data$Date <- lubridate::ymd(power.data$`YYYY-MMM`)

ggplot(power.data, aes(x=Date, y=KWH )) +
  geom_line(color="darkblue")
```



Data Cleaning

We will first create the time series of given data and then perform tsclean function.

```
power.ts <- ts(power.data$KWH, start=c(1998, 1), frequency = 12)
head(power.ts)
```

```
##          Jan     Feb     Mar     Apr     May     Jun
## 1998 6862583 5838198 5420658 5010364 4665377 6467147
```

```
power.ts %>% summary()
```

```
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.     NA's
##   770523  5429912  6283324  6502475  7620524 10655730        1
```

```
power.ts <- tsclean(power.ts)
power.ts %>% summary()
```

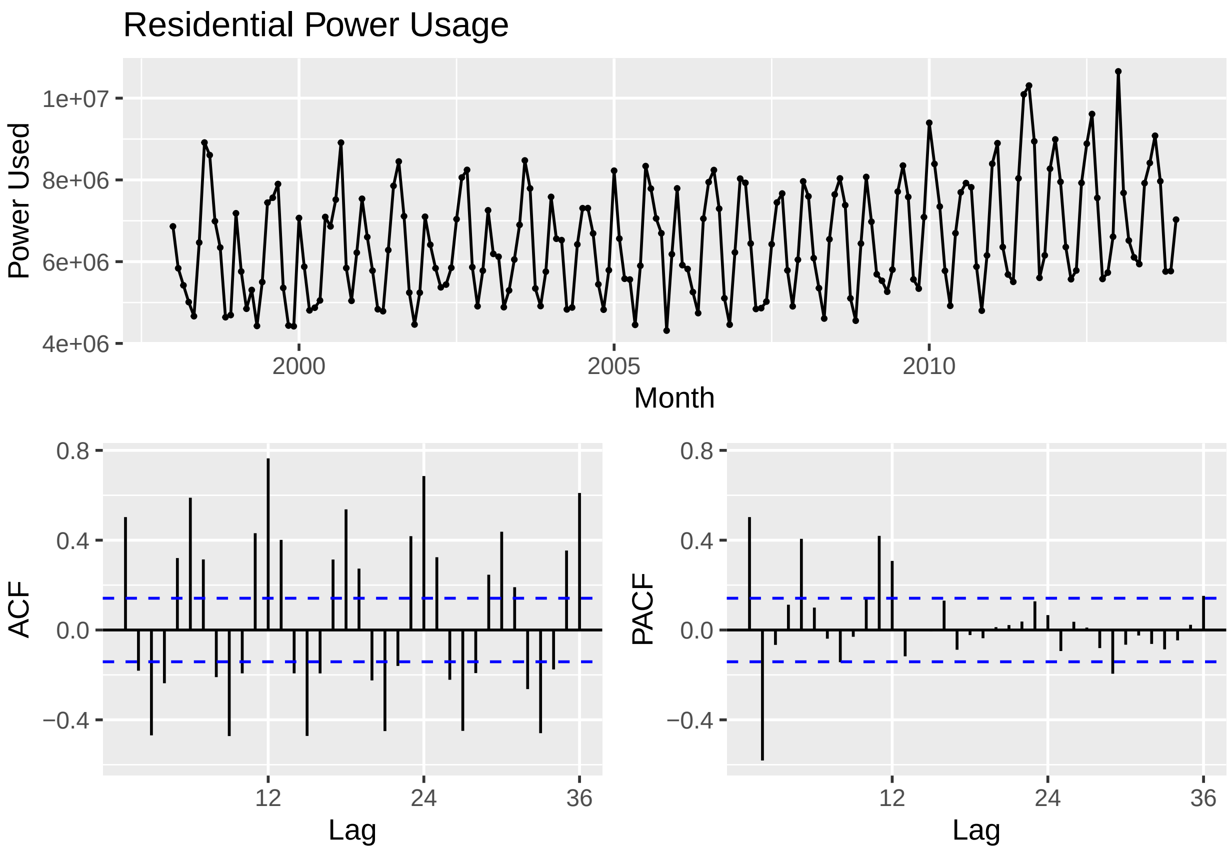
```
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
##  4313019  5443502  6351262  6529701  7608792 10655730
```

It is apparent that tsclean did take care of NA's and outlier in the data.

Time Series

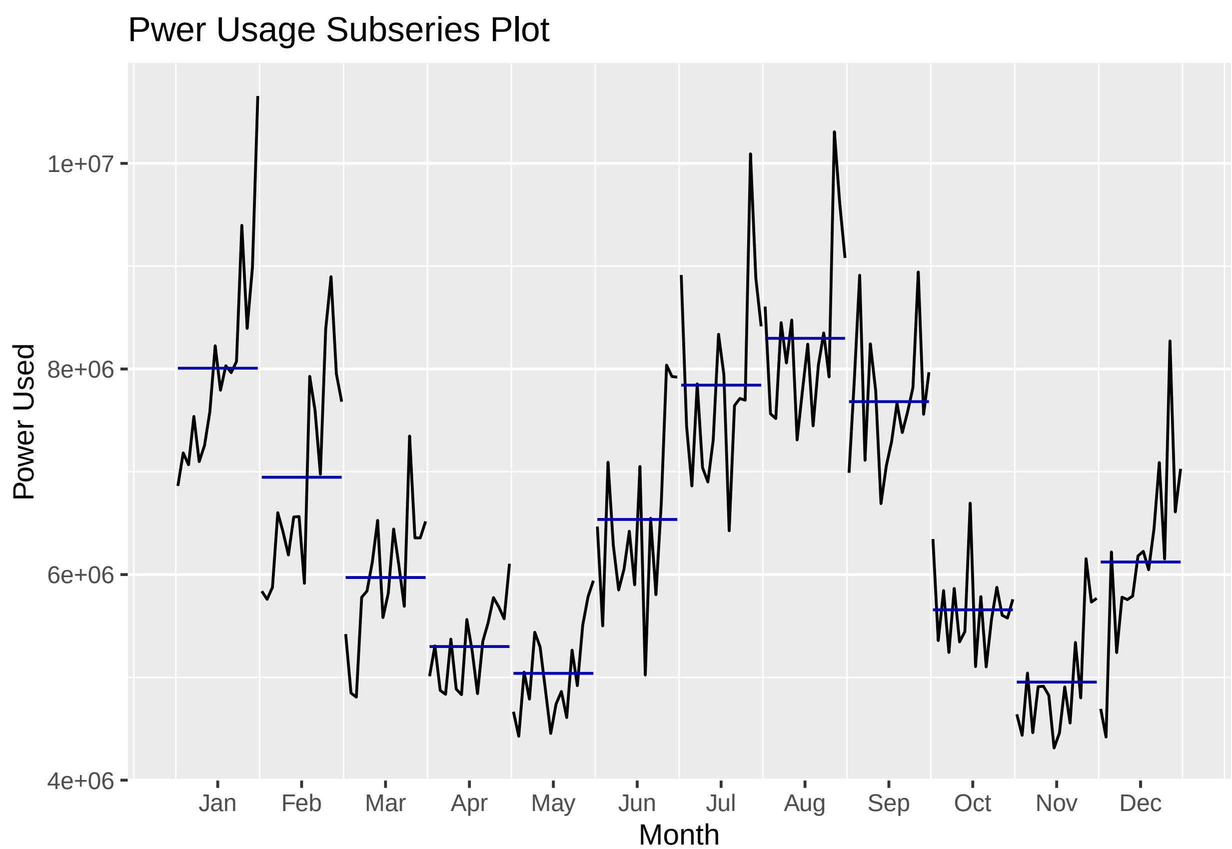
So far we have analyzed the data and perform data cleaning to handle missing and outlier data. In this section we will delve into the time series and see the models that perform best for prediction.

```
ggtsdisplay(power.ts, main="Residential Power Usage", ylab="Power Used", xlab="Month")
```

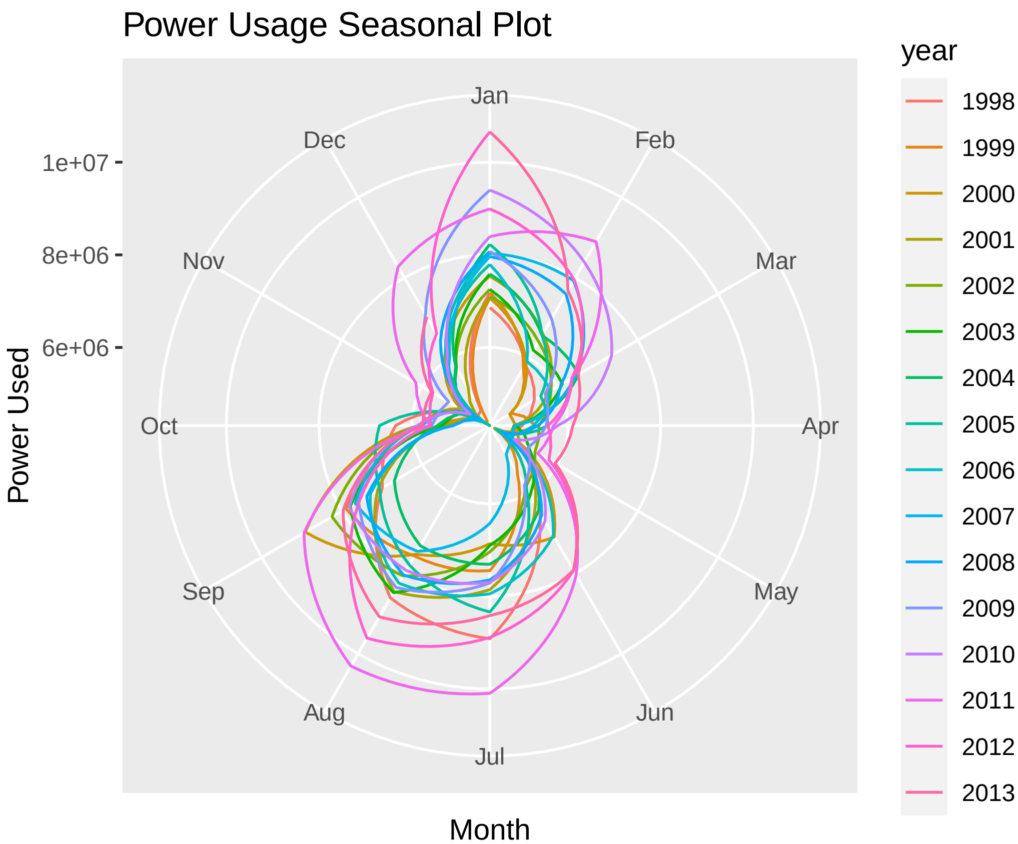


From the above time series plot, it is evident that seasonality exists in the data. We dont see a trend in the data. ACF plot sgows the auto correlation and PACF shows few significant lags in the beginning. Overall, it shows seasonality and non stationary data. It could require differencing to make it stationary which will be confirmed in further steps.

```
ggsubseriesplot(power.ts, main="Pwer Usage Subseries Plot", ylab="Power Used")
```

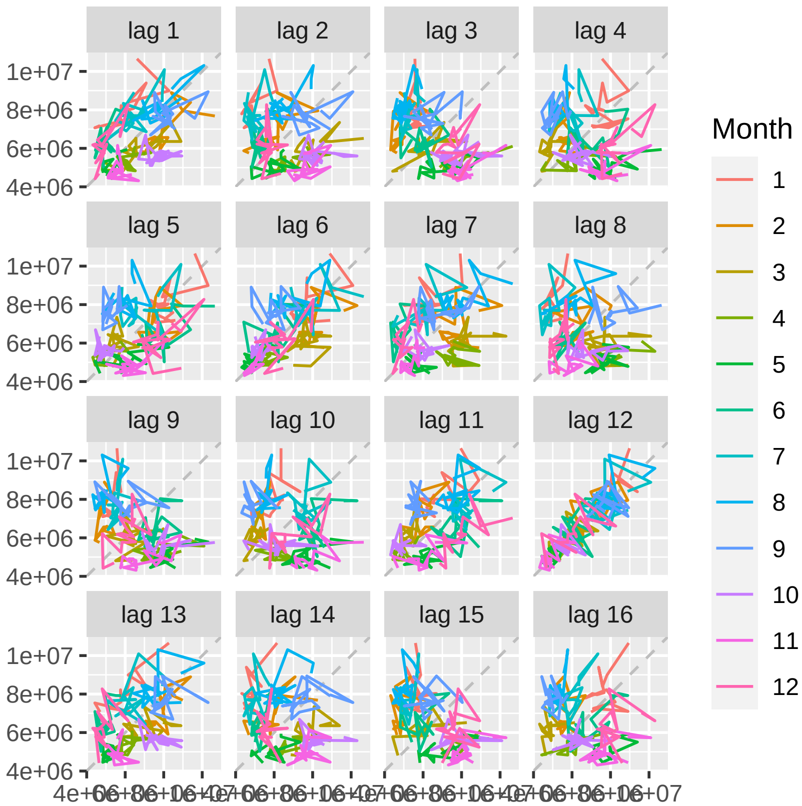



```
ggseasonplot(power.ts, polar=TRUE, main="Power Usage Seasonal Plot", ylab="Power Used")
```



The seasonal plots above shows a decline in power usage from Jan to May, increase till Aug and then decline in Nov. Aug is the month of most power consumption.

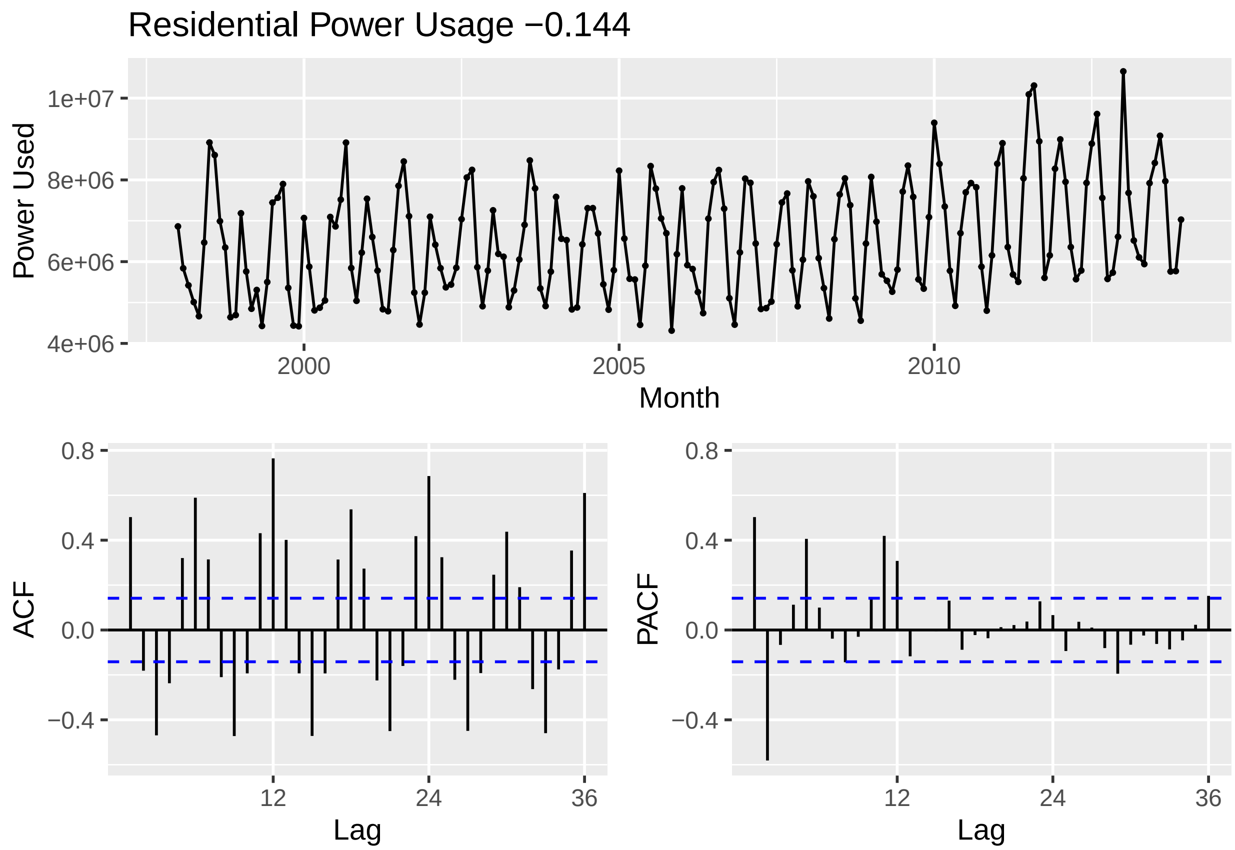
```
gglagplot(power.ts )
```



In the above lagplot, colors show different month. The lines connect points in chronological order. The relationship is strongly positive at lag 12, reflecting the strong seasonality in the data.

Next step is to apply Box-Cox transformation and check the transformed data.

```
powerts.lambda <- BoxCox.lambda(power.ts)
power.ts.bc <- BoxCox(power.ts, powerts.lambda )
ggtsdisplay(power.ts, main=paste("Residential Power Usage",round(powerts.lambda, 3)), ylab="Power Used"
```



The Box-Cox transformation above did handle the variation in the data with λ as 0.144 and appears stable now. Next we see that Number of differences required for a stationary and seasonally stationary series are 1.

```
# Number of differences required for a stationary series
ndiffs(power.ts.bc)
```

```
## [1] 1
```

```
# Number of differences required for a seasonally stationary series
nsdiffs(power.ts.bc)
```

```
## [1] 1
```

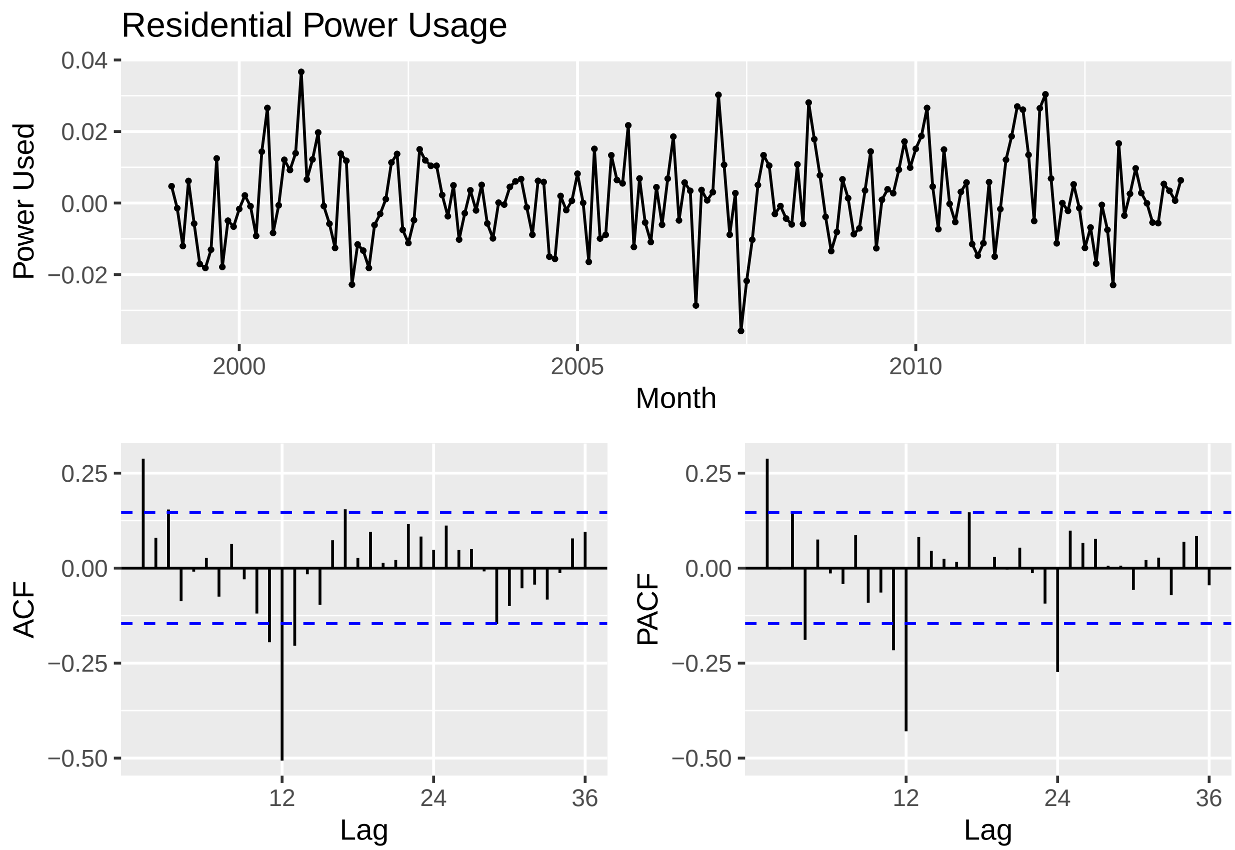
It shows number of differences required is 1 for boxcox transformed data.

```
power.ts.bc %>% diff(lag=12) %>% ur.kpss() %>% summary()
```

```
##
## #######################
## # KPSS Unit Root Test #
## #######################
##
## Test is of type: mu with 4 lags.
##
## Value of test-statistic is: 0.1049
##
## Critical value for a significance level of:
##                 10pct  5pct 2.5pct  1pct
## critical values 0.347 0.463  0.574 0.739
```

We can see the test statistic small and well within the range we would expect for stationary data. So we can conclude that the data are stationary.

```r
power.ts.bc %>%
  diff(lag=12) %>%
  ggtsdisplay(main="Residential Power Usage", ylab="Power Used", xlab="Month")
```



Now we will apply four models in this time series: Holt Winters additive with damped True, Holt Winters multiplicative with damped True, exponential smoothing and arima. First we will start with Holt-Winters damped method. Damping is possible with both additive and multiplicative Holt-Winters' methods. This method often provides accurate and robust forecasts for seasonal data is the Holt-Winters method with a damped trend.

```r
# Holt Winters additive with damped True
power.ts %>% hw(h=31, seasonal = "additive", lambda = powerts.lambda, damped = TRUE)
```

```
##          Point Forecast   Lo 80    Hi 80   Lo 95    Hi 95
## Jan 2014        9107297 8076875 10290936 7585779 10988269
## Feb 2014        7770646 6904466  8763438 6490967  9347335
## Mar 2014        6660179 5928390  7497188 5578499  7988664
## Apr 2014        5969397 5319026  6712381 5007781  7148238
## May 2014        5625182 5013393  6323915 4720557  6733732
## Jun 2014        7275964 6451637  8223053 6058824  8781111
## Jul 2014        8859946 7822939 10057288 7330606 10765524
## Aug 2014        9322020 8216844 10600620 7692933 11358099
## Sep 2014        8668636 7644836  9852384 7159284 10553344
## Oct 2014        6321057 5601315  7148606 5258532  7636511
## Nov 2014        5469798 4855427  6174761 4562382  6589737
## Dec 2014        6775208 5987467  7683813 5613190  8220830
```

```
## Jan 2015        9113992 8005052 10402262 7480984 11167935
## Feb 2015        7776112 6844659  8855485 6403639  9495747
## Mar 2015        6664665 5878334  7573701 5505361  8111924
## Apr 2015        5973271 5274971  6779388 4943398  7256143
## May 2015        5628725 4972370  6386125 4660623  6833931
## Jun 2015        7280622 6397096  8306589 5979421  8916161
## Jul 2015        8865659 7755195 10161867 7232276 10935129
## Aug 2015        9327948 8145442 10711046 7589442 11537448
## Sep 2015        8673977 7579322  9953345 7064335 10717313
## Oct 2015        6324700 5555572  7218128 5192069  7749092
## Nov 2015        5472821 4816718  6233216 4506100  6684315
## Dec 2015        6778989 5938447  7758475 5542135  8342027
## Jan 2016        9119188 7936962 10507290 7382692 11339177
## Feb 2016        7780354 6787930  8942347 6321671  9637208
## Mar 2016        6668146 5830831  7645926 5436663  8229419
## Apr 2016        5976278 5233146  6842661 4882887  7359020
## May 2016        5631476 4933411  6444895 4604266  6929491
## Jun 2016        7284237 6345305  8385579 5904772  9045098
## Jul 2016        8870093 7690866 10260839 7139837 11097210
```

```
# Holt Winters multiplicative with damped True
power.ts %>% hw(h=31, seasonal = "multiplicative", damped = TRUE)
```

```
##          Point Forecast   Lo 80    Hi 80   Lo 95    Hi 95
## Jan 2014        9017833 7957065 10078601 7395529 10640137
## Feb 2014        7828457 6875211  8781704 6370593  9286322
## Mar 2014        6739385 5891755  7587016 5443046  8035725
## Apr 2014        5958146 5185614  6730678 4776661  7139631
## May 2014        5658721 4903631  6413811 4503910  6813531
## Jun 2014        7362538 6353007  8372069 5818594  8906483
## Jul 2014        8756962 7524819  9989104 6872562 10641361
## Aug 2014        9316480 7972982 10659977 7261778 11371181
## Sep 2014        8596291 7327223  9865359 6655419 10537163
## Oct 2014        6299672 5348552  7250791 4845060  7754283
## Nov 2014        5499685 4651304  6348065 4202198  6797171
## Dec 2014        6805669 5733940  7877398 5166601  8444737
## Jan 2015        9020418 7571435 10469400 6804390 11236445
## Feb 2015        7830653 6548528  9112778 5869812  9791493
## Mar 2015        6741234 5616962  7865507 5021809  8460660
## Apr 2015        5959745 4947971  6971519 4412371  7507120
## May 2015        5660207 4682622  6637793 4165119  7155295
## Jun 2015        7364430 6071164  8657697 5386550  9342311
## Jul 2015        8759163 7195971 10322356 6368467 11149860
## Aug 2015        9318772 7629505 11008038 6735261 11902282
## Sep 2015        8598360 7015852 10180868 6178123 11018597
## Oct 2015        6301155 5124217  7478094 4501183  8101127
## Nov 2015        5500952 4458640  6543264 3906873  7095031
## Dec 2015        6807204 5499264  8115143 4806883  8807524
## Jan 2016        9022407 7265105 10779709 6334846 11709969
## Feb 2016        7832343 6286498  9378187 5468177 10196508
## Mar 2016        6742658 5394587  8090729 4680961  8804355
## Apr 2016        5960977 4754078  7167875 4115184  7806769
## May 2016        5661351 4500929  6821774 3886639  7436064
## Jun 2016        7365887 5837827  8893947 5028921  9702853
## Jul 2016        8760859 6921934 10599783 5948466 11573251
```

Next model to ETS: Exponential Smoothing methods.

```
# exponential smoothing
power.ts %>% ets(lambda = powerts.lambda, biasadj = TRUE)
```

```
## ETS(A,Ad,A)
##
## Call:
##  ets(y = ., lambda = powerts.lambda, biasadj = TRUE)
##
##   Box-Cox transformation: lambda= -0.1443
##
##   Smoothing parameters:
##     alpha = 0.118
##     beta  = 1e-04
##     gamma = 1e-04
##     phi   = 0.979
##
##   Initial states:
##     l = 6.1998
##     b = 1e-04
##     s = -0.006 -0.0285 -0.0132 0.019 0.0263 0.0212
##            0.0014 -0.0255 -0.0192 -0.0077 0.0081 0.024
##
##   sigma:  0.0094
##
##       AIC      AICc       BIC
## -765.9795 -762.0258 -707.3446
```

We can see here that the ets model that best describes the data is **ETS(A,Ad,A)** i.e. exponential smoothing with additive error, additive damped trend and additive seasonality.

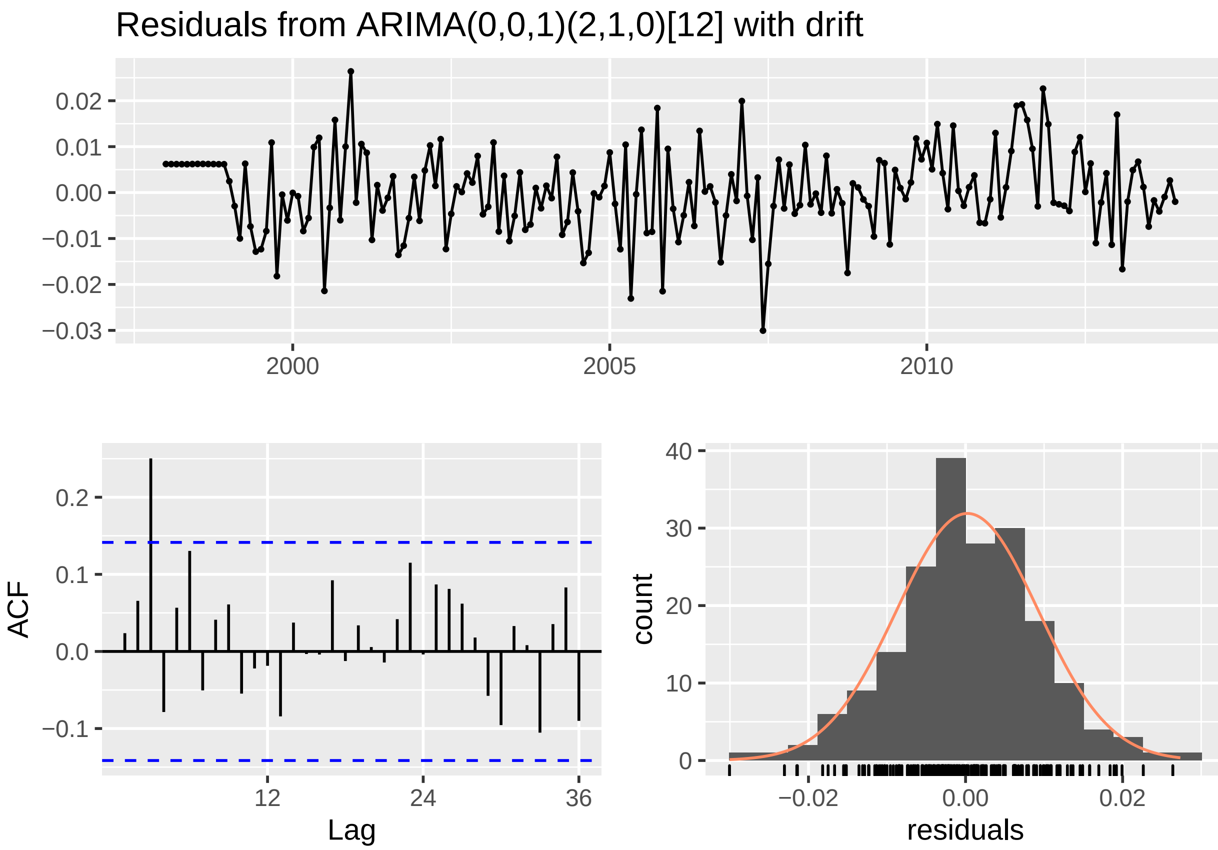
Next we will find the best Arima model that fits this time series data.

```
power.fit4 <- power.ts %>% auto.arima(lambda = powerts.lambda, biasadj = TRUE)
power.fit4
```

```
## Series: .
## ARIMA(0,0,1)(2,1,0)[12] with drift
## Box Cox transformation: lambda= -0.1442665
##
## Coefficients:
##          ma1     sar1     sar2  drift
##       0.2563  -0.7036  -0.3817  1e-04
## s.e.  0.0809   0.0734   0.0748  1e-04
##
## sigma^2 estimated as 8.869e-05:  log likelihood=585.32
## AIC=-1160.65   AICc=-1160.3   BIC=-1144.68
```

The best Arima model comes out is **ARIMA(0,0,1)(2,1,0)[12]** with drift.

```
checkresiduals(power.fit4)
```




```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(0,0,1)(2,1,0)[12] with drift
## Q* = 28.193, df = 20, p-value = 0.1049
##
## Model df: 4.   Total lags used: 24
```

Next is to plot the forecasts using all of 4 models described above: HW additive, HW multiplicative, ets and arima. For this, we will create a generic function which will accept the time series and plot the forecast for all these 4 models. There is also a zoomed in plot of the forecast for better clarity.

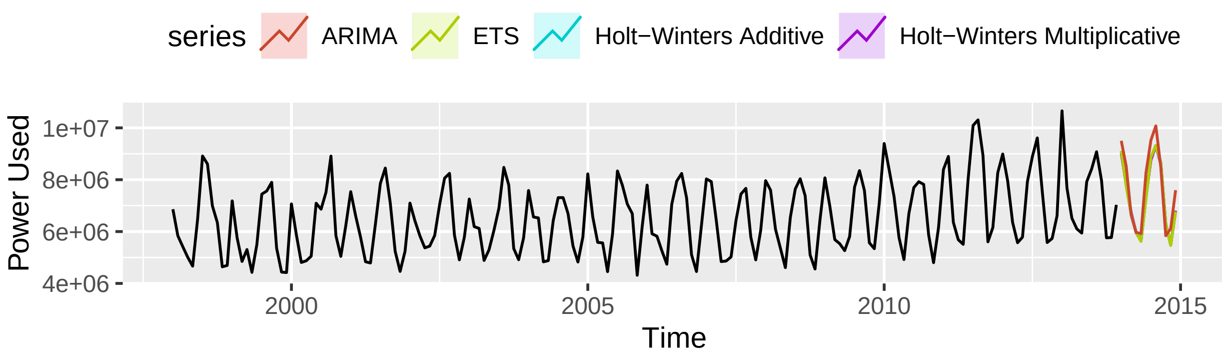
```
# function to plot forecast(s)
power.forecast <- function(timeseries) {
  # lambda value
  lambda <- BoxCox.lambda(timeseries)

  # models for forecast
  hwa.model <- timeseries %>% hw(h=12, seasonal = "additive", lambda = lambda, damped = TRUE)
  hwm.model <- timeseries %>% hw(h=12, seasonal = "multiplicative", damped = TRUE)
  ets.model <- timeseries %>% ets(lambda = lambda )
  arima.model <- timeseries %>% auto.arima(lambda = lambda, biasadj = TRUE)

  # forecast
  pow.hwa.fcst <- forecast(hwa.model, h=12)
  pow.hwm.fcst <- forecast(hwm.model, h=12)
  pow.ets.fcst <- forecast(ets.model, h=12)
  pow.arima.fcst <- forecast(arima.model, h=12)
```

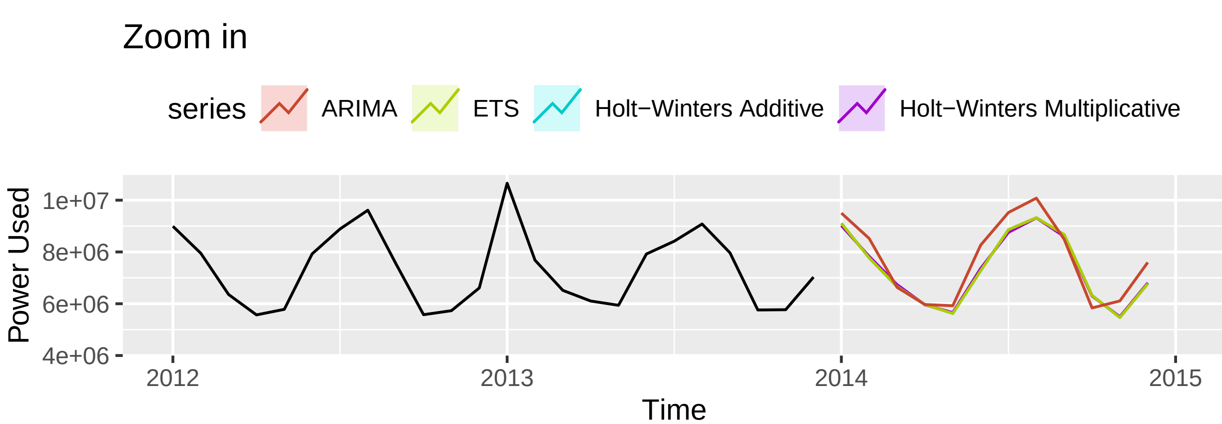
```
  # plot forecasts
  p1 <- autoplot(timeseries) +
    autolayer(pow.hwa.fcst, PI=FALSE, series="Holt-Winters Additive") +
    autolayer(pow.hwm.fcst, PI=FALSE, series="Holt-Winters Multiplicative") +
    autolayer(pow.ets.fcst, PI=FALSE, series="ETS") +
    autolayer(pow.arima.fcst, PI=FALSE, series="ARIMA") +
    theme(legend.position = "top") +
    ylab("Power Used")

  # zoom in plot
  p2 <- p1 +
    labs(title = "Zoom in ") +
    xlim(c(2012,2015))

  grid.arrange(p1,p2,ncol=1)

}
```

Lets plot the forecast now using the above function for power usage.

```
power.arima.fcst <- forecast(power.fit4, h=12)
power.forecast(power.ts)
```

```
## Scale for 'x' is already present. Adding another scale for 'x', which will
## replace the existing scale.
```





Now we will check the accuracy of all 4 models. Again for this purpose, we have created a function that accepts the timeseries and divide the data for training and testing. In this function we will first divide the data for training and testing, train all models with train set and then find out RMSE using test data.

```r
powm_accuracy <- function(timeseries) {
  # lambda value
  lambda <- BoxCox.lambda(timeseries)

  # split the data to train and test
  train <- window(timeseries, end=c(2009, 12))
  test <- window(timeseries, start=2010)

  # models for forecast
  hwa.model <- train %>% hw(h=length(train), seasonal = "additive", lambda = lambda, damped = TRUE)
  hwm.model <- train %>% hw(h=length(train), seasonal = "multiplicative", damped = TRUE)
  ets.model <- train %>% ets(model="AAA", lambda = lambda, biasadj = TRUE)
  arima.model <- train %>% Arima(order=c(0,0,1),
                                   seasonal = c(2,1,0),
                                   include.drift = TRUE,
                                   lambda = lambda,
                                   biasadj = TRUE)



  # forecast
  hwa.frct = forecast(hwa.model, h = length(test))$mean
  hwm.frct = forecast(hwm.model, h = length(test))$mean
  ets.frct = forecast(ets.model, h = length(test))$mean
  arima.frct = forecast(arima.model, h = length(test))$mean

  # dataframe having rmse
  rmse = data.frame(RMSE=cbind(accuracy(hwa.frct, test)[,2],
                               accuracy(hwm.frct, test)[,2],
                               accuracy(ets.frct, test)[,2],
                              accuracy(arima.frct, test)[,2]))
  names(rmse) = c("Holt-Winters Additive", "Holt-Winters Multiplicative", "ETS", "ARIMA")

  # display rmse
  rmse
}
```

```r
powm_accuracy(power.ts)
```

```
##   Holt-Winters Additive Holt-Winters Multiplicative     ETS    ARIMA
## 1               1172803                     1141901 1151275 950035.4
```

Thus **ARIMA(0,0,1)(2,1,0)**[**12**] with drift has been the best model to describe the gicen time series.

Forecast 2014

In this last step we will perform the forecast for 2014.

- Power Usage - ARIMA(0,0,1)(2,1,0)[12] with drift and Box-Cox transformation -0.144

```r
pow.fcst.date <- seq(as.Date('2014-01-01'), as.Date('2014-12-01'), by="month") %>% format("%Y-%b")

write.xlsx(data.frame('DateTime' = pow.fcst.date, 'Waterflow'= power.arima.fcst$mean),
           "Kapoor_data624_pow_forecasts.xlsx")
```

```r
pow.fcst.ak <- read_excel("Kapoor_data624_pow_forecasts.xlsx", skip=0, col_types = c("text","numeric"))
pow.fcst.ak %>%
```

DateTime	Waterflow
2014-Jan	9501939
2014-Feb	8519991
2014-Mar	6633101
2014-Apr	5970555
2014-May	5921709
2014-Jun	8262795
2014-Jul	9524528
2014-Aug	10077395
2014-Sep	8489194
2014-Oct	5838172
2014-Nov	6108522
2014-Dec	7596503

```
  kbl() %>%
  kable_paper() %>%
  scroll_box(width = "500px", height = "200px")
```

Part C - Waterflow Pipe

In part C we have been provided 2 datasets for waterflow pipes. These are simple 2 columns sets, however they have different time stamps. Each dataset contains 1000 records and has no missing data.

```
download.file(url="https://github.com/amit-kapoor/data624/blob/main/Project1/Waterflow_Pipe1.xlsx?raw=t
              destfile = temp.file,
              mode = "wb",
              quiet = TRUE)
pipe1.data <- read_excel(temp.file, skip=0, col_types = c("date","numeric"))

download.file(url="https://github.com/amit-kapoor/data624/blob/main/Project1/Waterflow_Pipe2.xlsx?raw=t
              destfile = temp.file,
              mode = "wb",
              quiet = TRUE)

pipe2.data <- read_excel(temp.file, skip=0, col_types = c("date","numeric"))
```

It is apparent here that the data is recorded on different time intervals for pipe1 and pipe2. For pipe1 it shows records for multiple time intervals within an hour i.e. not evenly distributed while for pipe2 it seems hourly recorded.

```
pipe1.data %>%
  kbl() %>%
  kable_paper() %>%
  scroll_box(width = "500px", height = "200px")
```

```
pipe2.data %>%
  kbl() %>%
  kable_paper() %>%
  scroll_box(width = "500px", height = "200px")
```

Date Time	WaterFlow
2015-10-23 00:24:06	23.369599
2015-10-23 00:40:02	28.002881
2015-10-23 00:53:51	23.065895
2015-10-23 00:55:40	29.972809
2015-10-23 01:19:17	5.997953
2015-10-23 01:23:58	15.935223
2015-10-23 01:50:05	26.617330
2015-10-23 01:55:33	33.282900
2015-10-23 01:59:15	12.426692
2015-10-23 02:51:51	21.833494
2015-10-23 02:59:49	8.483647
2015-10-23 03:14:40	29.336901
2015-10-23 03:18:09	19.809146
2015-10-23 03:22:13	31.019744
2015-10-23 03:46:57	18.339962
2015-10-23 03:59:21	16.888527
2015-10-23 04:11:50	13.664312
2015-10-23 04:45:43	17.300074
2015-10-23 05:05:41	23.260984
2015-10-23 05:13:49	8.152496
2015-10-23 05:14:38	19.875628
2015-10-23 05:15:41	32.886499
2015-10-23 05:16:57	22.260364
2015-10-23 05:32:35	5.778369
2015-10-23 05:42:52	32.545557
2015-10-23 05:44:30	30.687744
2015-10-23 05:45:52	29.080907
2015-10-23 06:03:38	30.047784
2015-10-23 06:17:16	5.752456
2015-10-23 06:33:18	30.414162
2015-10-23 06:33:38	26.175716
2015-10-23 06:38:30	27.155307
2015-10-23 06:42:23	13.605943
2015-10-23 06:56:22	11.184568
2015-10-23 06:59:29	20.383057
2015-10-23 07:36:34	13.405331
2015-10-23 07:55:43	14.461091
2015-10-23 07:56:42	27.234671
2015-10-23 08:11:22	9.089498
2015-10-23 08:26:45	29.162384
2015-10-23 08:58:29	24.123214
2015-10-23 09:00:59	6.207443
2015-10-23 09:11:30	27.666923
2015-10-23 09:35:45	29.781898
2015-10-23 10:01:02	19.035463
2015-10-23 10:05:50	14.539055
2015-10-23 10:35:35	16.304829
2015-10-23 11:02:31	9.089600
2015-10-23 11:03:49	24.160478
2015-10-23 11:38:25	33.013436
2015-10-23 12:05:33	14.924758
2015-10-23 12:35:50	20.688466
2015-10-23 12:51:15	25.396306
2015-10-23 13:3[illegible]:23	21.661800
2015-10-23 13:38:34	23.214093
2015-10-23 13:43:01	3.811189
2015-10-23 14:02:58	37.300056

Date Time	WaterFlow
2015-10-23 01:00:00	18.810791
2015-10-23 02:00:00	43.087025
2015-10-23 03:00:00	37.987705
2015-10-23 04:00:00	36.120379
2015-10-23 05:00:00	31.851259
2015-10-23 06:00:00	28.238090
2015-10-23 07:00:00	9.863582
2015-10-23 08:00:00	26.679610
2015-10-23 09:00:00	55.773785
2015-10-23 10:00:00	54.156889
2015-10-23 11:00:00	68.374904
2015-10-23 12:00:00	55.710359
2015-10-23 13:00:00	56.968260
2015-10-23 14:00:00	17.206276
2015-10-23 15:00:00	35.093275
2015-10-23 16:00:00	44.424928
2015-10-23 17:00:00	57.322408
2015-10-23 18:00:00	37.344924
2015-10-23 19:00:00	11.483011
2015-10-23 20:00:00	32.117940
2015-10-23 21:00:00	49.081861
2015-10-23 22:00:00	49.133546
2015-10-23 23:00:00	42.064648
2015-10-24 00:00:00	58.380027
2015-10-24 01:00:00	53.408031
2015-10-24 02:00:00	42.332775
2015-10-24 03:00:00	45.922190
2015-10-24 04:00:00	32.741215
2015-10-24 05:00:00	47.879252
2015-10-24 06:00:00	47.460516
2015-10-24 07:00:00	52.264966
2015-10-24 08:00:00	35.389582
2015-10-24 09:00:00	14.435578
2015-10-24 10:00:00	45.038179
2015-10-24 11:00:00	38.896592
2015-10-24 12:00:00	39.991833
2015-10-24 13:00:00	56.883595
2015-10-24 14:00:00	62.728660
2015-10-24 15:00:00	67.382484
2015-10-24 16:00:00	29.645108
2015-10-24 17:00:00	51.586668
2015-10-24 18:00:00	61.987103
2015-10-24 19:00:00	46.394571
2015-10-24 20:00:00	32.838673
2015-10-24 21:00:00	53.416554
2015-10-24 22:00:00	70.723677
2015-10-24 23:00:00	21.570847
2015-10-25 00:00:00	66.762107
2015-10-25 01:00:00	36.322123
2015-10-25 02:00:00	45.114342
2015-10-25 03:00:00	53.473562
2015-10-25 04:00:00	27.209341
2015-10-25 05:00:00	44.193703
2015-10-25 06:00:00	59.296910
2015-10-25 07:00:00	42.253496
2015-10-25 08:00:00	44.747970
2015-10-25 09:00:00	50.182502
2015-10-25 10:00:00	[illegible]

Exploratory Analysis

In this first step for analysis, We will check the daily frequency count for both datasets. It is apparent here that number of records daily for pipe1 is not evenly distributed and there are more recording per hour for pipe1.

```
p1 <- pipe1.data
p1$Date <- ymd_hms(p1$`Date Time`)
p1$Date <- as.Date(p1$Date)

p1 <- p1 %>% group_by(Date) %>% summarise("Pipe1 Records count"=n())

p2 <- pipe2.data
p2$Date <- ymd_hms(p2$`Date Time`)
p2$Date <- as.Date(p2$Date)

p2 <- p2 %>% group_by(Date) %>% summarise("Pipe2 Records count"=n())

merge(p1,p2,by="Date")
```

```
##          Date Pipe1 Records count Pipe2 Records count
## 1  2015-10-23                  96                  23
## 2  2015-10-24                 109                  24
## 3  2015-10-25                  95                  24
## 4  2015-10-26                 118                  24
## 5  2015-10-27                  99                  24
## 6  2015-10-28                 104                  24
## 7  2015-10-29                  96                  24
## 8  2015-10-30                 111                  24
## 9  2015-10-31                  91                  24
## 10 2015-11-01                  81                  24
```

It is evident here that pipe1 dataset has an uneven count distribution for given date while pipe2 has even count daily.

Data Cleaning

In this step we will make pipe1 data evenly distributed (per hour) for every day. As mentioned in the problem *for multiple recordings within an hour, take the mean*, we will take mean of records per hour and then recreate the `Date Time` column. Next we will do the same count comparison that was done earlier and check number of records per day.

```
pipe1.data <- pipe1.data %>%
  mutate(Date=date(`Date Time`), Hour=hour(`Date Time`)) %>%
  group_by(Date, Hour) %>%
  summarise(WaterFlow=mean(WaterFlow)) %>%
  ungroup() %>%
  mutate(`Date Time`=ymd_h(paste(Date, Hour))) %>%
  select(`Date Time`, WaterFlow)
```

```
## `summarise()` has grouped output by 'Date'. You can override using the `.groups` argument.
```

```
# check the number of records per hour daily
p1 <- pipe1.data
p1$Date <- ymd_hms(p1$`Date Time`)
p1$Date <- as.Date(p1$Date)
```

```
p1 <- p1 %>% group_by(Date) %>% summarise("Pipe1 Records count"=n())

p2 <- pipe2.data
p2$Date <- ymd_hms(p2$`Date Time`)
p2$Date <- as.Date(p2$Date)

p2 <- p2 %>% group_by(Date) %>% summarise("Pipe2 Records count"=n())

merge(p1,p2,by="Date")
```

```
##          Date Pipe1 Records count Pipe2 Records count
## 1  2015-10-23                  24                  23
## 2  2015-10-24                  24                  24
## 3  2015-10-25                  24                  24
## 4  2015-10-26                  24                  24
## 5  2015-10-27                  23                  24
## 6  2015-10-28                  23                  24
## 7  2015-10-29                  24                  24
## 8  2015-10-30                  24                  24
## 9  2015-10-31                  24                  24
## 10 2015-11-01                  22                  24
```

Time Series

In this section we will create the timeseries out of both datasets and check out the best model that will eventually provide a week forward forecast.

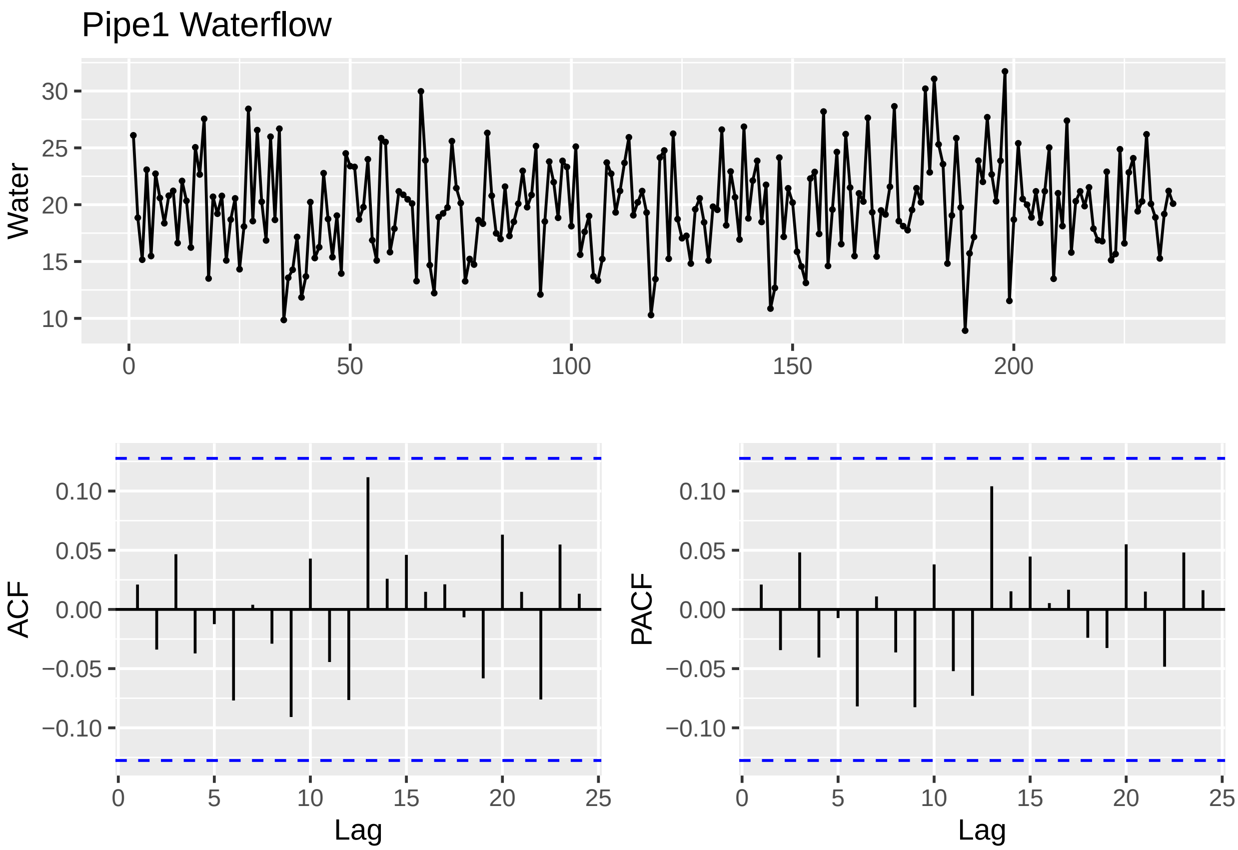
Pipe1

We will start with pipe1 dataset by creating its time series, plot the waterflow data and check the trend and seasonality, if exist.

```
pipe1.ts <- ts(pipe1.data$WaterFlow)
pipe1.ts %>% summary()
```

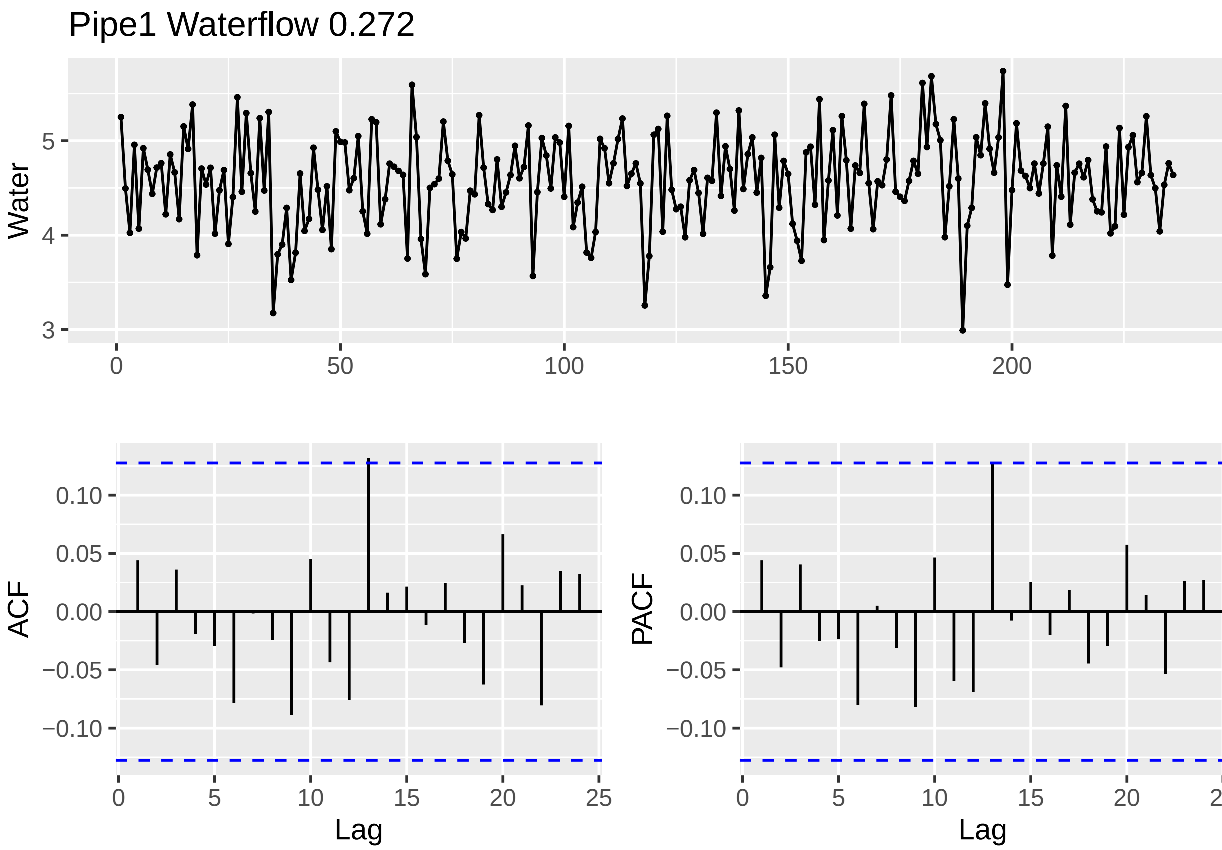
```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   8.923  17.033  19.784  19.893  22.789  31.730
```

```
ggtsdisplay(pipe1.ts, main="Pipe1 Waterflow", ylab="Water")
```



By seeing the time series, it is apparent there is no seasonality or trend in the data. The ACF and PACF plots shows white noise. It depicts that the time series is stationary and doesnt require diffencing.

```
pipe1.lambda <- BoxCox.lambda(pipe1.ts)
pipe1.ts.bc <- BoxCox(pipe1.ts, pipe1.lambda )
ggtsdisplay(pipe1.ts.bc, main=paste("Pipe1 Waterflow",round(pipe1.lambda, 3)), ylab="Water")
```




```r
# Number of differences required for a stationary series
ndiffs(pipe1.ts.bc)
```

```
## [1] 0
```

```r
pipe1.ts.bc %>% ur.kpss() %>% summary()
```

```
##
## #######################
## # KPSS Unit Root Test #
## #######################
##
## Test is of type: mu with 4 lags.
##
## Value of test-statistic is: 0.2346
##
## Critical value for a significance level of:
##                 10pct  5pct 2.5pct  1pct
## critical values 0.347 0.463  0.574 0.739
```

We can see the test statistic small and well within the range we would expect for stationary data. So we can conclude that the data are stationary.

```r
# ets
pipe1.ets.model <- pipe1.ts %>% ets(lambda = pipe1.lambda)
pipe1.ets.model
```

```
## ETS(A,N,N)
##
```

```
## Call:
##  ets(y = ., lambda = pipe1.lambda)
##
##   Box-Cox transformation: lambda= 0.272
##
##   Smoothing parameters:
##     alpha = 1e-04
##
##   Initial states:
##     l = 4.5771
##
##   sigma:  0.4936
##
##      AIC     AICc      BIC
## 960.1697 960.2731 970.5612
```

We can see here that the ets model that best describes the data is ETS(A,N,N) i.e. exponential smoothing with additive error, no trend and no seasonality.

Next we will find the best Arima model that fits this time series data.

```r
# arima
pipe1.arima.model <- pipe1.ts %>% auto.arima(lambda = pipe1.lambda)
pipe1.arima.model
```

```
## Series: .
## ARIMA(0,0,0) with non-zero mean
## Box Cox transformation: lambda= 0.271971
##
## Coefficients:
##         mean
##       4.5771
## s.e.  0.0320
##
## sigma^2 estimated as 0.2425:  log likelihood=-167.21
## AIC=338.42   AICc=338.47   BIC=345.35
```

The best Arima model comes out is ARIMA(0,0,0) with non-zero mean.

Next is to plot the forecasts using both the models described above: ets and arima. For this, we will create a generic function which will accept the time series and pipe number and plot the forecast using both the models.

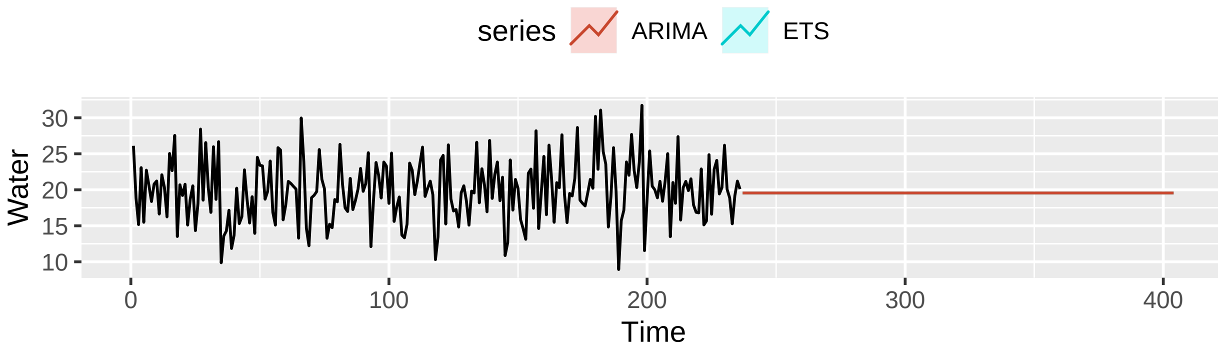
```r
# function to plot forecast(s)
pipe.forecast <- function(timeseries, pipe_num) {
  # lambda value
  lambda <- BoxCox.lambda(timeseries)

  # models for forecast
  ets.model <- timeseries %>% ets(lambda = lambda)
  arima.model <- timeseries %>% auto.arima(lambda = lambda)

  # forecast h=24*7=168
  pipe.ets.fcst <- forecast(ets.model, h=168)
  #print(pipe.ets.fcst$mean)
  pipe.arima.fcst <- forecast(arima.model, h=168)
  #print(pipe.arima.fcst$mean)
```

```r
  # plot forecasts
  p1 <- autoplot(timeseries) +
    autolayer(pipe.ets.fcst, PI=FALSE, series="ETS") +
    autolayer(pipe.arima.fcst, PI=FALSE, series="ARIMA") +
    theme(legend.position = "top") +
    ylab("Water")

  # zoom in plot
  if (pipe_num == 1) {
    p2 <- p1 +
      labs(title = "Zoom in ") +
      xlim(c(225,325))
  } else {
    p2 <- p1 +
      labs(title = "Zoom in ") +
      xlim(c(990,1150))
  }


  grid.arrange(p1,p2,ncol=1)

}
```

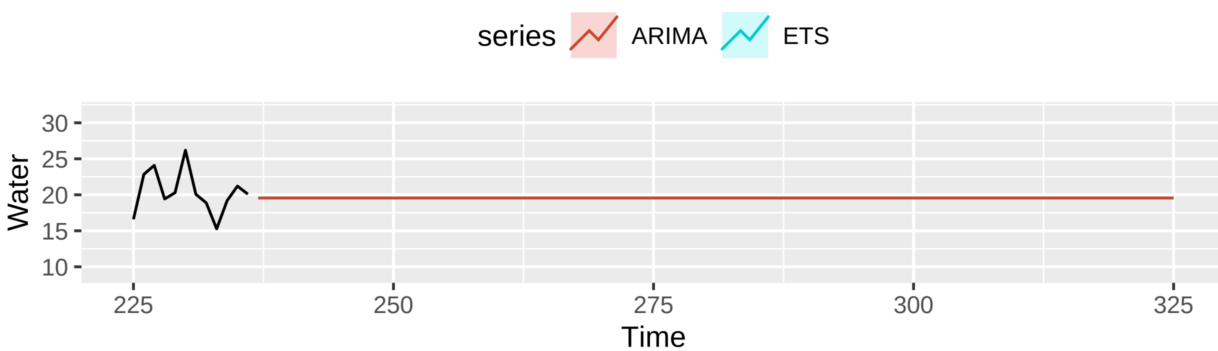
Lets plot the forecast for pipe1. The forecast is for every hour in a day for a week.

```r
pipe1.ets.fcst <- forecast(pipe1.ets.model, h=168)
pipe1.arima.fcst <- forecast(pipe1.arima.model, h=168)
pipe.forecast(pipe1.ts, 1)
```

```
## Scale for 'x' is already present. Adding another scale for 'x', which will
## replace the existing scale.
```



Zoom in



We can see that forecasts for both ETS and ARIMA models are almost on top of each other and for pipe1, the waterflow is forecasted to be 19.5548.

Now we will check the accuracy of both the models ETS and ARIMA. Again for this purpose, we have created a function that accepts the timeseries and a timebreak (for train and test data). In this function we will first divide the data for training and testing, train both models with train set and then find out RMSE using test data.

```
pipe_accuracy <- function(timeseries, time_break) {
  # lambda value
  lambda <- BoxCox.lambda(timeseries)

  # split the data to train and test
  train <- window(timeseries, end=time_break)
  test <- window(timeseries, start=time_break+1)

  # models for forecast
  ets.model <- train %>% ets(model="ANN", lambda = lambda, biasadj = TRUE)
  arima.model <- train %>% Arima(order=c(0,0,0),
                                 lambda = lambda,
                                 biasadj = TRUE)

  # forecast
  ets.frct = forecast(ets.model, h = length(test))$mean
  arima.frct = forecast(arima.model, h = length(test))$mean

  # dataframe having rmse
  rmse = data.frame(RMSE=cbind(accuracy(ets.frct, test)[,2],
                              accuracy(arima.frct, test)[,2]))
  names(rmse) = c("ETS", "ARIMA")
```

```
  # display rmse
  rmse
}
```

By passing multiple time breaks for training and test data, we see below RMSEs.

```
pipe_accuracy(pipe1.ts, 190)
```

```
##        ETS    ARIMA
## 1 3.950938 3.951593
```

```
pipe_accuracy(pipe1.ts, 178)
```

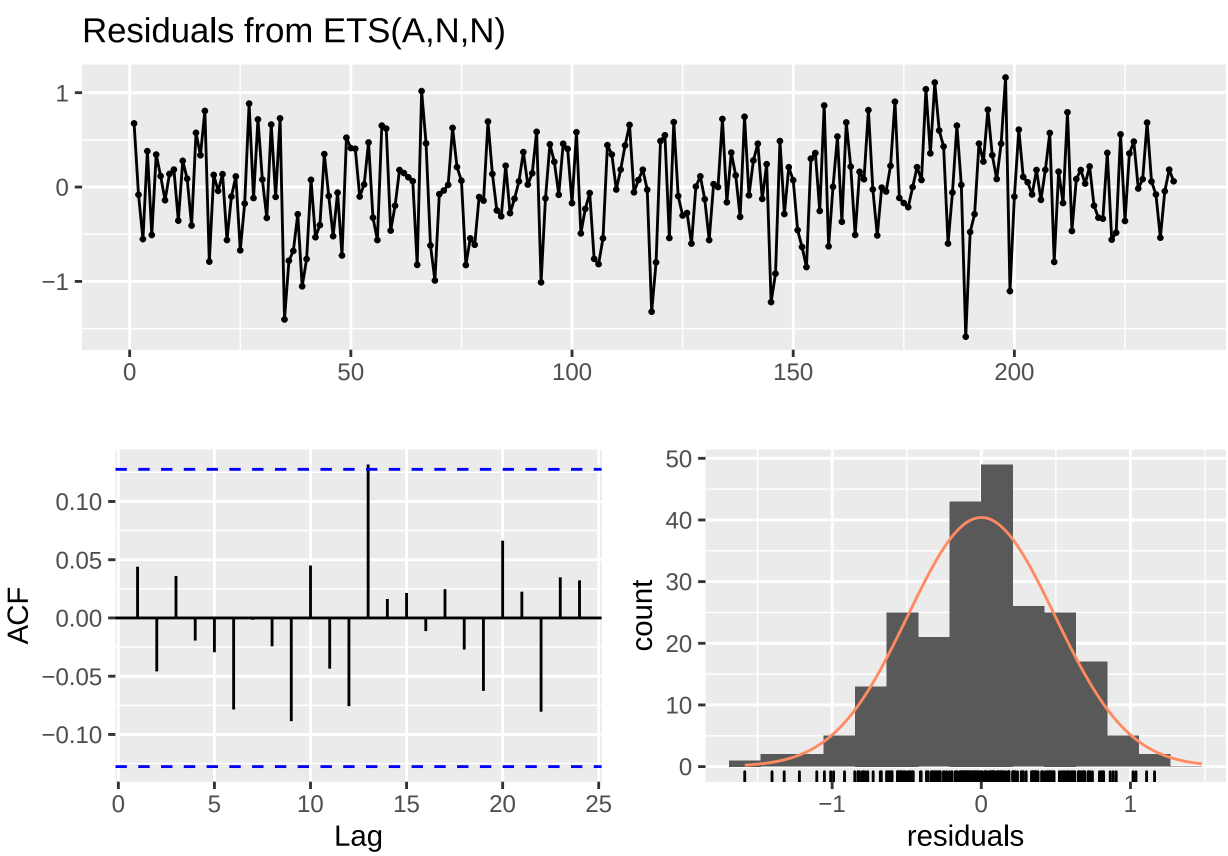
```
##        ETS    ARIMA
## 1 4.585535 4.585881
```

```
pipe_accuracy(pipe1.ts, 200)
```

```
##        ETS    ARIMA
## 1 3.275964 3.276062
```

It is evident here that the model best describes the pipe1 time series is **ETS(A,N,N) with Box-Cox transformation of 0.272**.

```
checkresiduals(pipe1.ets.model)
```




```
##
##  Ljung-Box test
##
## data:  Residuals from ETS(A,N,N)
```

```
## Q* = 5.684, df = 8, p-value = 0.6826
##
## Model df: 2.   Total lags used: 10
```

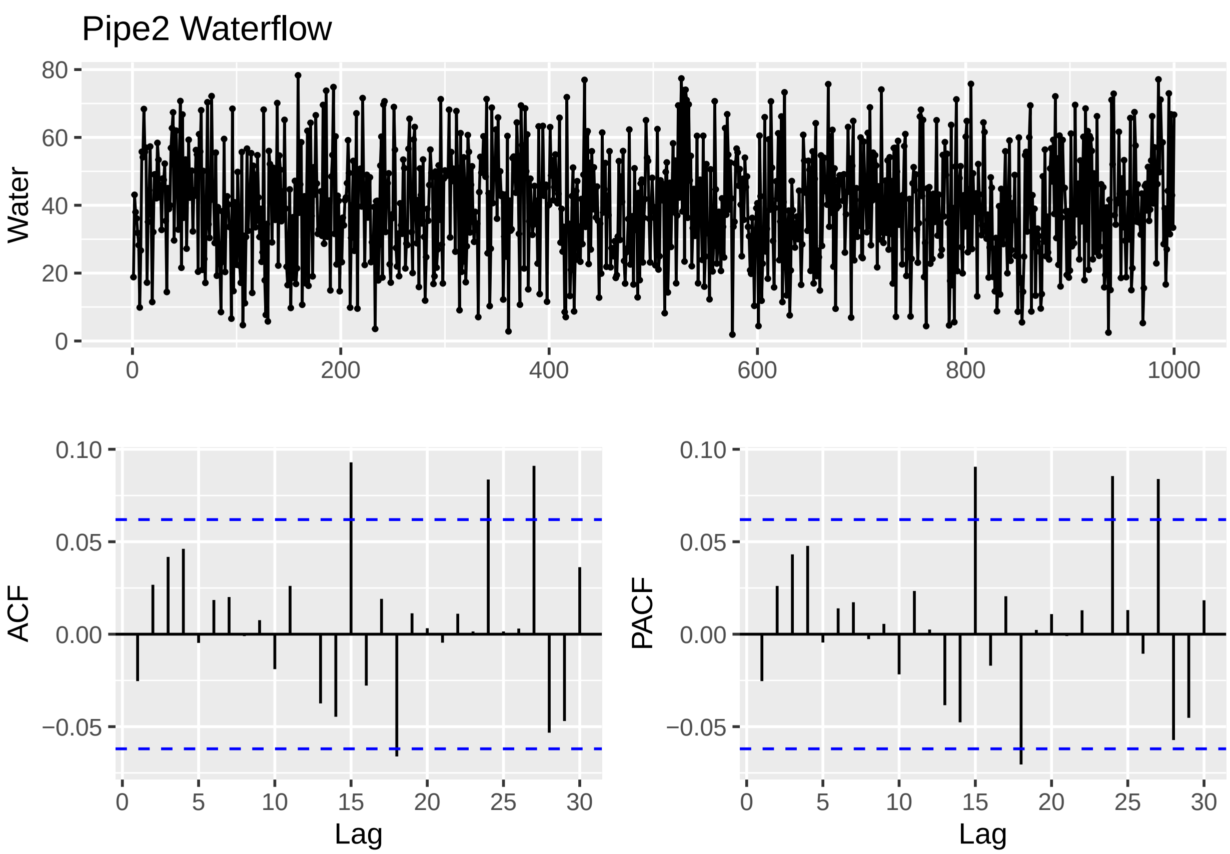
Pipe2

Similar to pipe1, we will create time series for pipe2, plot the waterflow data and check the trend and seasonality, if exist.

```
pipe2.ts <- ts(pipe2.data$WaterFlow)
pipe2.ts %>% summary()
```

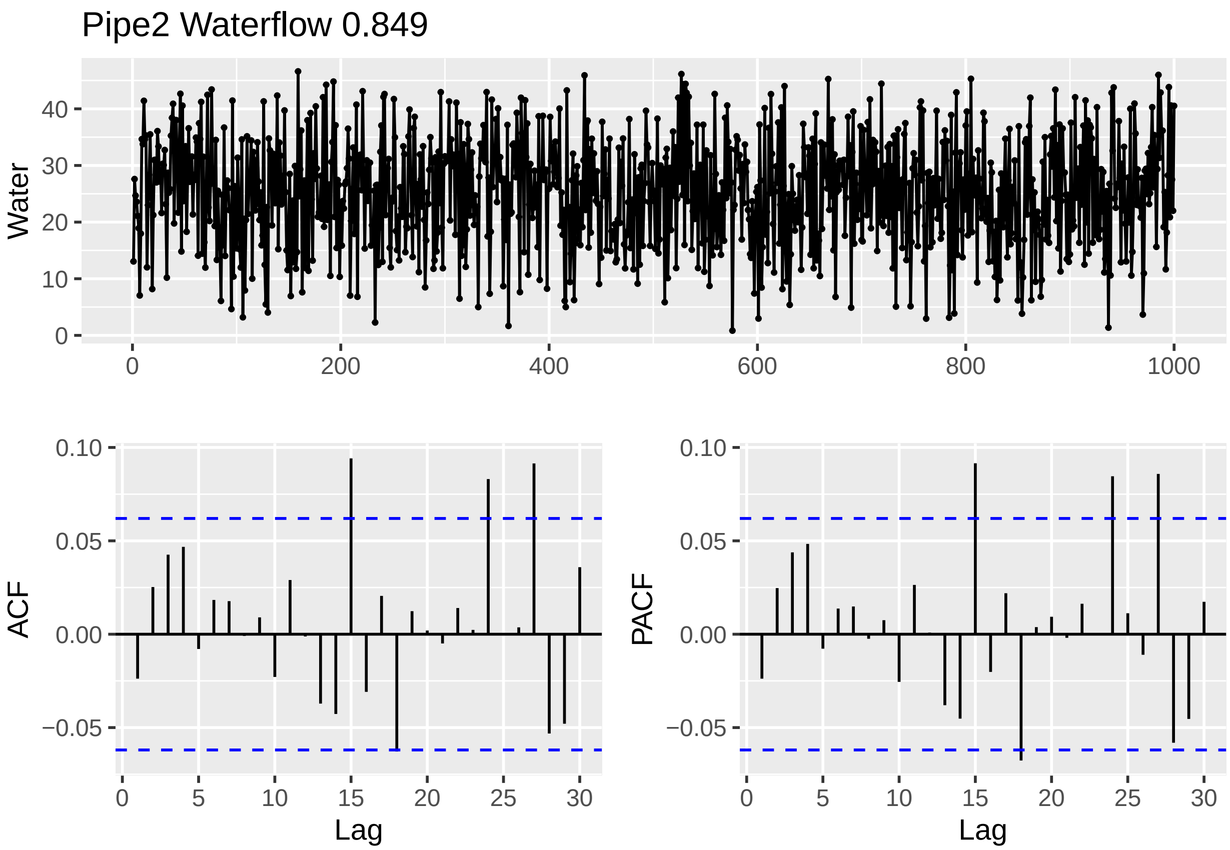
```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.885  28.140  39.682  39.556  50.782  78.303
```

```
ggtsdisplay(pipe2.ts, main="Pipe2 Waterflow", ylab="Water")
```



By seeing the time series, it is apparent there is no seasonality or trend in the data. The ACF and PACF plots shows few significant auto correlations.

```
pipe2.lambda <- BoxCox.lambda(pipe2.ts)
pipe2.ts.bc <- BoxCox(pipe2.ts, pipe2.lambda )
ggtsdisplay(pipe2.ts.bc, main=paste("Pipe2 Waterflow",round(pipe2.lambda, 3)), ylab="Water")
```




```r
# Number of differences required for a stationary series
ndiffs(pipe2.ts.bc)
```

```
## [1] 0
```

```r
pipe2.ts.bc %>% ur.kpss() %>% summary()
```

```
##
## #######################
## # KPSS Unit Root Test #
## #######################
##
## Test is of type: mu with 7 lags.
##
## Value of test-statistic is: 0.1067
##
## Critical value for a significance level of:
##                 10pct  5pct 2.5pct  1pct
## critical values 0.347 0.463  0.574 0.739
```

We can see the test statistic small and well within the range we would expect for stationary data. So we can conclude that the data are stationary.

```r
# ets
pipe2.ets.model <- pipe2.ts %>% ets(lambda = pipe2.lambda)
pipe2.ets.model
```

```
## ETS(A,N,N)
##
```

```
## Call:
##  ets(y = ., lambda = pipe2.lambda)
##
##   Box-Cox transformation: lambda= 0.8493
##
##   Smoothing parameters:
##     alpha = 1e-04
##
##   Initial states:
##     l = 25.2727
##
##   sigma:  9.3622
##
##      AIC     AICc      BIC
## 11385.12 11385.14 11399.84
```

We can see here that the ets model that best describes the data is ETS(A,N,N) i.e. exponential smoothing with additive error, no trend and no seasonality.

Next we will find the best Arima model that fits this time series data.

```r
# arima
pipe2.arima.model <- pipe2.ts %>% auto.arima(lambda = pipe2.lambda)
pipe2.arima.model
```

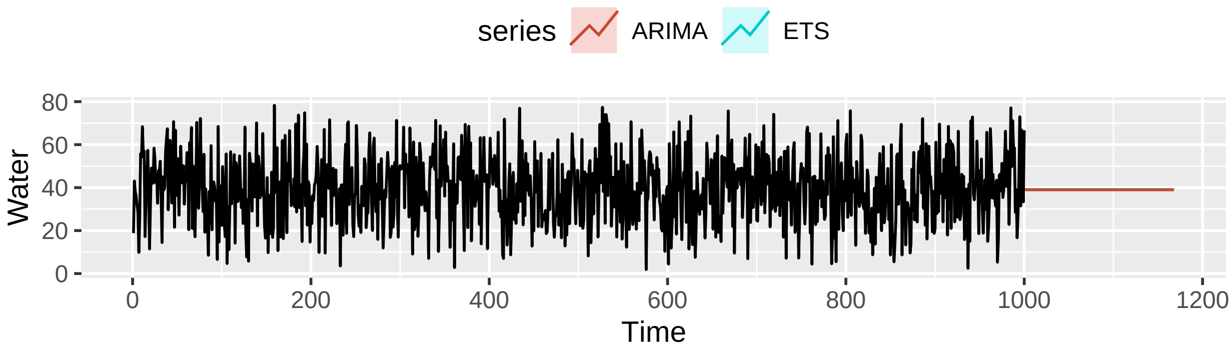
```
## Series: .
## ARIMA(0,0,0) with non-zero mean
## Box Cox transformation: lambda= 0.8493285
##
## Coefficients:
##          mean
##       25.2700
## s.e.   0.2957
##
## sigma^2 estimated as 87.55:  log likelihood=-3654.57
## AIC=7313.14   AICc=7313.15   BIC=7322.96
```

The best Arima model for pipe1 comes out is ARIMA(0,0,0) with non-zero mean, similar to pipe1.

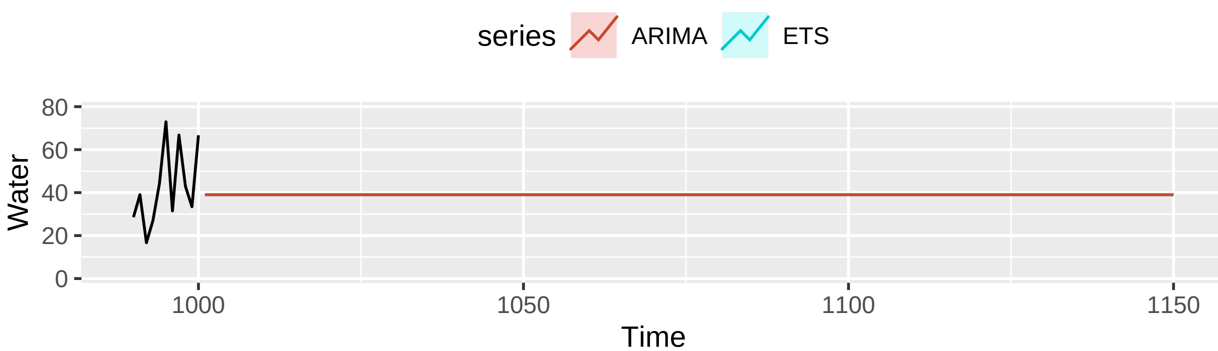
Next we will see the forecast plots using both these models for pipe1.

```r
pipe2.ets.fcst <- forecast(pipe2.ets.model, h=168)
pipe2.arima.fcst <- forecast(pipe2.arima.model, h=168)
pipe.forecast(pipe2.ts, 2)
```

```
## Scale for 'x' is already present. Adding another scale for 'x', which will
## replace the existing scale.
```



Zoom in



Similar to pipe1, ee can see that forecasts in this case for both ETS and ARIMA models are almost on top of each other and for pipe2, the waterflow is forecasted to be 39.012.

By passing multiple time breaks for training and test data, we see below RMSEs.

```
pipe_accuracy(pipe2.ts, 969)
```

```
##        ETS    ARIMA
## 1 18.36835 18.35826
```

```
pipe_accuracy(pipe2.ts, 850)
```

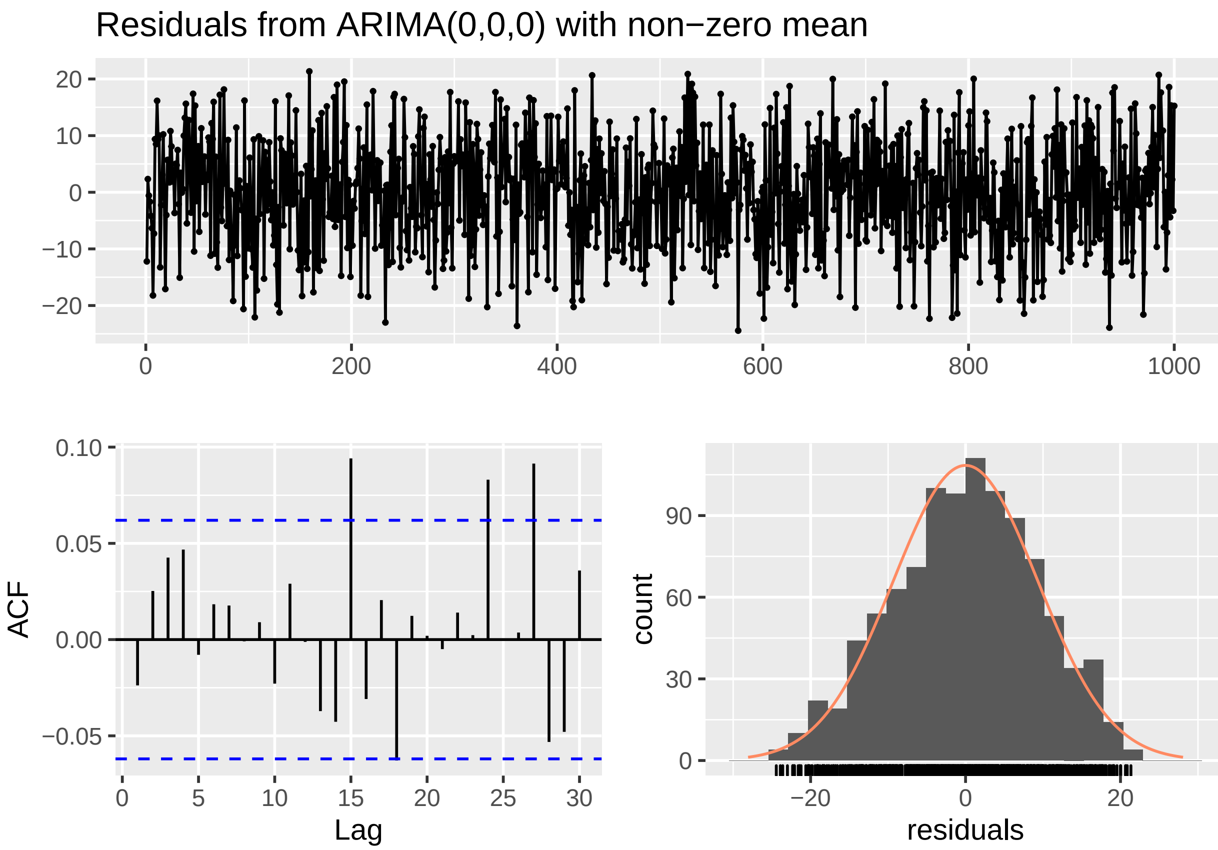
```
##        ETS    ARIMA
## 1 17.00739 17.00745
```

```
pipe_accuracy(pipe2.ts, 877)
```

```
##        ETS    ARIMA
## 1 16.60519 16.60477
```

It is evident here that the model best describes the pipe2 time series is ARIMA(0,0,0) with Box-Cox transformation of 0.849.

```
checkresiduals(pipe2.arima.model)
```




```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(0,0,0) with non-zero mean
## Q* = 6.564, df = 9, p-value = 0.6824
##
## Model df: 1.   Total lags used: 10
```

Forecast a week forward

Finally lets do the forecast for both pipes (pipe1 and pipe2) using the above selected best models and save the corresponding xlsx.

- Pipe1 - ETS(A,N,N) with Box-Cox transformation of 0.272
- Pipe2 - ARIMA(0,0,0) with Box-Cox transformation of 0.849

```
pipe1.fcst.date <- seq(ymd_hm('2015-11-01 24:00'), ymd_hm('2015-11-08 23:00'), by="hour")
pipe2.fcst.date <- seq(ymd_hm('2015-12-03 17:00'), ymd_hm('2015-12-10 16:00'), by="hour")

write.xlsx(data.frame('DateTime' = pipe1.fcst.date, 'Waterflow'= pipe1.ets.fcst$mean),
           "Kapoor_data624_pipe1_forecasts.xlsx")

write.xlsx(data.frame('DateTime' = pipe2.fcst.date, 'Waterflow'= pipe2.arima.fcst$mean),
           "Kapoor_data624_pipe2_forecasts.xlsx")
```

```
pipe1.fcst.ak <- read_excel("Kapoor_data624_pipe1_forecasts.xlsx", skip=0, col_types = c("date","numeri
pipe1.fcst.ak %>%
  kbl() %>%
```

```
  kable_paper() %>%
  scroll_box(width = "500px", height = "200px")
```

```
pipe2.fcst.ak <- read_excel("Kapoor_data624_pipe2_forecasts.xlsx", skip=0, col_types = c("date","numeri
pipe2.fcst.ak %>%
  kbl() %>%
  kable_paper() %>%
  scroll_box(width = "500px", height = "200px")
```

DateTime	Waterflow
2015-11-02 00:00:00	19.55481
2015-11-02 01:00:00	19.55481
2015-11-02 02:00:00	19.55481
2015-11-02 03:00:00	19.55481
2015-11-02 04:00:00	19.55481
2015-11-02 05:00:00	19.55481
2015-11-02 06:00:00	19.55481
2015-11-02 07:00:00	19.55481
2015-11-02 08:00:00	19.55481
2015-11-02 09:00:00	19.55481
2015-11-02 10:00:00	19.55481
2015-11-02 11:00:00	19.55481
2015-11-02 12:00:00	19.55481
2015-11-02 13:00:00	19.55481
2015-11-02 14:00:00	19.55481
2015-11-02 15:00:00	19.55481
2015-11-02 16:00:00	19.55481
2015-11-02 17:00:00	19.55481
2015-11-02 18:00:00	19.55481
2015-11-02 19:00:00	19.55481
2015-11-02 20:00:00	19.55481
2015-11-02 21:00:00	19.55481
2015-11-02 22:00:00	19.55481
2015-11-02 23:00:00	19.55481
2015-11-03 00:00:00	19.55481
2015-11-03 01:00:00	19.55481
2015-11-03 02:00:00	19.55481
2015-11-03 03:00:00	19.55481
2015-11-03 04:00:00	19.55481
2015-11-03 05:00:00	19.55481
2015-11-03 06:00:00	19.55481
2015-11-03 07:00:00	19.55481
2015-11-03 08:00:00	19.55481
2015-11-03 09:00:00	19.55481
2015-11-03 10:00:00	19.55481
2015-11-03 11:00:00	19.55481
2015-11-03 12:00:00	19.55481
2015-11-03 13:00:00	19.55481
2015-11-03 14:00:00	19.55481
2015-11-03 15:00:00	19.55481
2015-11-03 16:00:00	19.55481
2015-11-03 17:00:00	19.55481
2015-11-03 18:00:00	19.55481
2015-11-03 19:00:00	19.55481
2015-11-03 20:00:00	19.55481
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